ANALYSTS’ CONSENSUS AND PREDICTABILITY OF FORWARD P/E RATIOS

Mr. Thanakorn Petkajee

An Independent Study Submitted in Partial Fulfillment of the Requirements
for the Degree of Master of Science in Finance
Department of Banking and Finance
FACULTY OF COMMERCE AND ACCOUNTANCY
Chulalongkorn University
Academic Year 2020

ความคิดเห็นส่วนใหญ่ของนักวิเคราะห์และความสามารถในการทำนายของอัตราส่วน P/E แบบล่วงหน้า

นายธนากร เพ็ชรขจี

สารนิพนธ์นี้เป็นส่วนหนึ่งของการศึกษาตามหลักสูตรปริญญาวิทยาศาสตรมหาบัณฑิต
สาขาวิชาการเงิน ภาควิชาการธนาคารและการเงิน
คณะพาณิชยศาสตร์และการบัญชี จุฬาลงกรณ์มหาวิทยาลัย
ปีการศึกษา 2563

Independent Study Title	ANALYSTS' CONSENSUS AND PREDICTABILITY OF FORWARD P/E RATIOS
By	Mr. Thanakorn Petkajee
Field of Study	Finance
Thesis Advisor	Narapong Srivisal, Ph.D.

Accepted by the FACULTY OF COMMERCE AND ACCOUNTANCY, Chulalongkorn University in Partial Fulfillment of the Requirement for the Master of Science

INDEPENDENT STUDY COMMITTEE

Chairman

(Assistant Professor SIRA SUCHINTABANDID, Ph.D.)

Advisor

(Narapong Srivisal, Ph.D.)

Examiner

(Tanawit Sae-Sue, Ph.D.)

ธนากร เพ็ชรขจี : ความคิดเห็นส่วนใหญ่ของนักวิเคราะห์และความสามารถในการทำนายของอัตราส่วน P/E แบบล่วงหน้า. (ANALYSTS' CONSENSUS AND PREDICTABILITY OF FORWARD P/E RATIOS) อ.ที่ปรึกษาหลัก : อ. ดร.นราพงศ์ ศรีวิศาล

-

สาขาวิชา	การเงิน	ลายมือชื่อนิสิต	....
ปีการศึกษา	2563	ลายมือชื่อ อ.ที่ปรึกษาหลัก	....

6081922626 : MAJOR FINANCE
KEYWORD: Analysts' forecast error, P/E ratio

Thanakorn Petkajee : ANALYSTS' CONSENSUS AND PREDICTABILITY OF FORWARD P/E RATIOS. Advisor: Narapong Srivisal, Ph.D.

Analysts play a crucial role in providing some important investment data, such as firms' performance analysis, target prices, the forward P/E ratios, and so on, to investors. This special project studies the impact of analysts' consensus on predictability of the stocks listed on the Stock Exchange of Thailand. Two models of analysts' forecast error are proposed and used as a proxy for predictability in the study. The first model of analysts' forecast error, ln(AFE), is computed from the natural logarithm of the squared error in a median forecast of one year ahead, i.e. $(\text{Actual next 12M EPS} - \text{median forecast EPS})^2$, deflated by the beginning share price. The second model of the forecast error, |EPS FE|, is calculated from the difference in a median forecast error, i.e., Actual next 12M EPS – median forecast EPS, divided by the absolute value of Actual next 12M EPS. The study investigates the impact of analysts' consensus via the analyst variables, such as the previous forecast error, the number of analysts (NOA), the variance of target returns (VTR), the skewness of target returns (STR), and the percentage of "Buy" recommendation (PBR), while controlling firm's fundamental and macroeconomic factors, i.e., dividend yields, earnings growth, firm's leverage, firm's size, and the short-term interest rate. The empirical results show the forecast error in the first model is influenced by the previous forecast error whereas other analyst variables, as well as control variables, have no relationship with it. This implies that analysts improve their current forecast by learning from their previous forecast error. The regression results of the second model reveal that the previous forecast error, NOA, VTR, and PBR are the only factors affecting the current forecast error. However, the robustness test reveals that the second model may not be suitable for measuring analysts' forecast error because it is sensitive to the outlier data whereas the results of the first model remain unchanged after removing the outliers.

Field of Study:	Finance	Student's Signature ....
Academic Year:	2020	Advisor's Signature ....

ACKNOWLEDGEMENTS

First of all, I would like to express my sincerest gratitude to my advisor, Ajarn Narapong Srivisal, for his kind guidance, helpful advice, and constructive suggestions on my research. During my special project, he not only teaches me the systematic process of conducting the research, but he also encourages me and supports the solutions when I face problems.

I also would like to express my profound appreciation to Assistant Professor Sira Suchintabandid and Ajarn Tanawit Sae-Sue for their kindly serving as committees and giving several useful comments in this project.

I thankfully acknowledge all of the professors in the MSF program for lecturing most valuable financial background knowledge as well as the staff of the program, especially P'Pla who always helps me when I have problems.

Finally, I would like to give heartfelt thanks to my family for their understanding, encouragement and support during my study.

Thanakorn Petkajee

TABLE OF CONTENTS

Page

ABSTRACT (THAI) iii
ABSTRACT (ENGLISH) iv
ACKNOWLEDGEMENTS v
TABLE OF CONTENTS vi
ABSTRACT 1
1. INTRODUCTION 2
2. LITERATURE REVIEWS 4
3. DATA 8
4. METHODOLOGY 9
5. EMPIRICAL RESULTS 11
5.1 Data statistics 11
5.2 Regression Results 21
6. CONCLUSIONS 29
Appendix 31
REFERENCES 33
VITA 36

ABSTRACT

Analysts play a crucial role in providing some important investment data, such as firms' performance analysis, target prices, the forward P/E ratios, and so on, to investors. This special project studies the impact of analysts' consensus on predictability of the stocks listed on the Stock Exchange of Thailand. Two models of analysts' forecast error are proposed and used as a proxy for predictability in the study. The first model of analysts' forecast error, ln(AFE), is computed from the natural logarithm of the squared error in a median forecast of one year ahead, i.e. $(\text{Actual next 12M EPS} - \text{median forecast EPS})^2$, deflated by the beginning share price. The second model of the forecast error, |EPS FE|, is calculated from the difference in a median forecast error, i.e., Actual next 12M EPS – median forecast EPS, divided by the absolute value of Actual next 12M EPS. The study investigates the impact of analysts' consensus via the analyst variables, such as the previous forecast error, the number of analysts (NOA), the variance of target returns (VTR), the skewness of target returns (STR), and the percentage of "Buy" recommendation (PBR), while controlling firm's fundamental and macroeconomic factors, i.e., dividend yields, earnings growth, firm's leverage, firm's size, and the short-term interest rate. The empirical results show the forecast error in the first model is influenced by the previous forecast error whereas other analyst variables, as well as control variables, have no relationship with it. This implies that analysts improve their current forecast by learning from their previous forecast error. The regression results of the second model reveal that the previous forecast error, NOA, VTR, and PBR are the only factors affecting the current forecast error. However, the drawback of the second model is that it is sensitive to the outlier data. Therefore, the robustness test is applied to investigate whether the findings from both models are still valid after removing the outliers. The test shows that the results of the first model are unchanged but those of the second one change drastically. As a result, the second model may not be suitable for measuring analysts' forecast error. Finally, the study investigates why the forecast errors are high for some stocks covered by a lot of analysts. The reasons are that analysts may have bias, overconfidence, and over-optimistic expectations, especially on stocks performing well in the past but currently being subjected to some highly uncertain circumstances due to macroeconomic factors or structural changes in their industry. In this case, most of the analysts often predict the earnings higher than the actual ones.

1. INTRODUCTION

Background and significance of the problem

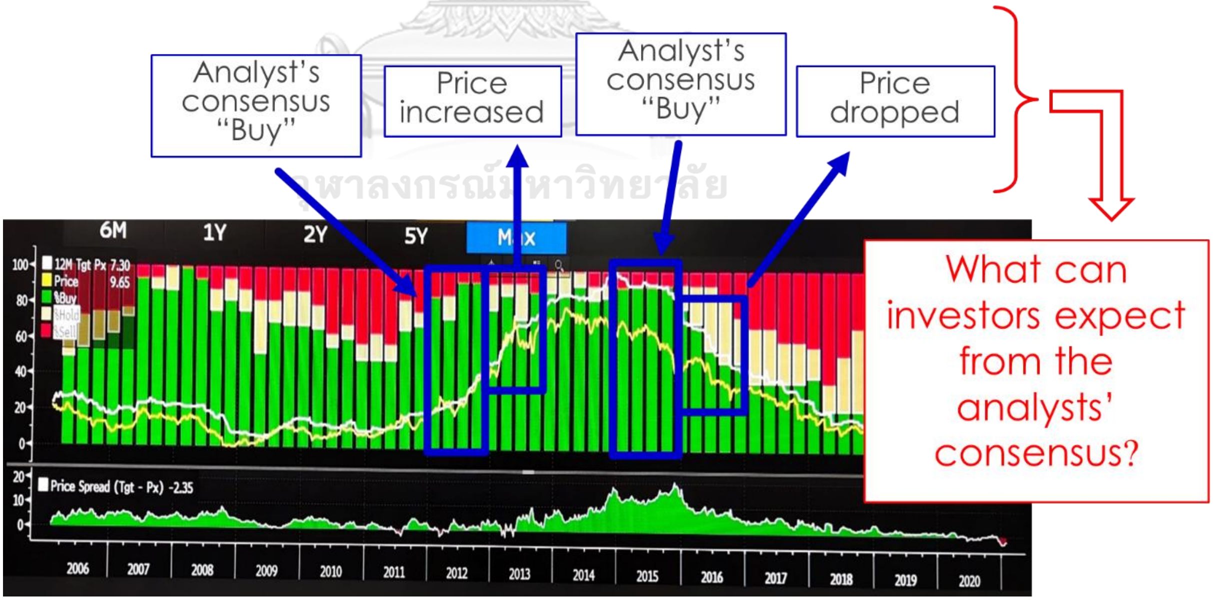
The price-to-earnings ratio (P/E ratio) is one of the most famous tools in the evaluation of stocks. Most investors, fund managers, and market analysts rely on this ratio to measure whether a stock or market is relatively attractive to investors when compared to others. The P/E ratio indicates how much investors would like to pay per Baht of a firm's profits. Moreover, it still reflects the expectation and confidence of investors about a firm's future performance and can affect the investment decision.

A stock with a low P/E ratio means that its current price is low when compared with the earnings, so it is possibly undervalued. In contrast, a stock with a high P/E ratio can imply an overvalued firm. Academic researchers often categorize stocks based on this ratio. They define a lower P/E stock as a "value" stock while a higher one as a "growth" stock. Some empirical studies showed that a portfolio of value stocks based on the P/E ratios could outperform a portfolio of growth stocks due to the value premium (Fama and French, 1998). However, some studies argued that such a strategy could not identify "value" stock (Kokm et al., 2017) and investors should not be confused with the "value" definition proposed by Graham and Dodd (1934).

In practice, the P/E ratios can be classified into "Trailing P/E" and "Forward P/E". The trailing P/E ratio (or P/E ratio in general) is computed by dividing the current share price by the actual earnings per share over the previous 12 months whereas the forward P/E ratio is calculated by dividing the current share price with the estimated earnings per share over the next 12 months. The advantage of the trailing P/E ratio is that it is easy to use and it is accurate under the assumption that the company reports its earnings correctly. However, the disadvantage is that the past performance cannot signal the future performance, so it cannot indicate whether the current share price is attractive to buy or sell. To solve this issue, most analysts prefer the forward P/E ratio when giving recommendations to investors because it better reflects the firm's future performance. Nevertheless, its drawback is that the forward P/E may be subject to analysts' miscalculations or biases, especially when analysts are too optimistic or too pessimistic in some situations.

In Thailand, most analysts make use of the forward P/E ratio by comparing it with the average of the past trailing P/E ratio before recommending investors whether to buy or sell stocks. Analysts' consensus recommendations can influence investors' investment decisions. For example, in Figure 1, most of the analysts issued a "Buy" recommendation (green bar) on a stock listed in SET during 2012 with the 12-month target price (white line) and after that the stock price went up as per their recommendation. However, sometimes they failed; for instance, in 2015 most of them recommended "Buy" with the evaluation that its target price was still higher than its current price (yellow line), but subsequently the stock price did not increase but decreased. Moreover, almost half of them tended to change their minds in the mid of 2016. Therefore, this causes the motivation of this study: what investors can expect from the analysts' consensus. Is there any measure to tell investors whether analysts' consensus is correct or incorrect? In other words, this study investigates the predictability of analysts' consensus via the forward P/E ratio which is the tool most analysts use when issuing recommendations.

Figure 1: Analyst's recommendation on a stock in Stock Exchange of Thailand (SET)



(Source: Bloomberg)

Objectives

The purpose of this study is to analyze the impact of analysts' consensus on the predictability of the stocks listed on the Stock Exchange of Thailand (SET).

Conceptual Framework

To determine predictability, the forecast error is used as a proxy. If the forecast error is low, it means that analysts' prediction is accurate and investors can expect that the stock price will move according to their recommendations. For this reason, the difference between the actual forward P/E ratio (current price/actual next 12M EPS) and its forecast (current price/next 12M forecast EPS) should be used as the measure of forecast error. However, the difference in the P/E ratio may not be appropriate for the measure of forecast error because the ratio can be very large if EPS is very small. Instead, most of the previous researches prefer using the difference in E/P ratio ([actual EPS – forecast EPS]/current price) as the measure of the forecast error (Aboud et. al. (2018); Basyah and Hartigan (2007); Dehning et. al. (2006); Gu and Wu (2003); Jones (2007); Lehavy and Merkley (2011)). Therefore, this study uses the difference in E/P ratio as the proxy of predictability.

Next, we identify the factors that can affect the forecast error. The factors are related to analysts' consensus while controlling firm's fundamental and macroeconomic factors. Lastly, we conduct a regression analysis to investigate how the analysts' consensus factors affect the predictability.

2. LITERATURE REVIEWS

Concept and Theory

According to the Gordon constant dividend discount model (Bodie, Kane and Marcus, 2014), investors can calculate the current intrinsic value of the firm (P_0) from the equation:

$$P_0 = D_1/(r - g)$$

where D_1 is next year dividend,

r is required rate of return by investor,

g is the growth rate of dividend.

The forward P/E ratio can be computed from

$$\text{Forward } P/E = \frac{P_0}{EPS_1} = \frac{D_1}{EPS_1} \times \frac{1}{r-g}$$

where $\frac{D_1}{EPS_1}$ is the next year's dividend payout ratio. Therefore, it can be noticed that factors affecting the forward P/E ratio are the next year's dividend payout ratio, the required rate of return by investors, and the dividend growth rate. The first and third factors have a positive correlation with the ratio while the second one has a negative correlation with the ratio.

Relevant research

Apart from the theoretical factors as mentioned above, several researchers identified several factors affecting the P/E ratio. Most of the studies found that dividend payout ratio had the positively significant impact on the P/E ratio (Afza and Tahir (2012); Anderson and Brooks (2006); Azam (2010); Cho (1994); Farah (2019); Huang and Wirjanto (2011); Kane et al. (1996); Loughlin (1996); Wenjing (2008)). Hence, this is consistent with the Gordon model. Some studies also found that firm's size had a positive relationship with the P/E ratio (Afza and Tahir (2012); Anderson and Brooks (2006); Farah (2019); Huang and Wirjanto (2011)). This implies that a big firm should have a higher P/E ratio than a small firm due to lower risk. Regarding the impact of earnings growth, there is still a doubt whether it affects the P/E ratio even if it is a part of the P/E ratio in the Gordon model. Azam (2010) and Loughlin (1996) found it had the positive influence in their studies, but some studies (Afza and Tahir (2012); Huang & Wirjanto (2011); Farah (2019)) concluded that it had no impact on the ratio. Moreover, some researchers found that firm's leverage had the negative impact on the ratio (Johan and Filip (2007); Mahmood and Zakaria (2007)) while others found that it had no impact (Afza and Tahir (2012); Farah (2019)).

With regard to the macroeconomic factors, the short-term interest rate was the most favorite factor in many studies, but most of them found that it had no impact on the P/E ratio (Afza and Tahir (2012); Farah (2019); Johan and Filip (2007); Wenjing (2008); Mahmood and Zakaria (2007)) even if a few found the negative impact (Azam (2010); Mahmood & Zakaria (2007)). There were other factors used in the studies such as net asset growth, ROE, GDP growth, CPI growth (Wenjing (2008)), including stock's beta (Huang and Wirjanto (2011); Wenjing (2008)), but all of them were not the popular factors.

In addition to the determinant of the P/E ratio, some studies investigated the influence of analysts. Yin et. al (2014) found that most analysts tended to give the high target P/E ratio to the firms with superior growth prospects whereas the firms with high risk measured by leverage, earnings volatility, book-to-market, and stock price volatility got the low P/E ratios. Park et. al. (2019) found that a long/short portfolio of "Strongly Buy/Sell" stocks as recommended by analysts' consensus could earn the abnormal return in the U.S. equity market during 2001-2016, but a portfolio of "Buy/Sell" stocks could not achieve the abnormal return.

Regarding the forecast error, Gu and Wu (2003) found that there was an earnings skewness in analysts' forecast and it also had the significant relationship with the biases in analysts' forecast. They also suggested that the optimal forecast from analysts' consensus is the median instead of the means of earnings. Dehning el. Al. (2006) found that the new investment of the firms in information technology could increase the earnings forecast error. Moreover, the more useful public information such as segment disclosures according to the adoption of new accounting standards could reduce the analyst forecast error (Aboud et. al. (2018))

Our study focuses on the impact of analysts' consensus on the predictability of the forward P/E ratio. As mentioned earlier, we observed most of the analysts tended to have the same recommendation when the stock price increased, but in the downturn cycle of business, they could not adjust their recommendation quickly enough for the investors. As a result, we would like to investigate the impact of their consensus on predictability. The forecast error is used as a proxy for predictability. The results from this study can contribute to investors whether they should depend on analysts' consensus before making the investment decision.

Research hypotheses

Based on the above literature reviews and previous studies, the following hypotheses are proposed.

Firms that provide more public information can attract more analysts to assess their valuation. Therefore, the number of analysts should increase, and the forecast error should decrease. In other words, the number of analysts should have a positive impact on the predictability.

H1: The more the number of analysts, the better the predictability (or the less the forecast error).

If the firm's public information is clear, most of the analysts should have similar opinions on the firm's future performance. As a result, the variance of target returns should be reduced, and the forecast error should decrease. The variance of target returns should have a negative impact on the predictability.

H2: The more the variance of target returns, the worse the predictability (or the more the forecast error).

If some analysts have extreme viewpoints different from others, the skewness of target returns given by the consensus should be different from zero. Hence, it can imply that the mean of the target returns should increase and the forecast error should increase. The skewness different from zero should have a negative impact on the predictability.

H3: The more the skewness is different from zero, the worse the predictability (or the more the forecast error).

If the firm's business and financial information is not vague, analysts should be able to evaluate the firm's future performance in the same direction. Therefore, they should have a similar recommendation on "Buy/Sell" of a stock. In other words, the similar recommendation on "Buy/Sell" should have a positive impact on the predictability.

H4: The higher the proportion of the "Buy/Sell" recommendation, the better the predictability (or the less the forecast error).

If analysts have realized their forecast error from their previous time, they will try to correct their forecast in order to reduce the error. As a result, the forecast error from the last prediction should have a positive impact on the predictability.

H5: The forecast error from the previous time causes analysts to correct their forecast next time, so the predictability will improve.

3. DATA

This study uses the quarterly firm-level and the analysts' forecast data from *Bloomberg*. The selections consist of the stocks in SET100, an index constituting top 100 companies listed in the Stock Exchange of Thailand where most analysts cover and always provide recommendations, over the period between Q1-2014 and Q4-2018 but exclude the financial sector in which the P/E ratio is not suitable for the stock evaluation. The list of stocks in SET100 over the study period can be obtained from the website of the Stock Exchange of Thailand. Moreover, this study also drops the stocks covered by less than three analysts. All the dependent, independent, and control variables used in the regression are summarized in Table 1-3.

Table 1: Dependent variables

Variables	Symbol	Measurements	Sources
Analysts' Forecast Error	AFE	$\frac{(Actual\ next\ 12M\ EPS - Median\ Forecast\ EPS)^2}{Price\ at\ the\ beginning\ period}$	Bloomberg
Analysts' Forecast Error	|EPS FE|	$\left\lvert\frac{Actual\ next\ 12M\ EPS - Median\ Forecast\ EPS}{\lvert Actual\ next\ 12M\ EPS\rvert}\right\rvert$	Bloomberg

Table 2: Independent variables

Variables	Symbol	Measurements	Sources
Number of analysts	NOA	Number of analysts	Bloomberg
Variance of target returns	VTR	Variance of $\left(\frac{12M\ Target\ Price}{current\ share\ price} - 1\right)$	Bloomberg
Skewness of target returns	STR	Skewness of $\left(\frac{12M\ Target\ Price}{current\ share\ price} - 1\right)$	Bloomberg
Percentage of "Buy" recommendation	PBR	Percentage of "Buy" from analysts' consensus	Bloomberg
Stock trend	ST	Dummy variable for the trend of the stock price over the past 12-month	-

Table 3: Control variables

Variables	Symbol	Measurements	Sources
Dividend yield	DY	$\frac{\text{Last 12} - \text{month dividend per share}}{\text{current share price}}$	Bloomberg
Financial leverage	LEV	$\frac{\text{Total debt}}{\text{Total assets}}$	Bloomberg
Earnings growth rate	EGR	12-month earnings growth rate	Bloomberg
Size (market value)	SIZE	Firm market capitalization	Bloomberg
Interest rate	INT	Interest rate on Treasury Bill 12 months (government bond)	ThaiBMA

4. METHODOLOGY

In order to investigate the impact of analysts' consensus on predictability, two panel data regression models are proposed in this study. The dependent variable is analysts' forecast error which is considered as the proxy of predictability.

Consistent with the previous studies (Aboud et. al. (2018); Basyah and Hartigan (2007); Dehning et. al. (2006); Gu and Wu (2003); Jones (2007); Lehavy and Merkley

(2011)), the first model of analysts' forecast error is computed from the squared error in a median forecast of one year ahead, i.e. (Actual next 12M EPS – median forecast EPS)^2, deflated by the beginning share price. The natural logarithm of the dependent variable is used to induce normality of regression residuals (Aboud et. al. (2018); Jones (2007)).

The second model uses a simple formula to calculate analysts' forecast error. It is computed from the difference in a median forecast error, i.e., Actual next 12M EPS – median forecast EPS, divided by the absolute value of Actual next 12M EPS. The absolute term in the denominator helps correct the forecast error value when the actual next 12M EPS is negative. Lastly, the absolute value is applied to the ratio in order to focus only on the magnitude of analysts' forecast error.

The time period of the data set is quarterly from Q1-2014 to Q4-2018, and this study sets the specific time to the date on which a firm announces its quarterly earnings. The effect of analysts' consensus on predictability is measured while controlling the fundamental factors such as dividend yield, leverage, earning growth, firm's size, and short-term interest rate. The regression equation is as follows:

$$
\begin{aligned}
FEM_{i,t} = \; & \beta_0 + \beta_1 FEM_{i,t-1} + \beta_2 NOA_{i,t} + \beta_3 VTR_{i,t} + \beta_4 |STR_{i,t}| \\
& + \beta_5 |PBR_{i,t} - 0.5| + \beta_6 NOA_{i,t} ST_{i,t} + \beta_7 VTR_{i,t} ST_{i,t} + \beta_8 |STR_{i,t}| ST_{i,t} \\
& + \beta_9 |PBR_{i,t} - 0.5| ST_{i,t} + \beta_{10}\, ln\left(\frac{DY_{i,t}}{DY_{i,t-4}}\right) + \beta_{11}\, ln\left(\frac{LEV_{i,t}}{LEV_{i,t-4}}\right) \\
& + \beta_{12} EGR_{i,t} + \beta_{13}\, ln\left(\frac{SIZE_{i,t}}{SIZE_{i,t-4}}\right) + \beta_{14}\, ln\left(\frac{INT_{i,t}}{INT_{i,t-4}}\right) + \epsilon_{i,t}
\end{aligned}
$$

where:

i (or ith stock) = 1, 2, 3, …, N,

t = quarter period from Q1-2014 to Q4-2018 (t is selected based on the EPS announcement date of each stock.),

$FEM_{i,t}$ = forecast error model which are ln $AFE_{i,t}$ and $|EPS\ FE|_{i,t}$,

$$\ln AFE_{i,t} = \ln \frac{(Actual\ next\ 12M\ EPS_{i,t} - Median\ Forecast\ EPS_{i,t})^2}{Price_{i,t}} \;,$$

$$|EPS\ FE_{i,t}| = \left|\frac{Actual\ next\ 12M\ EPS_{i,t} - \ Median\ Forecast\ EPS_{i,t}}{|Actual\ next\ 12M\ EPS_{i,t}|}\right|,$$

$$ST_{i,t} = \begin{cases} 1 & \text{if the stock price increased over the past } 12-\text{month} \\ 0 & \text{if the stock price decreased over the past } 12-\text{month,} \end{cases}$$

$ln\left(\frac{x_{i,t}}{x_{i,t-4}}\right)$ = 1-year continuous growth rate in factor x.

5. EMPIRICAL RESULTS

5.1 Data statistics

This section describes the data statistics in our empirical study. Based on the criteria in Section 3, there are 125 stocks in SET100 during 2014-2018 that are covered by at least 3 analysts and not in the financial sector. Table 4 provides summary statistics for the samples in this study. It can be noticed that the maximum number of analysts (NOA) to cover one stock per quarter is 32 whereas the average is 18.

Analysts' forecast error indicates how accurate analysts can estimate the earning over the next 4 quarters. The range of analysts' forecast error in the first model, ln(AFE), is between -18.6120 and 1.7110 whereas that in the second model, |EPS FE|, is between 0.0005 and 110.7308 (or 0.05% - 11073.08%). Obviously, the second model is definitely affected by the outlier data. Figure 2 and 3 illustrate the histograms of EPS FE and |EPS FE| respectively. The distribution of EPS FE contains extreme values at the left tail. They occur because the forecast value is much higher than the actual value; in other words, it implies that analysts are too optimistic in their forecast for the firm performance. Figure 4 shows the relationship between ln(AFE) and |EPS FE|. In fact, when the value of |EPS FE| is near zero, it means that the accuracy of analysts' forecast is very well; also, the value of ln(AFE) will approach to the high negative value in this case.

With regard to the expected target returns (TR) over the next 4 quarters, the range is between -44.10% and 92.17%, but the average is 13.17%. This means that most analysts are optimistic and predict the positive returns for a stock on average. The variance of target returns (VTR) has its mean of 0.0365 or 19.1% in term of standard deviation for a stock in one quarter estimation. This reflects that most analysts do not have the similar opinions on the performance of a stock. The absolute value of skewness of target returns (STR) has its mean of 0.8846 for a stock. The value different from zero indicates that the distribution of target returns is not normal; in other words, some analysts may have the extreme opinions on the performance of a stock. The percentage of "Buy" recommendation minus 0.5 in the absolute term indicates the direction of analysts' recommendation. If the value is near 0.5, it means that most of the analysts have the strong recommendation on "Buy/Sell". On the contrary, if the value is near 0, this tells that those analysts cannot reach a clear consensus whether to buy or sell the stock.

The stock trend variable (ST) is a dummy variable defined from the price return of a stock over the last 12 months. If past returns are positive, ST is assigned to 1. The interaction terms between ST and analyst variables, i.e., NOA, VTR, |STR|, and |PBR-0.5|, helps explain how analyst factors affect the forecast error during the past uptrend. In other words, the coefficients of analyst variables, i.e., β_2, β_3, β_4, and β_5, reflect the effect of analyst forecast error when the stock price went down in the past. If the stock price went up, the coefficients in the model are $\beta_2+\beta_6$, $\beta_3+\beta_7$, $\beta_4+\beta_8$ and $\beta_5+\beta_9$. It should be noted that if the 12-month return is equal to zero or the price does not change, the data are dropped from our study.

The control variables in this study consist of the growth of the last 12-month dividend yield, the growth of the last 12-month firm's leverage, the growth of the last 12-month earnings (or EPS growth), the growth of the last 12-month firm's size, and the change of last 12-month short-term interest rate. The mean of the dividend growth is 12.38% while the average of earnings growth is 5.95%. This indicates that the firm will try to increase the dividend to shareholders even if they have low growth in its earnings during 2014-2018. The average growth of firm's size is 6.03% whereas the average of its leverage growth is 2.78%. Lastly, the average of the short-term interest rate change is -9.27%.

Table 6 and 7 provide the descriptive statistics of correlations for ln(AFE) and |EPS FE| models respectively. For the first model, a high correlation exists between the 1-period lag of ln(AFE) and its current value whereas there is no high correlation between each variable. On the contrary, the 1-period lag of |EPS FE| lowly correlates with its current value, and other variables do not show the high correlation among themselves. Therefore, both proposed models do not face the multi-collinearity problem.

Table 4: Descriptive statistics of the data for the whole observations

Variables	Obs.	Mean	Median	Std. Dev.	Min	Max
$\ln AFE_{i,t}$	1,113	-7.3196	-7.2020	3.1513	-18.6120	1.7110
$EPS\ FE_{i,t}$	1,113	-0.3311	0.0030	3.8351	-110.7308	6.6977
$\left\|EPS\ FE_{i,t}\right\|$	1,113	0.4973	0.1029	3.8171	0.0005	110.7308
$NOA_{i,t}$	1,113	18.3145	19.0000	6.5001	3.0000	32.0000
$VTR_{i,t}$	1,113	0.0365	0.0220	0.0658	0.0010	1.4150
$\left\|STR_{i,t}\right\|$	1,113	0.8846	0.7170	0.7075	0.0010	3.7630
$\left\|PBR_{i,t} - 0.5\right\|$	1,113	0.2164	0.2140	0.1308	0.0000	0.5000
$NOA_{i,t}ST_{i,t}$	1,113	10.4528	9.0000	10.3931	0.0000	32.0000
$VTR_{i,t}ST_{i,t}$	1,113	0.0153	0.0070	0.0237	0.0000	0.2090
$\left\|STR_{i,t}\right\|ST_{i,t}$	1,113	0.5208	0.1770	0.7178	0.0000	3.7630
$\left\|PBR_{i,t} - 0.5\right\|ST_{i,t}$	1,113	0.1250	0.0600	0.1456	0.0000	0.5000
$ln\left(\frac{DY_{i,t}}{DY_{i,t-1}}\right)$	1,113	0.1238	0.0740	0.5873	-2.8520	3.1780
$ln\left(\frac{LEV_{i,t}}{LEV_{i,t-1}}\right)$	1,113	0.0278	-0.0140	0.6319	-5.8420	7.6300
$EGR_{i,t}$	1,113	0.0595	0.0600	6.8652	-119.3796	150.5017
$ln\left(\frac{SIZE_{i,t}}{SIZE_{i,t-1}}\right)$	1,113	0.0603	0.0640	0.3137	-1.1380	1.2530
$ln\left(\frac{INT_{i,t}}{INT_{i,t-1}}\right)$	1,113	-0.0927	-0.0710	0.1561	-0.3780	0.2520
Avg Target Returns	1,113	0.1317	0.1237	0.1384	-0.4410	0.9217

Figure 2: Distribution of EPS FE [(Actual-Forecast)/|Actual|)

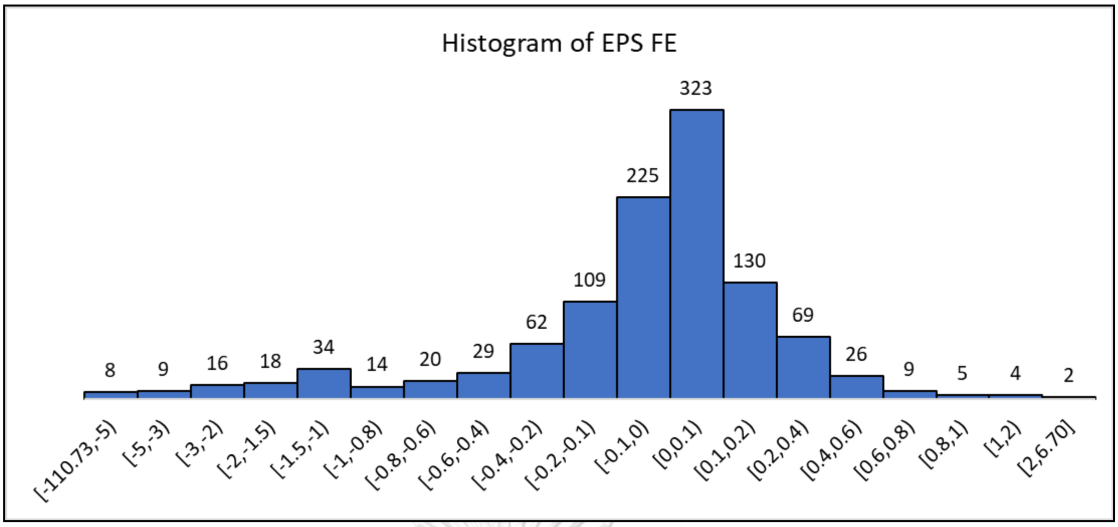


Figure 3: Distribution of |EPS FE|

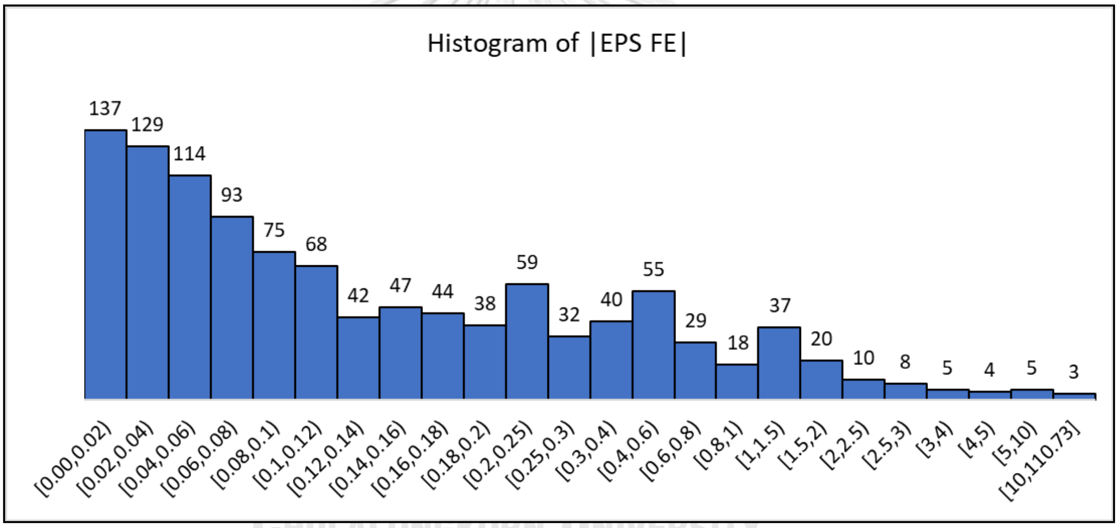


Table 5: Percentiles of EPS FE and |EPS FE|.

Percentile	1%	5%	25%	50%	75%	95%	99%
EPS FE	-4.1020	-1.4658	-0.1318	0.0030	0.0865	0.3368	0.8083
|EPS FE|	0.0021	0.0080	0.0423	0.1028	0.2311	1.4975	4.1020

Figure 4: Relationship between ln(AFE) and |EPS FE|

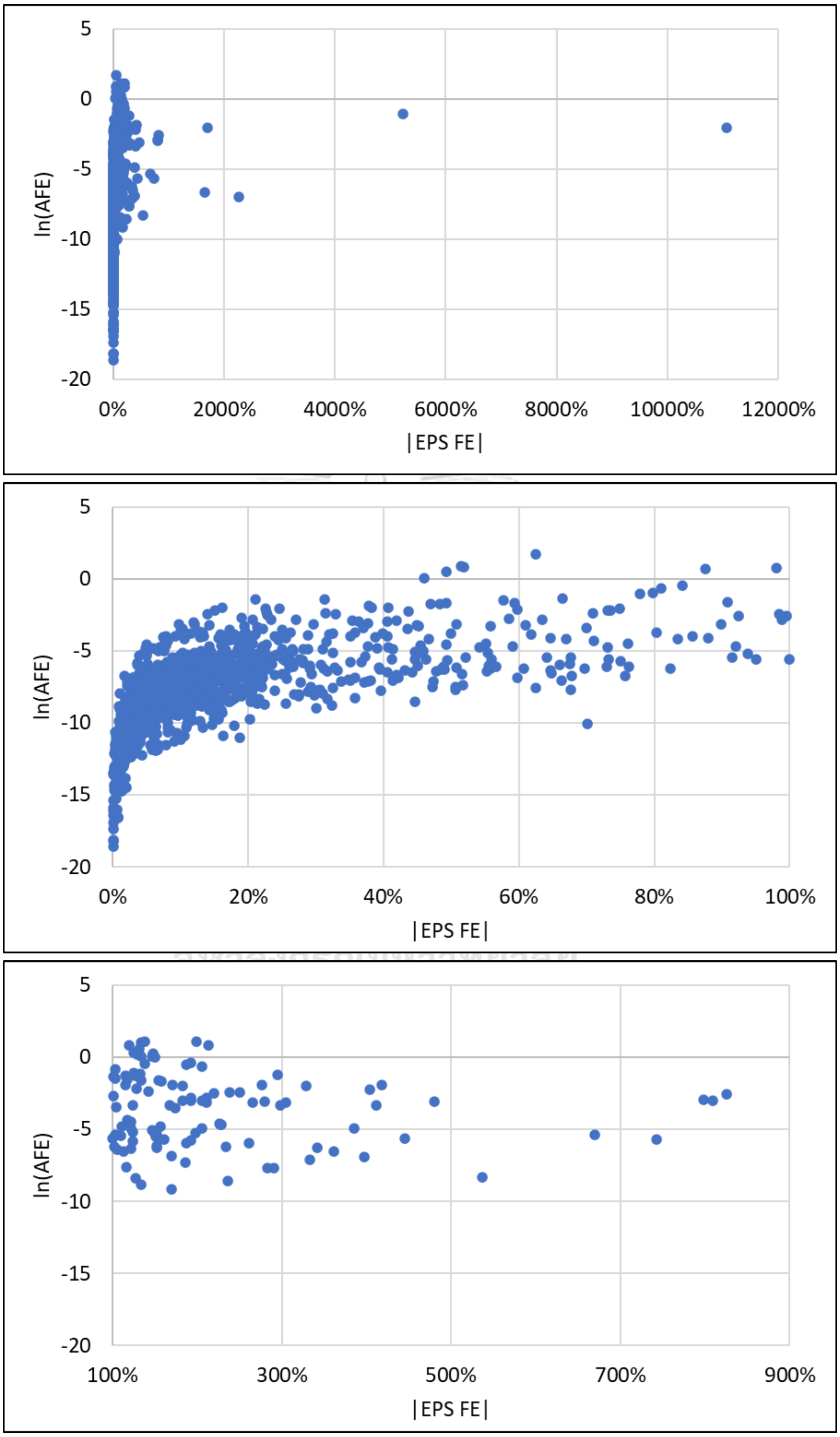


Figure 5: Relationship between ln(AFE) and NOA, VTR, |STR|, |PBR-0.5|

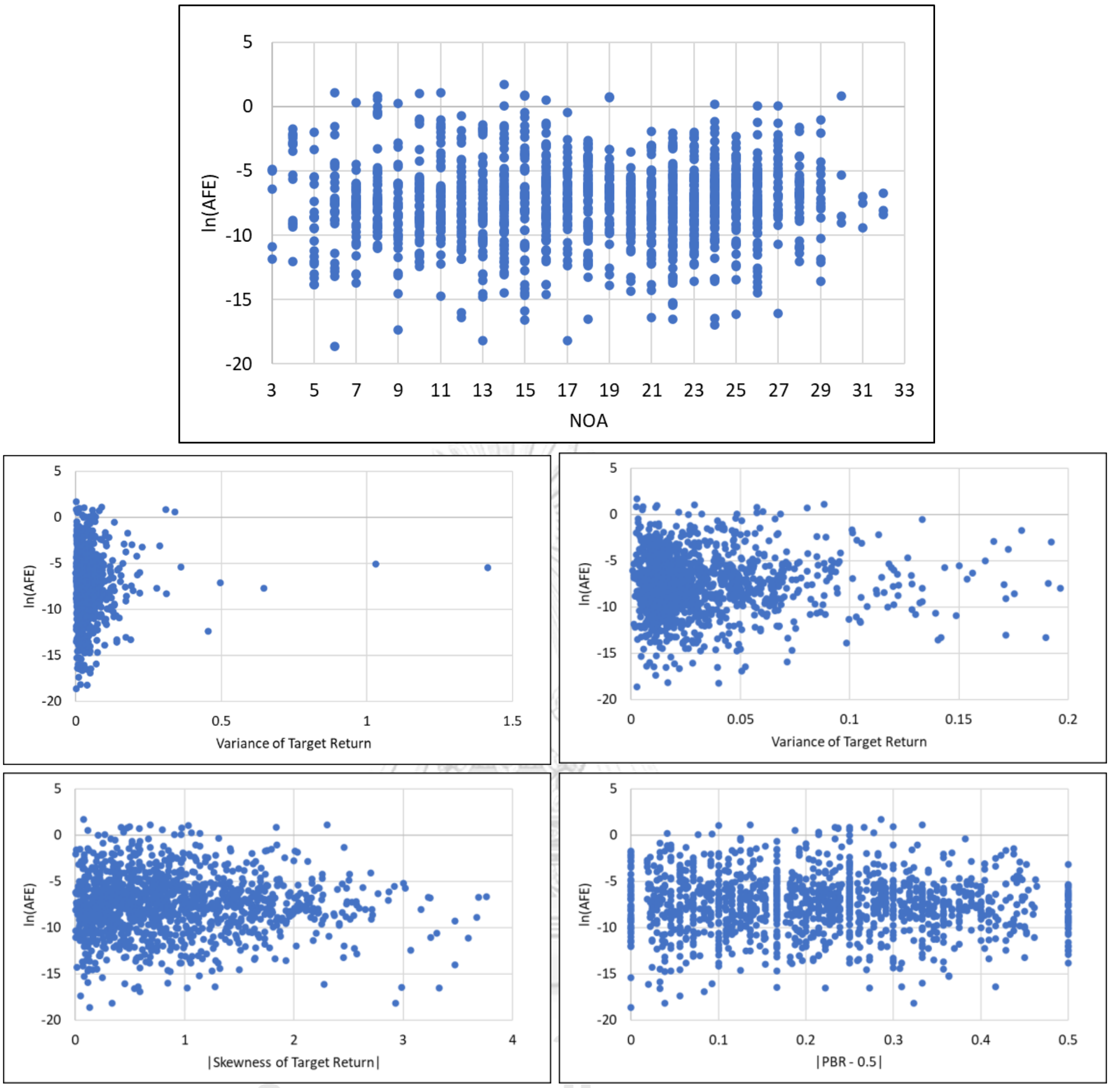


Figure 6: Relationship between |EPS FE| and NOA, VTR, |STR|, |PBR-0.5|

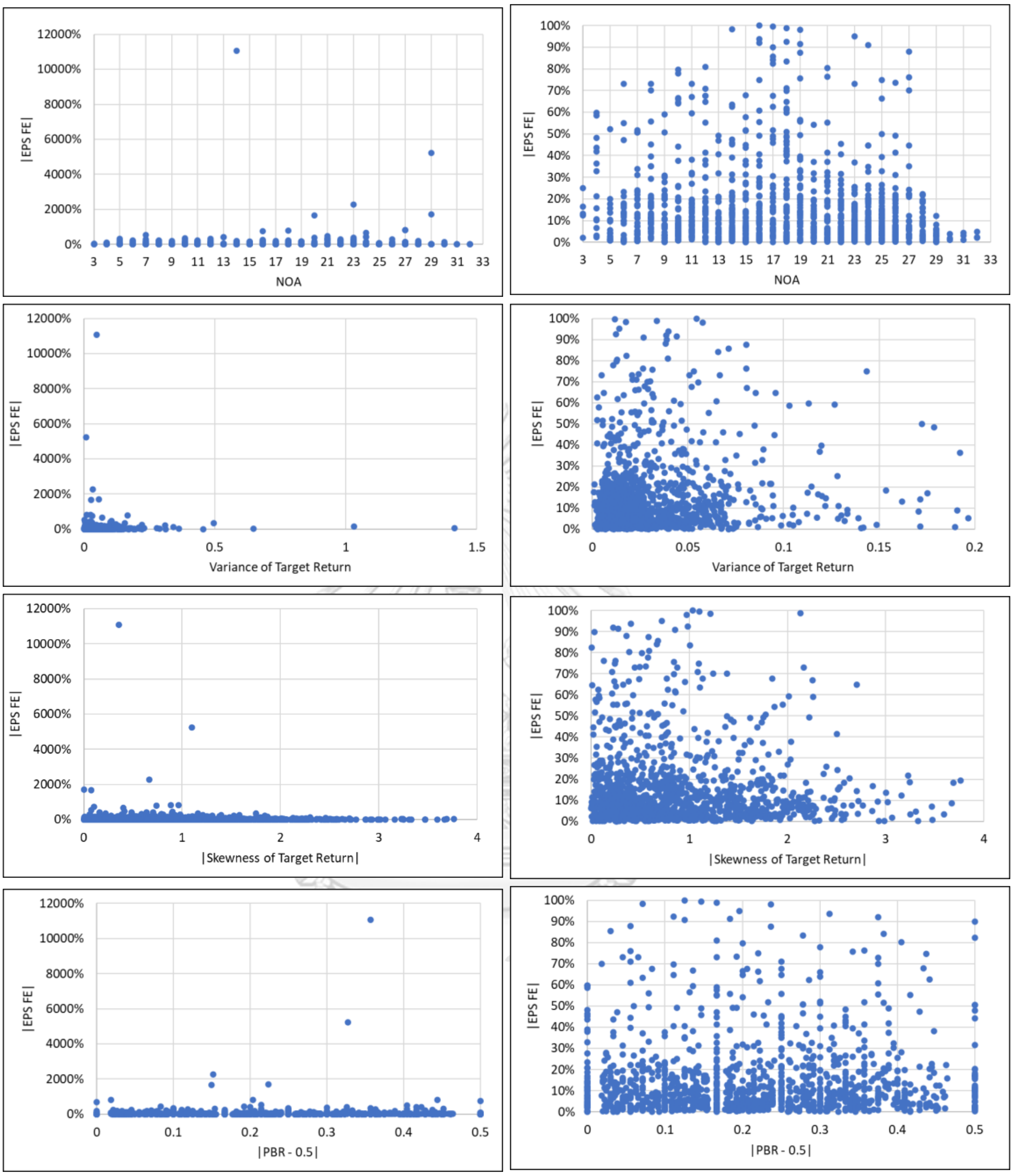


Table 6: Descriptive statistics of correlations for ln(AFE) model

	$\ln AFE_{i,t}$	$\ln AFE_{i,t-1}$	$NOA_{i,t}$	$VTR_{i,t}$	$\lvert STR_{i,t}\rvert$	$\lvert PBR_{i,t} - 0.5\rvert$	$NOA_{i,t}ST_{i,t}$	$VTR_{i,t}ST_{i,t}$	$\lvert STR_{i,t}\rvert ST_{i,t}$	$\lvert PBR_{i,t} - 0.5\rvert ST_{i,t}$	$ln\left(\frac{DY_{i,t}}{DY_{i,t-1}}\right)$	$ln\left(\frac{LEV_{i,t}}{LEV_{i,t-1}}\right)$	$EGR_{i,t}$	$ln\left(\frac{SIZE_{i,t}}{SIZE_{i,t-1}}\right)$	$ln\left(\frac{INT_{i,t}}{INT_{i,t-1}}\right)$
$\ln AFE_{i,t}$	1														
$\ln AFE_{i,t-1}$	0.722	1													
$NOA_{i,t}$	-0.026	-0.065	1												
$VTR_{i,t}$	0.045	0.051	-0.078	1											
$\lvert STR_{i,t}\rvert$	-0.056	-0.064	0.116	0.194	1										
$\lvert PBR_{i,t} - 0.5\rvert$	-0.034	-0.020	-0.144	-0.042	-0.057	1									
$NOA_{i,t}ST_{i,t}$	-0.096	-0.120	0.386	-0.164	0.114	-0.028	1								
$VTR_{i,t}ST_{i,t}$	-0.074	-0.053	-0.053	0.133	0.190	-0.105	0.460	1							
$\lvert STR_{i,t}\rvert ST_{i,t}$	-0.133	-0.144	0.120	-0.054	0.641	-0.003	0.622	0.519	1						
$\lvert PBR_{i,t} - 0.5\rvert ST_{i,t}$	-0.067	-0.075	-0.048	-0.164	0.026	0.501	0.616	0.322	0.460	1					
$ln\left(\frac{DY_{i,t}}{DY_{i,t-1}}\right)$	-0.013	-0.049	-0.094	-0.150	-0.004	-0.068	0.046	0.015	0.053	0.080	1				
$ln\left(\frac{LEV_{i,t}}{LEV_{i,t-1}}\right)$	-0.045	-0.059	-0.025	0.157	0.007	0.008	-0.109	-0.079	-0.073	-0.115	-0.120	1			
$EGR_{i,t}$ (%)	0.054	0.042	0.027	-0.041	0.010	-0.048	0.032	-0.011	0.029	0.047	0.032	-0.023	1		
$ln\left(\frac{SIZE_{i,t}}{SIZE_{i,t-1}}\right)$	-0.133	-0.132	-0.083	-0.247	0.022	0.005	0.573	0.527	0.467	0.547	0.136	-0.168	0.050	1	
$ln\left(\frac{INT_{i,t}}{INT_{i,t-1}}\right)$	-0.047	-0.055	0.077	-0.115	-0.005	0.049	0.171	0.062	0.102	0.167	0.061	-0.032	0.005	0.164	1

Table 7: Descriptive statistics of correlations for |EPS FE| model.

	$\lvert EPS\,FE_{i,t}\rvert$	$\lvert EPS\,FE_{i,t-1}\rvert$	$NOA_{i,t}$	$VTR_{i,t}$	$\lvert STR_{i,t}\rvert$	$\lvert PBR_{i,t}-0.5\rvert$	$NOA_{i,t}ST_{i,t}$	$VTR_{i,t}ST_{i,t}$	$\lvert STR_{i,t}\rvert ST_{i,t}$	$\lvert PBR_{i,t}-0.5\rvert ST_{i,t}$	$ln\left(\frac{DY_{i,t}}{DY_{i,t-1}}\right)$	$ln\left(\frac{LEV_{i,t}}{LEV_{i,t-1}}\right)$	$EGR_{i,t}$	$ln\left(\frac{SIZE_{i,t}}{SIZE_{i,t-1}}\right)$	$ln\left(\frac{INT_{i,t}}{INT_{i,t-1}}\right)$
$\lvert EPS\,FE_{i,t}\rvert$	1														
$\lvert EPS\,FE_{i,t-1}\rvert$	0.038	1													
$NOA_{i,t}$	0.001	-0.006	1												
$VTR_{i,t}$	0.015	0.017	-0.078	1											
$\lvert STR_{i,t}\rvert$	-0.036	-0.034	0.116	0.194	1										
$\lvert PBR_{i,t}-0.5\rvert$	0.032	0.024	-0.144	-0.042	-0.057	1									
$NOA_{i,t}ST_{i,t}$	-0.014	-0.012	0.386	-0.164	0.114	-0.028	1								
$VTR_{i,t}ST_{i,t}$	-0.023	0.007	-0.053	0.133	0.190	-0.105	0.460	1							
$\lvert STR_{i,t}\rvert ST_{i,t}$	-0.026	-0.025	0.120	-0.054	0.641	-0.003	0.622	0.519	1						
$\lvert PBR_{i,t}-0.5\rvert ST_{i,t}$	-0.020	0.014	-0.048	-0.164	0.026	0.501	0.616	0.322	0.460	1					
$ln\left(\frac{DY_{i,t}}{DY_{i,t-1}}\right)$	0.000	-0.014	-0.094	-0.150	-0.004	-0.068	0.046	0.015	0.053	0.080	1				
$ln\left(\frac{LEV_{i,t}}{LEV_{i,t-1}}\right)$	-0.005	0.008	-0.025	0.157	0.007	0.008	-0.109	-0.079	-0.073	-0.115	-0.120	1			
$EGR_{i,t}$ (%)	-0.005	-0.002	0.027	-0.041	0.010	-0.048	0.032	-0.011	0.029	0.047	0.032	-0.023	1		
$ln\left(\frac{SIZE_{i,t}}{SIZE_{i,t-1}}\right)$	-0.040	-0.023	-0.083	-0.247	0.022	0.005	0.573	0.527	0.467	0.547	0.136	-0.168	0.050	1	
$ln\left(\frac{INT_{i,t}}{INT_{i,t-1}}\right)$	-0.034	-0.003	0.077	-0.115	-0.005	0.049	0.171	0.062	0.102	0.167	0.061	-0.032	0.005	0.164	1

Table 8: Hypothesis summary and expected sign of each coefficient.

Hypothesis	Variables	Coefficient	Expected sign	Implications
H1	NOA	β_2 and $\beta_2 + \beta_6$	-	The more the number of analysts, the less the forecast error.
H2	VTR	β_3 and $\beta_3 + \beta_7$	+	The more the variance of target returns, the more the forecast error.
H3	STR	β_4 and $\beta_4 + \beta_8$	+	The more the absolute value of target returns skewness different from zero, the more the forecast error.
H4	|PBR-0.5|	β_5 and $\beta_5 + \beta_9$	-	The stronger the consensus recommendation on “Buy/Sell”, the less the forecast error.
H5	1-period lag	β_1	+ (for ln(AFE) model) - (for |EPS FE| model)	The forecast error from the previous prediction should help reduce the forecast error in this current period.

Note that β_2 (+ β_6) reflects the effect of NOA on the forecast error when the stock price goes down (up) during last 12 month.

5.2 Regression Results

Table 9: Regression results

Models	ln(AFE)		|EPS FE|	
Variables	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Constant	-6.7292*** (0.0000)	1.1310	1.4241 (0.5330)	2.2826
1-period Lag	0.3000*** (0.0000)	0.0470	-0.1247*** (0.0000)	0.0338
$NOA_{i,t}$	0.0910 (0.1010)	0.0555	-0.0850 (0.4850)	0.1217
$VTR_{i,t}$	-0.8534 (0.6860)	2.1095	-5.1496 (0.1980)	4.0043
$\lvert STR_{i,t}\rvert$	0.1897 (0.3810)	0.2165	-0.4851 (0.2840)	0.4529
$\lvert PBR_{i,t}-0.5\rvert$	-0.7105 (0.5060)	1.0679	5.2323** (0.0180)	2.2027
$NOA_{i,t}ST_{i,t}$	0.0037 (0.8410)	0.0184	0.0842** (0.0220)	0.0368
$VTR_{i,t}ST_{i,t}$	-7.3218 (0.2170)	5.9273	-22.1662* (0.0630)	11.9311
$\lvert STR_{i,t}\rvert ST_{i,t}$	-0.0878 (0.7220)	0.2468	0.6545 (0.2040)	0.5148
$\lvert PBR_{i,t}-0.5\rvert ST_{i,t}$	-0.0389 (0.9710)	1.0849	-5.9948*** (0.0070)	2.2372
$ln\left(\frac{DY_{i,t}}{DY_{i,t-4}}\right)$	0.2005 (0.2600)	0.1781	0.3448 (0.3290)	0.3530
$ln\left(\frac{LEV_{i,t}}{LEV_{i,t-4}}\right)$	0.1976 (0.2560)	0.1737	-0.3671 (0.3100)	0.3614
$EGR_{i,t}$	-0.0067 (0.7930)	0.0254	0.0000 (1.0000)	0.0478
$ln\left(\frac{SIZE_{i,t}}{SIZE_{i,t-4}}\right)$	0.1227 (0.7720)	0.4243	-1.4407 (0.1010)	0.8793
$ln\left(\frac{INT_{i,t}}{INT_{i,t-4}}\right)$	-0.2862 (0.5880)	0.5283	-0.7921 (0.5090)	1.1985

Note: p-value in parenthesis, ***/**/* = 1%, 5% and 10 % level of statistical significance.

The proposed linear dynamic panel-data models can be solved by Arellano–Bond estimator in STATA. Table 8 summarizes the expected sign of each coefficient that is consistent with the hypotheses. For example, the effect of NOA on the forecast error during the downtrend and uptrend is shown via β_2 and $\beta_2 + \beta_6$ respectively. According to the hypothesis H1, the sign of them should be negative so that the forecast error decreases when the number of analysts increases. Table 9 shows the regression results of two proposed models in this study.

Discussion on ln(AFE) model

There are only the one-period lag of ln(AFE) and the constant term that are statistically significant. The coefficient of the one-period lag of ln(AFE) is 0.3 with the significance level of 1%. It indicates that the forecast error from the previous quarter contributes to 30% of the current forecast error. Therefore, if the forecast error from the last period is less than the constant term divided by one minus β_5, i.e. -9.613 (= -6.7292/(1-0.3)), the forecast for the current period will be improved. On the other hand, if the previous forecast error is more than -9.613, the forecast error will increase. This means that if analysts can perform their forecast for the next 4-quarter earnings very well in the previous quarter, i.e., less error or a large negative value on ln(AFE), ceteris paribus, the forecast error for the next quarter will increase. On the other hand, if they perform the prediction very badly last quarter, the error will be reduced in the future too. Therefore, the result is consistent with the hypothesis H5 only when analysts make the large forecast error during the previous period. One of the reasons that the result is inconsistent with the hypothesis H5 for the small forecast error is that analysts may have overconfidence from their good performance or they may be too optimistic for the firm's future performance.

Apart from the one-period lag of ln(AFE) and constant term, other analyst variables including the control variables are not statistically significant. This means that they are not different from zero, i.e. they have no relationship with the forecast error. However, if all analyst variables were statistically significant, the result would be inconsistent with the hypotheses H1 and H2 but consistent with the hypotheses H3 and H4. This means that the high number of analysts and the low variance of target returns cannot reduce the forecast error.

Discussion on |EPS FE| model

There are five statistically significant coefficients. The coefficient of the one-period lag of |EPS FE| is -0.1247 with the significance level of 1%. It means that the current forecast error decreases by 12.47% of the previous forecast error. Therefore, the result is consistent with the hypothesis H5. The number of analysts affects the forecast error only when the stock price goes up during the last 12 months. The impact is shown via the coefficient $\beta_2 + \beta_6$, 0.0842, which is statistically significant at 5%. The positive sign indicates that the forecast error will increase as the number of analysts increases. Hence, the result is inconsistent with the hypothesis H1. The variance of target returns also only has an impact on the forecast error during the past uptrend. Its effect is revealed via the coefficient $\beta_3 + \beta_7$, -22.1662, which is statistically significant at 10%. The negative sign is opposite to the expected sign in the hypothesis H2. This indicates that the more the variance of target returns, the less the forecast error. Lastly, the direction of "Buy/Sell" recommendation from analysts affects the forecast error with the significance level of 5%. Its effect during the past downtrend is β_5, 5.2323, whereas that during the uptrend is $\beta_5 + \beta_9$, -0.7625. The positive sign in the past downtrend case means that the forecast error will decrease only when most of the analysts do not have the same opinion on either "Buy" or "Sell", i.e. |PBR-0.5| approaches to zero. Thus, this result is against the hypothesis H4 in the past downtrend case. On the contrary, the negative sign in the past uptrend case supports the hypothesis H4. This means that analysts' consensus on "Buy/Sell" can help reduce the forecast error.

Discussion on number of analysts (NOA)

Although the regression result shows that the number of analysts has no impact on the forecast error except for the |EPS FE| model in the past uptrend case, there is a possibility that the hypothesis H1 is wrong, i.e., the more the number of analysts, the more the forecast error. In order to investigate the causes, the raw data has been checked and there are some interesting cases on some popular stocks, such as PTT, PTTEP, BCP, IRPC, DTAC, TRUE, EGCO, RATCH, AAV, THAI, and so on, having the large forecast errors even if the number of analysts covering them is higher than the average. The large forecast errors often occur during the highly uncertain circumstances caused by macroeconomic factors or industry factors. Moreover, most of the large forecast errors are found in the form: of "higher forecast than actual EPS" (97 from 112 observations). This means most of the analysts are too optimistic and have some bias including overconfidence, especially on some stocks performing well in the past. For example, the stocks in the energy sectors, such as PTT, PTTEP, and others, often provided good performances in the past, but during the oil price crisis in Q1/14 – Q2/15 and Q1–Q2/17 most of the analysts could not predict their performances as accurately as they did in the normal situation. The large forecast errors from over-optimistic expectations also occurred with other sectors such as transportation (AAV, BA, THAI), ICT (DTAC), media (BEC, MCOT, MONO, WORK), and utility (DEMCO, GUNKUL, EGCO, RATCH), but all of these sectors were subjected to the structural change in their industry. It should be noted that there is a chance that the large forecast errors may come from the over-pessimistic viewpoint to the stocks that always report negative EPS. For instance, TRUE, one of the biggest firms in the ICT sector, always reported negative profits before 2014, but it has reported positive profits since 2014 after the structural change due to the spectrum auction in the ICT sector. As a result, most analysts made the large forecast errors, i.e, forecast lower than the actual, during 2014-2018 even if the number of analysts covering it was more than 20.

Disadvantage of |EPS FE| model

Obviously, the |EPS FE| model is subject to the outlier data shown in Table 4 and Figure 3. The outlier of the forecast error can occur when the denominator, i.e., the actual next 12M EPS, is very small. Table 10 shows an example of how the outlier data occurs. For example, the magnitude of the difference in the actual next 12M EPS and the forecast in Q1/14 is more than that in Q4/16, but the value of |EPS FE| in Q1/14 is lower due to the higher denominator. Moreover, the formula of EPS, i.e. (Actual-Forecast)/|Actual|, may not be suitable if the sign of the actual value is different from the forecast. Therefore, |EPS FE| may not be a good measure for analysts' forecast error.

Table 10: Example of outlier data from PTTEP

Period	Actual next 12M EPS	Forecast	Current Price	Diff. (A-F)	|EPS FE|	ln(AFE)
Q1/14	4.2341	9.884	161	-5.6499	-1.334	-1.618
Q2/14	-0.1459	7.478	168.5	-7.6239	-52.254	-1.064
Q1/15	-7.4925	3.522	113	-11.0145	-1.470	0.071
Q4/16	1.6614	6.564	83	-4.9026	-2.951	-1.239
Q3/17	3.9392	9.135	87.75	-5.1958	-1.319	-1.645

Robustness of ln(AFE) and |EPS FE| models

Since the |EPS FE| model is sensitive to the outlier data, the robustness test is applied to both ln(AFE) and |EPS FE| models by omitting the outlier data from the sample. This is to investigate whether the results of both models in the general case are affected by the outlier data or not.

In order to remove the outlier data from the study, the percentile of |EPS FE| ranging from 0% to 99% as shown in Table 5 is applied. With this criterion, the robustness test still covers 99% of the observations. Moreover, the test is extended to the case of dropping the data that have the different sign in the actual next 12M EPS and the forecast EPS. Table 11 shows the regression results for the robustness test of the ln(AFE) model. Obviously, the results do not change from the general case; that is, only the one-period lag of ln(AFE) and the constant term are statistically significant and the signs of their coefficients are the same. This is because the value of ln(AFE) is not subject to the outlier data.

Table 12 provides the regression results for the robustness test of the |EPS FE| model. The result under the criterion of the 0-90th percentile certainly changes from the general case; in other words, the number of coefficients with statistical significance increases from 5 to 10. The signs of five old coefficients, i.e., β_1, β_5, $\beta_2 + \beta_6$, $\beta_3 + \beta_7$, and $\beta_5 + \beta_9$, are still the same as those in the general case, so the implications and the consistencies to the hypotheses do not change. However, the results show there are two more analyst variables and three control variables having an impact on the forecast error. The variance of target returns affects the forecast error for both past downtrend and uptrend via the coefficients, β_3 and $\beta_3 + \beta_7$ respectively, at the significance level of 1%. The signs of both coefficients are negative, so the result is against the hypothesis H2. Next, the skewness of target returns in the absolute term has the impact on the forecast error during the past uptrend. Its effect is shown via the coefficient $\beta_4 + \beta_8$, 0.6621, at the significance level of 5%. The positive sign supports the hypothesis H3. This means that if there is the skewness of target returns, the forecast error will increase. Lastly, the control variables, i.e., the change in firm's leverage, size and 1-year interest rate, have the negative relationship with the forecast error.

If the robustness test excludes the observations having the different sign in the actual next 12M EPS and the forecast EPS, i.e., 47 data are omitted from the 0-99th percentile of |EPS FE|, the result under both criteria definitely changes from the general case. Only the one-period lag of |EPS FE| and two control variables have an impact on the forecast error. The positive sign of the one-period lag of |EPS FE| is opposite to the result from the general case. This means that the result is against the hypothesis H5, and the previous forecast error will increase the current forecast error by 28.78% of its previous error. However, other analyst variables have no relationship with the forecast error. Finally, the control variables, i.e., the change in firm's size and 1-year interest rate, have the negative relationship with the forecast error.

Table 11: Regression results for robustness test for ln(AFE) model

ln(AFE) model	0-99th Percentile		0-99th Percentile + omit data that have different sign in Actual and Forecast	
Variables	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Constant	-6.7607*** (0.0000)	1.1449	-6.8243*** (0.0000)	1.1915
1-period Lag	0.2908*** (0.0000)	0.0476	0.2794*** (0.0000)	0.0479
$NOA_{i,t}$	0.0889 (0.1140)	0.0563	0.0896 (0.1240)	0.0583
$VTR_{i,t}$	-0.9848 (0.6400)	2.1038	-4.8492 (0.1830)	3.6401
$\left\|STR_{i,t}\right\|$	0.1815 (0.4010)	0.2163	0.1831 (0.4110)	0.2228
$\left\|PBR_{i,t}-0.5\right\|$	-0.7644 (0.4750)	1.0713	-1.0245 (0.3530)	1.1023
$NOA_{i,t}ST_{i,t}$	-0.0015 (0.9360)	0.0187	-0.0071 (0.7120)	0.0193
$VTR_{i,t}ST_{i,t}$	-7.5906 (0.2010)	5.9296	-4.7020 (0.4510)	6.2425
$\left\|STR_{i,t}\right\|ST_{i,t}$	-0.0661 (0.7890)	0.2464	-0.0803 (0.7500)	0.2522
$\left\|PBR_{i,t}-0.5\right\|ST_{i,t}$	0.2608 (0.8110)	1.0908	0.3450 (0.7580)	1.1194
$ln\left(\frac{DY_{i,t}}{DY_{i,t-4}}\right)$	0.2118 (0.2370)	0.1792	0.2054 (0.2590)	0.1819
$ln\left(\frac{LEV_{i,t}}{LEV_{i,t-4}}\right)$	0.1866 (0.2860)	0.1750	0.1234 (0.5050)	0.1849
$EGR_{i,t}$	-0.0071 (0.7790)	0.0253	-0.0097 (0.7180)	0.0268
$ln\left(\frac{SIZE_{i,t}}{SIZE_{i,t-4}}\right)$	0.1442 (0.7340)	0.4245	0.1788 (0.6840)	0.4393
$ln\left(\frac{INT_{i,t}}{INT_{i,t-4}}\right)$	-0.3424 (0.5310)	0.5464	-0.5726 (0.3040)	0.5567

Note: p-value in parenthesis, ***/**/* = 1%, 5% and 10 % level of statistical significance.

Table 12: Regression results for robustness test of |EPS FE| model

|EPS FE| model	$0\text{-}99^{th}$ Percentile		$0\text{-}99^{th}$ Percentile + omit data that have different sign in Actual and Forecast	
Variables	**Coefficient**	**Std. Error**	**Coefficient**	**Std. Error**
Constant	-1.1326 (0.4400)	1.4674	-0.0678 (0.7670)	0.2293
1-period Lag	-0.1820*** (0.0000)	0.0220	0.2878*** (0.0000)	0.0275
$NOA_{i,t}$	0.0333 (0.6730)	0.0790	0.0122 (0.3180)	0.0122
$VTR_{i,t}$	-6.8276*** (0.0080)	2.5612	-0.7150 (0.2920)	0.6792
$\|STR_{i,t}\|$	-0.4272 (0.1410)	0.2905	-0.0081 (0.8520)	0.0434
$\|PBR_{i,t} - 0.5\|$	5.4578*** (0.0000)	1.4179	0.0227 (0.9160)	0.2137
$NOA_{i,t}ST_{i,t}$	0.0974*** (0.0000)	0.0240	0.0011 (0.7700)	0.0036
$VTR_{i,t}ST_{i,t}$	-25.1212*** (0.0010)	7.6884	-0.3372 (0.7750)	1.1773
$\|STR_{i,t}\|ST_{i,t}$	0.6621** (0.0460)	0.3322	-0.0061 (0.9010)	0.0495
$\|PBR_{i,t} - 0.5\|ST_{i,t}$	-7.3213*** (0.0000)	1.4396	0.0462 (0.8300)	0.2158
$ln\left(\frac{DY_{i,t}}{DY_{i,t-4}}\right)$	0.2275 (0.3240)	0.2309	-0.0324 (0.3540)	0.0350
$ln\left(\frac{LEV_{i,t}}{LEV_{i,t-4}}\right)$	-0.6571*** (0.0050)	0.2336	-0.0736** (0.0410)	0.0361
$EGR_{i,t}$	-0.0290 (0.3410)	0.0305	0.0030 (0.5150)	0.0046
$ln\left(\frac{SIZE_{i,t}}{SIZE_{i,t-4}}\right)$	-1.9389*** (0.0010)	0.5639	0.0068 (0.9370)	0.0853
$ln\left(\frac{INT_{i,t}}{INT_{i,t-4}}\right)$	-3.6967*** (0.0000)	0.7867	-0.2372** (0.0400)	0.1157

Note: p-value in parenthesis, ***/**/* = 1%, 5% and 10 % level of statistical significance.

6. CONCLUSIONS

Most investors rely on analysts' recommendation when making an investment decision by using the data such as P/E ratio, target price, and etc. This special project studies the impact of analysts' consensus on predictability of the stock. Analysts' forecast error is used as the proxy for predictability, and this study proposes 2 models to measure the forecast error. The first model of analysts' forecast error, ln(AFE), is computed from the natural logarithm of the squared error in a median forecast of one year ahead, i.e. (Actual next 12M EPS – median forecast EPS)^2, deflated by the beginning price per share. The second model of analysts' forecast error, |EPS FE|, is calculated from the difference in a median forecast error, i.e. Actual next 12M EPS – median forecast EPS, divided by the absolute value of Actual next 12M EPS. The effect of analysts' consensus is studied via the analyst variables such as the number of analysts (NOA), variance of target returns (VTR), skewness of target returns (STR), and the percentage of "Buy" recommendation (PBR). The control variables in this study are firm's fundamental factors, e.g., the growth of last 12-month dividend yield, the growth of last 12-month firm's leverage, the growth of last 12-month earnings (or EPS growth), the growth of last 12-month firm's size, and the growth of last 12-month short-term interest rate. The study also examines the effect of analysts' consensus during the downtrend and uptrend classified from last 12-month return of a stock.

The proposed models are dynamic panel-data models which can be solved by Arellano–Bond estimator in STATA. The sample data used to test the model are the stocks in SET100 during 2014-2018 in the quarterly form. The regression result for the first model, ln(AFE), indicates that only one-period lag of ln(AFE) and constant term have an impact on analysts' forecast error whereas other analyst variables and control variables have no relationship with the forecast error. The result supports the hypothesis, i.e., analysts improve their current forecast by learning from their previous forecast error. Regarding the second model, |EPS FE|, the result reveals that one-period lag of |EPS FE|, NOA, VTR and PBR affect the forecast error. In other words, the forecast error can be improved due to the previous forecast error, and during the past uptrend the similar analysts' recommendation on either "Buy" or "Sell" can help reduce the forecast error. However, the high number of analysts and the low variance of target returns cannot improve the forecast error, so it is against the hypotheses.

Since the |EPS FE| model is subject to the outlier data, the criteria, such as 0-99th percentile of |EPS FE| and omitting the data containing the different sign in actual next 12M EPS and the forecast EPS, are applied in order to investigate the robustness of the models. The result indicates the ln(AFE) model still provides the same result as the general case, so the model is robust and not subject to the outlier data. Nevertheless, the robustness test of the |EPS FE| model shows that the sign and the level of significant level of each coefficient depend on the outlier data. As a result, the |EPS FE| may not be suitable for measuring analysts' forecast error. Finally, this study investigates why there is a large forecast error for a stock even if there are a lot of analysts covering it. The reason is that analysts may have bias, over-confidence, and over-optimistic expectation on stocks that provide the good performance from the past. As a result, analysts often predict much higher EPS than the actual one especially when the stocks are subject to some highly uncertain circumstances due to the macroeconomic factors or industry factors, such as oil price crisis, structural change in industry, and so on.

Appendix

Table A1: List of Stocks in SET100 during 2014-2018 (* = stocks in financial sector)

2014-H1	2014-H2	2015-H1	2015-H2	2016-H1	2016-H2	2017-H1	2017-H2	2018-H1	2018-H2
AAV	AAV	AAV	AAV	AAV	AAV	AAV	AAV	AAV	AAV
ADVANC	ADVANC	ADVANC	ADVANC	ADVANC	ADVANC	ADVANC	ADVANC	ADVANC	ADVANC
AMATA	AMATA	AMATA	AMATA	AMATA	AMATA	AMATA	AMATA	AMATA	AMATA
AOT	AOT	ANAN	ANAN	ANAN	ANAN	AOT	ANAN	ANAN	AOT
AP	AP	AOT	AOT	AOT	AOT	AP	AOT	AOT	AP
ASP*	BANPU	AP	AP	AP	AP	BA	AP	AP	BANPU
BANPU	BAY*	BANPU	ASP*	BA	BA	BANPU	BA	BA	BBL*
BAY*	BBL*	BAY*	BA	BANPU	BANPU	BBL*	BANPU	BANPU	BCH
BBL*	BCH	BBL*	BANPU	BBL*	BBL*	BCH	BBL*	BBL*	BCP
BCH	BCP	BCH	BBL*	BCP	BCH	BCP	BCH	BCH	BCPG
BCP	BDMS	BCP	BCP	BDMS	BCP	BDMS	BCP	BCP	BDMS
BDMS	BEC	BDMS	BDMS	BEAUTY	BDMS	BEAUTY	BCPG	BCPG	BEAUTY
BEC	BECL**	BEC	BEAUTY	BEC	BEAUTY	BEC	BDMS	BDMS	BEM
BECL**	BH	BECL**	BEC	BEM	BEC	BEM	BEAUTY	BEAUTY	BGRIM
BH	BIGC**	BH	BECL**	BH	BEM	BH	BEC	BEC	BH
BIGC**	BJC	BIGC**	BH	BJCHI	BH	BIG	BEM	BEM	BJC
BJC	BJCHI	BJC	BJCHI	BLA*	BJCHI	BLA*	BH	BH	BLA*
BLA*	BLA*	BJCHI	BLAND	BLAND	BLA*	BLAND	BIG	BIG	BLAND
BLAND	BLAND	BLAND	BMCL**	BTS	BLAND	BTS	BJC	BJC	BPP
BMCL**	BMCL**	BMCL**	BTS	CBG	BTS	CBG	BLA*	BLAND	BTS
BTS	BTS	BTS	CBG	CENTEL	CBG	CENTEL	BLAND	BPP	CBG
CENTEL	CENTEL	CENTEL	CENTEL	CHG	CENTEL	CHG	BPP	BTS	CENTEL
CHG	CK	CK	CK	CK	CHG	CK	BTS	CBG	CHG
CK	CPALL	CPALL	CKP	CKP	CK	CKP	CBG	CENTEL	CK
CPALL	CPF	CPF	CPALL	CPALL	CKP	COM7	CENTEL	CHG	CKP
CPF	CPN	CPN	CPF	CPF	COM7	CPALL	CHG	CK	COM7
CPN	DCC	DELTA	CPN	CPN	CPALL	CPF	CK	CKP	CPALL
DCC	DELTA	DEMCO	DELTA	DELTA	CPF	CPN	CKP	COM7	CPF
DELTA	DTAC	DTAC	DEMCO	DTAC	CPN	DELTA	COM7	CPALL	CPN
DTAC	EARTH**	EARTH**	DTAC	EARTH**	DELTA	DTAC	CPALL	CPF	DELTA
EGCO	EGCO	EGCO	EARTH**	EGCO	DTAC	EGCO	CPF	CPN	DTAC
ERW	ERW	ERW	EGCO	EPG	EGCO	EPG	CPN	DTAC	EA
ESSO	ESSO	FPT	ERW	FPT	EPG	GLOBAL	DELTA	EA	EGCO
FPT	FPT	GFPT	FPT	GL*	ERW	GLOW**	DTAC	EGCO	EPG
GFPT	GFPT	GLOBAL	GFPT	GLOW**	GL*	GPSC	EA	EPG	ERW
GLOBAL	GLOBAL	GLOW**	GLOBAL	GPSC	GLOBAL	GUNKUL	EGCO	ESSO	ESSO
GLOW**	GLOW**	GUNKUL	GLOW**	GUNKUL	GLOW**	HANA	EPG	GFPT	GFPT
GUNKUL	GUNKUL	HANA	GUNKUL	HANA	GPSC	HMPRO	GFPT	GGC	GGC
HEMRAJ**	HEMRAJ**	HEMRAJ**	HANA	HMPRO	GUNKUL	ICHI	GLOBAL	GLOBAL	GLOBAL
HMPRO	HMPRO	HMPRO	HMPRO	ICHI	HANA	IFEC	GLOW**	GPSC	GLOW**
INTUCH	INTUCH	ICHI	ICHI	INTUCH	HMPRO	INTUCH	GPSC	GUNKUL	GPSC
IRPC	IRPC	INTUCH	INTUCH	IRPC	ICHI	IRPC	GUNKUL	HANA	GUNKUL
ITD	ITD	IRPC	IRPC	ITD	IFEC	ITD	HMPRO	HMPRO	HANA
IVL	IVL	ITD	ITD	IVL	INTUCH	IVL	INTUCH	INTUCH	HMPRO
JAS	JAS	IVL	IVL	JAS	IRPC	KAMART	IRPC	IRPC	INTUCH
JCK	KBANK*	JAS	JAS	KBANK*	ITD	KBANK*	ITD	ITD	IRPC
JMART	KCE	KBANK*	KBANK*	KCE	IVL	KCE	IVL	IVL	ITD
KBANK*	KKP*	KCE	KCE	KKP*	JWD	KKP*	KBANK*	JMART	IVL
KCE	KTB*	KKP*	KKP*	KTB*	KBANK*	KTB*	KCE	JWD	KBANK*
KKP*	KTC*	KTB*	KTB*	KTC*	KCE	KTC*	KKP*	KBANK*	KCE
KTB*	LH	KTC*	KTC*	LH	KKP*	LH	KTB*	KCE	KKP*
KTC*	LOXLEY	KTIS	LH	LHFG*	KTB*	LHFG*	KTC*	KKP*	KTB*
LH	LPN	LH	LHFG*	LPN	KTC*	LPN	LH	KTB*	KTC*
LOXLEY	M	LOXLEY	LOXLEY	M	LH	MAJOR	LHFG*	KTC*	LH
LPN	MAJOR	LPN	LPN	MAJOR	LHFG*	MINT	LPN	LH	LPN
MAJOR	MC	M	M	MINT	LPN	MTC*	MAJOR	LPN	MAJOR
MBK	MCOT	MAJOR	MAJOR	PLANB	MAJOR	PLANB	MALEE	MAJOR	MEGA

Table A1: List of Stocks in SET100 during 2014-2018 (* = stocks in financial sector)

2014-H1	2014-H2	2015-H1	2015-H2	2016-H1	2016-H2	2017-H1	2017-H2	2018-H1	2018-H2
MCOT	MEGA	MC	MC	PLAT	MINT	PRINC	MEGA	MC	MINT
MINT	MINT	MEGA	MINT	PRINC	MTC*	PSH	MINT	MEGA	MTC*
PRINC	NOK	MINT	MONO	PSH	PLANB	PTG	MONO	MINT	ORI
PSH	NYT	NOK	PRINC	PTG	PRINC	PTT	MTC*	MONO	PRINC
PTT	PRINC	PRINC	PSH	PTT	PSH	PTTEP	PLANB	MTC*	PRM
PTTEP	PSH	PSH	PSL	PTTEP	PTG	PTTGC	PRINC	ORI	PSH
PTTGC	PSL	PSL	PTT	PTTGC	PTT	QH	PSH	PRINC	PSL
QH	PTT	PTG	PTTEP	QH	PTTEP	ROBINS**	PTG	PSH	PTG
RATCH	PTTEP	PTT	PTTGC	ROBINS**	PTTGC	RS	PTL	PSL	PTT
ROBINS**	PTTGC	PTTEP	QH	RS	QH	S	PTT	PTG	PTTEP
RS	QH	PTTGC	RATCH	S	ROBINS**	SAMART	PTTEP	PTT	PTTGC
SAMART	RATCH	QH	ROBINS**	SAMART	RS	SAWAD*	PTTGC	PTTEP	QH
SC	ROBINS**	RATCH	RS	SAMTEL	S	SCB*	QH	PTTGC	RATCH
SCB*	RS	ROBINS**	S	SAWAD*	SAMART	SCC	RATCH	QH	ROBINS**
SCC	SAMART	SAMART	SAMART	SCB*	SAWAD*	SCN	ROBINS**	ROBINS**	RS
SCCC	SCB*	SAWAD*	SAPPE	SCC	SCB*	SGP	S	SAWAD*	SAWAD*
SF	SCC	SCB*	SAWAD*	SCCC	SCC	SIRI	SAWAD*	SCB*	SCB*
SIRI	SCCC	SCC	SCB*	SCN	SGP	SPALI	SCB*	SCC	SCC
SPALI	SIRI	SCCC	SCC	SGP	SIRI	SPCG	SCC	SGP	SGP
SPCG	SPALI	SDC	SF	SIRI	SPALI	SPRC	SCCC	SIRI	SIRI
SRICHA	SPCG	SF	SGP	SPALI	SPCG	STEC	SIRI	SPALI	SPALI
SSI**	SRICHA	SGP	SIRI	SPCG	STEC	STPI	SPALI	SPRC	SPRC
STA	STA	SIRI	SPALI	STEC	STPI	SUPER	SPRC	STA	STA
STEC	STEC	SPALI	SPCG	STPI	SVI	TASCO	STEC	STEC	STEC
STPI	STPI	SPCG	STEC	SVI	TASCO	TCAP*	STPI	SUPER	SUPER
SVI	SVI	STA	STPI	TASCO	TCAP*	THAI	SUPER	TASCO	TASCO
TASCO	TASCO	STEC	SVI	TCAP*	THAI	THANI*	TASCO	TCAP*	TCAP*
TCAP*	TCAP*	STPI	TCAP*	THAI	THCOM	THCOM	TCAP*	THAI	THAI
THAI	THAI	SVI	THAI	THCOM	TISCO*	TISCO*	THAI	THCOM	THANI*
THCOM	THCOM	TCAP*	THCOM	TISCO*	TMB*	TKN	THANI*	TISCO*	TISCO*
THRE*	THRE*	THAI	TISCO*	TMB*	TOP	TMB*	THCOM	TKN	TKN
TISCO*	THREL*	THCOM	TMB*	TOP	TPIPL	TOP	TISCO*	TMB*	TMB*
TMB*	TISCO*	THREL*	TOP	TPIPL	TRC	TPIPL	TKN	TOP	TOA
TOP	TMB*	TISCO*	TPIPL	TRUE	TRUE	TRUE	TMB*	TPIPL	TOP
TPIPL	TOP	TMB*	TRUE	TTA	TTA	TTA	TOP	TPIPP	TPIPL
TRUE	TPIPL	TOP	TTA	TTCL	TTCL	TTCL	TPIPL	TRUE	TPIPP
TTA	TRUE	TPIPL	TTCL	TTW	TTW	TTW	TRUE	TTA	TRUE
TTCL	TTA	TRUE	TTW	TU	TU	TU	TTA	TU	TTW
TTW	TTCL	TTA	TU	UNIQ	TVO	TVO	TU	TVO	TU
TU	TTW	TTCL	U	UV	UNIQ	UNIQ	TVO	UNIQ	TVO
U	TU	TTW	UNIQ	VGI	VGI	VGI	UNIQ	UV	UV
UV	UV	TU	UV	VNG	VNG	VIBHA	VGI	WHA	WHA
VGI	VGI	UV	VGI	WHA	WHA	VNG	WHA	WHAUP	WHAUP
WHA	WHA	VGI	WHA	WORK	WORK	WHA	WORK	WORK	WORK

* = stocks in financial sector

** = stocks that are delisted.

REFERENCES

Aboud, A., C. Roberts and A. Mansour Zalata (2018). "The impact of IFRS 8 on financial analysts' earnings forecast errors: EU evidence." Journal of International Accounting, Auditing and Taxation **33**: 2-17.

Afza, T. and S. Tahir (2012). "Determinants of Price-Earnings Ratio: The Case of Chemical Sector of Pakistan." International Journal of Academic Research in Business and Social Sciences **2**: 331-343.

Anderson, K. and C. Brooks (2006). "Decomposing the price-earnings ratio." Journal of Asset Management **6**(6): 456-469.

Azam, M. (2010). "Factors Influencing the Price-earnings Multiples and Stock values in the Karachi stock exchange."

Basyah, M. and J. C. Hartigan (2007). "Analyst earnings forecast revisions and the persistence of antidumping relief." International Review of Economics & Finance **16**(3): 383-399.

Bodie, Z., Kane, A. and Marcus, A. (2014). Investments. 10th ed., New York: McGraw-Hill Education.

Cho, J. Y. (1994). "DETERMINANTS OF EARNINGS-PRICE RATIOS: A REEXAMINATION." Review of Financial Economics **3**(2): 105-120.

Dehning, B., G. M. Pfeiffer and V. J. Richardson (2006). "Analysts' forecasts and investments in information technology." International Journal of Accounting Information Systems **7**(3): 238-250.

Fama, E. F. and K. R. French (1998). "Value versus Growth: The International Evidence." The Journal of Finance **53**(6): 1975-1999.

Freihat, A. R. (2019). "Factors affecting price to earnings ratio (P/E): Evidence from the emerging market." Risk Governance and Control: Financial Markets & Institutions **9**: 47-56.

Graham, B. a. D., D. L. (1934). Security analysis, New York: McGraw-Hill Book Company.

Gu, Z. and J. S. Wu (2003). "Earnings skewness and analyst forecast bias." Journal of Accounting and Economics **35**(1): 5-29.

Huang, A. G. and T. S. Wirjanto (2012). "Is China's P/E ratio too low? Examining the role of earnings volatility." Pacific-Basin Finance Journal **20**(1): 41-61.

Huang, S., X. Liu and C. Yin (2019). "Investor target prices." Journal of Empirical Finance **54**: 39-57.

Johan, K., and Filip, L. (2007). A quantitative study of the P/E ratio on the Swedish market (Unpublished Master thesis, Lunds University, Lund, Sweden).

Jones, D. A. (2007). "Voluntary Disclosure in R&D-Intensive Industries*." Contemporary Accounting Research **24**(2): 489-522.

Kane, A., A. J. Marcus and J. Noh (1996). "The P/E Multiple and Market Volatility." Financial Analysts Journal **52**(4): 16-24.

Kok, U. W., J. Ribando and R. Sloan (2017). "Facts about Formulaic Value Investing." Financial Analysts Journal **73**(2): 81-99.

Lehavy, R., F. Li and K. Merkley (2011). "The Effect of Annual Report Readability on Analyst Following and the Properties of Their Earnings Forecasts." The Accounting Review **86**(3): 1087-1115.

Loughlin, J. J. (1996). Determinants of the price-earnings multiple for the standard & poor's 500 composite stock index and the effects of determinants volatility (Doctoral dissertation, St. Louis University, MO).

Mansor Wan Mahmood, W. and R. Zakaria (2007). "Profitability and Capital Structure of the Property and Construction Sectors in Malaysia." Pacific Rim Property Research Journal **13**(1): 92-105.

Park, S. J. and K. Y. Park (2019). "Can investors profit from security analyst recommendations?: New evidence on the value of consensus recommendations." Finance Research Letters **30**: 403-413.

Wenjing, H. (2008). Price-earnings ratio and influence factors: Evidence from China (Unpublished Master's Thesis in Accounting and Finance, University of Vaasa, Finland).

Yin, Y., K. Peasnell, M. Lubberink and H. G. Hunt (2014). "Determinants of Analysts' Target P/E Multiples." The Journal of Investing **23**(3): 35.

VITA

NAME	Thanakorn Petkajee
DATE OF BIRTH	17 April 1988
PLACE OF BIRTH	Bangkok
INSTITUTIONS ATTENDED	Chulalongkorn University
HOME ADDRESS	611/166 Soi Watchannai Charoenkrung Roard Bangkho Bangkholaem Bangkok 10120