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Article

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Target price accuracy of sell-side analysts: evidence from India

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ABSTRACT

Target prices forecasted by sell-side equity research analysts play a crucial role in market participants' investment decisions. We, using a large sample for Indian markets, determine during the period and end of the period 12-month ahead target price achievements, examine the effectiveness of valuation methods for determining target prices, evaluate target price accuracy using prediction error metrics, and investigate the factors influencing target price accuracy. Our findings indicate that sell-side analysts have reasonable forecasting abilities, achieving 63% of their target prices over a 12-month forecasting horizon. The level of achievement decreased with increasing optimism in predictions. Analysts generally prefer holistic and multiple-based valuation approaches to determine the target prices. The DCF methodology was less effective than the SOTP hybrid and multiple-based approaches in predicting target prices. We find that more optimistic target prices and higher beta contribute to increased prediction errors, whereas better market returns reduce errors. Analysts struggle to predict prices for loss-making enterprises, and have difficulty forecasting target prices in capital-intensive sectors. These findings contribute to the existing body of knowledge and have significant implications for stakeholders in financial markets.

IMPACT STATEMENT

The study examines the accuracy of analysts' target price forecasts and the factors influencing that accuracy. We find that analysts demonstrate reasonable forecasting abilities, with 63% of their target prices being accurate within a 12-month period. Our results suggest that analysts and brokerage firms should utilize more rigorous valuation models, such as the Sum of the Parts (SOTP) Hybrid, when setting target prices, whenever relevant. Investors should be aware of the limitations linked to analysts' stock price forecasts, particularly in capital-intensive industries, and should be cautious when considering overly optimistic target price recommendations, especially for small-cap or loss-making companies. Our insights into the impact of valuation methods and capital intensity on target price accuracy contribute new knowledge to the existing literature.

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1. Introduction

Analysts play an important role in disseminating valuable information to the market participants (B. Barber et al., 2001). A typical sell-side analyst equity research report includes an earnings forecast, recommendation (for example buy, hold, sell), and target price. Previous research has found that these recommendations are important for share price discovery (Asquith et al., 2005). Given that the total market capitalization of domestic companies listed on stock exchanges worldwide is estimated at 112 trillion USD as of July 2023,[1] equity research firms spend billions of dollars annually analyzing companies and publishing research reports for investors. Over the years, academic research has been devoted to analyzing the value, impact, and accuracy of analysts' reports. One valuable measure that emerged from these reports was the target price. The target represents the potential change in security value and may have an impact on investors' investment decisions.

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Analysts often provide target prices to support their recommendations (Bradshaw, 2002) and are correlated with value-relevant fundamentals, such as earnings expectations (Frankel & Lee, 1998). Target prices significantly affect market prices (Brav & Lehavy, 2003) and investors consider the target price forecast to be valuable (Asquith et al., 2005). Academic research was largely silent on target prices, a fact mainly attributed to the late coverage of target prices by major databases (Kerl, 2011). Previous studies of analyst reports have focused on the impact of *recommendations* and *earnings forecast* on stock prices and the accuracy of earnings forecasts, along with studies determining the factors for such an impact. Analyst recommendations were found to generate abnormal returns and outperform benchmarks (B. M. Barber & Loeffler, 1993; Beneish, 1991; Desai et al., 2000; Womack, 1996). Analyst coverage promotes corporate innovation (Zhang & Wang, 2023). Recommendations are expected to have a greater price impact if they are accompanied by long-term earnings growth forecasts (Jung et al., 2012; Stickel, 1995). Better forecast accuracy resulted in more profitable recommendations (Hall & Tacon, 2010). Large-sample studies across the US (Asquith et al., 2005; Bradshaw, Brown, et al., 2013), German (Kerl, 2011) and Italian (Bonini et al., 2010) markets have documented various levels of predictive ability of analysts and factors impacting analyst accuracy.

This study aims to expand and contribute to the existing research on the accuracy of target price achievement by sell-side equity research analysts. Therefore, our study addresses the following research questions: (i) Do sell-side analysts have superior ability to predict target prices? (ii) Effectiveness of the choice of valuation method used by analysts in predicting target prices, (iii) impact of recommendation classes on target price accuracy, and (iv) determinants of target price accuracy. Our sample consists of 22,807 analyst recommendations for the period of five years from 1 January 2016 to 31 December 2020, from 34 equity research firms for 805 companies, covering about 95% of the total market cap of all listed companies in India. All reports were individually analyzed to capture the necessary data points required for empirical analysis. Very few studies have been conducted on analysts' recommendations in the Indian market, and those that exist have used small and restrictive samples (Chatterjee et al., 2020; Patel, 2021; Sayed, 2015; Sayed & Chaklader, 2014). Our research expands the existing literature on the analysts target prices for Indian stock market.

Our empirical analysis was conducted in five stages: First, we determine the target price achievements for all recommendations and further analyze each recommendation class (ie strong buy, buy, hold, sell, strong sell') at the end of the 12-month period from the recommendation date and any time during the 12-month period. We also observe the cross-sectional achievement of the target price along the market cap of companies (grouped as large-cap, mid-cap, and small-cap) and sectors. Second, we study the valuation methods analysts use to arrive at the target price and categorize them. We study the effectiveness of various valuation methods for predicting target prices. Third, we use the accuracy metric model developed by Bonini et al. (2010), from the perspective of an investor, to test target price accuracy. Fourth, we studied the impact of recommendation class on accuracy. Fifth, we analyze the factors that determine the target price accuracy.

Our findings demonstrate that the achievement of the target price surpasses the majority of previously documented results in the literature (Asquith et al., 2005; Bonini et al., 2010; Bradshaw & Brown, 2006; Kerl, 2011) and is in line with Bradshaw, Brown, et al. (2013) with 63% achievement during the 12-month period and 38% at the end of the 12-month period, indicating reasonable predictive abilities of analysts. Achievement decreases with optimistic predictions ('strong buy', 'strong sell'). Analysts prefer holistic and multiple-based valuation approaches to arrive at the target prices. The DCF methodology has limited effectiveness, whereas the sum of the parts (SOTP) hybrid and multiples-based approaches to valuation are highly effective in predicting target prices. The recommendation classes significantly impact target price accuracy. Ex-post market returns, firm beta, DCF valuation methodology, and business capital intensity contribute to prediction errors. Our findings on the effects of valuation methods and capital intensity on target price accuracy are a new addition to the literature.

The rest of the paper is organized as follows: Section 2 reviews prior research; Section 3 outlines the hypotheses; Section 4 covers data collection; Section 5 details the methodology; Section 6 presents the results; and Section 7 concludes the paper.

2. Literature review

2.1. Market impact of analyst recommendations

Analysts play a vital role in disseminating information to financial markets in the form of earnings forecasts, recommendations (such as buy, hold, and sell), and target prices. Earlier research focused mainly on earnings forecasts and stock recommendations.

Cowles (1933) noted that stock market forecasters fail to generate abnormal returns. However, abnormal returns were documented by Beneish (1991) and B. M. Barber and Loeffler (1993). Womack (1996) noted that post-recommendation excess returns are not mean reverting. Desai et al. (2000) also observed that stocks recommended by All Star analysts in the Wall Street Journal outperformed benchmarks controlled for size and industry. Several studies (Jegadeesh & Kim, 2006; Moshirian et al., 2009; Womack, 1996) have noted that analysts publish more buy recommendations than sell recommendations. Stickel (1995) found that downgrades have a greater negative impact than upgrades. Bradley et al. (2014) noted that the market reaction to the contrarian (recommendation in opposite direction to recent price movement) upgrades and downgrades is more than non-contrarian, concluding that contrarian upgrades are expected to have private information. Analyst recommendation changes are more likely to be influential if they are from leaders, stars, previously influential analysts, issued away from consensus, accompanied by earnings forecasts, and issued on growth, small, high institutional ownership, or high forecast dispersion firms (Loh & Stulz, 2011).

Contrary to what has been observed in other studies, B. Barber et al. (2003) point out that from 2000 to 2001, stock recommendations from analysts performed *worse* than stocks least favored by analysts. Loh and Stulz (2011) studied whether individual recommendations are influential and documented that only 12% of the recommendation changes are influential. Michaely and Womack (1999) observed that underwriters' recommendations are biased and, in the long run, inferior to those of non-underwriters. Jegadeesh and Kim (2010) noticed that analysts herd around this consensus. Chan et al. (2018) noticed that about 56% of analysts terminated their ownership of the stock while having outstanding buy recommendations.

2.2. Target price

Although target price is one of the key components of analyst research output, the focus has recently shifted toward target prices. Kerl (2011), based on the information taken from Brav and Lehavy (2003) and other studies (Asquith et al., 2005; Bradshaw, Brown, et al., 2013; Gleason et al., 2013), attributed this late interest in target prices to the fact that major databases such as *First Call* from *Thomson Financial* began coverage of target prices only at the end of 1996.

Brav and Lehavy (2003) found that target prices significantly affect market prices and concluded that target price information to market participants is incrementally informative beyond earnings forecasts and stock recommendations. According to Bradshaw (2002), analysts use target price justifications in a majority of their reports. Additionally, higher target prices are linked to more favorable recommendations.

Asquith et al. (2005) performed a detailed study of target prices. The authors analyzed the achievement of target prices during the 12 months post-recommendation and noted that price forecasts were achieved in 54.28% of all cases. They documented overshooting of achieved target prices by 37.27% and undershooting in the case of unachieved target prices by 15.62%. Asquith et al. (2005) noted that the target prices provide valuable information to the market. Kerl and Walter (2008) provides similar evidence for the German market.

Bonini et al. (2010) developed an accuracy metric for target price accuracy and tested it in the Italian market. They noted 20.0% (end of period) and 33.12% (any time during the period) accuracy for target prices with prediction errors of up to 36% and concluded that forecasting accuracy of analysts is very limited and target prices are systematically biased. Kerl (2011) noted a target price accuracy of 56.53% during this period and found a negative correlation between accuracy and analyst optimism in the German market.

Bradshaw, Brown, et al. (2013) examined overall and individual analyst accuracy and noted that, on average, 38% (end of period) and 64% (any time during the period) of analysts' target prices are met. They concluded that the frequency of accurate prediction is low, with an absolute target price forecast error of 45%, and attributed the lack of accuracy to the fact that target price forecasting was mostly an

unmonitored activity. In their working paper (Bradshaw & Brown, 2006) for the sample period from 1997 to 2002, the accuracy noted was 24% (end of the period) and 45% (any time during the period).

Gleason et al. (2013) studied analysts' valuation techniques for setting target prices and noted that target price accuracy improves with more rigorous valuation techniques than with simple heuristics. In a similar study on valuation techniques, Erkilet et al. (2022) note that the income and market approach leads to more accurate prices along with holistic valuation, instead of the sum of parts valuation. Bonini et al. (2022) observed that target price forecasts that differ from those of the multiple-based valuation approach are more accurate.

Bradshaw et al. (2019) argued that analysts in countries with strong institutional frameworks provide more value-relevant target prices. Antônio et al. (2017) also showed that accuracy increases with greater government effectiveness and greater analyst consensus in a Latin American study. Bouteska and Mili (2022) observed that analysts issue more accurate recommendations for well-governed firms and that strong corporate governance improves target price accuracy (Cheng et al., 2019). Umar et al. (2022) noted that ESG scores positively impacted target price accuracy. Umar et al. (2023) observed that financial restatements negatively impacted target price precision. Fredj and Gana (2023) observed that target price accuracy is negatively related to board independence. Institutions closely follow analyst recommendations and tend to overreact to analyst target price revisions, thereby destabilizing stock prices due to herding behavior (Gu et al., 2022).

In the Indian market context, Sayed and Chaklader (2014) analyzed 1000 target prices with buy ratings and documented a target price accuracy of 57.6%. Sayed (2015) analyzed 340 research reports for Nifty 50 index firms and studied the valuation models used by analysts for 'buy' recommendations and observed the highest target price accuracy of 70% with the DCF model and the lowest TPA of 51.1% with book value-based forecasts. Chatterjee et al. (2020) analyzed the target price accuracy for analyst calls for a specific window (30 days for technical calls and 180 days for fundamental calls) and noted that 43% of technical calls and 52% of fundamental calls met the target prices. Patel (2021) analyzed Banking Stocks listed on the National Stock Exchange and noted that promoter holdings have a significant negative association with target price accuracy.

Our literature review uncovers the following gaps (a) the sector-based cross-sectional analysis of the target price achievements of the analyst recommendations is not effectively evaluated, (b) the impact of valuation methods on the accuracy of analyst stock recommendations is studied with limited classification of valuation models or for a restricted sample of large capitalization index stocks, (c) the impact of business capital intensity as measured by the capital-intensive or labor-intensive nature of the business on analyst stock recommendation accuracy is not explored and (d) the studies on analyst target price accuracy in the Indian context use a restricted sample (only buy recommendations and majorly for large listed firms), and results are thus not comparable with similar studies in other economies.

Our study aims to fill in the research gaps and lays out the following objectives.

1. To study whether the sell-side analysts have superior target price predicting abilities.
2. To study the effectiveness of valuation methods analysts use in predicting target prices.
3. To study the impact of recommendation classes on target price accuracy.
4. To study the determinants of the target price accuracy.

3. Hypotheses

Based on our research objectives, we test the following hypotheses.

H1: Sell-side analysts have superior target price predicting abilities, and recommendation class, firm size, and sector have an impact on the target price achievements of analysts' recommendations.

H2: Valuation methods used by sell-side analysts to arrive at a target price impact the target price achievements of the analyst.

H3: Recommendation classes (strong buy, buy, sell, strong sell) have an impact on the target price accuracy of the analyst recommendations.

H4: Valuation methods, business capital intensity (capital/labor), firm profitability, analyst optimism, firm volatility, and post-market returns have an impact on the target price accuracy of the analyst recommendations.

4. Data

We collected 28,486 sell-side analysts' recommendations from the database of ET Intelligence, the research arm of The Economic Times, India's largest business paper, and part of The Times Group, India's largest media group. The recommendations are for a period of five years, from 1 January 2016 to 31 December 2020. All the reports are manually analyzed to extract necessary information such as company name, date of report, recommendation, target price, and valuation methods.

The reports are further filtered by removing those reports that are (a) without any specific recommendation such as buy, sell, etc.; (b) without any specific target price; (c) where there is a stock split or bonus issue within the recommendation period of 12 months from the date of publication of the report; (d) where the report is of REIT or INVIT; (e) where the valuation method is not specified; and (f) where the recommendations are before the listing of the stocks on the stock market. Finally, we analyzed 22,807 recommendations by 34 research firms for 805 companies, which covers about 95% of the total market cap of all listed companies in India.

Analyst recommendations are classified in a stepwise manner. Initially, recommendations were classified according to the ranking adopted by the research firm. As each research firm has its own scale for ranking the recommendations, we reclassified recommendations on a standard five-point scale of 'strong buy/buy/hold/sell/strong sell'. This is consistent with the classifications in the literature reviewed, and our sample can be compared cross-sectionally with other studies. The process followed for conversion of recommendations to standard five-point scale is (a) if the original scale of the research firm is a five-point scale having central recommendation as 'hold' or 'neutral' then we have converted the original recommendation directly to the standard five-point scale adopted by us; (b) if the original scale of the research firm is a three-point scale then the central recommendation is classified as 'hold', a buy recommendation with an implicit return above 20% is classified as 'strong buy' and balance as 'buy', a sell recommendation with an implicit fall of larger than 20% are classified as 'strong sell' and balance as 'sell'.

The breakdown of the data is presented in Table 1. Panel A presents the month-wise breakup of the recommendations for the five-year period. The recommended data were fairly distributed across years. Higher recommendations are observed in January, May, July, October, and November, consistent with the hypothesis that analysts update their recommendations on the availability of new information through quarterly results, shareholder meetings, and so on. Panel B presents the distribution of the data according to the recommendation class. It can be observed that 'strong buy' and 'buy' recommendations exceed 'hold,' 'sell' and 'strong sell' recommendations across the years. This is consistent with the hypothesis that analysts tend to provide more buy recommendations than sell recommendations (Jegadeesh & Kim, 2006; Moshirian et al., 2009; Womack, 1996). Panel C represents the distribution of data according to the 11 sector classifications. The highest recommendations were observed in the consumer discretionary (23.3%) sector, followed by financial services (14.8%). It can be seen that all sectors are well represented in the sample.

The data cover 805 companies, and the highest coverage for a company (IndusInd Bank Ltd.) is 189. The average and median coverage per company are 28.30 and 13%, respectively. Of the 34 research firms, the highest recommendation from a firm (Edelweiss Securities Ltd.) was 3283. The average and median recommendations for research firms were 670 and 210, respectively.

We review each report to determine the valuation method used to establish the target prices. Segregation of the valuation methods is performed, as shown in Figure 1. The first broad category is the holistic approach to the sum of the parts (SOTP) approach (Erkilet et al., 2022). Holistic valuation is further categorized into a multiples-based approach, a discounted cash flow approach, and others. Multiples have subcategories such as income, earnings, sector multiples (P/E, EV/EBITDA, Relative PE, PEG, etc.), and book value multiples (P/B). SOTP is categorized into homogeneous (using the same approach across parts) or hybrid (using different valuation approaches for different parts).

Table 2 presents the various approaches used by the analysts for their recommendations. Analysts preferred a holistic approach (83%) to the sum of the parts (17%). DCF was used in only 4% of recommendations. The multiplet-based approach is the most preferred approach for analysts to arrive at target prices. Overall, 93% of the recommendations used a multiple approach (78% under holistic and 15% under homogeneous SOTP). These observations are consistent with those of previous studies.

Table 1. Details of analyst recommendations.

Panel A[a]						
Month	2016	2017	2018	2019	2020	Total
Jan	497 (11.3%)	381 (8.5%)	343 (7.6%)	423 (8.5%)	535 (11.9%)	2179 (9.6%)
Feb	541 (12.3%)	676 (15.2%)	509 (11.3%)	405 (8.2%)	667 (14.8%)	2798 (12.3%)
Mar	141 (3.2%)	124 (2.8%)	102 (2.3%)	167 (3.4%)	98 (2.2%)	632 (2.8%)
Apr	327 (7.4%)	265 (5.9%)	283 (6.3%)	296 (6%)	201 (4.5%)	1372 (6%)
May	585 (13.3%)	719 (16.1%)	831 (18.5%)	665 (13.4%)	400 (8.9%)	3200 (14%)
Jun	200 (4.5%)	194 (4.4%)	204 (4.5%)	216 (4.4%)	639 (14.2%)	1453 (6.4%)
Jul	358 (8.1%)	493 (11.1%)	481 (10.7%)	563 (11.3%)	522 (11.6%)	2417 (10.6%)
Aug	509 (11.6%)	606 (13.6%)	532 (11.9%)	754 (15.2%)	554 (12.3%)	2955 (13%)
Sep	217 (4.9%)	181 (4.1%)	144 (3.2%)	166 (3.3%)	200 (4.4%)	908 (4%)
Oct	447 (10.2%)	226 (5.1%)	485 (10.8%)	534 (10.8%)	268 (6%)	1960 (8.6%)
Nov	417 (9.5%)	444 (10%)	447 (10%)	629 (12.7%)	294 (6.5%)	2231 (9.8%)
Dec	159 (3.6%)	148 (3.3%)	128 (2.9%)	144 (2.9%)	123 (2.7%)	702 (3.1%)
Total	4398 (100%)	4457 (100%)	4489 (100%)	4962 (100%)	4501 (100%)	22,807 (100%)
Panel B[b]						
Recommendation	2016	2017	2018	2019	2020	Total
Strong buy	1469 (33.4%)	1292 (29%)	2072 (46.2%)	1885 (38%)	1540 (34.2%)	8258 (36.2%)
Buy	1597 (36.3%)	1792 (40.2%)	1378 (30.7%)	1377 (27.8%)	1566 (34.8%)	7710 (33.8%)
Hold	966 (22%)	1094 (24.5%)	852 (19%)	1298 (26.2%)	1046 (23.2%)	5256 (23%)
Sell	280 (6.4%)	209 (4.7%)	144 (3.2%)	335 (6.8%)	269 (6%)	1237 (5.4%)
Strong sell	86 (2%)	70 (1.6%)	43 (1%)	67 (1.4%)	80 (1.8%)	346 (1.5%)
Total	4398 (100%)	4457 (100%)	4489 (100%)	4962 (100%)	4501 (100%)	22,807 (100%)
Panel C[c]						
Sector	2016	2017	2018	2019	2020	Total
Commodities	554 (12.6%)	651 (14.6%)	568 (12.7%)	636 (12.8%)	656 (14.6%)	3065 (13.4%)
Consumer discretionary	1012 (23%)	1047 (23.5%)	1106 (24.6%)	1151 (23.2%)	996 (22.1%)	5312 (23.3%)
Energy	167 (3.8%)	156 (3.5%)	217 (4.8%)	325 (6.5%)	328 (7.3%)	1193 (5.2%)
Fast moving consumer goods	297 (6.8%)	280 (6.3%)	273 (6.1%)	337 (6.8%)	348 (7.7%)	1535 (6.7%)
Financial services	595 (13.5%)	593 (13.3%)	699 (15.6%)	727 (14.7%)	771 (17.1%)	3385 (14.8%)
Healthcare	422 (9.6%)	482 (10.8%)	441 (9.8%)	424 (8.5%)	359 (8%)	2128 (9.3%)
Industrials	601 (13.7%)	648 (14.5%)	685 (15.3%)	694 (14%)	525 (11.7%)	3153 (13.8%)
Information technology	423 (9.6%)	348 (7.8%)	280 (6.2%)	390 (7.9%)	324 (7.2%)	1765 (7.7%)
Services	110 (2.5%)	84 (1.9%)	92 (2%)	132 (2.7%)	95 (2.1%)	513 (2.2%)
Telecommunication	96 (2.2%)	71 (1.6%)	70 (1.6%)	68 (1.4%)	45 (1%)	350 (1.5%)
Utilities	121 (2.8%)	97 (2.2%)	58 (1.3%)	78 (1.6%)	54 (1.2%)	408 (1.8%)
Total	4398 (100%)	4457 (100%)	4489 (100%)	4962 (100%)	4501 (100%)	22,807 (100%)

[a]Panel A presents the month-wise breakup of the recommendations for five years of data.
[b]Panel B presents the breakup of the recommendations as per the recommendation class, namely, strong buy, buy, hold, sell and strong sell.
[c]Panel C presents the breakup of recommendations per sector classification. These classifications are based on the classification of stocks provided by BSE Limited, one of the oldest and largest stock exchanges in India.

5. Methodology, tools and techniques

Asquith et al. (2005) introduced the first measure of target price achievement where they devised a simple metric as the target price prediction should be considered 'achieved' if the stock price of the analyzed company equals or exceed (falls below, in case of sell recommendations) the target price at any time during the 12-month period from the release of the recommendation. Bradshaw, Brown, et al. (2013) divided the 12 months prediction horizon into two segments, namely, during the period and the end of the period, and measured the target price achievements for the two segments separately.

Bonini et al. (2010) developed a measure to test for inaccuracy from an investor perspective. They developed two metrics to define the ideal strategy that an investor can adopt during the prediction horizon and a feasible strategy by focusing only on the end of the prediction horizon along with the prediction errors. Kerl (2011) improved on Bonini et al. (2010) measures by focusing on precise accuracy and considering the absolute values for errors over and under achieving the target price. Kerl (2011) argued that accuracy may be determined by the capacity of an analyst to predict exact prices. Bradshaw, Brown, et al. (2013) added ex ante and ex post optimism measures to determine the level of optimism and accuracy. Antônio et al. (2017) derived the target price accuracy of analyst consensus estimates and hypothesized a relationship between the standard deviation of consensus estimates and prediction error. Patel (2021) models for target price accuracy beyond a one-year horizon.

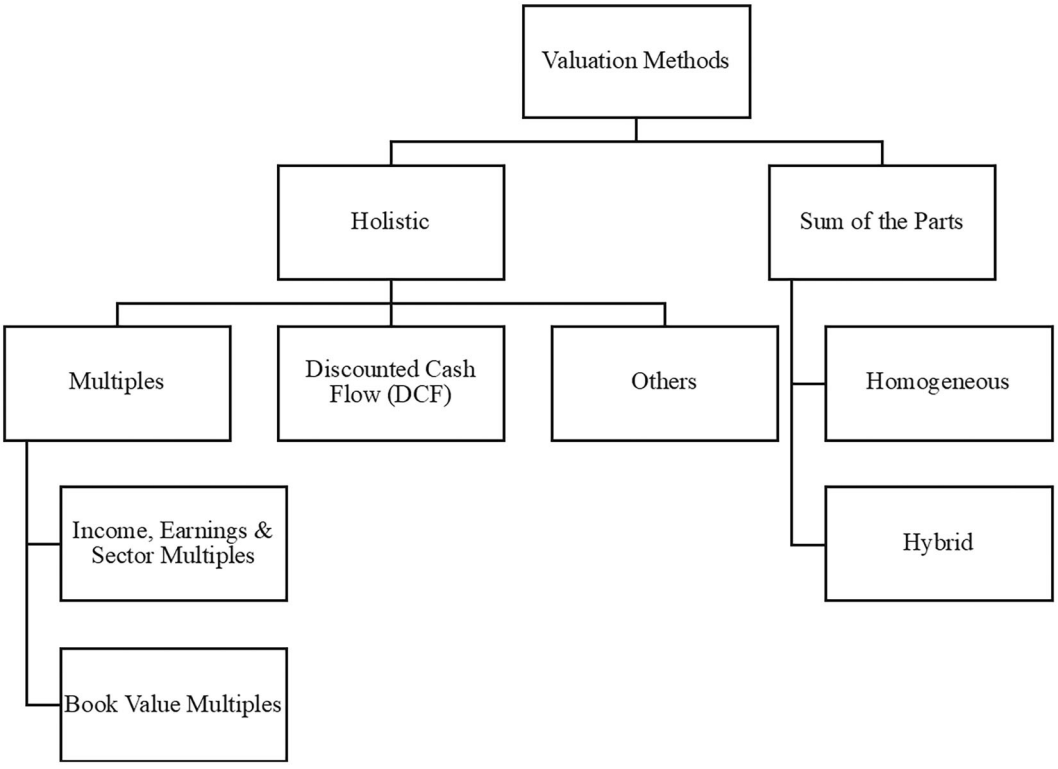

Figure 1. Classification of valuation methodologies.

Table 2. Analyst recommendations as per valuation methodologies.

Methodology	Total	%
Holistic valuation	18,852	83%
Multiples	17,854	78%
Income, earnings & sector multiples	15,219	67%
Book multiples	2635	12%
DCF	829	4%
Others	169	1%
Sum of the parts valuation	3955	17%
Homogeneous[a]	3342	15%
Hybrid	613	2%
Total	22,807	100%

[a]Homogenous in our dataset using multiples approaches for different parts.

5.1. Target price achievement

To determine the target price achievement, we adopted the methodology in Bradshaw, Brown, et al. (2013). First, for each recommendation, we determine the target price achievement by computing 'TPMetEnd' and 'TPMetDuring'.

Where,

TPMetEnd = 1 if the underlying share price reaches or exceeds (falls below in the case of sell recommendations) the target price at the end of the year from the recommendation date.

TPMetDuring = 1 if the underlying share price reaches or exceeds (falls below, in case of sell recommendations) the target price during or at the end of the year from the recommendation date.

Further, the cross-section of the recommendations is analyzed across recommendation classes (Strong Buy, Buy, Hold, Sell, Strong Sell), the market capitalization of the firm (Large-cap, Mid-Cap, Small-Cap), the sector of the firm, and the year of recommendation.

5.2. Valuation model effectiveness

To determine the effectiveness of the valuation methodologies on the target price achievements, we compute TPMetEnd and TPMetDuring for each recommendation and map them with the valuation methodologies used by the analysts. The categorization of the methodologies is illustrated in Figure 1.

5.3. Target price accuracy

We modify the model developed by Bonini et al. (2010) to test target price accuracy. It is developed from the perspective of an investor, wherein, an investor can have an 'Ideal Return Strategy (IRS)' or a 'Feasible Return Strategy (FRS).' So we call the model, 'Investor Return Strategy Accuracy Model (IRSAM)' for the purpose of this paper.

The IRS determines the degree of proximity of the share price to the target price during or at the end of a one-year period from the recommended date. Two metrics to determine accuracy were developed as follows:

$$\mathrm{ISR} = (\mathrm{P_m}/\mathrm{P_t}) - 1$$
$$\mathrm{IS\_PE} = ((\mathrm{TP_t}/\mathrm{P_m}) - 1 | \mathrm{TP_t} > \mathrm{P_t}; 1 - (\mathrm{TP_t}/\mathrm{P_m}) | \mathrm{TP_t} < \mathrm{P_t})$$

where:

t = publication date of the research report

P_t = Price of the share on the date t

TP_t = Target price specified by the analyst in the research report published at t

P_m = maximum or minimum share price during the time horizon. The maximum value of the share price is considered if TP_t is greater than P_t indicating a bullish view; the minimum value of the share price is considered if TP_t is less than Pt, indicating a bearish view.

ISR = an ideal strategy return computed as the difference between the minimum/maximum price during the year and the price at recommendation date t.

IS_PE = determines the IRS prediction error for a recommendation as the difference between the target price at t and the maximum/minimum market price in the relevant period.

Following the Ideal Return Strategy, it is difficult for an investor to understand when a price will be minimum/maximum is difficult to predict. Thus, the FRS determines the return at the end of a one-year period from the recommended date. Two metrics to determine the accuracy of the FRS were developed as follows:

$$\mathrm{FSR} = (\mathrm{P_e}/\mathrm{P_t}) - 1$$
$$\mathrm{FS\_PE} = ((\mathrm{TP_t}/\mathrm{P_e}) - 1 | \mathrm{TP_t} > \mathrm{P_t}; 1 - (\mathrm{TP_t}/\mathrm{P_e}) | \mathrm{TP_t} < \mathrm{P_t})$$

where:

t = publication date of the research report

P_t = Price of the share on the date t

TP_t = Target price specified by the analyst in the research report published at t

P_e = share price at the end of the time horizon. We defer the study of Bonini et al. (2010) model, as we consider only the price at the end of the prediction time horizon and no adjustment for any subsequent report issued by the security firm on the same company. This assists in checking the accuracy of each recommendation, which has a 12 month prediction horizon on the date of the issue.

FSR = a feasible return computed as the difference between the price at the end of the time horizon and the price at recommendation date t.

FS_PE = determines the FRS prediction error for a recommendation as the difference between the target price at t and the maximum or minimum market price in the relevant period.

The graphical representation of the variables is provided in Figure 2.

This study models a null hypothesis of zero average forecast error, with prediction errors being normally distributed with zero mean and known variance.

We further compute two metrics to analyze the target price accuracy.

IS_PE_M = Modified IS_PE with the value set to '0' if the target price is met during the year, else, the value of IS_PE. This metric specifies the error if the target price is not met.

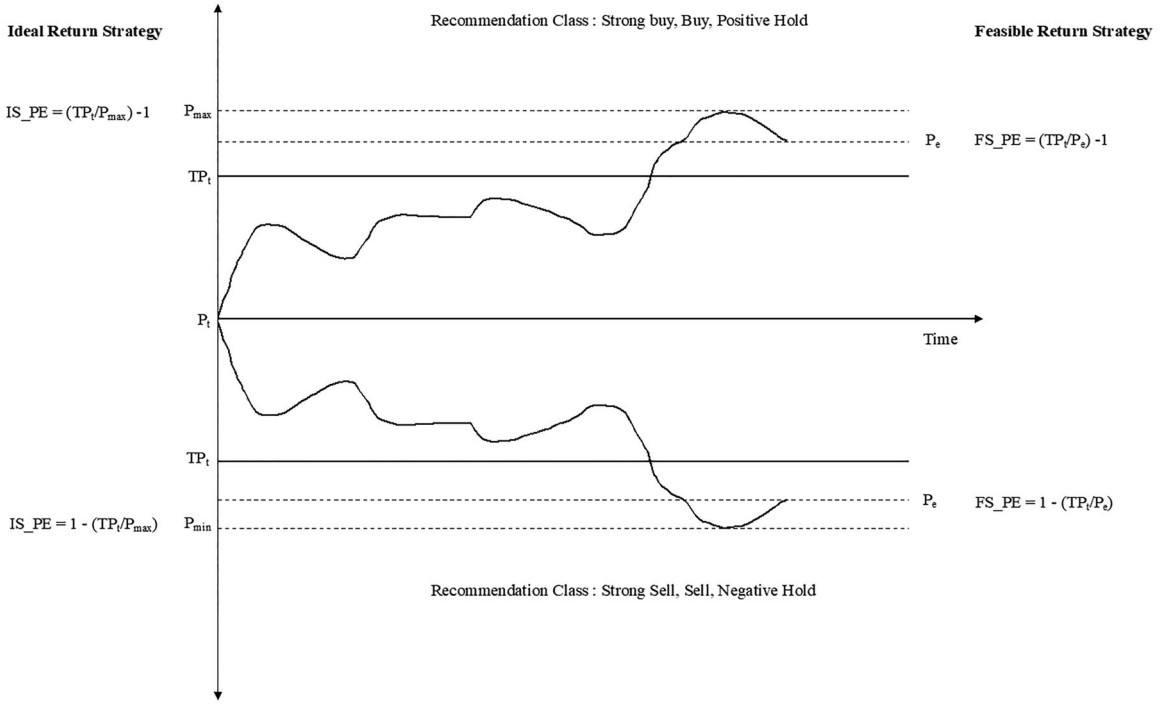

Figure 2. Graphical representation of ideal return strategy and feasible return strategy and its prediction errors.

FS_PE_M = Modified FS_PE with the value set to '0' if the target price is met at the end of the year, else, the value of FS_PE. This metric specifies the error if the target price is not met. IS_PE_M and FS_PE_M will not have negative values.

5.3.1. Recommendation class level accuracy using IRSAM metrics

Brav and Lehavy (2003) observed stock market reactions to target prices and noted that information conveyed by qualitative recommendations, such as buy, hold, sell, etc., is different among recommendation classes. When a recommendation report is released with the target price, the analyst invariably conveys the implicit return embedded in the recommendation.

$$\text{Implicit Return } (\text{IR}) = (\text{TP}_t/\text{P}_t) - 1$$

Where,

P_t = Price of the share on the date t

TP_t = Target price specified by the analyst in the research report published at t

As expected, implicit returns would be homogeneous with the recommendation that Strong Buy recommendations are expected to have higher implicit returns. Therefore, recommendation classes can act as proxies for levels of implicit returns, and we analyze the accuracy of target prices across recommendation classes using *IRSAM* metrics.

5.3.2. Recommendation class impact on accuracy

We develop a regression model to analyze the joint impact of recommendations on accuracy, controlling for implicit returns. The regression takes the following form.

$$IS\_PE\_M = \alpha + \beta_1\ IR + \beta_2\ Strong\_Buy + \beta_3\ Buy + \beta_4\ Sell + \beta_5\ Strong\_Sell + \varepsilon$$
$$FS\_PE\_M = \alpha + \beta_1\ IR + \beta_2\ Strong\_Buy + \beta_3\ Buy + \beta_4\ Sell + \beta_5\ Strong\_Sell + \varepsilon$$

Where:

IR is the implicit return of the recommendation.

Strong_Buy, Buy, Sell and Strong_Sell are dummy variables, taking value '1' if the recommendation belongs to that class else '0. ' We exclude 'Hold' as the control class.

5.3.3. Determinants of target price accuracy

The literature shows that the factors that affect the performance of recommendations include the size of the firm, market performance, firm-specific factors, price volatility, and valuation methods used by analysts. We develop a regression model to analyze the impact of these market factors on the accuracy of target prices.

$$\begin{aligned} IS\_PE\_M = {} & \alpha + \beta_1 IR + \beta_2\ KT\_CAP + \beta_3 MKTRTN\_PAST + \beta_4 PB\_RATIO \\ & + \beta_5 FIRM\_BETA + \beta_6 MKTRTN\_POST + \beta_7 EPS + \beta_8 VAL\_MULT \\ & + \beta_9 VAL\_DCF + \beta_{10} VAL\_SOTP + \beta_{11} CAP\_INT + \beta_{12} LAB\_INT + \varepsilon \\ FS\_PE\_M = {} & \alpha + \beta_1 IR + \beta_2 MKT\_CAP + \beta_3 MKTRTN\_PAST + \beta_4 PB\_RATIO \\ & + \beta_5 FIRM\_BETA + \beta_6 MKTRTN\_POST + \beta_7 EPS + \beta_8 VAL\_MULT \\ & + \beta_9 VAL\_DCF + \beta_{10} VAL\_SOTP + \beta_{11} CAP\_INT + \beta_{12} LAB\_INT + \varepsilon \end{aligned}$$

Where:

IR: Implicit returns to the recommendation. Bonini et al. (2010), Kerl (2011) and Patel (2021).

MKT_CAP: Natural log of the market capitalization of the firm on the report publication date (in INR Crore). (Bonini et al., 2010; Kerl, 2011).

MKTRTN_PAST: This is a momentum parameter computed as six months returns of the market index (BSE SENSEX) before the date of publication of the report (Bonini et al., 2010).

PB_RATIO: Price to Book ratio of the firm on the date of publication of the report (Bonini et al., 2010; Chatterjee et al., 2020; Kerl, 2011; Patel, 2021).

FIRM_BETA: Beta of the firm for the pre-recommendation period (90 days) (Chatterjee et al., 2020).

MKTRTN_POST: Market return for the target prices forecasting period (Bonini et al., 2010).

EPS: EPS of the firm.

VAL_MULT: Set to '1' if the target price is determined using multiples (earnings/book/sector) valuation approach, else '0'

VAL_DCF: Set to '1' if the target price is determined using discounted cash flow valuation approach, else '0'

VAL_SOTP: Set to '1' if the target price is determined using sum of the parts valuation approach, else '0'

CAP_INT: Set to '1' if the company is a part of the capital-intensive sector, else '0'. Recommendations belonging to commodities, energy, industrials, telecommunications, and utilities sectors (Table 1) are classified as capital-intensive (Soni & Subrahmanya, 2020).

LAB_INT: Set to '1' if the company is part of a labor-intensive sector, else '0.' Recommendations belonging to sectors such as consumer discretionary, fast-moving consumer goods, financial services, healthcare, information technology, and services (Table 1) are classified as labor-intensive (Soni & Subrahmanya, 2020).

6. Results

In this section, we discuss our results.

6.1. Target price achievement

Panel A of Table 3 provides the achievement of the target prices for the end of the prediction period and during the prediction period as per the recommendation classes.

We observe the achievement during the period of 63%, as opposed to Bradshaw, Brown, et al. (2013), Kerl (2011), Bonini et al. (2010), Bradshaw and Brown (2006) and Asquith et al. (2005) of 64%, 56%, 33%, 45% and 54% respectively. At the end of the period, we document an achievement of 38% as opposed to Bradshaw, Brown, et al. (2013), Bonini et al. (2010) and Bradshaw and Brown (2006) of 38%, 20% and 24%, respectively. The cross-sectional achievements for buy, hold, and sell are also slightly improved compared to Kerl (2011). Previous studies on the target price accuracy of research analysts in India by Sayed and Chaklader (2014) registered 57.6% accuracy during the period analysis for buy recommendations. Patel (2021) observed a 43% accuracy for buy recommendations in the banking industry.

Table 3. Target price achievement.

PANEL A					
Recommendation	Total	TPMetEnd	% Achievement	TPMetDuring	% Achievement
Strong buy	8258	8258	100%	3616	44%
Buy	7710	7710	100%	5482	71%
Hold	5256	5256	100%	4268	81%
Sell	1237	1237	100%	796	64%
Strong sell	346	346	100%	128	37%
Total	22,807	22,807	100%	14,290	63%
PANEL B					
Market capitalization	Total	TPMetEnd	% Achievement	TPMetDuring	% Achievement
Large cap	8945	3504	39%	5835	65%
Mid cap	6307	2714	43%	4344	69%
Small cap	7555	2514	33%	4111	54%
Total	22,807	8732	38%	14,290	63%
PANEL C					
Sector	Total	TPMetEnd	% Achievement	TPMetDuring	% Achievement
Commodities	3065	1350	44%	2039	67%
Consumer discretionary	5312	2014	38%	3411	64%
Energy	1193	437	37%	683	57%
Fast moving consumer goods	1535	623	41%	1060	69%
Financial services	3385	1278	38%	2095	62%
Healthcare	2128	818	38%	1338	63%
Industrials	3153	1045	33%	1762	56%
Information technology	1765	784	44%	1194	68%
Services	513	162	32%	296	58%
Telecommunication	350	112	32%	193	55%
Utilities	408	109	27%	219	54%
Total	22,807	8732	38%	14,290	63%

We recorded the highest achievement rate of 63% during the prediction period, indicating that analysts have a reasonable ability to make predictions. However, the predictive ability seems to be declining with optimism as a 'strong buy' and 'strong sell' recommendations have lower achievements as against 'hold', 'buy' or 'sell' recommendations. More buy recommendations than sell recommendations confirm analysts' bias toward buy recommendations.

Panel B of Table 3 provides target price achievements as a cross-section of analysts' recommendations for large market capitalization, mid-market capitalization, and small market capitalization stocks. The classification of the companies into large-cap, mid-cap, and small-cap is performed according to guidelines from the Securities Exchange Board of India (SEBI).[2] Analysts find it difficult to predict the future performance of small-cap stocks, as indicated by the lowest accuracy of 54% during the period; however, analysts tend to recommend small capitalization growth stocks (B. Barber et al., 2003).

Panel C of Table 3 provides the target price achievements for recommendations of stocks belonging to various sectors. The highest accuracy was observed for the FMCG sector (69%), followed by the IT sector (68%). The lowest accuracy was observed for the utility sector at 54%, followed by telecommunication at 55%. Although analysts seem to have reasonable accuracy across sectors, the lower accuracy in utilities, telecommunications, and energy may be attributed to the capital-intensive nature of the sector and the influence of government regulations.

6.2. Valuation methodology effectiveness

Table 4 shows the effectiveness of the valuation methodologies in predicting target prices. The SOTP Hybrid methodology is most effective with 65% achievement; however, analysts rarely use this methodology, with only 3% of the total recommendations attributed to it. Analysts primarily use multiple-based valuation, which is effective at 64% during the year and 39% at the end of the year's target price achievement. The effectiveness of DCF in predicting 12-month ahead target prices is the lowest, with 53% achievement.

Our findings resonate with those of Asquith et al. (2005), who found that most analysts use simple multiple based valuation as opposed to DCF and other models fancied by MBA curricula. These findings

Table 4. Effectiveness of valuation methodology on target price achievement.

Methodology	Count	TPMetEnd	% Achievement	TPMetDuring	% Achievement
Holistic valuation	18,852	7231	38%	11,882	63%
Multiples	17,854	6923	39%	11,346	64%
Income multiples	15,219	5959	39%	9757	64%
Book multiples	2635	964	37%	1589	60%
DCF	829	263	32%	442	53%
Others	169	45	27%	94	56%
Sum of the parts valuation	3955	1501	38%	2408	61%
Homogeneous	3342	1230	37%	2007	60%
Hybrid	613	271	44%	401	65%
Total	22,807	8732	38%	14,290	63%

Table 5. Target price accuracy summary statistics for investor return strategy accuracy model.

		Ideal return strategy		Feasible return strategy	
Recommendation	Implicit return	ISR	IS_PE	FSR	FS_PE
Strong buy					
Mean	35%	44.31%	1.86%***	16.84%	48.48%***
Median	30%	26.90%	4.21%	4.39%	27.20%
Std. dev.	17%	56.32%	27.16%	61.69%	102.85%
No of observations	8258				
Buy					
Mean	13%	38.1%	−12.5%***	17.0%	17.5%***
Median	15%	25.5%	−10.0%	9.9%	2.9%
Std. dev.	5%	51.0%	19.0%	53.0%	221.6%
No of observations	7710				
Hold					
Mean	4%	21.09%	−21.97%***	18.47%	10.68%***
Median	4%	11.33%	−13.64%	8.62%	4.75%
Std. dev.	8%	53.82%	56.11%	61.35%	73.81%
No of observations	5256				
Sell					
Mean	−10%	−21.14%	−26.45%***	18.86%	10.72%***
Median	−10%	−16.26%	−7.53%	10.97%	19.75%
Std. dev.	5%	18.83%	68.90%	47.27%	51.53%
No of observations	1237				
Strong sell					
Mean	−28%	−24.29%	−13.42%**	13.02%	16.08%***
Median	−26%	−19.53%	10.34%	4.85%	31.21%
Std. dev.	8%	19.64%	109.18%	52.63%	83.34%
No of observations	346				

Note: Significance at the 10%, 5% and 1% levels are denoted by *, **, and ***, respectively.

refute Erkilet et al. (2022) observations of the ineffectiveness of the SOTP approach over a holistic approach. We find merit in Bonini et al. (2022) and Gleason et al. (2013) that the use of more rigorous valuation techniques, such as the SOTP Hybrid approach, may improve accuracy. Our findings suggest that both the holistic and SOTP methods are at par. In the Indian context, our findings contradict Sayed (2015) the observations that the DCF methodology provides superior target price accuracy.

6.3. Target price accuracy

6.3.1. Recommendation class level accuracy using IRSAM metrics

Table 5 provides summary statistics for the ideal return strategy and return strategy as part of the Investor Return Strategy Accuracy Model considered in this study. Mean implicit returns are decreasing across the recommendation classes from 'strong buy' to 'strong sell,' thus the qualitative measures and target price recommendations are aligned. The mean *ISR* is higher for all recommendation classes except for 'strong sell, ' indicating slightly conservative estimates from the analysts. This is also confirmed by the significant negative prediction errors of *IS_PE* for 'buy, hold, sell,' and 'strong sell'. A slight overshooting of the Ideal Return Strategy is observed only in the case of a 'strong buy'. Our results differ from Bonini et al. (2010) who observed large overshooting for 'strong buy' and 'strong sell' recommendations for an Ideal Strategy. This can be attributed to the lower target price achievement, for during the

Table 6. Impact of the recommendation class on accuracy.

	IS_PE_M		FS_PE_M	
	Coefficient	T-stat	Coefficient	T-stat
Intercept	0.0489***	37.21	0.2447***	12.12
IR	0.4308***	65.80	1.2726***	12.66
Strong buy	−0.0818***	−30.55	−0.1356***	−3.30
Buy	−0.0816***	−46.27	−0.13930***	−5.14
Sell	0.0230***	8.33	0.1052***	2.48
Strong sell	0.1894***	38.36	0.4145***	5.47
Adj R^2	0.307		0.017	
F-statistic	1949***		75.28***	
Observations	17,551		17,551	

Note: Significance at the 10%, 5% and 1% levels are denoted by *, **, and ***, respectively.

prediction horizon, of 33% observed in the Bonini et al. (2010) study, as opposed to 63% observed in our study. Analysts provide conservative estimates overall for the Ideal Return Strategy.

For the Feasible Return Strategy, the prediction errors are large, positive and significant, indicating overshooting. High values of 48.48% and 16.08% of *FS_PE* are observed for 'strong buy' and 'strong sell' recommendations, respectively. The results are aligned with Bonini et al. (2010) who had a large, positive overshooting of 36.85% for the 'strong buy' class and 29.14% for the 'strong sell' class.

Analysis of *IS_PE* and *FS_PE* indicates that when analyst recommendations are issued, there is an impact on stock prices, and they move in the direction of the recommendation, which results in lower or negative *IS_PE*. However, eventually, stock prices reverse, resulting in a high, positive *FS_PE*.

6.3.2. Recommendation class impact on accuracy

Table 6 shows the impact of the recommendation class on accuracy. The significance of the regression was high, as represented by the F-statistic. Implicit return (IR) associated with the target price for each recommendation was observed to have the largest impact on accuracy. A positive prediction error (*IS_PE_M* or *FS_PE_M*) indicates overshooting. Thus, a positive coefficient of IR indicates IR impacting accuracy and is significant at the 1% level. These results are consistent with those of Bonini et al. (2010) and Bradshaw and Brown (2006) who observed the negative effect of implicit returns on analysts' target price accuracy. 'Strong Sell' and 'Sell' recommendation are also observed to impact accuracy. A significant positive coefficient indicates that although analysts give a very low number of 'strong sell' and 'sell' signals, they tend to overshoot when they recommend a sell. A significant negative coefficient for 'strong buy' and 'buy' recommendations indicates analysts' conservatism while providing these recommendations. Our findings document a significant impact of recommendation classes on target price accuracy.

6.3.3. Determinants of target price accuracy

Table 7 provides the results for the determinants of the target price accuracy. A positive coefficient indicates an addition to the prediction error. Implied Return (IR) has a large significant positive coefficient, indicating that more optimistic target prices contribute to added prediction errors. A large significant negative coefficient is observed for ex-post market returns for the prediction period, indicating that better market returns reduce prediction error. This can be explained by the fact that analysts issue substantially more buy recommendations than sell ones. An upward market movement will affect the general market sentiment and positively impact stocks, which results in achieving their target prices for buy recommendations. The coefficients of the beta of stock are significant and positive. A higher-beta firm is expected to be volatile and to contribute to prediction errors. It also highlights analysts' inability to comprehend volatility when calculating target prices. Significant negative coefficients for EPS indicate that negative values increase prediction errors. This finding indicates analysts' difficulty in predicting prices for loss-making enterprises. The significant positive coefficient of the DCF valuation methodology in the case of IS indicates that analysts' use of the DCF methodology adds to prediction errors. Capital intensive sectors show significant positive coefficients, indicating the limited ability of analysts to forecast the benefits of capex and its impact on target prices.

Table 7. Determinants of target price accuracy.[a]

	IS_PE_M		FS_PE_M	
	Coefficient	T-stat	Coefficient	T-stat
Intercept	0.0101	1.47	0.3338***	3.33
IR	0.2947***	84.14	0.8930***	17.45
MKT_CAP	0.0000	0.18	−0.0105***	−2.59
MKTRTN_PAST	0.0109*	1.68	−0.1934**	−2.04
PB_RATIO	0.0001	0.55	−0.0052***	−3.44
FIRM_BETA	0.0069***	5.54	0.1364***	7.52
MKTRTN_POST	−0.1290***	−28.88	−1.4008***	−21.46
EPS	−0.0000***	−3.91	−0.0004***	−2.80
VAL_MULT	0.0018	0.24	0.0740	0.68
VAL_DCF	0.0239***	2.92	0.1911	1.60
VAL_SOTP	0.0000	0.00	0.0385	0.35
CAP_INT	0.0092***	2.59	0.1412***	2.73
LAB_INT	0.0009	0.27	0.1927***	3.80
Adj R^2	0.284		0.044	
F-statistic	821.5***		95.45***	
Observations	22,807		22,807	

Note: Significance at the 10%,5% and 1% levels are denoted by *,**, and ***, respectively.
[a]We have also performed a robustness check to determine the significance of the determinants of the factors affecting accuracy. The robustness check is performed by modifying the dependent variables of our determinants of target price accuracy 'IS_PE_M' and 'FS_PE_M' to '0' if the target prices are achieved and '1' if the target prices are not achieved under the Ideal and Feasible strategy. We find similar significance of variables and signs of the coefficients for the significant variables, which assures the robustness of our results.

Our findings for analyst optimism, firm volatility, and post-market returns are negatively related to target price accuracy, which matches the findings of Bonini et al. (2010) and Kerl (2011). Our EPS findings are consistent with those of previous studies of Bonini et al. (2010). Our findings on the effects of valuation methods and capital intensity on target price accuracy are a new addition to the literature.

7. Conclusion

We analyzed a large sample of 22,807 recommendations over a five-year period from 2016 to 2020 for the Indian Stock Market, covering 805 companies. We observed higher recommendations after the availability of new information through quarterly results, shareholder meetings, and so on. These recommendations were particularly high in January, May, July, October, and November. 'Strong Buy' and 'Buy' recommendations significantly exceeded sell recommendations. In our analysis,

i. We observed that the target price was achieved by 38% at the end of the 12-month period and 63% at any time during the 12-month period after the recommendation. According to our literature review, 63% achievement is the highest recorded across similar studies in the US, German, and Italian markets, suggesting that analysts demonstrate reasonable predictive ability in the Indian market. Target price achievement is slightly lower for small-cap stocks, which can be attributed to their high volatility. We found the highest target price achievement for the FMCG and IT sectors and the lowest achievement for the utilities and telecommunications sectors, indicating analysts' limited predictive abilities in capital-intensive sectors.
ii. We document the limited effectiveness of the DCF methodology and the high effectiveness of the SOTP hybrid and multiple-based approach to valuation in predicting target prices. Our findings suggest that both the holistic and SOTP methods are at par. Analysts prefer holistic and multiple-based valuation approaches to arrive at the target prices. We find merit in the use of more rigorous valuation techniques, such as the SOTP Hybrid approach, to improve accuracy.
iii. Target price accuracy was tested using a model developed by Bonini et al. (2010). The prediction errors for the ideal return strategy are significant and negative, indicating conservative estimates by analysts for the time horizon; here, our results differ from Bonini et al. (2010). For a feasible return strategy, the prediction errors were large, positive, and significant, indicating overshooting. Our results indicate that stock prices move in the direction of recommendation, primarily meet the target prices,

and consolidate/mean revert during the 12-month horizon. We document the significant impact of recommendation classes on target price accuracy, especially, although analysts give a very low number of 'strong sell' and 'sell' signals, they tend to overshoot when they recommend a sell.

iv. We found that analyst optimism, represented by implicit returns in target prices, negatively impacts target price accuracy. 'Strong sell' and 'sell' recommendations are low in number but overshoot. Ex-post market returns positively impact accuracy, owing to more buy recommendations than sell recommendations. A higher firm beta contributes to prediction errors, indicating analysts' limited ability to model volatility. The significant negative coefficients for EPS underscore analysts' difficulty in predicting prices for loss-making enterprises. The use of the DCF methodology was observed to add to the prediction errors. The capital-intensive nature of a firm adds to the prediction error, indicating the limited ability of analysts to forecast the benefits of capex and its impact on target prices.

Our research indicates that analysts have reasonable predictive abilities, and over-optimism reduces the prediction accuracy. Our findings on valuation methods and capital intensity impacting target price accuracy further add to the existing literature. The study offers practical insights for both investors and policymakers. Investors should recognize the limitations of analysts' stock price forecasts, particularly in capital-intensive industries, and exercise caution when evaluating highly optimistic target price recommendations, especially for small-cap or loss-making companies. Analysts and brokerage firms are encouraged to adopt more rigorous valuation models, such as the SOTP Hybrid, wherever applicable, when setting target prices. From a policy perspective, there is a need to develop regulations and disclosure requirements to better protect investors by ensuring transparency from analysts and brokerage firms. We have analyzed sector capital intensity impact on the accuracy of target prices, future research could investigate the influence of analyst characteristics, brokerage firm attributes, and additional sector-specific factors on the accuracy of target price predictions.

Notes

1. See https://www.statista.com/statistics/274490/global-value-of-share-holdings-since-2000/.
2. SEBI has, vide its circular no. SEBI/HO/IMD/DF3/CIR/P/2017/114 dated 6th October 2017, defined large cap, mid-cap and small-cap companies.

Author contributions

Suresh Kadam: conceptualization; data curation; methodology; formal analysis; writing–original draft; writing – review & editing (equal). Madhvi Sethi: supervision; validation; writing – review & editing (equal).

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Data availability statement

The data that support the findings of this study are available from the corresponding author, Madhvi Sethi, upon reasonable request.

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