Article

Are Stars Worth Following? Measuring the Target Price Predictive Ability of Star Analysts in an Emerging Market

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Abstract

This article investigates whether star analysts, identified as the best stock pickers by Thomson Reuters' StarMine Awards, have superior target price forecasts than non-star analysts in an emerging market. The difference between star and non-star analysts is the former's use of attention-seeking tactics by issuing aggressive target price forecasts. Empirical results indicate that the performance of star analysts is not significantly different from that of non-star analysts in the short term or at the end of the forecast horizon. However, star analysts have better short-term performance than non-star analysts for a sub-set of technology-driven, high-growth stocks which have higher liquidity and rapid incorporation of information. In essence, star-analysts have better short-term predictive ability than non-star analysts for stocks with higher trading volume and better flow of information. The key finding of this study is that investors in emerging markets like India have limited advantage in following target price forecasts issued by star analysts.

Keywords

Equity research, star analysts, target price, emerging markets.

Introduction

The sell-side analysts, or the analysts belonging to firms that sell investment services, have been widely investigated in academic literature for their role as information providers in equity capital markets. Analysts, in general, are considered as an important source of information for an assortment of market participants including retail investors, fund managers, pension managers and high-net-worth investors (Kerl, 2011). Some of the previous studies yield evidence to suggest that analyst recommendations have investment value (Asquith, Mikhail, & Au, 2005; Barber, Lehavy, McNichols, & Trueman 2001; Da & Schaumburg, 2011; Gleason, Johnson, & Li, 2013; Kerl, 2011; Sayed & Chaklader, 2014; Stickel, 1995; Womack, 1996). Some others, on the other hand, have questioned the investment value associated with analyst recommendations (Bonini, Zanetti, Bianchini, & Salvi, 2010; Jackson, 2005). In a recent research, it has been argued that analysts possess differential forecasting abilities (Bradshaw, Brown, & Haung, 2013). This, to some extent, explains why some studies find evidence in favour of the superior forecasting abilities of financial analysts and some do not. To help investors identify analysts with superior forecasting abilities, financial services firms—including *Institutional Investor* (Magazine), *The Wall Street Journal* and Thomson Reuters—provide lists of such analysts. Thomson Reuters' StarMine, for instance, provides a sector-wise list of star analysts on the basis of their earnings forecast accuracy and stock-picking abilities.

Do these star analysts continue to outperform the non-star analysts after receiving an award? Fang and Yasuda (2014) find that analysts who are rated as star analysts by *Institutional Investor* have superior forecasting abilities compared to other analysts. In an earlier research, Leone and Wu (2007) argued that superior forecasting abilities of

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star analysts are associated with skills rather than luck. In essence, these studies imply that star analysts continue to outperform non-star analysts, even after receiving an award, primarily on the basis of their superior analytical abilities. Although there have been a few studies that express doubt on the ability of star analysts (Hall & Tacon, 2010), the overall impression is that star analysts possess superior forecasting abilities. In yet another research, Kerl and Ohlert (2015) find that star analysts perform better in the developed countries having a higher level of corporate governance. Since the focus of most of the previous studies have been on the developed markets, a research on measuring the predictive ability of star analysts in the different institutional setting of emerging markets may provide a fresh perspective.

Bonini et al. (2010) suggest that analysts get less incentive to issue accurate target price forecasts, because their compensation is generally linked to accurate earnings forecasts. This explains why two previous studies (Hall & Tacon, 2010; Kerl & Ohlert, 2015) did not find evidence to support the hypothesis that star analysts issue more accurate target price forecasts than non-star analysts. However, from an investor's point of view, target price forecasts offer the most direct advice with regard to generating profit from equity investments. Moreover, for the rankings to be relevant, star analysts should be able to provide investors with better target price forecasts than non-star analysts. This study extends research on the target price performance of star analysts in an institutional setting associated with low regulatory framework and poor reporting.[1] The main objective of this research is to test whether investors in India can benefit by adhering to the recommendations of star analysts who are expected to have better stock price forecasting abilities than non-star analysts.

The results of the study show that star analysts, recognized as the best stock pickers in the Thomson Reuters StarMine Awards database, do not have superior stock price forecasting abilities in the short-term or at the end of the one-year forecast horizon for the overall sample. However, once the sample is split, there is statistical evidence to suggest that star analysts have superior short-term target price performance for technology stocks when compared with non-star analysts. Emerging markets like India are shallow in nature with high information asymmetry. From this study, it can be observed that star analysts are more accurate than non-star analysts in making target price forecasts for high-growth, technology stocks. Growth stocks tend to be called glamour stocks and such stocks are more liquid and tend to receive higher media attention. DellaVigna and Pollet (2009) find that higher media coverage leads to more rapid incorporation of information. It can be inferred that higher stock liquidity and rapid incorporation of information in glamour, technology stocks possibly helps skilled star analysts in outperforming non-star analysts in an emerging market like India. The study also finds that star analysts underperform non-star analysts with non-technology stocks, which have lower liquidity and slower incorporation of information. In essence, star analysts outperform non-star analysts only for stocks which have higher stock liquidity and rapid incorporation of information. The key finding of this study is that investors are able to reap only limited advantage in following target price forecasts issued by star analysts. The study also finds that star analysts are more aggressive with their target price forecasts than non-star analysts, reflecting a deliberate attempt by star analysts to grab the limelight with bolder forecasts.

The article has been arranged as follows: first, a detailed review of relevant literature is presented which is followed by hypothesis development. It then discusses the dataset and research design, followed by a detailed recording of the statistical findings. The conclusion sums up the findings.

Literature Review

Star analysts have been a subject of academic interest over the past few decades. One strand of literature focuses on the persistent abilities of star analysts. Stickel (1995) finds a positive association between reputation and performance, while Desai, Liang and Singh (2000) document that the star analysts identified by *The Wall Street Journal* outperform benchmarks controlled for size and industry. In a similar vein, recent studies (Bonner, Hugon, & Walther, 2007; Fang & Yasuda, 2014; Leone & Wu, 2007) have shown evidence to suggest that star analysts have better earnings forecasting abilities than non-star analysts. Another strand of literature focuses on the career aspects and portability of star analysts. Groysberg, Lee and Nanda (2008) report that brokerages hiring star analysts may not gain competitive advantage as their performance generally drops after switching jobs. Clarke, Khorana, Patel and Rau (2007) suggest that a star analyst's decision to cover a firm after changing his or her job is influenced by the investment bank's relationship with the firm. These studies provide insights on the impact of switching jobs over the performance and coverage of star analysts. Kerl and Ohlert (2015) provide yet another perspective related to star analysts. They investigated the performance of analysts in different institutional settings across Europe and the US and found that star analysts have superior forecasting abilities with respect to earnings in countries with better corporate governance. In an earlier study, Bilinski, Lyssimachou and Walker (2013) also reported that the target price performance of analysts improves in countries with better corporate governance. The survey of literature reveals the fact that most of the research on star analysts have been conducted on data from developed markets only. This study aims to fill the gap in research that has been created due to the lack of studies on the data coming from emerging markets.

Asquith et al (2005) document that analysts issue three summary outputs in their research reports—earnings forecasts, stock recommendations and target price forecasts. The survey of literature reveals that the works of Hall and Tacon (2010) and Kerl and Ohlert (2015) are the only studies which deal with target price performance, more specifically the stock price predictive ability of star analysts in developed markets across Europe, US and Australia. To get more information on the relevance of target price forecasts of star analysts, this research investigates target price performance of star analysts, as compared to non-star analysts, in the emerging market of India.

Hypothesis Development

Broadly, the review of literature suggests that star analysts have superior forecasting abilities compared to non-star analysts. Bilinski et al. (2013) observe that literature is heavily skewed in favour of earnings forecast accuracy than target price performance. Even while taking into account the emerging market perspective, evidence which proposed that star analysts in China have superior forecasting abilities was with respect to earnings forecasts (Xu, Chan, Jiang, & Yi, 2013). In one of the few studies that addresses target price accuracy of star analysts, Kerl and Ohlert (2015) do not find any difference in the target price performance of star analysts and non-star analysts across US and Europe. However, according to them, better corporate governance was positively correlated with the performance of star analysts. Fang and Yasuda (2014), on the other hand, find that reputed analysts are more skilled and are able to resist conflict of interest better than non-reputed analysts. This study builds on the investigations of Fang and Yasuda (2014) and Kerl and Ohlert (2015) and evaluates the performance of star analysts in India.

Emerging markets like India are different from developed markets in their institutional settings. Bekaert and Harvey (2013) observe that even after 20 years of globalization, emerging market equities are treated as a basket of equities which offer high returns to compensate for higher perceived risks. The higher perceived risk is partly associated with the speculative and shallow nature of emerging markets. These characteristics are bestowed upon Indian equity markets because of two reasons—only a few stocks are actively traded and there is less public shareholding on account of high promoter holding (Chandrashekhar, 2013). Based on this discussion, the first hypothesis of this research has been formulated as:

Hypothesis 1 (H1): Star analysts will issue significantly more accurate target price forecasts than non-star analysts in India.

Since emerging markets are typically associated with shallow trading patterns, it is quite possible that star analysts produce better results with stocks which promise higher returns. In fact, Fang and Yasuda (2014) find that the reputed analysts significantly outperform other analysts with forecasts on technology stocks. Based on this discussion, the second and third hypotheses of this study are formulated as follows:

Hypothesis 2 (H2): Star analysts will issue significantly more accurate target price forecasts for technology-driven stocks than non-star analysts in India.

Hypothesis 3 (H3): Star analysts will issue significantly more accurate target price forecasts for non-technology driven stocks than non-star analysts in India.

Dataset and Research Design

Star Analyst Data

The primary databases from which the list of star analysts with superior forecasting abilities in the Indian equity market can be achieved are *Institutional Investor* (Magazine), *The Wall Street Journal* and the Thomson Reuters StarMine. For this study the data from Thomson Reuters StarMine database[2] has been used. The relevant data objectively measures the performance of analysts based on the returns of their buy/sell recommendations and the accuracy of their earnings estimates. The sample for the study consists of 41 star analysts with superior stock-picking abilities, who were identified from different sectors between 2009 and 2011 by StarMine. To represent star analysts, a dummy variable *STAR* has been created which takes a value of 1 if the analyst receives an award; otherwise the value is 0. The logic behind this is that analysts who possess superior stock-picking abilities[3] should be able to predict stock prices with better accuracy than other analysts. Table 1 provides a formal definition for *STAR* and other variables used in this research.

Table 1. Variable Description

Variable	Description
Forecast Measures	
TPMETANY	*TPMETANY* is a dummy variable with value 1 if target price has been achieved anytime during forecast horizon, or the value is 0. This is a short-term measure of analyst target price performance.
TPERROR	*TPERROR* provides evidence of absolute investment error related to stock price at the end of forecast horizon and is calculated as |(P12-TP)/P| error, where the absolute difference between stock price at end of 12 months (P12) and target price (TP) is scaled to stock price at time of issue of target price forecast (P).
Firm specific factors	
PB RATIO	*PB RATIO* is measured as the price to book value at the time of issue of target price forecast.
STOCKVOL	*STOCK VOL* is the annualized volatility of stock based on past one year's historical returns of the stock. It is calculated as the standard deviation of log normal returns of the stock over the past one year multiplied by the square root of 252.
LOGMKTCAP	*LOGMKTCAP* is the log of market capitalization of stock at the time of issue of target price forecast in terms of USD.
Analyst specific factors	
ABS_BOLD	*ABS_BOLD is* measured as |(TP – P)/P| where TP is target price issued by analyst and P is the price of the stock at the time of issue of target price forecast.
SIGN_BOLD	*SIGN_BOLD is* measured as (TP – P)/P where TP is target price issued by analyst and P is the price of the stock at the time of issue of target price forecast.
INTBROKER	*INTBROKER* is a dummy variable where a value of 1 is assigned to skilled analysts working with international brokers, or a value of 0 is assigned.
STAR	*STAR* is a dummy variable which has a value of 1 if analyst has been identified by Thomson Reuters StarMine as a star analyst with superior stock-picking abilities.

Source: Author's own.

Dataset

The overall sample consists of 859 target price forecasts issued by analysts between 2010 and 2013. Research reports containing these target price forecasts have been collected from Thomson Reuters' Firstcall database, which contains research reports from domestic as well as international brokerages. The target price forecasts have been issued for 124 stocks trading in the Indian equity market. Out of these 124 stocks, 50 belong to the NIFTY 50 index which represents almost 70 per cent of the free-float market capitalization on National Stock Exchange.[4] The overall sample consists of 68 per cent buy ratings, 20 per cent hold ratings and 12 per cent sell ratings. A part of the sample also comprises the 114 target price forecasts issued by star analysts after receiving the award.

The sample is divided into two subsets for the purpose of further analysis. Subset 1 consists of high-growth, technology-driven stocks in India. These stocks belong to sectors such as biotechnology, information technology, media and telecom.[5] All the other stocks are categorized in subset 2 as stable-growth, non-technology stocks.

Target Price Accuracy Measures

Target price forecasts are usually issued by analysts for a 12-month period. Bilinski et al. (2013) have used two measures of target price accuracy to capture analyst performance in the short term and at the end of the forecast horizon. Both these measures have been used in this study as well. *TPMETANY*[6] is as a short-term measure of target price forecast suitable for limit order trading strategy.[7] *TPMETANY* takes a value of 1 if the target price is achieved anytime during the forecast horizon; otherwise the value is 0. *TPERROR*[8] is a measure of analyst performance at the end of the forecast horizon and is calculated as the investment error associated with stock price. *TPERROR* is calculated as follows:

$$TPERROR = |(P12 - TP) / P|$$

where $P12$ is the actual stock price at the end of the forecast horizon,[9] TP is the target price forecast issued by the analyst and P is the stock price at the time of issue of the forecast.

Control Variables

Next, the study presents control variables which adjust for complexity of a task while generating target price forecasts. To begin with, Kerl (2011) associates target price accuracy negatively with price-to-book and volatility of a firm. Based on this assumption, a negative association is expected between analyst performance and price-to-book (*PB RATIO*) and volatility of stock (*STOCKVOL*). *PB RATIO* is calculated as the ratio of stock price-to-book value per share at the time of issue of the forecast, whereas *STOCKVOL* is calculated as the standard deviation of log normal returns of the stock over the past one year multiplied by the square root of 252. Dvořák (2005) opines that analysts working with international brokerages are sophisticated and provide more useful investment advice. *INTBROKER* is, therefore, used as a control variable when an analyst works for an international brokerage, and this is expected to reflect a positive association with target price performance. *INTBROKER* is a dummy variable where a value of 1 is assigned to analysts working with international brokerages; otherwise a value of 0 is assigned. Kerl (2011) also finds that firm size is positively associated with target price performance. Firm size *(LOGMKTCAP)* is introduced as a control variable with an expectation that target price performance improves with larger firms. *LOGMKTCAP* is the log of market capitalization of stock at the time of issue of target price forecast in terms of US Dollar.

Demirakos, Strong and Walker (2010) define analyst boldness as the absolute distance or difference between the current stock price and the target price scaled to the current stock price. In fact, they have defined signed distance (boldness) as the difference between the current stock price and target price divided by the current stock price. The absolute value of the difference is absolute distance (Demirakos et al., 2010). However, they use and recommend absolute boldness *(ABS_BOLD)* in regression analysis with an expectation that higher absolute boldness reduces analyst accuracy (Demirakos et al., 2010). Analyst boldness (or optimism), by itself, has received considerable academic interest with studies focusing on factors affecting it (Bradshaw, Huang, & Tan, 2014; Ciccone, 2003; Cowen, Groysberg, & Healy, 2006; Demirakos et al., 2010). Along with target price accuracy, this study also investigates the differences in analyst optimism of star and non-star analysts. It is expected that analysts, in general, are more optimistic with smaller, riskier stocks (Demirakos et al., 2010). *SIGN_BOLD* is measured as (TP–P)/P and *ABS_BOLD* is measured as |(TP–P)/P|, where TP is target price issued by analyst and P is the price of the stock at the time of issue of target price forecast.

Regression Equations

Analyst boldness can be measured as soon as the target price has been issued, while analyst performance can be measured later, that is, during the forecast horizon of one year. Since boldness comes first in this sequence, regression equations for *ABS_BOLD* and *SIGN_BOLD* are introduced first, followed by the regression equations which address the main hypothesis.

To test whether star analysts are significantly more aggressive and optimistic with target price forecasts when compared with non-star analysts, the following Ordinary Least Squares (OLS) regression equation is set up:

$$\begin{aligned}&\{ABS\_BOLD/SIGN\_BOLD\} =\\ &\beta_0 + \beta_1 LOGMTKCAP +\\ &\beta_2 STOCKVOL + \beta_3 STAR + \varepsilon\end{aligned} \tag{1}$$

All variables used in this regression equation are defined in Table 1.

To test the main hypothesis through regression, that is, whether star analysts outperform non-star analysts, two dependent variables *TPMETANY* and *TPERROR* were used. *TPMETANY* is a dummy variable; Greene (2002) suggests the use of logit regression[10] when the dependent variable is binary. It is assumed that P_i is the probability of the target price being achieved and $(1–P_i)$ is the probability of the target price not being achieved. A logit model is based on cumulative logistic probability distribution function (Gujarati and Porter, 2008). It is specified as

$$P_i = F(L_i) = F(\alpha + \beta X_i) = \frac{1}{1 + e^{-L_i}} \tag{2}$$

where

L_i = $\alpha + \beta X_i$
P_i = the probability of i^{th} target price being achieved.
$1–P_i$ = the probability of i^{th} target price not being achieved
e = base of the natural logarithm
X = a vector of independent variables
β = a vector of parameters to be estimated
α = a constant term in the model
L_i = the logarithm of odds that the i^{th} target price will be achieved.

It can be noted from (2) that

$$\frac{P_i}{1 - P_i} = \frac{1 + e^{Li}}{1 + e^{-Li}} = e^{Li}$$

Therefore,

$$L_i = \ln\left(\frac{P_i}{1 - P_i}\right) = \alpha + \beta X_i \tag{3}$$

From the above equation, the probability P_i of the i^{th} target price, being classified as the one where accuracy has been achieved, can be computed. If this probability P_i is greater than 0.5, the target price accuracy is achieved and if it is below 0.5 the target price accuracy will not be achieved.

$$\begin{aligned}&LOG\left(\frac{P(TPMETANY)}{1 - P(TPMETANY)}\right) =\\ &b_0 + \beta_1 ABS\_BOLD + \beta_2 PB\ RATIO +\\ &\beta_3 LOGMKTCAP + \beta_4 STOCKVOL +\\ &\beta_5 INTBROKER + \beta_6 STAR + C\end{aligned} \tag{4}$$

All variables used in regression equation are defined in Table 1. The regression equation with *TPERROR* as dependent variable is set up as OLS regression equation:

$$\{TPERROR\} = \beta_0 + \beta_1 ABS\_BOLD + \beta_2 PB\ RATIO + \beta_3 LOGMKTCAP + \beta_4 STOCKVOL + \beta_5 INTBROKER + \beta_6 STAR + \varepsilon \quad (5)$$

Regression on Equations (4) and (5) are conducted three times each on the overall sample, for the subsets of both technology and non-technology stocks.

Statistical Findings

Descriptive Statistics

Table 2 displays results on the descriptive statistics for the sample. Panel A in Table 2 shows that star analysts have a *SIGN_BOLD* of 19.3 per cent and an *ABS_BOLD* of 22.7 per cent, whereas non-star analysts have a *SIGN_BOLD* and an *ABS_BOLD* of 15.7 per cent and 19.8 per cent, respectively. The results suggest that star analysts issue bolder forecasts than non-star analysts both in terms of distance and direction. Distance implies that star analysts are more willing to issue target price forecasts that deviate from current stock price, while direction implies that they have an upward bias or optimism. With regard to the performance measures, Panel A in Table 2 shows that star analysts have *TPMETANY* and *TPERROR* of 56.6 per cent and 37.3 per cent, respectively, while those for non-star analysts are 58.6 per cent and 37.2 per cent, respectively. Clearly, there is not much difference in the performance of star and non-star analysts on both measures of target price performance.

The overall sample has an average PE ratio[11] of 22.6 and average PB ratio of 4.4. The subset of high-growth, technology-driven stocks has an average PE ratio of 24.9 and average PB ratio of 5.4, which is higher than the average PE ratio and PB ratio of the overall sample. The second subset of non-technology stocks has an average PE ratio of 21.7 and average PB ratio of 4.0, which are lower than the first subset. Stocks which trade at high PE ratio and high PB ratio are typically called 'glamour' stocks for which naive investors are willing to pay a premium (La Porta, 1996).

Panel B in Table 2 presents descriptive statistics associated with boldness and performance of star analysts versus non-star analysts for high-growth, technology-driven stocks. Star analysts expect an average increase of 22.6 percent from high-growth, technology-driven stocks and they are willing to deviate 24.7 per cent from the current price of these stocks. With respect to the measures of boldness, That is, *SIGN_BOLD* and *ABS_BOLD*, non-star analysts have a lower expectation of 16.1 per cent and

Table 2. Star Analysts Versus Non-star Analysts: Descriptive Statistics

PANEL A: Overall Sample (Avg. PE ratio = 22.6, Avg. PB ratio = 4.4)

Type of Analyst	N	*SIGN_BOLD*	*ABS_BOLD*	*TPMETANY*	*TPERROR*
Star	114	19.3%	22.7%	56.6%	37.3%
Non-star	745	15.7%	19.8%	58.6%	37.2%

PANEL B: High Growth Technology Stocks (Avg. PE ratio = 24.9, Avg. PB ratio = 5.3)

Type of Analyst	N	*SIGN_BOLD*	*ABS_BOLD*	*TPMETANY*	*TPERROR*
Star	34	22.6%	24.7%	62.5%	39.9%
Non-star	195	16.1%	19.7%	53.3%	40.1%

PANEL C: Stable Growth Non-Technology Stocks (Avg. PE ratio = 21.7, Average PB ratio = 4.0)

Type of Analyst	N	*SIGN_BOLD*	*ABS_BOLD*	*TPMETANY*	*TPERROR*
Star	80	17.9%	21.8%	53.4%	36.5%
Non-star	550	15.5%	19.8%	60.3%	35.8%

Source: Author's own.

Notes: *SIGN_BOLD* is measured as (TP – P)/P where TP is target price issued by analyst and P is the price of the stock at the time of issue of target price forecast. ABS_BOLD is measured as |(TP – P)/P| where TP is target price issued by analyst and P is the price of the stock at the time of issue of target price forecast. *TPMETANY* is a dummy variable with value 1 if target price has been achieved anytime during forecast horizon or the value is 0. *TPERROR* is calculated as |(TP12-TP)/P| error where the absolute difference between stock price at end of 12 months(TP12) and target price (TP) is scaled to stock price at time of issue of target price forecast (P). Star analysts are those analysts who are indentified as star-analysts by Thomson Reuters StarMine awards.

19.7 per cent, respectively. This suggests that star analysts are more aggressive with high-growth, technology-driven stocks than non-star analysts. As far as the performance measures of technology-driven stocks are concerned, Panel B in Table 2 shows that star analysts have the *TPMETANY* of 62.5 per cent, whereas that of non-star analysts is 53.3 per cent. Despite being aggressive with technology-driven stocks, star analysts produce significantly better results than non-star analysts on the short-term measure of target price accuracy. For *TPERROR*, there is no significant difference in the performance of star and non-star analysts, with investment error of 39.9 per cent and 40.1 per cent, respectively.

Panel C in Table 2 presents descriptive statistics associated with non-technology stocks. Star analysts have boldness of 17.9 per cent and 21.8 per cent on *SIGN_BOLD* and *ABS_BOLD*, respectively, while that for non-star analysts stand at 15.5 per cent and 19.8 per cent, respectively. For non-technology stocks, star analysts have a *TPMETANY* measure of 53.4 per cent, whereas non-star analysts have a higher measurement of 60.3 per cent. Descriptive statistics suggest that star analyst accuracy is lower with non-technology stocks when target price performance is measured in the short term. However, for *TPERROR*, there is no difference between performance of star analysts and non-star analysts with investment error of 36.5 per cent and 35.8 per cent, respectively.

To sum up, descriptive statistics reveal that star analysts are more aggressive with target price forecasts. With respect to analyst performance for the overall sample, there is no difference in the performance of star analysts and non-star analysts. However, star analysts have better short-term target price accuracy than non-star analysts for technology-driven, glamour stocks, despite the fact that star analysts are more aggressive with these stocks.

Correlation Table

Table 3 presents the correlation table for target price measures and variables associated with target price performance. The two target price measures, *TPMETANY* and *TPERROR*, are negatively correlated (–0.28, $p<0.01$), suggesting that these measures capture different aspects associated with analyst performance. *TPMETANY* is significantly and negatively correlated with *ABS_BOLD* (–0.28, $p<0.01$), suggesting that higher absolute boldness leads to lower target price accuracy. *TPERROR*, on the other hand, is positively correlated with *ABS_BOLD* (0.34, $p<0.01$) suggesting that investment error increases with absolute boldness. *TPERROR* is negatively correlated with *LOGMKTCAP* (–0.27, $p<0.01$) and positively correlated with *STOCKVOL* (0.24, $p<0.01$), which indicates that investment error increases with smaller, more volatile firms. *STAR* is positively correlated with *INTBROKER* (0.07, $p<0.05$) suggesting a high possibility that a star analyst will belong to an international brokerage like JP Morgan and Goldman Sachs. Also, *STAR* is positively correlated with *ABS_BOLD* (0.06, $p<0.10$) suggesting that star analysts record higher absolute boldness than non-star analysts.

Cross–tabulation Results

Table 4 presents results from the cross-tabulation of variables used in this study. The Pearson chi-square is significant ($p<0.01$) when *TPMETANY* is a dependent variable and *ABS_BOLD* is an independent variable. This indicates that analyst short-term accuracy is lower when analysts have higher boldness. Cross-tabulation results for *TPMETANY* as a dependent variable and *PB RATIO, LOGMKTCAP, STOCKVOL, INTBROKER* and *STAR* as

Table 3. Correlation Table

	TP METANY	*TP ERROR*	*ABS_ BOLD*	*PB RATIO*	*LOG MKTCAP*	*STOCK VOL*	*INT BROKER*
TPMETANY							
TPERROR	–0.28***						
ABS_BOLD	–0.28***	0.34***					
PB RATIO	0.001	–0.04	–0.10***				
LOGMKTCAP	–0.05	–0.27***	–0.22***	0.13***			
STOCKVOL	–0.01	0.24***	0.21***	–0.15***	–0.40***		
INTBROKER	–0.03	–0.03	0.07**	0.004	0.19***	–0.10***	
STAR	–0.02	0.002	0.06*	–0.002	–0.14**	–0.30***	0.07**

Source: Author's own.

Notes: ***/**/* significance at 1% / 5% / 10%, respectively.

Table 4. Cross-tabulation Results

Target Price Achieved (*TPMETANY*)	*ABS_BOLD* (0 = BELOW AVERAGE, 1 = ABOVE AVERAGE)		*PB RATIO* (0 = BELOW AVERAGE, 1 = ABOVE AVERAGE)		*LOGMKTCAP* (0 = BELOW AVERAGE, 1 = ABOVE AVERAGE)		*STOCKVOL* (0 = BELOW AVERAGE, 1 = ABOVE AVERAGE)		*INTBROKER* (0 = DOMESTIC BROKER, 1= INTERNATIONAL BROKER)		*STAR* (0 = NON-STAR ANALYST, 1 = STAR ANALYST)	
	Pearson Chi-square $p = 0.00$		Pearson Chi-square $p = 0.12$		Pearson Chi-square $p = 0.260$		Pearson Chi-square $p = 0.98$		Pearson Chi-square $p = 0.34$		Pearson Chi-square $p = 0.61$	
	0	1	0	1	0	1	0	1	0	1	0	1
No	32.4%	56.5%	43.5%	37.9%	39.7%	43.4%	41.6%	41.7%	40.5%	43.8%	41.3%	43.9%
Yes	67.6%	43.5%	56.5%	62.1%	60.3%	56.6%	58.4%	58.3%	59.5%	56.2%	58.7%	56.1%

Source: Author's own.

Notes: 1. TPA*ABS_BOLD: 0 cells (0.0%) have expected count less than 5. The minimum expected count is 137.95.
2. TPA*PB RATIO: 0 cells (0.0%) have expected count less than 5. The minimum expected count is 115.44.
3. TPA*LOGMKTCAP: 0 cells (0.0%) have expected count less than 5. The minimum expected count is 167.12.
4. TPA*STOCKVOL: 0 cells (0.0%) have expected count less than 5. The minimum expected count is 165.87.
5. TPA*INTBROKER: 0 cells (0.0%) have expected count less than 5. The minimum expected count is 130.45.
6. TPA*STAR: 0 cells (0.0%) have expected count less than 5. The minimum expected count is 47.51.

TPMETANY is a dummy variable with value 1 if target price has been achieved anytime during forecast horizon or the value is 0. *TPERROR* is calculated as |(TP12-TP)/P| error where the absolute difference between stock price at end of 12 months(TP12) and target price (TP) is scaled to stock price at time of issue of target price forecast (P). *PB RATIO* is measured as the price to book value at the time of issue of target price forecast. *STOCKVOL* is the annualized volatility of stock based on past one year historical returns of the stock. It is calculated as the standard deviation of log normal returns of the stock over past one year multiplied by square root of 252. *LOGMKTCAP* is the log of market capitalization of stock at the time of issue of target price forecast in terms of USD. *ABS_BOLD* is measured as |(TP – P)/P| where TP is target price issued by analyst and P is the price of the stock at the time of issue of target price forecast. *INTBROKER* is a dummy variable where a value of 1 is assigned to skilled analysts working with international brokers or a value of 0 is assigned. *STAR* is a dummy variable which has a value of 1 if analyst has been identified by Thomson Reuters Starmine as a star analyst with superior stock picking abilities.

independent variables do not have significant Pearson chi-square values. This means that the short-term accuracy has no association with these five variables when analysis is conducted with each independent variable separately. For such chi-square estimates to remain unbiased, cross-tabulations involving the concerned dependent and independent variables should have no expected frequencies below 1 and should only exhibit an expected count value of less than 5 for 20 per cent of the expected frequencies at the most (Field, 2005, 262). In all the cases, the minimum expected count is more than 1, while 0 per cent cells have expected count value of less than 5. This indicates that both conditions are satisfied and chi-square test is valid.[12]

Regression Results

Table 5 displays results from OLS regression of *ABS_BOLD* and *SIGN_BOLD* on *STAR* in the presence of control variables discussed in Equation (1). There is a significant and positive association between *ABS_BOLD* and *STAR* for the overall sample (0.05, p<0.01), the subset of technology stocks (0.05, p<0.01) and the subset of non-technology stocks (0.04, p<0.01). OLS regression of *SIGN_BOLD* on *STAR* also reflects a positive and significant relationship for the overall sample (0.05, p<0.01), the subset of technology stocks (0.06, p<0.01) and the subset of non-technology stocks (0.05, p<0.01). These results suggest that star analysts are more aggressive than other analysts with regard to target price forecasts. The control variables, *LOGMKTCAP* and *STOCKVOL*, used in OLS regression provide expected results. Overall, the six regression equations presented in Table 5 are significant (p<0.01).

Table 6 presents results from three variants of logit regression discussed in Equation (4). For the overall sample, there is no significant relationship between *TPMETANY* and *STAR*. This implies that there is no difference in short-term performance of star analysts and non-star analysts. *ABSBOLD* and *LOGMKTCAP* have a significant and negative association with *TPMETANY* (–4.53, p<0.01 and –0.43, p<0.01, respectively). This suggests that target price accuracy is higher when analysts are conservative with target price forecasts and when forecasts are issued on smaller firms. *PB RATIO, STOCKVOL* and *INTBROKER* are insignificant but provide expected signs. The overall regression is significant (*LR Stat* = 82.1, p<0.01) with Pseudo R^2 of 7.0 per cent. For the subset of high-growth, technology-driven stocks shown in Table 6, *TPMETANY* has a positive association with *STAR* (0.64, p<0.10). This means that star analysts outperform non–star analysts in the short term with target price forecasts on technology stocks. Among other variables, *ABS_BOLD* has a negative

Table 5. OLS Regression Results of *ABS_BOLD* and *SIGN_BOLD*

Table 5 presents result from OLS regressions of *ABS_BOLD / SIGN_BOLD* on *STAR* with control variables including *LOGMKTCAP* and *STOCKVOL*. Results are presented for the overall sample, technology stocks and non-technology stocks.

		ABS_BOLD			*SIGN_BOLD*		
Variable	Expected Sign	Overall	Tech Stocks	Non-Tech Stocks	Overall	Tech Stocks	Non-tech Stocks
LOGMTKCAP	–	–0.04 (–3.50)***	–0.07 (–3.15)***	–0.02 (–1.95)***	–0.04 (–3.10)***	–0.06 (–2.60)***	–0.03 (–1.82)*
STOCKVOL	+	0.30 (4.97)***	0.22 (1.65)*	0.32 (4.73)***	0.29 (3.73)***	0.15 (0.89)	0.34 (3.81)***
STAR	?	0.05 (2.78)***	0.05 (1.60)*	0.04 (2.27)***	0.05 (2.41)***	0.06 (1.60)*	0.05 (1.92)*
INTERCEPT		0.10 (3.15)	0.15 (2.22)	0.08 (2.21)	0.07 (1.71)	0.15 (1.82)	0.04 (0.76)
ADJ. R^2		7.3%	9.8%	6.2%	4.8%	5.7%	4.3%
F-STAT		23.5***	9.3***	14.8***	15.5***	5.60***	10.4***
N		859	229	630	859	229	630

Source: Author's own.

Notes: 1. ***/**/* significance at 1% / 5% / 10%, respectively.

2. The OLS regression equation used in this analysis is:

$$\{\mathrm{ABS\_BOLD} \;/\; \mathrm{SIGN\_BOLD}\} = \beta_0 + \beta_1 \mathrm{LOGMTKCAP} + \beta_2 \mathrm{STOCKVOL} + \beta_3 \mathrm{STAR} + \varepsilon$$

3. Three variants of this equation are used – once with overall sample, once with technology stocks and once with non-technology stocks. *ABS_BOLD* is measured as |(TP – P)/P| where TP is target price issued by analyst and P is the price of the stock at the time of issue of target price forecast. *SIGN_BOLD* is measured as (TP – P)/P where TP is target price issued by analyst and P is the price of the stock at the time of issue of target price forecast. *STOCK VOL* is the annualized volatility of stock based on past one year historical returns of the stock. It is calculated as the standard deviation of log normal returns of the stock over past one year multiplied by square root of 252. *LOGMKTCAP* is the log of market capitalization of stock at the time of issue of target price forecast in terms of USD. *STAR* is a dummy variable which has a value of 1 if analyst has been identified by Thomson Reuters Starmine as a star analyst with superior stock picking abilities.

Table 6. Logit Regression Results Associated with Star Analyst Performance

Table 6 presents result from logit regressions of *TPMETANY* on *STAR* with control variables including *ABS_BOLD, PB RATIO, LOGMKTCAP, STOCKVOL* and *INTBROKER*. Regressions are conducted on the overall sample, subset of technology stocks and subset of non-technology stocks.

		TPMETANY	*TPMETANY*	*TPMETANY*
Variable	Expected Sign	Overall Sample	High Growth Tech Stocks	Non-Tech Stocks
ABS_BOLD	–	–4.53 (–7.91)***	–4.21 (–3.80)***	–4.65 (–6.77)***
PB RATIO	–	–0.01 (–0.40)	0.03 (0.73)	–0.01 (–0.58)
LOGMTKCAP	+	–0.43 (–2.96)***	–0.07 (–0.25)	–0.65 (–3.62)***
STOCKVOL	–	0.18 (0.21)	1.07 (0.59)	–0.20 (–0.21)
INTBROKER	+	0.05 (0.29)	–0.49 (–1.52)	0.22 (1.21)
STAR	+	–0.13 (–0.52)	0.64 (1.64)*	–0.45 (–1.62)*
INTERCEPT		1.55 (3.40)	0.59 (0.68)	1.99 (3.62)
PSEUDO R^2		7.0%	8.4%	7.8%
LR STAT (Prob.)		82.1***	26.4***	66.6***
N		859	229	630

Source: Author's own.

Notes: 1. ***/**/* significance at 1% / 5% / 10%, respectively.

2. The primary logit regression equation used in this analysis is:

$$\mathrm{LOG}\left(\frac{\mathrm{P(TPMETANY)}}{1-\mathrm{P(TPMETANY)}}\right)=b_0+\beta_1\mathrm{ABS\_BOLD}+\beta_2\mathrm{PB\ RATIO}+\beta_3\mathrm{LOGMKTCAP}+\beta_4\mathrm{STOCKVOL}+\beta_5\mathrm{INTBROKER}+\beta_6\mathrm{STAR}+C$$

3. Three variants of this equation are used—once with overall sample, once with technology stocks and once with non-technology stocks. *TPMETANY* is a dummy variable with value 1 if target price has been achieved anytime during forecast horizon or the value is 0. *ABS_BOLD* is measured as |(TP – P)/P| where TP is target price issued by analyst and P is the price of the stock at the time of issue of target price forecast. *PB RATIO* is measured as the price to book value at the time of issue of target price forecast. *LOGMKTCAP* is the log of market capitalization of stock at the time of issue of target price forecast in terms of USD. *STOCKVOL* is the annualized volatility of stock based on past one year historical returns of the stock. It is calculated as the standard deviation of log normal returns of the stock over past one year multiplied by square root of 252. *INTBROKER* is a dummy variable where a value of 1 is assigned to skilled analysts working with international brokers or a value of 0 is assigned. *STAR* is a dummy variable which has a value of 1 if analyst has been identified by Thomson Reuters StarMine as a star analyst with superior stock picking abilities.

relationship with *TPMETANY* (–4.21, p<0.01), again implying that short-term performance improves with lower target price boldness. All other variables used in regression analysis are insignificant. The overall regression analysis is significant (*LR Stat* = 26.4*,* p<0.01) with a Pseudo R^2 of 8.4 per cent. For the subset of non–technology stocks, results from Table 5 indicate that *TPMETANY* has a negative association with *STAR* (–0.45, p<0.10). This suggests that target price performance of star analysts is significantly lower than non-star analysts with respect to non-technology stocks. As far as control variables are concerned, *TPMETANY* is negatively associated with *ABS_BOLD* (–4.65, p<0.01) and *LOGMKTCAP* (–0.65, p<0.01), while all the other variables are insignificant. Based on the results displayed in Table 6, the study fails to reject the null hypothesis for H1 and H3, while the null hypothesis is rejected and an alternate hypothesis is accepted for H2.

Table 7 displays results from OLS regression of *TPERROR* on *STAR* with control variables as presented in Equation (5). For the overall sample, the results reveal that there is no association between *TPERROR* and *STAR*. When the control variables are considered, *TPERROR* shows positive association with *ABS_BOLD* (0.61, p<0.01) and *STOCK_VOL* (0.43, p<0.01), but negative association with *LOGMKTCAP* (–0.10, p<0.01); these results are on expected lines. The overall equation is significant (*F-stat* = 28.9, p<0.01) with an Adj. R^2 of 16.3 per cent. Table 7 further exhibited results from regression of a variant of Equation (5) with the subset of technology stocks. The results show that there is no association between *TPERROR* and *STAR*. However, when the control variables are accounted for, *TPERROR* associated positively with *ABS_BOLD* (0.63, p<0.01) and negatively with *LOGMKTCAP* (–0.10, p<0.10), which again are expected results. All the other control variables used in the regression analysis are not significant. The overall equation is significant (*F-stat* = 6.29*,* p<0.01) with an Adj. R^2 of 12.2 per cent. Table 7 also provides results from regression of another variant of Equation (5) with the subset of non-technology, stable-growth stocks. The results show that there is no association between *TPERROR* and *STAR*. With respect to control variables, *TPERROR* is positively associated with *ABS_BOLD* (0.59, p<0.01) and *STOCK_VOL* (0.52, p<0.01), but negatively associated with *LOGMKTCAP*

Table 7. OLS Regression Results Associated with Star Analyst Performance

Table 7 presents result from OLS regressions of *TPERROR* on *STAR* with control variables including *ABS_BOLD, PB RATIO, LOGMKTCAP, STOCKVOL, INTBROKER* and *MKTVOL*. Regressions are conducted on the overall sample, subset of technology stocks and subset of non-technology stocks.

		TPERROR	*TPERROR*	*TPERROR*
Variable	Expected Sign	Overall Sample	High Growth Tech Stocks	Stable Non-Tech Stocks
ABS_BOLD	+	0.61 (8.51)***	0.63 (3.98)***	0.59 (7.40)***
PB RATIO	+	0.002 (0.92)	0.00 (0.09)	0.002 (0.92)
LOGMTKCAP	–	–0.10 (–4.60)***	–0.10 (–1.82)*	–0.10 (–4.12)***
STOCKVOL	+	0.43 (3.30)***	0.15 (0.48)	0.52 (3.70)***
INTBROKER	–	0.02 (0.67)	0.08 (1.33)	–0.001 (–0.03)
STAR	–	–0.002 (–0.07)	–0.06 (–0.74)	0.02 (0.49)
INTERCEPT		0.14 (2.01)	0.25 (1.63)	0.10 (1.32)
ADJ. R^2		16.3%	12.2%	17.8%
F- STAT (Prob.)		28.9***	6.29***	23.7***
N		859	229	630

Source: Author's own.

Notes: 1. ***/**/* significance at 1% / 5% / 10%, respectively.

2. The primary OLS regression equation used in this analysis is:
$\{TPERROR\} = \beta_0 + \beta_1 ABS\_BOLD + \beta_2 PB\ RATIO + \beta_3 LOGMKTCAP + \beta_4 STOCLVOL + \beta_5 INTBROKER + \beta_6 STAR + \varepsilon$

3. Three variants of this equation are used – once with overall sample, once with technology stocks and once with non-technology stocks. TPERROR is calculated as |(TP12-TP)/P| error where the absolute difference between stock price at end of 12 months(TP12) and target price (TP) is scaled to stock price at time of issue of target price forecast (P). ABS_BOLD is measured as |(TP – P)/P| where TP is target price issued by analyst and P is the price of the stock at the time of issue of target price forecast. PB RATIO is measured as the price to book value at the time of issue of target price forecast. LOGMKTCAP is the log of market capitalization of stock at the time of issue of target price forecast in terms of USD. STOCKVOL is the annualized volatility of stock based on past one year historical returns of the stock. It is calculated as the standard deviation of log normal returns of the stock over past one year multiplied by square root of 252. INTBROKER is a dummy variable where a value of 1 is assigned to skilled analysts working with international brokers or a value of 0 is assigned. STAR is a dummy variable which has a value of 1 if analyst has been identified by Thomson Reuters StarMine as a star analyst with superior stock picking abilities.

(–0.10, $p<0.01$). These results are also on expected lines. The overall equation is significant (*F-stat* = 23.7, $p<0.01$) with an Adj. R^2 of 17.8 per cent. Based on the results displayed in Table 7, the study fails to reject the null hypothesis for H1, H2 and H3.

Interpreting the Results

To begin with, OLS regression analysis in Table 5 shows that star analysts are willing to deviate more from existing stock prices than non-star analysts. It can be interpreted that star analysts have higher appetite for risk than non-star analysts for all types of stocks considered in our sample. Star analysts use aggressive target price forecasts to grab attention of investors in a speculative emerging market environment. This result is in contrast to the results from developed markets where reputation partly restrains analyst optimism (Mola & Guidolin, 2009). Star analysts are willing to risk reputation to attract clients with higher profit potential for trading.

The main objective of this study is to investigate if investors can benefit by following the target price forecasts issued by star analysts. Empirical results from Tables 6 and 7 show that there is not much difference between the performances of star analysts and non-star analysts for the overall sample. However, once the sample is split, there is empirical evidence to suggest that star analysts outperform non-star analysts in the short term with target price forecasts on technology stocks. Interestingly, empirical evidence is also there to suggest that star analysts are not able to outperform non-star analysts in the short term with target price forecasts when non-technology stocks are considered. Star analysts' outperformance with technology stocks is levelled by their underperformance with non-technology stocks. This explains why star analysts do not outperform non-star analysts in the short term for the overall sample. Bekaert, Harvey and Lundblad (2007) explain that the process of liberalization has not fully reduced the impact of liquidity on returns in emerging markets. Technology-driven, glamour stocks are typically associated with higher liquidity (Lee & Swaminathan, 2000) and higher perceived risk or return which leads to higher media coverage (Seasholes & Wu, 2007). Star analysts find it easier to predict stock prices of these popular, liquid stocks having better flow of information in an emerging market environment. When the performance of the analysts is measured at the end of the forecast horizon, the investment error for target price forecasts issued by star analysts for all types of stocks used in this study does not significantly differ from that of non-star analysts. The key finding of this empirical analysis is that star analysts have limited advantage over non-star analysts, which is reflected only in their superior short-term performance for technology-driven, glamour stocks having high trading volume and better flow of information.

Conclusion

In the broader market, the performance of star analysts does not differ much from non-star analysts when performance is measured in the short term or at the end of the forecast horizon. However, the study finds evidence to support the proposition that star analysts have better forecasting abilities in the short term with technology-driven, glamour stocks. Such an outperformance by star analysts, however, does not reflect in the overall sample owing to their short-term underperformance while dealing with the subset of non-technology stocks. The findings reflect the speculative and shallow nature of emerging markets where even sophisticated market participants like star analysts have limited advantage over other participants, that too in the short term. It can thus be concluded that there is limited benefit for investors in following stock price forecasts issued by star analysts in emerging markets like India.

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Notes

1. Sayed and Chaklader (2014) find that buy recommendations issued by analysts in India have investment value. However, their research does not discuss differences between the forecasting abilities of star analysts and non-star analysts.
2. The Thomson Reuters StarMine Analyst Awards are recognized as a premier ranking for measurement of sell-side analyst performance. The awards recognize the world's top individual sell-side analysts and sell-side firms. The awards intend to measure the performance of sell-side analysts based on the returns of their buy/sell recommendation relative to industry benchmark, and the accuracy of their earnings estimates in 16 regions across the globe. For more information visit http://www.starmineawards.com
3. Analysts with better stock-picking abilities should be able to predict stock prices more accurately. Most of the previous research (e.g., Leone & Wu, 2007) have focused on earnings forecast abilities of star analysts. This research, on the other hand, provides a fresh perspective on the target price forecasting abilities of analysts who are rated as better stock-pickers.
4. National Stock Exchange is one of the leading stock exchanges in India.
5. Khan (2010) identifies these sectors as high growth sectors which attract private equity investments.
6. This measure has been used in various studies including Asquith, Mikhail and Au (2005); Demirakos, Strong and Walker (2010).
7. A limit-order strategy is used to buy or sell a set number of shares at a specified price or better. This strategy is used primarily for short-term trading purpose rather than long-term investment purpose.
8. This measure has been used as *TPERROR* by Bradshaw, Brown and Huang (2013). They suggest the use of unsigned investment error.
9. Share price data for this study has been collected from National Stock Exchange.
10. Greene (2002) states that a formal logit or probit allows estimation of probabilities and, in this case, the probability that analyst will meet the target price during the forecast horizon is being measured.
11. PE ratio is price-to-earnings ratio of stock as provided by analysts in research report at the time of the issue of target price forecast.
12. Logit regression techniques employ chi-square tests to measure the contribution of each independent variable with regard to predicting the probability of the dependent variable exhibiting a specific state. For logit regression analysis also, the chi-square conditions needs to be satisfied. From the cross-tabulation results, it can be seen that logit regression can be applied using the variables in consideration. For this study, logit regression will be applied on Equation (4).

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