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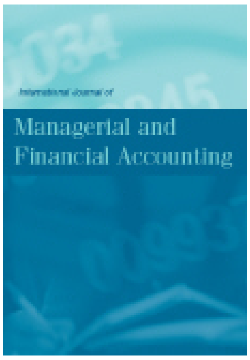

International Journal of Managerial and Financial Accounting

ISSN online: 1753-6723 - ISSN print: 1753-6715
https://www.inderscience.com/ijmfa

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DOI: 10.1504/IJMFA.2024.10053983

Article History:

Received:	25 June 2021
Last revised:	08 December 2022
Accepted:	12 December 2022
Published online:	02 April 2024

Financial analysts' forecast accuracy, informativeness and its implications for market efficiency: evidence from an emerging market

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Abstract: In this work, we study the connection between analyst forecast accuracy and the well-known systematic risk factors of momentum and size, which are important from the market efficiency point of view. Using an extensive 21 years (1998–2018) analyst forecast data for Indian companies extracted from the 'Refinitiv Eikon' database for BSE-500 stocks, we evaluate if consensus forecast errors are predictable with respect to size and momentum. Our results indicate the presence of cognitive bias in analysts' forecasts due to market and stock momentum. We also find that analysts forecast more aggressively for smaller sized companies, particularly in a poorer information environment. To explore the impact of these biased forecasts on market efficiency, we also check for their informativeness. We find that the biased analyst forecasts are informative, thus contributing to market inefficiency, however their informativeness is somewhat reduced, depending on the magnitude of the momentum and size factors.

Keywords: analyst forecasts; forecast accuracy; market informativeness; size; momentum.

JEL codes: JEL, G17.

Reference to this paper should be made as follows: Chaudhury, A., Sahoo, S. and Dawar, V. (2024) 'Financial analysts' forecast accuracy, informativeness and its implications for market efficiency: evidence from an emerging market', *Int. J. Managerial and Financial Accounting*, Vol. 16, No. 2, pp.159–179.

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1 Introduction

The market efficiency literature argues that predictable returns are not necessarily due to any inefficiency of market participants, but due to certain risk factors which are priced by the market. Existing literature, i.e., Fama and French (1992, 2015, 2018) and Carhart (1997) suggested that certain firm characteristics including size, value and stock momentum among others represent risk factors which drive market returns. However, the debate on whether these factors indicate an in-built risk or linked to some inherent market inefficiency, is still not settled. Jegadeesh and Titman (1993) show that buying past winners and selling past losers generate abnormal returns over a 3 to 12 month horizon which are not explained by systematic risk factors and can be linked to market inefficiency. We investigate the market inefficiency angle in our work, which is brought upon due to some firm and market characteristics causing bias in the forecasts of financial analysts. We also check if the markets are at least partially able to incorporate the same.

In this paper, we try to connect the established factors like momentum and size to the inherent bias of the market agents (financial analysts). We suggest that the market inefficiency could be due to analyst's extrapolating recent good (or bad) performance into the future leading to over (or under) estimation of firm value and causing market inefficiencies. These inefficiencies face reversal in future periods as the markets price-in actual numbers after earnings announcements. Market analysts could exacerbate this bias by forecasting aggressively in case of strong near-term returns shown by the stock or the overall market, leading to over-optimism and negative forecast errors, while the actual numbers fail to meet the expectations. In our case, we attribute the forecast bias of the analysts to predictable factors like cognitive bias (Dreman and Berry, 2006; Easterwood and Nutt, 1999) which arise due to behavioural reasons like anchoring, and as a result the analysts are influenced by the strong recent stock and market returns while making their forecasts, especially when accompanied by strong EPS growth. This bias is also aggravated in case of smaller (midcap) firms, where analysts have to encounter a poor information environment which could again lead to optimism and negative forecast errors (Gu and Wu, 2003; Zhang, 2005; Tse and Yan, 2008).

Since the analyst estimates serve as a benchmark for market expectations (Ohlson, 2001), biased forecasts could lead to markets becoming inefficient. Forecast errors are associated with excess returns since the market overweighs or naively follows analyst forecasts (Hughes and Ricks, 1987; So, 2013). Authors like Lakonishok et al. (1994), La Porta (1996) and Dechow and Sloan (1997) investigate the 'value' factor driving market returns and find that the contrarian strategy of 'value' outperforming 'glamour' stocks is due to markets naively following analysts' forecasts of lower future earnings growth for 'value' stocks. In this paper, we investigate the 'momentum' and 'size' factors and how they are linked to the bias in analyst forecasts and also whether the markets are able to account for the same.

To test the hypothesis that analyst forecasts are biased in case of higher stock/market momentum as well as for smaller sized firms, we track the forecast error of the analyst forecasts for the broad market of BSE-500 stocks in India, from 1998 to 2018. We first try to relate the forecast bias due to the market momentum from the past 12 month returns of the BSE-500 index and those of the individual stock returns. Next, we try to see if forecast bias is higher for smaller firms by using a 'midcap' dummy representing companies below the market capitalisation of \$100 mn. In the second stage, we test whether the markets are able to incorporate the above bias due to market/stock momentum and size. For this purpose, we use a residual earnings framework suggested by Ohlson (2001) as applied by Barth et al. (2005), which includes a term for the 'extra' information in analyst forecasts, and relate it to the momentum and size factors in our models to test whether the market price factors in the bias. To moderate the effects of endogeneity in our models, we use the dynamic panel method using GMM and control for other factors affecting forecast bias like EPS growth, forecast dispersion (indicating the information environment), change in analyst estimates (to account for under-reaction of the analysts), size, analyst coverage, market turnover (to account for information environment) and whether firm is profit/loss making.

Our results show that financial analysts suffer from anchoring bias due to recent stock and market performance and forecast aggressively resulting in negative forecast errors, controlling for other sources of bias like EPS growth, forecast dispersion and forecast revisions. The bias is even higher, if the strong stock and market performance is accompanied by higher EPS growth. Further, analysts forecast more aggressively for smaller firms which have a market capitalisation of less than \$100 million. We attribute this bias to the poor information environment (measured by dispersion in the analyst forecasts) for smaller mid-cap firms, which makes the analysts forecast aggressively. This could be either due to their cognitive bias (or innate optimism) or strategic bias (to curry management favours) of the analysts. Predictably, the forecast error is higher if the information environment is poorer. Finally, our residual income models based on Ohlson (2001) framework show that the markets are partially able to account for the bias in the analyst forecasts due to the momentum and size factors by accordingly reducing the informativeness of the 'other information' in the forecasts.

Our paper contributes to literature by linking the 'size' and 'momentum' factors which are considered dominant 'risk factors' in asset pricing literature, to the bias in analyst forecasts which causes market inefficiency not related to any risk. We also use a different framework using the ‘other’ information in the analyst forecasts to measure whether informativeness of the forecasts is affected by the bias due to ‘size’ and ‘momentum’. There are not too many studies in literature in the context of an emerging market like India, where analysts face a weaker regulatory and governance framework which could affect the accuracy of their forecasts, where our study hopes to make a contribution.

The rest of the paper proceeds as follows. Prior literature is discussed in Section 2, the hypotheses are explained in Section 3 and the research design and models are explained in Section 4. Data sources and sample selection including descriptive statistics and correlation matrix are discussed in Section 5, followed by analysis and interpretation of results in Section 6. Finally, Section 7 provides the concluding remarks including suggestions for future research

2 Literature review

Market inefficiencies have often been attributed to analyst forecasts, which the markets treat as a benchmark for future expectations, leading to predictable anomalies. The role of analysts, particularly from the sell side, in the capital markets, has been extensively studied in literature. They help in reducing information asymmetries, making markets more efficient and improving the information flow (Givoly and Lakonishok, 1979; Womack, 1996; Barber et al., 2001; Gleason and Lee, 2003; Jegadeesh et al., 2004; Chan and Hameed, 2006). They act as an effective information intermediary between firms and their investors by publishing their analysis of company performance, future expectations, investment recommendations as well as financial forecasts for companies under their coverage (Bradshaw, 2011). The consensus earnings forecasts, which is the mean/median forecast of the analysts tracking the company, serves a tangible benchmark which can used as a proxy for the expectation of future earnings (Ohlson, 2001).

The drivers of analyst forecast bias has been extensively studied in literature. Most of the studies infer that analyst forecast bias is predictable, however the markets do not fully account for the same. Lim (2001) show that along with several other characteristics, previous stock price reactions (momentum) and size, also have an effect on forecast bias.

2.1 Momentum

One of the early works on how price momentum leads to market inefficiencies and subsequent reversals was by De Bondt and Thaler (1985, 1987). They found that stock markets overreact and extrapolate past performance leading to recent ‘losers’ outperforming and recent ‘winners’ underperforming. Jegadeesh and Titman (1993) find that outperformance of a portfolio of recent winners over a 3 to 12 month horizon could be due to overreaction by investors due to biased expectations of future prospects. La Porta (1996) find that value stocks outperform growth stocks over a four-year period following earnings announcements since markets price in higher expected growth for growth stocks and are disappointed when actual numbers are released. This indicates that the markets extrapolate future expectations of earnings based on the past. Chan et al. (2003) show that stock values are actually inversely related to future growth over a five year horizon, driven by the analysts’ institutional brokers estimate system (IBES) growth forecasts, which are too optimistic.

However, inefficiencies in analyst forecasts could lead to inefficiency in the market. De Bondt and Thaler (1990), attribute the overreaction and subsequent reversal of stock prices to security analysts making extreme forecasts leading to predictable forecast errors. They argue that analysts make biased forecasts due to behavioural reasons. Lakonishok et al. (1994) argue that the outperformance of value stocks over glamour stocks is due to investors (or analysts) naively extrapolating past bad (or good) performance into the future resulting in value (glamour) stocks being underpriced (overpriced) benefiting contrarian investors. It is not due to any inherent risk factor. Dechow and Sloan (1997) find similar conclusions that stock prices naively follow the biased analyst forecasts leading to predictable returns from contrarian strategies.

2.2 Size

Size has an impact on the forecast error because smaller firms have a weaker information environment and are more difficult to value. Analyst forecast bias due to company size could be either due to cognitive or strategic reasons. Lys and Soo (1995) find that analyst forecast accuracy is negatively related to firm size. Zhang (2005) find that analysts make biased forecasts for smaller firms due to cognitive bias. However, there are a large number of studies which attribute 'strategic reasons' for analyst forecast bias in case of smaller firms. Tse and Yan (2008) find that in case of small firms with large forecast dispersion, analysts bias their forecasts upward, to improve their career prospects. Das et al. (1998) show that analysts issue more optimistic forecasts for low predictability firms in order to facilitate access to management's non-public information. Gu and Wu (2003) propose that analysts provide optimistic forecasts for smaller firms to get better management information since public information is less for these firms. Keskek and Tse (2018) find that analysts tend to bias their forecast upward in poor information environments and downwards in rich environments, which is due to attempts to curry favour with the management.

All the studies we discussed which relate market momentum and size to the analyst forecast bias are based on developed market studies and few studies are done in the context of emerging markets like India. Emerging markets are supposed to be more inefficient because of weaker governance and regulatory environment. The accounting practices might also differ from developed markets (Basu et al., 1998). Our study addresses an important gap in literature by exploring the sources of analyst inefficiency in emerging markets and relating them to the size and momentum anomalies which have their source in asset pricing literature, and also investigate whether the markets incorporate the bias or not.

3 Hypothesis

3.1 Momentum

To test the effect of momentum on forecast accuracy, we choose the trailing one year returns of the broad market (BSE-500)[1] and those of the individual stocks. This is to investigate whether strong (weak) market momentum causes the analysts to become more optimistic (pessimistic) and make aggressive forecasts, leading to forecast error. This effect should be more pronounced if accompanied by strong (weak) actual EPS growth, exacerbating the bias.

Subsequently, we test whether the markets are able to discern the presence of the biased forecasts by the analysts and adjust their informativeness accordingly. To test for market informativeness, we use a market model based on Ohlson's (2001) residual earnings framework, based on the trailing one year stock and market returns. We hypothesise that the consensus earnings forecasts by the analysts should remain informative and drive the stock prices. However, we investigate whether the informativeness is affected due to the momentum from trailing one year stock/market returns.

In summary, we intend to test the following hypothesis:

H_{1a} Forecast errors arise due to anchoring bias of the analysts resulting in negative (positive) forecast errors when the market and stock momentum is positive (negative). The bias is also higher (lower) in case EPS growth is higher (lower).

H_{2a} For firms with stronger market or stock price momentum, the biased forecasts are still informative. However, the incremental informativeness of the biased forecasts is lower, as per the interaction term between analyst estimates and stock/market returns.

3.2 Size

In our second test, we try to check whether size (based on market capitalisation) has any impact on forecast accuracy since smaller firms are more difficult to forecast and have a poorer information environment. In other words, we check whether analysts are more biased while forecasting the earnings for midcap firms (defined as firms having a market capitalisation of less than \$100 million). Again, this effect should be stronger if the information environment (represented by forecast dispersion) is poorer.

Subsequently, we investigate the effect of size on the informativeness of analyst forecasts. To test for market informativeness, we use a market model based on Ohlson's (2001) residual earnings framework and use a midcap dummy (market capitalisation < \$100 million) to test whether the informativeness is effected due to the company size.

In summary, we intend to test the following hypothesis:

H_{1b} Forecast errors are higher for mid-cap companies since they have a poor information environment due to which analysts forecast aggressively. The bias is more if information environment is poor (high forecast dispersion).

H_{2b} For midcap firms, the biased forecasts are still informative. However, the incremental informativeness of the biased forecasts is lower, as per the interaction term between the analyst estimates and the midcap dummy.

4 Research design

4.1 Model for forecast error

For measuring analyst forecast error, we find the difference between the actual earnings and latest analyst forecasts made at the end of the fiscal year, which is supposed to be the last updated forecast incorporating all the information about the firm:

$$FE_{it} = \left(NI_{actual} - NI_{consensus\ estimate}\right)$$

where *FE* = forecast error and *NI* = net income.

In our first model, we evaluate whether the analysts suffer from any cognitive bias from strong (or weak) market performance in the last 12 months. In case of a strong (or weak) market performance, analysts are expected to be more aggressive (pessimistic), due to anchoring bias leading to negative (positive) forecast errors. To measure this effect, we test whether the last 12 months' stock or market returns have a negative correlation with forecast error.

Our models to test for the effect of momentum on forecast error are:

$$\begin{aligned} FE_{it} &= a_1 + a_2 BSE\_ret_{i,t-1} + a_3 \sigma_{e,it} + a_4 \Delta Est_{it} + a_5 EPS\_gr_{it} \\ &+ a_6 BSE\_ret_{i,t-1} * EPS\_gr_{it} + a_7 MVE_{it} + a_8 Coverage_{it} + a_9 Loss\ dummy_{it} \\ &+ a_{10} Market\ turnover_{it} + a_{11} \sum Industry + u_{it} \end{aligned} \tag{1a}$$

$$\begin{aligned} FE_{it} &= a_1 + a_2 Stock\_ret_{i,t-1} + a_3 \sigma_{e,it} + a_4 \Delta Est_{it} + a_5 EPS\_gr_{it} \\ &+ a_6 Stock\_ret_{i,t-1} * EPS\_gr_{it} + a_7 MVE_{it} + a_8 Coverage_{it} + a_9 Loss\ dummy_{it} \\ &+ a_{10} Market\ turnover_{it} + a_{11} \sum Industry + u_{it} \end{aligned} \tag{1b}$$

In model (1a), we use the trailing one year BSE-500 index trailing returns to measure momentum. In model (1b), we use the respective trailing one-year stock returns to capture momentum instead of the index returns.

In order to effectively measure whether market performance has any bearing on forecast bias, we need to control for some of the known elements affecting analyst forecasts. One of the key parameters analysts look out for while forecasting is the actual EPS growth rate. A strong (weak) actual EPS growth rate, indicates strong (weak) company performance and might cause the analysts to over-react. This could cause biased forecasts by the analysts due to extrapolation of the strong (weak) EPS growth, leading to aggressive (pessimistic) forecasts for faster (slower) growing firms. Since the market returns should also be positively (negatively) affected due to strong (weak) actual EPS growth, by controlling for the actual EPS growth, we can identify whether stock or market momentum causes an additional cognitive bias in analyst forecasts, in addition to that contributed by EPS growth. We include an interaction term between the past 12-month stock (or market returns) and the actual EPS growth rate to ascertain if the forecast bias due to market/stock momentum is higher (lower) in case of higher (lower) EPS growth. A negative and significant coefficient of the interaction term would mean that the actual EPS growth rate exacerbates the analyst forecast bias due to market or stock momentum.

We also control for the uncertainty in the information environment through the dispersion of analyst forecasts σ_e. We expect a negative relationship between information uncertainty (leading to high dispersion in analyst forecasts) and the forecast error due to analysts not having clear information to forecast the earnings properly. In the case of higher uncertainty and lower information environment, analysts become more optimistic and thus forecast errors become more negative. Gu and Wu (2003) finds negative relation between forecast errors and forecast dispersion, which is a proxy for earnings uncertainty. Zhang (2005) show that greater information uncertainty causes negative forecast errors and subsequent forecast revisions following bad news. In line with literature, we hypothesise a negative relationship between forecast error and dispersion, since analysts are more likely to be optimistic in a poor information environment.

We include the term for forecast revisions over the full year, ΔEst_{it} in our model. This is to measure over (or under) reaction of analyst forecasts. Analysts might update their forecasts throughout the year in response to new information, however they might not incorporate all the information (Mendenhall, 1991; Abarbanell and Bernard, 1992). A positive correlation of forecast change with forecast error would show that analysts underreact to information while revising their earnings.

To incorporate the effects of poor environment, governance and information asymmetry, we control for additional factors affecting forecast accuracy like company market value (Lim, 2001; Beckers et al., 2004; Espahbodi et al., 2015), number of analysts covering the company (Alford and Berger, 1999; Lys and Soo, 1995; Beckers et al., 2004; Espahbodi et al., 2015) and whether or not the company is loss making (Brown, 2001; Ang and Ciccone, 2001; Ciccone, 2005; Coen et al., 2009). We also control for market turnover which captures the information environment. Additionally, we use dummies to control for industry level fixed effects [model (1a)].

In our second model of forecast error, we relate the analyst forecast bias to size and check whether the analysts are biased in their forecasts for midcap firms. We define midcap firms as those having a market capitalisation below \$100 million. We hypothesise that smaller firms have a poor information environment, and it is more difficult to forecast their earnings. Thus, the analysts make aggressive forecasts for smaller firms. The reason could be the cognitive bias of the analysts, or for strategic reasons, for, e.g., to curry favour from the management. Other control factors for size, coverage, market turnover and loss dummy are the same in model 1(b) as in model 1(a).

Our model to test for the effect of size on forecast error is:

$$\begin{aligned} FE_{it} &= a_1 + a_2 Midcap_{i,t} + a_3 \sigma_{e,it} + a_4 \Delta Est_{it} + a_5 EPS\_gr_{it} + a_6 Midcap_{i,t} * \sigma_{e,it} \\ &\quad + a_7 Coverage_{it} + a_8 Loss\ dummy_{it} + a_9 Market\ turnover_{it} + a_{10} \sum Industry + \varepsilon_{it} \end{aligned} \tag{2a}$$

To identify whether the size of the firm has an impact on forecast error, we include a midcap dummy, which we assign as 1, if the market capitalisation of the firm is below \$100 million and 0 otherwise. We hypothesise that the coefficient of the midcap dummy is negative and significant which would mean that the analysts forecast more aggressively for smaller midcap companies. In our model (2a), we control for other factors which affect analyst forecast errors, as explained before for equations 1(a) and 1(b), like EPS growth rate and the change in EPS forecasts over the year ΔEst_{it} to control for analyst over or under reaction while making their forecasts.

We also control for the dispersion of analyst forecasts σ_e representing the information environment and hypothesise a negative relationship with forecast error as in models 1(a) and 1(b). Since the smaller midcap firms are more likely to suffer from a poorer information environment, this could lead to more biased forecasts. To test our hypothesis, we include an interaction term between the midcap dummy and forecast dispersion in our model (2a). We hypothesise that the interaction term is negative, which means that the analysts forecast more optimistically for midcap firms in a poorer information environment (higher forecast dispersion). The reason for greater bias while tracking mid-cap companies could be due to lower disclosures from those companies compared to large caps resulting in poorer information environment and aggressive forecasts (Das et al., 1998; Gu and Wu, 2003; Zhang, 2005; Tse and Yan, 2008; Keskek and Tse, 2018). It could also be due to ease in currying management favours from smaller companies compared to larger ones (Francis and Philbrick, 1993; Lim, 2001; Richardson et al., 2004; Ke and Yu, 2006).

We use the other control factors like analyst coverage, loss dummy and market turnover to incorporate the effects of poor environment and information asymmetry, and also the industry dummies similar to models 1(a) and 1(b).

4.2 Model for market informativeness

In our subsequent analysis, we investigate whether the market informativeness of analyst forecasts are affected due to stock and market momentum as well as company size. In order to measure forecast informativeness, instead of following a direct regression model, we use an Ohlson (2001) framework which is essentially a residual earnings framework with time series forecasts of the residual earnings components. The model includes the 'other information' term to capture information about future earnings not explained by present accounting parameters in a time series, using observable analyst estimates. This 'other information' term allows us to isolate how much 'additional' information analyst forecasts are actually adding over and above information already embedded in accounting parameters. This 'other information' term is used in a structured residual earnings framework along with other components of abnormal earnings, book value and accruals (Barth et al., 2005).

In our model, we find the 'incremental' informativeness of analyst forecasts in the presence of earnings management in a two-step process. In the first step, we extract the 'other information' from the analyst forecasts [equation 3(c)]. To derive our model, we first find how much past accounting parameters explain current abnormal earnings [equation (3a)]. Then, we subtract this from the analyst expectations of abnormal earnings to find the 'incremental information' of analyst forecasts over accounting parameters, which we call v_1, in equation (3c). This is in line with the method followed by Dechow et al. (1999).

In summary, our model for extracting 'other information' in analyst forecasts is:

$$NI_{it}^{a} = \omega_{10} + \omega_{11} NI_{it-1}^{a} + \omega_{12} ACC_{it-1} + \omega_{13} BV_{it-1} + \varepsilon_{it} \tag{3a}$$

where NI^a is the abnormal earnings, defined as earnings minus capital charge on book value BV, ACC stands for total accruals and ε_{it} is the error term.

The mean of the above equation $\overline{NI_{it}^{a}}$ will give us the expected value of abnormal income as indicated by historical accounting parameters. The additional information provided by the analyst forecasts will be on top of this. The 'incremental information' of the expectation of abnormal earnings, over and above what is expected from the past accounting parameters is given by the expression:

$$v_{1_{it}} = E\left(NI_{it}^{a}\right) - \overline{NI_{it}^{a}} \tag{3b}$$

Substituting the value of $\overline{NI_{it}^{a}}$ from equation (3a) in the above expression (3b) and using the analyst forecasts in place of expectations, we get:

$$v_{1_{it}} = f_{it}^{a} - \left(\omega_{10} + \omega_{11}\overline{NI_{it-1}^{a}} + \omega_{12}\overline{ACC_{it-1}} + \omega_{13}\overline{BV_{it-1}}\right) \tag{3c}$$

v_1 stands for incremental 'other information' from analyst forecasts apart from accounting parameters, and f_{it}^{a} stands for analyst forecasts of abnormal earnings.

In the second step, we use this 'other information' in a residual earnings framework using abnormal earnings, book value and total accruals. The coefficient of the 'other information' term shows the informativeness of analyst forecasts for the market over and above other accounting parameters. If the coefficient is significant, the analyst forecasts are informative for the markets even if they are shown to be biased. A more interesting observation would be to test the informativeness of the analyst forecasts with respect to:

1 the market momentum as measured by the past 12-month stock or market returns

2 the firm size.

If the markets are able to discern the fact that the analysts suffer from bias in their forecasts in the case of higher stock or market returns as well as for smaller firms, the informativeness of those estimates would be lower and the interaction terms with the stock or market returns and the midcap dummy (for firms with market cap < \$100 mn) respectively, would have a 'negative' sign.

After we obtain v_1 from equation (3c), at the first stage, we find the informativeness of analyst forecasts, by using a modified form of residual income model which has an interaction of the last 12 month returns for individual stocks and the BSE-500 index respectively with the 'other information' in analyst forecasts:

$$\begin{aligned} MVE_{it} &= b_1 + b_2 NI_{it}^{a} + b_3 ACC_{it} + b_4 BV_{it} + b_5 BSE\_ret_{i,t-1} + b_6 v_{1_{it}} \\ &\quad + b_7 v_{1_{it}} * BSE\_ret_{i,t-1} + u_{it} \end{aligned} \tag{4a}$$

$$\begin{aligned} MVE_{it} &= b_1 + b_2 NI_{it}^{a} + b_3 ACC_{it} + b_4 BV_{it} + b_5 stock\_ret_{i,t-1} + b_6 v_{1_{it}} \\ &\quad + b_7 v_{1_{it}} * stock\_ret_{i,t-1} + u_{it} \end{aligned} \tag{4b}$$

Here, *MVE* stands for market value of equity while other terms are as defined earlier.

At the next stage, we find the informativeness of analyst forecasts for midcap firms using a similar model but which has an interaction term between the midcap dummy (mcap < \$100 mn) and the 'other information' in analyst forecasts:

$$MVE_{it} = b_1 + b_2 NI_{it}^{a} + b_3 ACC_{it} + b_4 BV_{it} + b_5 Midcap_{it} + b_6 v_{1_{it}} + b_7 v_{1_{it}} * Midcap_{it} + u_{it} \tag{4c}$$

We test if b_6 is positive and significant so that analyst forecasts are informative. In equations 4(a) and 4(b), we test if b_7 is negative and significant so that incremental informativeness of analyst forecasts is lower for firms having seen a strong last 12 months' market momentum, which leads to analyst forecast bias. In equation 4(c), we test if b_6 is positive and significant and b_7 is negative and significant so that even through the analyst forecasts are informative, the incremental informativeness of the forecasts is lower for midcap firms having a market cap of less than \$100 million.

5 Data and inputs

We consider the sample of 500 listed stocks of BSE-500 index in India for our analysis. This is because the BSE-500 represents the broadest universe of investible companies listed in India which are under analysts' coverage. We consider the period of last 21 years from 1998 onwards to 2018, since 1998 is the earliest period for which we could find analyst forecast data for Indian companies from the 'Refinitiv Eikon' software. We also consider the analyst earnings forecasts of the current fiscal year at the fiscal end as on 31st March as the last available forecast for the year updated for all information. This allows us to work with the updated forecast numbers and avoid the problem of stale earnings forecasts (Stickel, 1989; Loh and Mian, 2006). We consider the mean of all available analyst forecasts as the consensus estimate for the firm's earnings. However, there are several firms, whom analysts have started covering only in the later years or those who got listed or included in BSE-500 in the interim period, for whom analyst forecast data are not available for the whole period. Thus, we have to work with an unbalanced panel.

Table 1 Descriptive statistics for our sample of BSE-500 firms

	Mean	*Median*	*Q1*	*Q3*	*No. of obs.*
Forecast error (Rs bn)	–0.04	0.00	–0.368	0.251	4,480
Stdev of earnings forecast (Rs bn)	9.18	1.85	0.51	7.39	4,006
Change in analyst forecast %	–18.19	–5.69	–24.99	10.18	4,258
EPS growth %	14.5	16.2	–15.3	48.6	9,519
BSE-500 returns %	20.7	11.8	–7.8	33.2	9,519
Stock returns %	42.4	14.3	–14.4	60.8	9,519
Accruals by total assets	0.04	–0.01	–0.05	0.03	7,094
Book value (Rs bn)	46.38	10.16	3.61	30.91	7,411
Net income (Rs bn)	6.41	1.27	0.38	4.40	7,412
Abnormal income (Rs bn)[&]	0.63	0.21	–0.51	1.29	7,773
Market value of equity (Rs bn)	86.11	14.69	1.92	55.14	7,787
Other information in forecasts* (Rs bn)	2.20	0.32	–0.21	1.67	4,849

Notes: [&]Abnormal income is defined as (net income – cost of equity $*$ book value). Cost of equity is calculated using 'beta' from Eikon and 5% as equity risk premium for India.
*Indicates 'other information' from model 3(b).

Source: Refinitiv Eikon

We collate the descriptive statistics of our data in Table 1. Since we are analysing companies across the spectrum of market capitalisation, there are larger companies which are outliers as seen from the quartile 1 and quartile 3 data that cause a skew between the mean and median values of net income, book value and market value of equity (see Table 1).

Table 2 Correlation table of key variables in the sample of BSE-500 firms

	Forecast error	*Stdev of earnings forecast*	*Change in analyst forecast %*	*EPS growth %*	*BSE 500 returns (lagged) %*	*Stock returns (lagged) %*	*Accruals by total assets*	*Book value*	*Net income*	*Abnormal income*	*Market value of equity*	*Other information in forecasts**
Forecast error	*1.00*											
Stdev of earnings forecast	–0.32	*1.00*										
Change in analyst forecast %	0.12	–0.23	*1.00*									
EPS growth %	–0.05	–0.03	0.02	*1.00*								
BSE 500 returns (lagged) %	–0.01	–0.02	0.01	–0.01	*1.00*							
Stock returns (lagged) %	–0.01	–0.05	0.05	0.00	0.40	*1.00*						
Accruals by total assets	0.00	–0.01	0.01	0.00	0.01	0.02	*1.00*					
Book value	0.01	0.24	–0.23	–0.01	–0.03	–0.06	–0.01	*1.00*				
Net income	0.15	0.12	0.01	0.00	–0.01	–0.02	0.00	0.83	*1.00*			
Abnormal income	0.28	–0.11	0.39	0.01	0.02	0.04	0.01	0.19	0.63	*1.00*		
Market value of equity	0.01	0.00	–0.14	–0.01	–0.03	–0.04	0.00	0.63	0.70	0.27	*1.00*	
Other information in forecasts*	0.01	–0.01	–0.33	–0.01	–0.02	–0.04	–0.01	0.48	0.32	–0.09	0.44	*1.00*

Note: *Indicates ‘other information’ from model 3(b).

Source: Refinitiv Eikon

Regarding the change in analyst forecast data, we find that both the mean and median change in forecasts over the year is negative. This means that analysts reduce their forecasts as the financial year progresses. This shows that analysts might forecast on an optimistic note at the start of the year and management might guide the forecasts downwards to make them beatable as the year progresses (Richardson et al., 2004). We also see the presence of large skewed negative forecast errors making mean forecast errors negative (optimistic forecasts), while the median forecast error is actually a small positive number, which means that companies just manage to beat the forecasts. This tallies well with literature which talks about large negative forecast errors in the tail due to companies doing kitchen sinking during poor results, while there is a small positive forecast error in the middle (Abarbanell and Lehavy, 2003; Burgstahler and Eames, 2006) which gives the impression of average forecast errors being negative and analysts being optimistic. The 'other information' terms from our model 3(b) are also positive which means that the analysts' forecasts of future earnings are actually higher than what is implied by past information.

The coefficient of correlation among variables is given in Table 2. The forecast error is negatively correlated with the standard deviation of forecasts (forecast dispersion) reflecting the role of poor information environment in making forecasts more optimistic. It is also negatively related to EPS growth reflecting the anchoring effect of analysts. The change in analyst estimates is positively correlated to the forecast error which means that the analysts adjust their forecasts throughout the year but cannot reduce the error entirely. The market value of equity is positively correlated to both the book value and net income in line with Ohlson (2001). The market value is also positively correlated to the 'other information' in the analyst forecasts [equation 3(b)]. This shows that the analysts do create value by providing 'additional information' over and above the information embedded in accounting parameters like abnormal earnings, accruals and book value.

Our models for forecast error and forecast informativeness are prone to endogeneity. This could be due to two reasons:

1 Omitted variables which might affect the forecast error (like analyst biases, characteristics of the brokerage firm, analyst experience, etc.) all of which are not possible to consider in a model.

2 Reverse causality, which may arise from analyst estimates also being driven by market prices and not just vice versa.

To deal with the endogeneity issue, a dynamic panel method of GMM using Arenallo bond method is used for all our models. It uses first differences of variables (which eliminates stationarity) along with lagged values of covariates as instrumental variables to control for endogeneity. The results are also adjusted for heteroscedasticity. The robustness of the model is tested using the Sargan's J test (p value of the J statistic), which tests whether the instrumental variables are correlated with the error terms. If the null of no correlation cannot be rejected using the p value, this means that the model is robust. Autocorrelation of error terms are tested using AR (1) and AR (2) tests of error differences (not tabulated).

6 Results and discussion

6.1 Momentum factor

6.1.1 Forecast error model

We find that analysts suffer from anchoring bias due to the momentum effect of the previous year's market returns and make extreme forecasts. This momentum effect is borne out by the negative and significant relation between the consensus forecast error and lagged one year BSE-500 index returns and the stock returns (Table 3). This means, that in years following higher market index returns and stock returns, analysts forecast more aggressively and vice versa. This could be a result of cognitive bias due which causes analysts to be more aggressive following bull markets. Thus, we prove a part of our Hypothesis H_{1a} that analyst forecast errors arise from the cognitive bias of the analysts due to market and stock momentum.

Table 3 Forecast error relation with BSE-500 and stock returns

Method: dynamic panel (Arenallo bond)

Period included: FY 1998–2018

Model

$$FE_{it} = a_1 + a_2 BSE\_ret_{i,t-1} + a_3 \sigma_{e,it} + a_4 \Delta Est_{it} + a_5 EPS\_gr_{it} + a_6 BSE\_ret_{i,t-1} * EPS\_gr_{it} + a_7 MVE_{it} + a_8 Coverage_{it} + a_9 Loss\_dummy_{it} + a_{10} Market\ turnover_{it} + a_{11} \sum Industry + u_{it} \quad 1(a)$$

$$FE_{it} = a_1 + a_2 Stock\_ret_{i,t-1} + a_3 \sigma_{e,it} + a_4 \Delta Est_{it} + a_5 EPS\_gr_{it} + a_6 Stock\_ret_{i,t-1} * EPS\_gr_{it} + a_7 MVE_{it} + a_8 Coverage_{it} + a_9 Loss\_dummy_{it} + a_{10} Market\ turnover_{it} + a_{11} \sum Industry + u_{it} \quad 2(b)$$

Variable	*Dependent variable: forecast error*	
	Equation 1(a)	*Equation 1(b)*
BSE500_returns (lagged)	*–1.955**** (0.0086)	
Stock_returns (lagged)		*–1.682**** (0.049)
Forecast dispersion (price scaled)	*–0.063**** (2.1E–04)	*–0.059**** (2.15E–04)
Change in estimates	*0.276**** (2.9E–04)	*0.344**** (9.2E–04)
EPS growth	*–0.321**** (0.0102)	*–0.362**** (0.0103)
BSE500_returns (lagged) * EPS growth	*–0.933**** (0.006)	
Stock_returns (lagged) * EPS growth		*–0.453**** (0.0274)
Market value of equity (MVE)	*1.031**** (0.0034)	*0.952**** (0.0063)
Coverage	*6.135**** (0.038)	*6.075**** (0.027)
Loss (dummy)	*–2.857**** (0.302)	*–2.766**** (0.460)
Market turnover	*0.515**** (0.0298)	*0.489**** (0.0166)
Industry dummies	Present	Present
Prob. (J stat.)	0.41	0.38

Note: Numbers in parenthesis are the standard errors of the coefficients.

We also find that the information environment (for which forecast dispersion is the proxy) has an effect on the analyst forecasting process. High dispersion (poor information environment) is linked to aggressive forecasts and negative forecast errors (Gu and Wu, 2003; Zhang, 2005; Tse and Yan, 2008; Keskek and Tse, 2018). The change in estimates term also has a positive relation with forecast error. This means that analysts revise their forecasts to reduce the forecast error but unable to complete their revisions leading to 'under-reaction' in their forecast changes (Mendenhall, 1991; Abarbanell and Bernard, 1992).

A higher (lower) actual EPS growth might also lead to more aggressive (pessimistic) analyst forecasts causing more negative (positive) forecast errors. This could arise due to analysts extrapolating the EPS growth in the future, leading to biased forecasts. To control for this factor, we include the actual EPS growth term in the forecast error model. We find a negative relationship between EPS growth and forecast error, as expected. We also include an interaction effect between EPS growth and market as well as stock returns to check whether the bias is more in case the higher (lower) market/stock returns is accompanied by higher (lower) EPS growth. A negative sign for the interaction term confirms the rest of our Hypothesis H_{1a}. This means that the actual EPS growth is an additional source of bias for the analyst forecasts on top of the trailing market returns.

Finally, the analyst forecasts become less optimistic (positive and significant coefficient) as the company market value and the analyst coverage improves as well as the market turnover increases, indicating a positive effect of improved information environment on the forecast bias, while for loss making companies, analysts forecast more optimistically, reflecting in a negative coefficient for the loss dummy.

6.1.2 Market informativeness model

In the second stage, we use a modified version of the Ohlson (2001) residual earnings framework in a market value model using residual earnings components like abnormal earnings and book value to find whether the market is able to adjust for the bias in the analyst forecasts due to the momentum factor (trailing BSE-500 returns and stock returns). This model uses the 'other information' ($v_{1_{it}}$) in analyst forecasts (Barth et al., 2005), which are not explained by other accounting parameters [equation 3(b)]. To find out whether the market adjusts for the momentum bias of analysts, we use an interaction term of 'other information' and the trailing BSE-500 returns/stock returns, in order to test our Hypothesis H_{2a}.

From our results in Table 4, along with significant coefficients of residual income parameters (abnormal income and book value), we find that the coefficient of ranked accruals is negative and significant (Barth et al., 2005), which means that the markets partially prices in the reversal of total accruals. The lagged BSE-500 market returns as well as the stock returns also have a negative relation with market value which means that the markets price in a reversal of the momentum factor. The 'other information' term is also positive and significant which means that the markets ascribe value to the additional information in analyst forecasts which are not present in past accounting parameters. Interestingly, the interaction term between 'other information' and lagged market and stock returns is negative and significant. This means that the markets adjust the informativeness of analyst forecasts due to the cognitive bias they might suffer due to the momentum of lagged market/stock returns, confirming our Hypothesis H_{2a}.

Table 4 Market value relation with analyst forecasts and BSE-500 as well as stock returns

Dependent variable: market value
Total panel (unbalanced observations): 8,517
Period included: FY 1998–2018

Model

$$MVE_{it} = b_1 + b_2 NI_{it}^a + b_3 ACC_{it} + b_4 BV_{it} + b_5 BSE\_ret_{i,t-1} + b_6 v_{it} + b_7 v_{1it} * BSE\_ret_{i,t-1} + \varepsilon_{it} \quad 4(a)$$

$$MVE_{it} = b_1 + b_2 NI_{it}^a + b_3 ACC_{it} + b_4 BV_{it} + b_5 stock\_ret_{i,t-1} + b_6 v_{it} + b_7 v_{1it} * stock\_ret_{i,t-1} + \varepsilon_{it} \quad 4(b)$$

Variable	*Dependent variable: market value of equity*	
	Equation 4(a)	*Equation 4(b)*
Abnormal earnings	*0.938**** (0.0136)	*1.135**** (0.057)
Ranked accruals	*–0.507**** (0.037)	*–0.840**** (0.011)
Book value	*0.259**** (0.0019)	*0.3384**** (0.004)
BSE500_returns (lagged)	*–1.020**** (0.919)	
Stock_returns (lagged)		*–0.223**** (1.409)
v_1	*3.501**** (0.0378)	*2.600**** (0.105)
v_1 * BSE_returns (lagged)	*–0.1254*** (0.0562)	
v_1 * Stock_returns (lagged)		*–0.354*** (0.159)
Prob. (J stat)	0.23	0.23

Note: Numbers in parenthesis are the standard error of the coefficients.

Our results show that the markets find the biased forecasts due to momentum to be informative, leading to market inefficiency. However, it is able to adjust the informativeness somewhat for the bias due to the stock and market momentum factors.

6.2 Size factor

6.2.1 Forecast error model

Subsequently, we investigate whether the analysts suffer from greater bias while forecasting for midcap stocks. We define midcap stocks as those stocks having market capitalisation < \$100 million (< INR 8 billion), which might carry a higher bias in their forecasts, for reasons discussed earlier.

We find a negative and significant coefficient of the midcap dummy, which means that analyst forecasts are more optimistic for midcap companies (Table 5), confirming a part of our Hypothesis H_{1b}. In addition, we find that analyst forecasts are more optimistic in poorer information environments (represented by forecast dispersion). The analysts also underreact while revising their forecasts, since the ‘change in forecasts’ term is positively related to forecast error (Mendenhall, 1991; Abarbanell and Bernard, 1992). An interaction term of the midcap dummy with forecast dispersion is negative and significant, which shows that analysts are more optimistic for midcap firms in a poorer information environment, which confirms our Hypothesis H_{1b} fully. This could be either due to cognitive or due to strategic reasons, as discussed earlier. To control for the fact that analysts might be more (less) optimistic in case of higher (lower) actual EPS growth, we include the ‘EPS growth’ term in our forecast error model and find a negative and significant coefficient, as seen in our earlier results as well. Improved information environment (coverage, market turnover) has a mitigating effect on forecast optimism (positive and significant coefficients) while forecasts are more optimistic for loss making companies (negative and significant coefficient).

Table 5 Forecast error relation with size (midcap)

Method: dynamic panel (Arenallo bond)

Period included: FY 1998–2018

Model

$$FE_{it} = a_1 + a_2 Midcap_{i,t} + a_3 \sigma_{e,it} + a_4 \Delta Est_{it} + a_5 EPS\_gr_{it} + a_6 Midcap_{i,t} * \sigma_{e,it} + a_7 Coverage_{it} + a_8 Loss\ dummy_{it} + a_9 Market\ turnover_{it} + a_{10} \sum Industry + \varepsilon_{it} \quad 2(a)$$

Variable	*Dependent variable: forecast error*
	Equation 2(a)
Midcap dummy	*–1.169**** (0.0066)
Forecast dispersion (price scaled)	*–0.013**** (2.3E–04)
Change in estimates	*0.266**** (2.7E–04)
EPS growth	*–0.473**** (2.65E–04)
Midcap dummy * forecast dispersion (price scaled)	*–0.010**** (3.96E–05)
Coverage	*4.232**** (0.0037)
Loss (dummy)	*–2.863**** (0.430)
Market turnover	*0.382**** (0.0284)
Industry dummies	Present
Prob. (J stat)	0.34

Notes: We define midcap stocks as those stocks have market capitalisation < \$100 million. In our model, we use a dummy factor for midcap companies, which we code as 1 if the market capitalisation is < \$100 mn and 0 otherwise. Numbers in parenthesis are the standard error of coefficients.

6.2.2 Market informativeness model

In the next stage, using the Ohlson (2001) framework for residual income, we try to investigate whether the market adjusts the informativeness of analyst forecasts for midcap firms due to their higher bias. We find that the coefficients of the residual income terms (abnormal earnings, book value) are positive and significant while that of ranked accruals are negative and significant (Barth et al., 2005) (Table 6). The 'other information' term of analyst forecasts are also positive and significant. This shows that the markets find the biased forecasts for midcap stocks as informative, increasing market inefficiency. Finally, the interaction term of the midcap dummy and the 'other information' is negative and significant. This shows that the markets reduce the informativeness of analyst forecasts for midcap companies, confirming our Hypothesis H_{2b}.

We can conclude from the results that the markets find the biased analyst forecasts for the midcap companies as informative, leading to market inefficiencies for smaller companies. However, it is able to adjust the informativeness somewhat for the bias due to the size factor.

Table 6 Market value relation with analyst forecasts and size (midcap)

Method: dynamic panel (Arenallo bond)
Period included: FY 1998–2018

Model

$$MVE_{it} = b_1 + b_2 NI_{it}^{a} + b_3 ACC_{it} + b_4 BV_{it} + b_5 Midcap_{i,t-1} + b_6 v_{it} + b_7 v_{1it} * Midcap_{i,t} + \varepsilon_{it} \quad 4(c)$$

Variable	*Dependent variable: market value of equity*
	Equation 4(c)
Abnormal earnings	*0.618**** (0.021)
Ranked accruals	*–0.617**** (0.0059)
Book value	*0.335**** (0.0017)
Midcap dummy	*–10.44*** (4.04)
v_1	*2.222**** (0.0384)
v_1 * Midcap dummy	*–8.111*** (2.135)
Prob. (J stat)	0.14

Notes: We define midcap stocks as those stocks have market capitalisation < \$100 million. In our model, we use a dummy factor for midcap companies, which we code as 1 if the market capitalisation is < \$100 mn and 0 otherwise. Numbers in parenthesis are the standard error of coefficients.

7 Implications and conclusions

While financial analyst forecast accuracy from a market efficiency viewpoint remains a well-researched topic in developed markets, there remains a lacunae, particularly, with respect to emerging markets like India where institutional settings and information flows are quite different. We attempt to address this issue by investigating whether analysts' consensus forecast errors are driven by well-known systematic risk factors like size and momentum, leading to market inefficiency. Using an extensive 21 years (1998–2018) analyst forecast data for Indian companies extracted from the 'Refinitiv Eikon' database for BSE-500 stocks, we consider the trailing 12 month returns for both the respective stocks and the BSE-500 index to measure momentum and evaluate if it causes a bias in analysts' consensus earnings forecasts for these stocks.

Our study of analyst forecasts of BSE-500 companies in India suggests that analysts are prone to cognitive and other biases which contribute to market inefficiency. We find that analysts suffer from anchoring bias due to the recent market and stock returns and forecast more aggressively (pessimistically), when a past 12-month stock and markets returns are higher (lower). We also find that when analysts make their earnings forecasts for smaller companies having market capitalisations below \$100 million which suffer from a weaker information environment, they forecast more aggressively. This could be either due to the inherent cognitive bias in analyst forecasts (Zhang, 2005) or due to strategic reasons like seeking management favours (Francis and Philbrick, 1993; Lim, 2001; Richardson et al., 2004; Ke and Yu, 2006). Using a modified residual earnings model suggested by Ohlson (2001), we find that the markets still find these biased forecasts informative, which might be a driver of inefficiency, even though the informativeness is reduced somewhat based on the magnitude of the size and momentum factors.

Our study is one of the few in emerging markets exploring the bias in analyst forecasts and how they are linked to the risk factors discussed in asset pricing literature. Hence, it makes a contribution to the literature on how behavioural biases affect market efficiency, especially in the context of emerging markets which suffer from a weaker governance and information environment.

Our study suggests that analyst forecast bias could be responsible for market inefficiencies, especially in large emerging markets like India. Hence, investors should do their own due diligence before investing, and not trust analyst forecasts blindly. This is true, especially in scenarios like investing in smaller companies and during phases of strong price/market momentum, when the chances of market inefficiencies are even higher.

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Notes

1 BSE-500: an index of 500 stocks listed in the Bombay Stock Exchange (BSE) representing the broad market