Evaluation of Pooled Cross-Sectional Earnings Forecasting Models : An Indian Evidence

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Abstract

Purpose : Earnings forecasts are essential for valuation, and a bleak coverage of analysts' forecasts in emerging economies withholds the valuation research and practices. This study compared the pooled cross-sectional earnings forecasting models in the Indian market to choose alternative sources for earnings forecasts to solve the unavailability of analysts' earnings forecasts. Specifically, evaluating the theoretical earnings forecasting models of three different propositions: the earnings persistence (Li & Mohanram, 2014, EP) model, the Hou, Van Dijk, and Zhang (2012, HVZ) model, and the Pope and Wang (Harris & Wang, 2019, PW) model.

Methodology : This study considered all companies listed on NSE from 1995 – 2022 in an unbalanced panel structure with 36,591 firm years observations. Robust regression was used for the coefficient estimation because of its capability to handle outliers and provide a better model fit.

Findings : The results showed that the pooled cross-sectional models are reasonably accurate with the Indian data, restricting average forecast errors between 3% to 10%. The coefficient of earnings greater than one across models signified a high persistence in earnings. The PW model outperformed the other two models in the short run with share prices as predictor variables; whereas, the EP model performed best in the long run. The PW and EP forecast offered incremental information fully encompassing the HVZ forecast.

Practical Implications : This study elevated the application of valuation in theories in research and managerial practices where firms' earnings forecasts are an essential input.

Originality : This study uniquely compared the earning forecasting models of three proportions in a single setup to validate and suggest sources of earnings forecast for the Indian capital market.

Keywords : model-based earnings forecast, mechanical earnings forecast, robust regression, cross-sectional models, earnings persistence

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Earnings forecasts are crucial for academic research in accounting and finance and its application. Earnings forecasts are an essential input in valuation-based concepts, whether in investment decisions, equity valuation, or calculating the implied cost of capital (Brown & Zhou, 2015; Easton & Monahan, 2016;

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Sinha, 2021). Hence, searching for reliable, unbiased, and wide-covering sources of earnings forecasts is an ongoing research pursuit.

The sell-side analysts, specifically the Institutional Brokers Estimate System (IBES), are the most widely used source of earnings forecast in the valuation research arena (Brown & Zhou, 2015; Hess et al., 2019). IBES (Analysts') earnings forecasts are reasonably accurate (Easton, 2004; Wang & Huang, 2015). Still, they have two significant limitations: firstly, the coverage of firms in the IBES database and the availability of earnings forecast data in India is bleak (Chacko & Padmakumari, 2023). Secondly, the analyst's earnings forecast is optimistically biased, assuming every company will generate higher profits in the subsequent years (Aggarwal et al., 2018; Mishra & O'Brien, 2019; Mohanram & Gode, 2013).

Regression-based time series models are an established alternative to the IBES earnings forecast data (Brown, 1993; Monahan, 2018; O'brien, 1988). The forecasts generated using the time series models are free from optimism bias but suffer through survivorship bias, requiring 10 years of a firm's history to predict its future earnings (Bradshaw et al., 2012). The survivorship requirement in the time series models reduces the coverage of firms for generating earnings forecasts (Hou et al., 2012; Paton et al., 2020). The recent introduction of pooled cross-sectional approach has provided a more generalizable and wide-covering approach to forecast earnings (Li & Mohanram, 2014). The pooled cross-sectional method of earnings forecasting neither has survivorship requirements like time series models nor is optimistically biased as the analyst forecasts (Brownen-Trinh, 2019; Gerakos & Gramacy, 2012).

This study evaluates prominent earnings forecasting models to determine an accurate, bias-free, reliable source of earnings forecast for the Indian market. Three prominent pooled cross-sectional models are used: The benchmark model in the literature – the HVZ model (Hou et al., 2012); the earnings persistence (EP) model (Li & Mohanram, 2014); and the recent Pope and Wang model (Harris & Wang, 2019).

There are prior studies to evaluate and compare the model-based earnings forecast (Azevedo & Gerhart, 2016; Hess et al., 2019), but this study stands unique in two ways. First, it chooses to compare models of different propositions in a single evaluation setup, and second, the study focuses on the Indian market. India has different accounting quality and market efficiency compared to the country (USA) of origin and validations of these models (Iqbal & Mallikarjunappa, 2010; Kumar & Kar, 2021). The country where the model is evaluated plays a critical role in the model fitting, accuracy, and significance (Griffin, 2002; Lithin et al., 2023). Evaluation of the earnings forecasting model in an emerging market setup like India strengthens the empirical literature on earnings forecasting (Echterling et al., 2015) and opens the terrain for valuation-based research, which is challenging due to the unavailability of earnings forecast (Kundu & Banerjee, 2021; Ledwani et al., 2022).

This study implements the earnings forecasting model using robust regression (MM-estimator) instead of ordinary least squares (OLS) regression. The ordinary least squares (OLS) regression is found to be less reliable in the accounting research literature as it overweight's weighs the outliers and is incapable of handling heteroscedasticity in the predictor variables (Chang et al., 2021; Kordzakhia et al., 2001). Prior studies used the OLS regression with winsorization (Harris & Wang, 2019; Hou et al., 2012; Li & Mohanram, 2014), overweighting the extreme observations leading to an improper model fit (Leone et al., 2019). Therefore, using an advanced regressions approach, like Theil-Sen regression (Sen, 1968; Theil, 1950) and robust regressions (Andersen, 2008; Huber, 1973), has become an implicit choice for accounting and valuation research in recent times.

Review of Literature

Earnings Forecast

Earnings forecasts are essential parameters for any firm's performance evaluation, whether the valuation or the measure of its profitability (Nikhil et al., 2023). There are prominent studies that theoretically utilize the forecast of earnings as an essential input for the estimation of implied cost of capital[1] (ICC) and equity valuation (Claus & Thomas, 2001; Easton & Monahan, 2005; Gebhardt et al., 2001; Penman, 2016). Such studies use the analysts' earnings per share forecast and the earnings growth rate.

Easton and Sommers (2007) noted the presence of optimistic bias in the analysts' earnings forecast. They evaluated the effect of analysts' optimism on the ICC estimates and found that analysts' optimism is the primary source of estimation errors. Additionally, the coverage of firms in the analysts' forecast is restricted to large firms and developed markets ; whereas, it is bleak in emerging markets and developing countries.

Mohanram and Gode (2013) established a systematic process of adjusting the forecast for analysts' optimism and removing the systematic errors from the analysts' earnings forecasts. These suggestive techniques corrected the analysts' optimism about the earnings forecast. Still, the problem of low coverage is an unanswered question, restricting the generalizability of the valuation-based principles in research and practice.

Model-Based Earnings Forecast

Suggesting the solution to the problem of optimistic bias and low firm coverage in the analysts' forecast, Hou et al. (2012) used a pooled cross-sectional earnings forecasting model to replace the analysts' earnings forecasts. The HVZ model performs better in terms of forecast bias and firm coverage. Before Hou et al. (2012), time series earnings forecasts are a deep-rooted and well-established source of earnings forecasts in the literature (Bradshaw et al., 2012). Forecasts generated using the time series models suffer through survivorship bias requiring 10 years of earnings history of a firm to predict its future earnings (Brown, 1993; Brown & Zhou, 2015). The survivorship requirement reduces the coverage of firms for generating earnings forecasts (Hou et al., 2012; Monahan, 2018; Paton et al., 2019).

Hou et al. (2012) made an earnings forecasting model based on the pooled cross-sectional setup to alternate the analyst's forecast. Hou et al. (2012) built on the previous literature on cross-sectional earnings forecast (Fama & French, 2000, 2006; Hou & Van Dijk, 2010), and used a pooled cross-sectional model with ordinary least square regression for forecasting earnings in a rolling window of 10 years to predict the future earnings.

Challenging the forecasting capabilities of the HVZ model, Li and Mohanram (2014) tested two more models of earnings forecasting, the earnings persistence (EP) model and the residual income (RI) model for forecasting earnings. The earnings persistence model is an elaborated form of the auto-regressive [AR(1)] model in the cross-sectional form, and the model consists of an additional dummy variable for negative earnings and an interaction term (negative earnings dummy * earnings) capturing the persistence of negative earnings in the forecasting model. In contrast, the RI model is based on the framework using capital expenditure (Capex) as an input variable, as explained in Richardson et al. (2005).

All the pooled cross-sectional models anchor the earnings predictors to the accounting variables ignoring the qualitative information available in the market. Harris and Wang (2019, PW model) utilized the share price as the predictor of future earnings, capturing the information available in the market.

Paton et al. (2020) and Qu (2021) used a robust regression instead of the ordinary least square regression as the OLS is unable to handle the outliers, and even after winsorization of the data set, the remaining extreme values drag the regression line to a manipulated slope. They utilized the weight-assigning capabilities of the robust regression where the outliers are weighted less automatically by the Huber function algorithm.

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[1] **Implied cost of capital** is the rate of return which equates the current share price of the company to its forecasted earnings per share.

Need for Earnings Forecast in India

Tripathi (2018) evaluated the proxies of expected returns in India, considering the Nifty 500 as the study sample. The author restricted the study to dividend-based and market-based models, leaving the earnings-based models due to the unavailability of earnings forecasts in the Indian market. The unavailability of earnings forecasts in emerging markets (India) is a major problem for adopting advanced concepts coined in developed markets (Echterling et al., 2015).

Chacko and Padmakumari (2023) utilized the model-based earnings forecast in their study to evaluate the impact of ownership structure on the ex-ante cost of capital. Their study is the first study considering the Indian market for the application of the earnings persistence (EP) model for forecasting two years ahead of EPS. The evaluation of earnings forecast was not an objective of the study, and the choice of EP model was influenced by convenience and ease of application. Therefore, the validation of the earnings forecasting models of various proportions in the Indian market for an appropriate choice of reliable and accurate source of earnings forecast is a must.

Methodology and Research Design

Data

Our study sample comprises of all the companies listed on the National Stock Exchange of India available on the CMIE Prowess IQ database. The CMIE Prowess IQ is a standardized and consistent source for financial data of Indian firms. The database is rigorously used in practice and for conducting scientific and academic studies (Mainrai & Mohania, 2021; Venkataramanaiah et al., 2018). The sample period for this study consists of all the available companies from 1995 – 2022, making our sample data of 36,591 firm years. Companies with even one year of data availability during the study period are included in the estimation process. Hence, the unbalanced panel data pooled for the estimation period allows all companies fulfilling one year of survivorship requirements to be part of this study.

The accounting variables' data, including earnings, accruals, dividends, total assets, share price, share outstanding, and other market-related information, were collected every year on July 31st, allowing four months for the market to absorb the relevant information and reflect it in the share prices (the Indian financial year ends March 31st every year). All the firm-level variables are divided by the number of shares outstanding at the time *t* to convert them to per-share value. For scaling the variables at the per-share level, the number of shares at time *t* are used to reduce the unwanted noise in the EPS caused due to the change in the number of shares outstanding across the estimation process (Harris & Wang, 2019; Li & Mohanram, 2014).

Pooled Cross-Sectional Earnings Forecasting Models

This study carefully selected models considering data availability, model adequacy, and practical implacability. Models for which the data was unavailable or inconsistent are not considered part of our analysis. Existing models in the literature used IBES forecast as an input variable in the cross-sectional setup to make it more comprehensive (Azevedo et al., 2021). These models are not suitable for low analyst coverage markets like India. Hence, this study does not consider the models which use analyst forecasts as an input variable.

Additionally, this study eliminates panel-based models that forecast earnings at the ratio level, such as ROE and ROCE (Sneed, 1996), despite their superior performance. The ratio-level models are not an alternative to analysts' dollar-level forecasts (Brownen-Trinh, 2019). Hence, the following three models of earnings forecasting become the primary focus of this study:

HVZ Model

The HVZ model is the benchmark pooled cross-sectional model. The HVZ model is an alteration to the Fama and French (2006) profitability framework extended to be used in the pooled cross-sectional setup (Hou & Van Dijk, 2010).

$$E_{t+n} = \beta_0 + \beta_1 TA_t + \beta_2 E_t + \beta_3 NegE_t + \beta_4 ACC_t + \beta_5 Div_t + \beta_6 DivD_t + e \qquad (1)$$

The HVZ model represents future earnings as a function of total assets *(TA)*, dividend *(Div)*, Earnings *(E)*, and Accruals *(ACC)*. Additionally, dummy variables are used for earnings quality *(NegE)* and dividend decision *(DivD)*. The dummy variable *NegE* is taken as 1 if earnings are negative and 0 otherwise. *DivD* is 1 if the firm declares a dividend and 0 if it does not.

EP Model

The earnings persistence (EP) model is the cross-sectional execution of the time series properties of earnings based on the argument that past earnings are the best predictor of future earnings. The EP model allows for growth, which the other time series models, like the random walk model, fail to capture (Bradshaw et al., 2012; Li & Mohanram, 2014). The EP model is an improvement over the AR(1) model by introducing the interaction term between earnings and negative earnings dummy to capture a different slope for firms with negative earnings (Li, 2011).

$$E_{t+n} = \beta_0 + \beta_1 E_t + \beta_2 NegE_t + \beta_3 NegE_t * E_t + e \qquad (2)$$

Li and Mohanram (2014) stated future earnings as a function of earnings *(E)*, a dummy variable *(NegE)* representing the earnings quality, and an interaction between the earnings and earnings quality *(NegE*E)*, allowing the model to capture different persistence for profit & loss.

PW Model

Relying purely on the accounting variables does not empower the models to capture the information available in the market, underutilizing the advanced rigors of valuation theories (Ashton & Wang, 2013). Harris and Wang (2019) extended the framework of Pope and Wang (2005, PW) and theoretically derived an earnings forecast model with share price as a predictor variable.

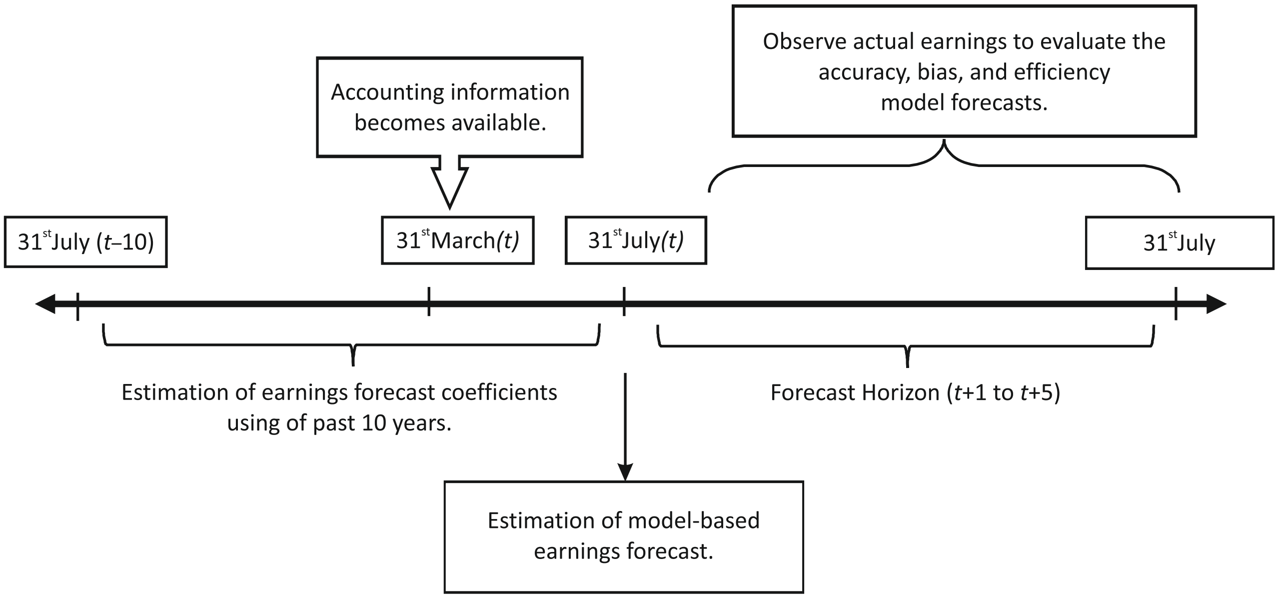
$$E_{t+n} = \beta_0 + \beta_1 E_t + \beta_2 NegE_t + \beta_3 P_t + \beta_4 P_{t-1} + \beta_5 Bv_t + \beta_6 Bv_{t-1} + \beta_7 ACC_t + e \qquad (3)$$

The PW model shows future earnings as a function of earnings *(E)*, earnings quality *(NegE)*, market price *(P)*, book value *(Bv)*, and accruals *(ACC)*.

Forecasting Procedure

This study follows the methodology of Harris and Wang (2019) and Li and Mohanram (2014) to estimate the pooled cross-sectional forecasting model to predict earnings (EPS) for year *t*+1 to year *t*+5. All the predictor variables are scaled at the per-share level in the procedure. Elaboratively shown in Figure 1, all the regression coefficients are generated using the past 10 years of data in a rolling window for each model, i.e., standing at time *t*, data of all the available firms from time *t*–10 to *t*–1 is pooled, and regressed on the earnings at time *t*–9 to *t*. The

Figure 1. ***Timeline of the Forecasting Process***



Note. Figure 1 provides a pictorial representation of the timeline of the forecasting process. The data for the accounting variables were collected at the end of the financial year, i.e., March 31 of every year. The market variables were collected on July 31 every year with four months gap after the end of the financial year, allowing the market to absorb the financial information and reflect it in the company's share prices.

Table 1. ***Maps the Forecast Horizon, and Relevant Pooled Data for Coefficient Estimation are Reported***

Forecast Horizon	Forecast Point	Data Used for Coefficient Estimation (Regressed on t–9 to t)
t+1	t	t–10 to t–1 (1-year lag)
t+2	t	t–11 to t–2 (2-year lag)
t+3	t	t–12 to t–3 (3-year lag)
t+4	t	t–13 to t–4 (4-year lag)
t+5	t	t–14 to t–5 (5-year lag)

regression coefficients are further multiplied with the variable values of individual firms at time t to calculate the earnings forecasts in the time horizon t+1.

The estimation method is repeated across all the forecast horizons with a rolling window of the past 10 years' data. Ensuring the forecasting process is free from the look-ahead bias, the coefficients are estimated using t–10 to t–1 for the forecasting of t+1 ; whereas, to forecast t+2, the coefficients are calculated using data from t–11 to t–2, respectively, as shown in Table 1.

Table 1 presents the forecast horizon, forecast point, and data pooled for coefficient estimation for model-based earnings forecasts. The forecast horizon t+1 has a lag of 1 year between the forecast horizon and forecast point, and data used for coefficient and forecast point, respectively. The lag increases with longer forecast horizons.

Choice of Regression Techniques

Ordinary least square (OLS) regression has been a consistent choice for coefficient estimation in past studies (Hou et al., 2012; Li & Mohanram, 2014; Paton et al., 2020). But it suffers a biased pull by the extreme values and adversely influences the coefficient estimation. Even the OLS with Newey & West adjusted standard error does not lead to a better regression line fit. Rather, it just adjusts the standard error to correctly show the significance of the independent variable in the model (Kordzakhia et al., 2001; Yohai, 1987). Hence, this study implements robust regression (MM-estimator) for coefficient estimation as it algorithmically underweighs and removes outliers if necessary for a proper model fitting (Qu, 2021).

Forecast Performance

The evidence of validating the earnings forecast is collected by measuring the accuracy and bias in the modeled forecasts. The bias in the estimates is assessed to find the direction of the errors in the forecast. This study follows the approach of Hou et al. (2012) and calculated forecast bias and forecast accuracy. The forecast bias is the difference between the forecasted earnings and real earnings scaled by the current share price to make it comparable across firms and years. The forecast bias score provides the direction of the forecast error to highlight the model's positive or negative sentiments. If the forecast score is positive, that represents a pessimistic bias, and if negative, it represents an optimistic bias.

$$Forecast\,Bias = \frac{(Actual\,Earnings - Forecasted\,Earnings)}{Share\,Price} \tag{4}$$

The forecast accuracy is the absolute error in the forecast earnings scaled by the June end share price, i.e., the absolute value of forecast bias is forecast accuracy. The larger the forecast accuracy number, the lesser would be the accuracy of the model forecast.

$$Forecast\,Accuracy = \frac{|(Actual\,Earnings - Forecasted\,Earnings)|}{Share\,Price} \tag{5}$$

Forecast Efficiency Test

The forecast efficiency of HVZ, EP, and PW models is evaluated using the regression-based test coined by Mincer-Zarnowitz (1969). The efficiency test captures the incremental information in the individual models' forecast about the actual earnings. If the forecast is not correlated with the actual earnings, then the model has a weak efficiency and vice versa. The efficiency is examined through the Mincer-Zarnowitz regression:

$$EPS_{i,t+n} = \alpha + \beta\, FEPS_{i,t} + \varepsilon_{t+n} \tag{6}$$

where, $EPS_{i,t+n}$ are the actual earnings and $FEPS_{i,t+n}$ are the forecasted earnings. The α and β are the intercept and the coefficient, respectively, and ε_{t+n} is the error term in the test regression. The efficiency test hypothesizes the β to be close to 1, representing a strong relation between the forecast and actual earnings. A coefficient close to 1 ensures that all the information available at the time of the forecasting is captured by the model and does not possess systematic error.

Encompassing Test

The Mincer and Zarnowitz (1969) regression is executed with multiple competing forecasts to evaluate for encompassing information capability of one model. Irrespective of the bias and accuracy of the forecast, the encompassing test evaluates the presence of unique incremental information captured by the individual models about the actual earnings. Specifically, the actual earnings are regressed on the K - competing model forecasts:

$$EPS_{i,t+n} = \alpha + \beta_1 FEPS^1_{i,t} + \ldots + \beta_K FEPS^K_{i,t} + \varepsilon_{t+n} \quad (7)$$

The Mincer and Zarnowitz (1969) test checks whether one model has unique information to offer if controlled for the other models. The β_K is hypothesized as not equal to 0. If the coefficient from the model forecast is different from 0, then the model has unique incremental information to offer beyond the controlled models (Mincer & Zarnowitz, 1969; Sen & Mehrotra, 2016).

Analysis and Results

Coefficients of the Forecasting Models

Table 2 presents the average variable coefficients and the time series average *t* - statistics of the HVZ, EP, and PW models estimated each year from 1995 – 2022 based on adequately lagged 10 years of pooled data. The actual earnings for the last 5 years (from 2018 – 2022) are used to validate the 5 years' ahead forecast estimated from 2017. Table 2 shows that the coefficients' direction (signs) aligns with the theoretical expectation and is consistent across the forecast horizons (*t*+1 to *t*+5). Earnings *(E)* are highly persistent and positively related to future earnings (Richardson et al., 2005). The persistence in earnings and its significance reduces as the forecast horizon becomes longer, reflected in the *t*-statistics reported for the HVZ and the PW models; whereas, in the case of the EP model (Table 2B), earnings persistence grows as the forecast horizon becomes longer due to the presence of past earnings as a predictor in the model capturing the non-noisy estimates. The reported coefficients for earnings *(E)* are slightly above one, showing a higher magnitude compared to the prior USA-based studies but at par with the Australian counterparts. The coefficients of the dummy variable for negative earnings *(NegE)* are negative and

Table 2. *Coefficient Estimation for the Forecasting Models*

Panel A : Coefficient Estimation and Model Fitting Results for the HVZ Model

Variables	*C*	TA_T	Div_T	$DivD_T$	E_T	$NegE_T$	Acc_T	Adj. R^2 (%)
T+1	–0.4076****	0.0017****	0.1446****	0.7514****	1.0157****	1.8693****	–0.0025***	93.99%
	(–3.32)	(24.06)	(18.31)	(5.34)	(763.34)	(10.7)	(–2.9)	
T+2	0.1243	0.0055****	0.7874****	0.96****	0.7588****	1.5216****	–0.0074****	81.43%
	(0.44)	(47.89)	(60.82)	(4.08)	(303.59)	(5.25)	(–5.27)	
T+3	0.4001	0.0093****	1.0277****	1.2676****	0.6415****	1.4636****	0.0004	74.46%
	(1.31)	(62.75)	(54.66)	(4.26)	(179.48)	(4.04)	(0.52)	
T+4	1.0916***	0.0124****	1.3661****	1.2525****	0.487****	0.5246	–0.0102****	66.97%
	(3.25)	(67.89)	(56.24)	(3.44)	(106.56)	(1.2)	(–4.53)	
T+5	1.6694****	0.0148****	1.7534****	1.0471**	0.3608****	–0.3241	–0.0218****	62.32%
	(4.29)	(69.81)	(57.59)	(2.4)	(65.77)	(–0.64)	(–8.88)	

Panel B : Coefficient Estimation and Model Fitting Results for the EP Model

	C	$NegE_T$	E_T	$NegE_T*E_T$	Adj. R^2 (%)
T+1	0.0911	–0.7756****	1.0985****	–0.6927****	93.36%
	(1.07)	(–4.15)	(855.71)	(–112.56)	
T+2	0.2258*	–0.9993****	1.1544****	–0.9682****	83.81%
	(1.68)	(–3.69)	(544.36)	(–139.6)	
T+3	0.8949****	–1.3219****	1.1501****	–1.0311****	77.32%
	(6.05)	(–3.87)	(377.58)	(–116.35)	
T+4	1.4876****	–1.4621****	1.1785****	–1.1091****	67.60%
	(8.1)	(–3.46)	(300.76)	(–102.5)	
T+5	1.8661****	–1.2264**	1.2321****	–1.2002****	65.11%
	(8.55)	(–2.47)	(262.76)	(–97.1)	

Panel C : Coefficient Estimation and Model Fitting Results for the PW Model

	C	P_T	P_{T-1}	E_T	$NegE_T$	BV_T	BV_{T-1}	Acc_T	Adj. R^2 (%)
T+1	–0.3304****	0.017****	–0.0122****	0.9375****	1.4697****	0.0297****	–0.0191****	–0.0102****	93.95%
	(–4.51)	(78.3)	(–49.05)	(514.21)	(9.08)	(20.69)	(–13.4)	(–12.81)	
T+2	–0.2275*	0.0314****	–0.0104****	0.6811****	1.0995****	–0.0008	0.0286****	–0.026****	85.01%
	(–1.75)	(87.39)	(–24.74)	(213.63)	(4.08)	(–0.79)	(9.44)	(–19.91)	
T+3	0.3224*	0.0406****	–0.0109****	0.5646****	0.597*	0.0034	0.0265****	–0.0576****	78.99%
	(1.9)	(84.66)	(–20.01)	(125.69)	(1.73)	(1.36)	(6.19)	(–35.54)	
T+4	0.8613****	0.0525****	–0.0132****	0.4423****	–0.3231	–0.0147***	0.053****	–0.0819****	72.89%
	(4.33)	(87.58)	(–19.63)	(78.07)	(–0.8)	(–3.17)	(10.82)	(–42.45)	
T+5	0.7608***	0.0547****	–0.0088****	0.3818****	–0.6178	–0.0258****	0.0845****	–0.1076****	72.16%
	(3.12)	(75.16)	(–11.27)	(56.54)	(–1.23)	(–4.21)	(14.11)	(–47.26)	

Note. The average coefficient estimates from the robust regression for the HVZ model (Panel A), EP model (Panel B), PW model (Panel C), and the respective adjusted t-statistics (parenthesis) are reported based on data from 1995 – 2017 on a rolling window of 10 years for up to 5 years of the forecast horizon. Where, C is the intercept, TA_T is the value of the total assets scaled at the per share level, Div_T is the dividend paid per share by the company, $DivD_T$ is the dummy variable for dividend decision, 1 if the company chooses to pay a dividend, and 0 otherwise. E_T is the earnings at time T. $NegE_T$ is the dummy with negative earnings, which is 1 if the earnings at time T are negative and 0 otherwise. $NegE_T*E_T$ is the interaction term created by the multiplication of $NegE_T$ and E_T. P_T is the share price on 31st July. P_{T-1} is the lagged share price on 31st July adjusted for the number of shares outstanding at the time T. BV_T is the book value per share at time T. BV_{T-1} is the lagged book value per share. Acc_T is accrual calculated using the cash flow method, i.e., the difference between earnings and cash flow from operating activities scaled by the number of shares outstanding to get a per-share figure. ****, ***, **, and * on coefficient value represent that the variable is significant at 0.1%, 1%, 5%, and 10%, respectively.

statistically significant for up to the 3 years forecast in HVZ and PW models and across all the forecast horizons for the EP model, exhibiting a persistence of losses in the Indian firms.

Table 2(A) shows the dividend *(Div)* and the decision to pay dividends *(DivD)* positively impact future earnings. Total Assets *(TA)* positively influence future earnings and become more significant as the forecast horizon increases. The increasing significance of total assets portrays positive long-run returns on the earnings, consistent with the theoretical arguments. Accruals show a constant negative relation with future earnings across forecast horizons.

Table 2 (C) shows that the price and lagged price coefficients are consistent with theoretical expectations. As the unique aspect of the model captures the information available in the market, current and lagged prices remain statistically significant in our findings. The current price positively relates to future earnings. In contrast, the lagged price portrays a negative relation, suggesting the change in share prices is significant in explaining the future earnings and reflects a positive association with future earnings.

The PW models show a relatively higher adjusted R^2 value than the EP and HVZ models in the longer forecast horizons. The adjusted R^2 of all three models is similar for the one-year-ahead forecast horizon, but the difference becomes significantly noticeable as the forecast horizon becomes lengthier. The PW model exhibits higher adjusted R^2 of 79%, 73%, and 72% compared to 77%, 68%, and 65% for the EP model and 74%, 67%, and 62% for the HVZ model.

Forecast Performance

The prima facie evidence to evaluate the performance of the model-based earnings forecasts is through the forecast accuracy (the absolute forecast error or the absolute difference between the actual earnings and the forecasted earnings scaled to the current share price) and forecast bias (the absolute forecast error or the difference between the actual earnings and the forecasted earnings scaled to the current share price). The forecast accuracy and bias scores are expected to be 0 if the model is perfectly accurate. The closer the score is to 0, the model will prove to be more accurate and bias-free. The direction of the bias, i.e., positive and negative, will appropriately show the presence of optimistic or pessimistic bias in the model forecast.

Although in Table 3 and Table 4, the mean and median of the forecast accuracy and forecast bias are mentioned, the median to compare and draw inferences about the performance of individual forecasting models, being the exposure of mean to the outlier, may mislead the interpretations.

Forecast Accuracy

The median forecast error (Accuracy score) for the T+1 forecast horizon is just above 3% for all three models. The PW model (3.34%) outperforms the EP model (3.37%) and the HVZ model (3.52%) by a tiny margin. But as the

Table 3. ***The Forecast Accuracy and Bias for HVZ, EP, and PW Models***

		Accuracy			Bias		
		HVZ	***EP***	***PW***	***HVZ***	***EP***	***PW***
T+1	Mean	0.3221	0.3018	0.3138	–0.0777	–0.1866	–0.0790
	Median	*0.0352*	*0.0337*	*0.0334*	*–0.0046*	*–0.0042*	*–0.0057*
T+2	Mean	0.4541	0.4163	0.3697	–0.2229	–0.2791	–0.1737
	Median	*0.0544*	*0.0509*	*0.0529*	*–0.0130*	*–0.0079*	*–0.0190*
T+3	Mean	0.3702	0.3364	0.3552	–0.1801	–0.2124	–0.1819
	Median	*0.0721*	*0.0666*	*0.0702*	*–0.0215*	*–0.0172*	*–0.0325*
T+4	Mean	0.3846	0.3563	0.3706	–0.1926	–0.2053	–0.1901
	Median	*0.0853*	*0.0793*	*0.0857*	*–0.0282*	*–0.0239*	*–0.0447*
T+5	Mean	0.3887	0.3741	0.3836	–0.1933	–0.2026	–0.1944
	Median	*0.0980*	*0.0899*	*0.1012*	*–0.0290*	*–0.0274*	*–0.0516*

Note. Table 3 reports the mean and median of the forecast accuracy and forecast bias of all three models across the five forecast horizons. The average results are reported based on the forecast made from 2010 – 2017.

Table 4. *Difference in Forecast Accuracy and Bias*

		Accuracy			Bias		
		EP–HVZ	***PW–HVZ***	***EP–PW***	***EP–HVZ***	***PW–HVZ***	***EP–PW***
T+1	Mean	–0.0202	–0.0082	–0.012	–0.1089****	–0.0013	–0.1076****
	t-stat	*–0.84127*	*–0.31676*	*–0.50861*	*–4.47496*	*–0.04827*	*–4.50808*
	Median	–0.0015	–0.0019	0.0003	0.0003	–0.0011	0.0014
	z-stat	*–1.39179*	*–0.76493*	*0.208118*	*–0.07364*	*1.033163*	*–0.27736*
T+2	Mean	–0.0378	–0.0844	0.0466	–0.0562	0.0493	–0.1054**
	t-stat	*–0.5849*	*–1.62696*	*0.907492*	*–0.86616*	*0.945218*	*–2.04621*
	Median	–0.0034***	–0.0015	–0.0019***	0.005****	–0.0061***	0.0111****
	z-stat	*–3.17539*	*0.77112*	*–2.90251*	*–3.78286*	*–3.21567*	*–7.50237*
T+3	Mean	–0.0339*	–0.015	–0.0189	–0.0323*	–0.0018*	–0.0305
	t-stat	*–1.92637*	*–0.84209*	*–1.09536*	*–1.78984*	*–1.72371*	*–0.09909*
	Median	–0.0055***	–0.0019	–0.0036****	0.0043**	–0.0109****	0.0153****
	z-stat	*–3.32945*	*–0.55733*	*–4.55519*	*–2.56174*	*–4.89751*	*–8.06311*
T+4	Mean	–0.0283	–0.014	–0.0143	–0.0127	0.0024	–0.0152
	t-stat	*–1.28957*	*–0.6454*	*–0.65664*	*–0.56844*	*0.109498*	*–0.68297*
	Median	–0.006****	0.0004*	–0.0064****	0.0043*	–0.0165****	0.0208****
	z-stat	*–3.5993*	*–1.80412*	*–5.88271*	*–1.92755*	*–6.08646*	*–8.76135*
T+5	Mean	–0.0146	–0.0051	–0.0095	–0.0093	–0.0011	–0.0082
	t-stat	*–0.70612*	*–0.46397*	*–0.24713*	*–0.44045*	*–0.39078*	*–0.05388*
	Median	–0.0081****	0.0032**	–0.0112****	0.0016*	–0.0226****	0.0242****
	z-stat	*–3.42383*	*–2.54726*	*–6.39948*	*1.908451*	*–7.67503*	*–8.15092*

Note. Table 4 reports differences in the three models' mean and median forecast bias and accuracy. The *t* - statistics for the difference in the mean forecast accuracy and mean forecast bias are reported. At the same time, the *z* - statistics of the Wilcoxon sign rank test for the difference in the median forecast accuracy and forecast bias are reported for all three models. ****, ***, **, and * on coefficient value represent that the variable is significant at 0.1%, 1%, 5%, and 10%, respectively, for both the *t* and *z* - statistics.

forecast horizon increases, the EP model generates a much more accurate forecast than the two counterparts. The median forecast accuracy for the EP model is consistently best for the two-, three-, four- and five years prediction horizon. The accuracy of all the models reduces as the forecast horizon increases. The fall is evident due to the loss of information due to the time lag and higher uncertainty in the longer horizons.

The errors for two- and three-years ahead forecast horizons are the least for the EP model (5.09% and 6.66%), followed by the PW model (5.29% and 7.02%) and the HVZ model (5.44% and 7.21%) ; whereas, for the four- and five-years ahead horizon, the forecast error in the PW model surpasses even the HVZ model to become the least accurate model among the three. The forecast errors are the smallest for the EP model at 7.93% & 8.99% for the four- and five- years ahead forecast horizons, respectively, compared with 8.53% & 9.80% for the HVZ model and 8.57% & 10.12% for the PW model.

Table 4 shows the difference between the accuracy of the models is insignificant for the one-year ahead forecast. But the EP model is statistically different from the HVZ and PW models in the two-, three-, four- and five- years of forecast horizons. Although there are differences between the forecast accuracy of PW and HVZ models, the differences are statistically significant for the forecast horizon of *T*+4 and *T*+5.

Forecast Bias

As reported in Table 3, the negative forecast bias scores suggest the presence of optimistic bias in the forecasts of all the models. The EP model is the least biased, followed by the HVZ and PW models. In terms of median forecast, the PW model becomes the most biased model with a score of –0.57% compared to –0.42% and –0.46% for the EP and PW models, respectively.

As shown in Table 4, the difference in the median forecast bias of EP–HVZ, PW–HVZ, and EP–PW are all statistically insignificant for the one-year ahead forecast (*T*+1). The forecast bias of the PW model is statistically different from that of the EP model and the HVZ model for all the remaining forecast horizons. The difference is because the price is a predictor variable in the PW model. The Indian stock market generally exhibits optimistic investor sentiments (Kamath et al., 2022), reflected in the optimistic noise in the share prices. This optimistic noise must reflect in the forecast from the PW model as it uses price as an input.

Efficiency Test of the Models

Table 5 reports the efficiency test results for HVZ, EP, and the PW model forecasts. For both the PW and the HVZ models, the slope coefficients are close to 1 in all the forecast horizons. The EP model shows a lower slope value, between 0.62 – 0.47, suggesting that the error in the model prediction is systematically related to the dependent variable. These findings are consistent with the argument of Feng (2014). The simplicity of the EP model saves it

Table 5. *Efficiency Test*

Forecast Horizon	Name of the Model	Cons.	*t*-stat.	Slope	*t*-stat.	*R*-sqr.
T+1	HVZ	–1.044***	*–3.29*	0.922****	*–3.86*	36.51%
	EP	1.84**	*2.21*	0.614****	*–6.27*	61.50%
	PW	–1.551****	*–5.14*	0.913****	*–4.96*	41.25%
T+2	HVZ	–3.585****	*–8.19*	1.022	*0.7*	21.98%
	EP	2.656**	*2.335*	0.478****	*–6.94*	36.21%
	PW	–4.383****	*–11.1*	0.915****	*–4.16*	29.26%
T+3	HVZ	4.834****	*–9.68*	1.039	*1.06*	16.64%
	EP	2.305*	*1.829*	0.5****	*–6.35*	31.41%
	PW	–5.778****	*–12.2*	0.878****	*–5.01*	21.80%
T+4	HVZ	–5.12****	*–10.7*	1.097**	*2.39*	14.15%
	EP	1.604	*1.361*	0.59****	*–6.12*	35.90%
	PW	–5.719****	*–11.3*	0.831****	*–6.34*	18.44%
T+5	HVZ	–4.96****	*–7.86*	1.188****	*3.51*	13.72%
	EP	4.619***	*3.192*	0.524****	*–6.39*	28.41%
	PW	–6.374****	*–8.44*	0.862****	*–3.58*	20.70%

Note. Table 5 provides estimates of Mincer-Zarnowitz regression: $EPS_{i,t+n} = \alpha + \beta\, FEPS_{i,t} + \varepsilon_{t+n}$ for the HVZ model, EP model, and PW model. For each model, coefficients of constant and slope are reported along with their respective *t*-statistics and R^2 value. ****, ***, **, and * on coefficient value represent that the variable is significant at 0.1%, 1%, 5%, and 10%, respectively, for both the *t* and *z* - statistics.

from unnecessary noise in other variables. Still, on the other hand, there is scope to enrich the input content of the model beyond past earnings to make it much more efficient.

The R^2 value reveals that the EP model's forecast has higher explanatory power than the PW and HVZ models, irrespective of their higher efficiency compared to the EP model. The R^2 of the EP (61.5%) model is consistently higher than that of the PW (36.51%) and HVZ (41.25%) models. All the models lose the information content as the forecast horizon grows longer. The same is reflected in the forecast accuracy of the model and is consistent with the prior USA-based studies.

Encompassing Test

Table 6 reports the results of the encompassing test for the EP model forecast, HVZ model forecast, and PW model forecast (Model 1), the EP model forecast and PW model forecast (Model 2), the EP model forecast and HVZ model forecast (Model 3), and the HVZ model forecast and PW model forecast (Model 4). In the one-year ahead

Table 6. *Encompassing Test*

		Const	*t*-stats.	*EP*	*t*-stats.	*HVZ*	*t*-stats.	*PW*	*t*-stats.	R^2(%)
T+1	Model 1	–1.888****	–6.90	0.143	1.22	–0.583	0.25	1.345****	5.40	39%
	Model 2	–1.63****	–5.78	0.044	0.38			0.874****	7.91	41%
	Model 3	–1.79****	–6.08	0.336***	3.13	0.62****	5.96			37%
	Model 4	–1.599****	–5.21			–0.51**	–2.05	1.4****	5.84	39%
T+2	Model 1	–4.401****	–10.97	0.046	0.46	0.082	0.78	0.807****	10.61	27%
	Model 2	–4.462****	–11.45	0.098	1.31			0.83****	12.17	29%
	Model 3	–3.934****	–8.90	0.352****	3.50	0.658****	6.47			22%
	Model 4	–4.37****	–10.58			0.116	1.41	0.82****	11.85	27%
T+3	Model 1	–5.814****	–12.21	0.252**	2.46	–0.14	–1.43	0.779****	11.63	20%
	Model 2	–6.022****	–12.89	0.202***	2.66			0.722****	11.27	22%
	Model 3	–5.062****	–10.13	0.583****	5.72	0.424****	3.92			17%
	Model 4	–5.801****	–12.16			0.052	0.70	0.84****	14.07	20%
T+4	Model 1	–5.921****	–12.54	0.527****	4.76	–0.219**	–2.17	0.587****	8.98	18%
	Model 2	–6.445****	–12.93	0.395****	5.02			0.556****	8.83	19%
	Model 3	–5.168****	–11.08	0.89****	9.70	0.129	1.29			17%
	Model 4	–6.115****	–12.74			0.173**	2.24	0.726****	12.77	17%
T+5	Model 1	–6.633****	–9.82	0.4***	3.35	–0.159*	–1.74	0.683****	6.69	19%
	Model 2	–7.016****	–10.89	0.292***	2.75			0.672****	7.03	21%
	Model 3	–5.427****	–8.89	0.917****	11.46	0.196*	1.95			17%
	Model 4	–6.711****	–10.10			0.102	1.06	0.809****	10.54	19%

Note. Table 6 provides estimates of Mincer-Zarnowitz regression for encompassing test : $EPS_{i,t+n} = \alpha + \beta_1 FEPS^1_{i,t} + \ldots + \beta_K FEPS^K_{i,t} + \varepsilon_{t+n}$.

For HVZ forecast, EP forecast, and PW forecast (Model 1), EP forecast and PW forecast (Model 2), EP forecast and HVZ forecast (Model 3), HVZ forecast and PW forecast (Model 4): For each model, coefficients for constant and coefficients for slope are reported along with their respective *t*-statistics (testing the null hypothesis, i.e., the coefficient in each case equals 0) and adjusted R^2 value.

****, ***, **, and * on coefficient value represent that the variable is significant at 0.1%, 1%, 5%, and 10%, respectively, for both the *t* and *z* - statistics.

forecast, the HVZ forecast is insignificant if the PW forecast is included in the regression test (Model 1 and Model 4) but carries substantial information when controlled only for the EP forecast (Model 3). Instead, the HVZ forecast has a negative coefficient representing an information overlap with EP and PW models. The PW forecast contains incremental information after controlling for HVZ and EP models individually (Model 2 and 4) and together (Model 1).

Indeed, the information contained in all the model's forecasts decreases as the forecast horizon becomes longer, reflected in the R^2 of the models across forecast horizons. The combination of EP and PW forecast (Model 2) has the highest R^2 amongst other models across forecast horizons. Adding the HVZ forecast shows no incremental information and reduces the adjusted R - square (Model 1). In the absence of the PW forecasts, the EP forecast and the HVZ forecast both show significant information content. The information relevance of the PW forecast reduces as the horizon increases, but the vice - versa is applicable in the case of EP and HVZ forecasts. When studied combined with the EP and PW forecasts, the HVZ model remains insignificant for all the forecast horizons (Model 1).

These findings highlight that the optimal forecast of future earnings is likely a combination of the model-based earnings forecast. The EP and PW forecast (Model 2) complement each other's information content to form a better forecast combination. The combination of weights of 87.4% from the PW forecast and 4.44% from the EP forecast for the one year ahead of earnings provides the most informative forecast. Similarly, the weights can be assigned to the two forecasts per model 2 of the encompassing test to find the best-modeled earnings forecast.

Conclusion

This paper attempts to evaluate three prominent pooled cross-sectional earnings forecasting models, the HVZ model (Hou et al., 2012), the earnings persistence (EP) model (Li & Mohanram, 2014), and the recent Pope and Wang model (Harris & Wang, 2019) to determine an accurate, bias-free, and reliable source of earnings forecast for the Indian market.

This study shows that the PW model outperforms the EP and HVZ models in terms of accuracy in the short run. In contrast, the earnings persistence (EP) model dominates in the longer horizons as the most accurate model. The results show that all the models are optimistically biased, where the EP model generates the least biased forecasts, followed by the HVZ model and PW models. The bias in the PW model is likely due to the optimism in the share prices in the Indian markets. The efficiency test reveals that although the EP model generates the least efficient forecast, it is still the most informative and even outperforms the PW model, which has the information advantage in terms of share prices.

The study suggests utilizing the advantage of the better information content of the PW model in the form of share prices for the short run. However, the EP model must be the choice for horizons longer than two years to get an accurate and bias-free earnings forecast. The EP model also has the edge over the two models in terms of low information (input variables) requirements, as it only requires past earnings of a firm to forecast its future earnings.

Theoretical and Managerial Implications

This study suggests alternative sources of earnings forecasts in emerging markets. This solves the long-sought-after problem of the unavailability of earnings forecasts in the emerging market setup. The findings are useful for academicians and practitioners in the area of accounting, financial markets, and corporate governance practices for selecting a generalizable and bias-free source of earnings forecast for financial evaluation. Specially, an appropriate source of earnings forecasts provides ground for the estimation of implied cost of capital and equity valuation in the Indian financial markets.

Limitations of the Study and Future Directions

Although the EP model comes out to be the most accurate pooled cross-sectional model to forecast earnings, the efficiency test indicates the presence of predictable errors in its forecasts. This opens the scope for future researchers to develop the EP model further for better predictive capabilities, efficiency, and forecast accuracy.

This paper is an initial step toward facilitating valuation-based research in emerging economies like India, with low analysts' coverage and unavailability of earnings forecast data. The results open the scope to utilize the earnings forecasts and the forecasting method reported in this paper for valuation-based research and practice, such as estimating an Indian implied cost of capital.

Authors' Contribution

Sanket Ledwani and Dr. Suman Chakraborty conceptualized the study. Sanket Ledwani collected and curated the data, and performed the analysis. Dr. Suman Chakraborty verified the analytical methods and supervised the study. The results were further interpreted jointly by both authors to present the conclusory findings. Sanket Ledwani wrote the manuscript under the supervision of Dr. Suman Chakraborty.

Conflict of Interest

The authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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