Profit Forecast Accuracy of Time Series Model - A Case Study of Associated British Foods

Yunfan Sun

Abstract:

Accurate earnings per share (EPS) forecasting is crucial for financial decision-making. This study explores the potential of improving EPS forecasting accuracy by integrating economic lead indicators into time-series models. By incorporating macroeconomic factors like GDP growth and interest rates, the models capture the influence of the broader economic environment on a company's financial performance. Results demonstrate that including economic lead indicators significantly enhances EPS predictability beyond traditional time-series models. This integration offers a forward-looking perspective, comprehensive analysis, and context to the forecasting process, enabling stakeholders to make more informed investment decisions and develop better strategies. Further research can investigate additional lead indicators, assess their impact in different industries, and develop hybrid forecasting models for refined EPS predictions.

Keywords: Earnings per share (EPS), Economic lead indicators, Time-series models

1. Introduction

Accurate earnings per share (EPS) forecasting is paramount in the financial industry. While traditional approaches rely on historical financial data, they may overlook the broader economic environment's impact on a company's performance. Researchers have recognized the value of incorporating economic lead indicators into EPS forecasting models to address this. These indicators, such as GDP growth, interest rates, consumer spending, and business sentiment, provide insights into the overall economic health and can predict future EPS behavior. Integrating these indicators enhances forecasting accuracy by offering a forward-looking perspective, comprehensive analysis, and context. It allows forecasters to anticipate market changes and understand the macroeconomic forces shaping a company's financial performance. However, challenges exist in selecting relevant indicators and addressing data availability and reliability. This study aims to contribute to the literature by exploring the integration of economic lead indicators into EPS forecasting, providing stakeholders with more robust information for financial decision-making.

2. Background of the company

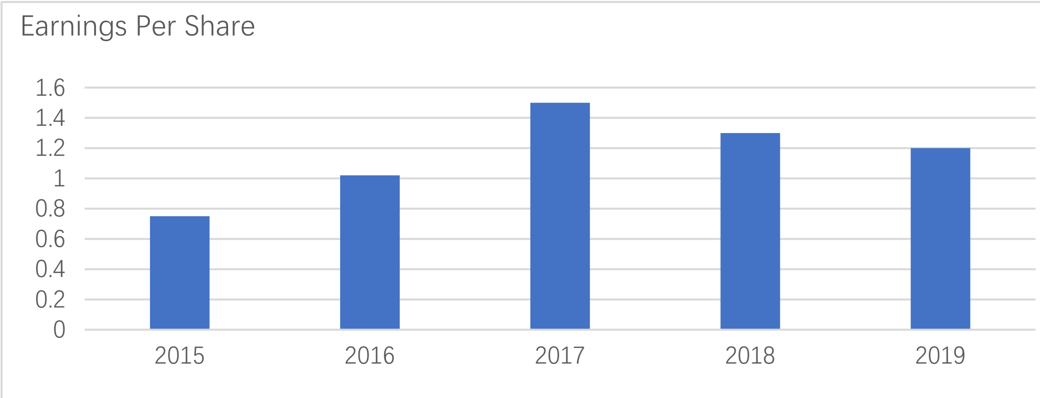
Associated British Foods is a British food company listed on the London Stock Exchange. It is also one of the top 100 companies in the UK today by market value. An Italian, w. Garfield Weston was founded in 1935 (Food Investments Limited was renamed twice before it was renamed in 1960).

In 1862, Associated British Foods acquired the British business of Aerated Bread Company, which brought huge profits. But in 2011 and 2013, the company received media attention for its alleged unethical tax avoidance.

Nowadays, associated British Foods is the world's second-largest producer of sugar and bread yeast -- and one of the world's leading food producers.

According to public figures on its website, the company made 1,5574million pond in revenue in 2018 and had more than 137,000 employees in 2019

The figure below shows the change in EPS of ABF company from 2015 to now. Although the data of ABF company has been adjusted slightly in the past two years, the overall upward trend is still obvious. (All the data in the figure is from financial times.)



3.1 The benefits of broadening the information set for earnings forecasts to include segmental information and leading economic indicators.

Extrapolatory methods make forecasts depending on a time-series past behavior. An average growth model, an exponential smoothing model, and a random walk model are used in this method. However, the noisy data in this forecasting method were ignored. So, leading economic indicators methods take advantage of future economic conditions to make more accurate predictions. Added three different types of economic indicators in three different improved models to measure the forecasting ability of EPS. Three economic indicators include the money supply variable, the stock

price index variable and the bank loan variable. The lead-indicator models are:

A money supply model : $Y_{t+1}=Y_t (MS_t / MS_{t-1})$

A stock index model : $Y_{t+1}=Y_t (SPI_t / SPI_{t-1})$

A bank loan model : $Y_{t+1}=Y_t (BL_t / BL_{t-1})$

As the statistical analysis of results shows, the money supply model is significantly more accurate compared with the random walk model. These illustrate that the money supply increases the predictability of EPS.

3.2 How do model-based forecasts generally compare with those of professional financial analysts?

In financial forecasting, a critical question arises concerning the comparative performance of model-based forecasts and those generated by professional financial analysts. Extensive research has been conducted to shed light on this matter. Evidence from studies conducted in the US (Brown and Rozeff, 1978) and the UK (Patz, 1989) suggests that at horizons greater than 12 months, analysts' forecasts do not exhibit superiority over random walk forecasts. However, it should be noted that such tests may have inherent biases against analysts, as the data used in the random walk model, such as the current year's earnings, may not yet be available. Conversely, at horizons of less than 12 months, studies conducted in the UK by Patz (1989) and Barber et al. (2001) indicate significant analyst superiority over random walk forecasts. Nevertheless, it is crucial to consider the limitations and biases associated with both approaches. Model-based forecasts, which rely on quantitative techniques and algorithms, may oversimplify complex financial dynamics, overlook qualitative factors, and be sensitive to incorrect assumptions or model specifications. While possessing valuable insights and access to relevant information, financial analysts can be subject to cognitive biases, limited access to privileged information, and conflicts of interest."

4. Empirical Evidence

In this part, we employed three OLS models (linear trend, quadratic trend, and S-shaped curve) using SPSS to forecast the EPS for 2014-2018 based on the EPS data of Associated British Foods from 1965-2013. Graphical representations of these models were created to assess their fit to the EPS data. The models' R-squared values were used to determine the best fit. Subsequently, the selected model was used to generate EPS forecasts for 2014-2018, and their accuracy was evaluated by comparing them to the actual values using mean absolute error. Finally, we compared the forecasts from the chosen model with those from a random walk model and a money-supply adjusted model.4.1 Linear trend model analysis.

To create a linear trend model, we assumed that the EPS of the company would increase in constant absolute amounts each period. The structure of the standard linear trend model is as follows:

$${Y}_{t}=constant+{b}_{1}*t$$

In this analysis, Y means the EPS, t means the period.

4.1.1 Model building and graphical

1. Graphical

In the linear trend model, we use 1965-2013 EPS data to obtain the value of b_1 and constant, and the linear trend model generated by SPSS software is shown in Figure 1.

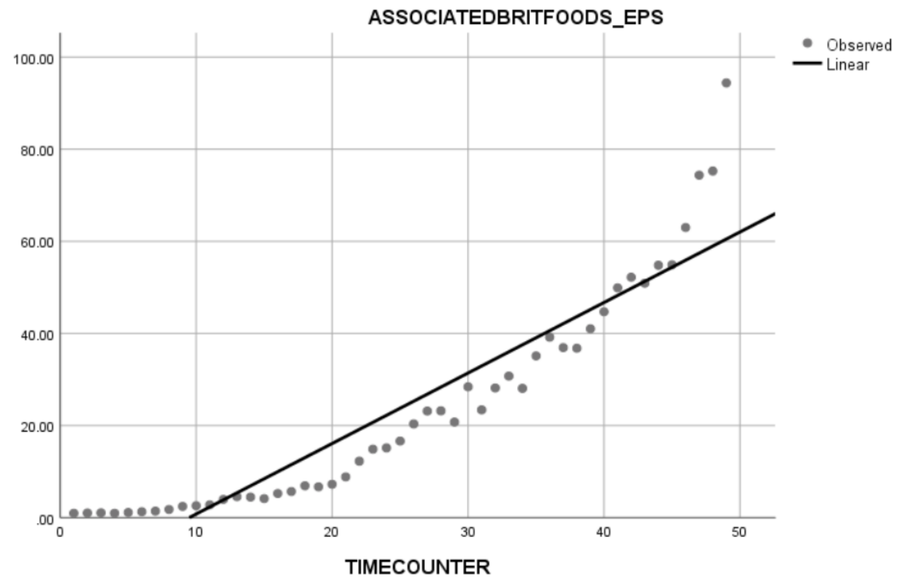


Figure 1: The linear trend curve obtained by SPSS

The general model in this background can be shown as the following formula:

$$ASSOCIATEDBRITFOOD\_EPS=constant+{b}_{1}*TIMECOUNTER$$

In this model, $constant$ means the constant of this curve, b_1 means the slope of this line.

2. Model building

(1) The definition of the slope

The particular line is identified by the value of b_1 and constant, and the formula of the slope is (use EPS to replace ASSOCIATEDBRITFOOD_EPS at some place in the formula):

$${b}_{1}=\frac{\sum \left(TIMECOUNTER,EPS\right)-\frac{\left(\sum TIMECOUNTER*\sum EPS\right)}{N}}{\sum \left({TIMECOUNTER}^{2}\right)-\frac{{\left(\sum TIMECOUNTER\right)}^{2}}{N}}$$

(2) The definition of the constant

Having obtained our estimate of the slope, we can use the knowledge that the regression line passes the sample to get the constant, so we need to accumulate the average of EPS and TIMECOUNTER on the line; the formula of the constant is:

$$constant=\stackrel{-}{EPS}-{b}_{2}*\stackrel{-}{TIMECOUNTER}$$

4.1.2 Result analysis

1. Model result analysis

Then, we obtained the Model Summary and Parameter Estimates of data from SPSS, as shown in Table 1. We can obtain the values of the constant and the slope of the curve from the table 1.

Table 1: Summary of statistics for the linear trend analysis

Model Summary and Parameter Estimates							
Dependent Variable: ASSOCIATEDBRITFOODS_EPS							
Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.867	306.228	1	47	.000	-14.522	1.531
The independent variable is TIMECOUNTER.							

As shown in Table 1 above, the slope value is 1.531, and the constant value is -14.522. Hence, we can conclude that the model for this linear trend as of the following:

$$EPS=-14.522+1.531TIMECOUNTER$$

We could predict that the value of EPS in the next period (TIMECOUNTER+1) will be 1.531 units higher than the value of EPS in the current period (TIMECOUNTER).

2. R-square value analysis

We can see that the estimated line shown in Figure 1 does not match the actual EPS. The gap between the line and the point represents the error. If the point is above the line, it is a positive one, and vice versa. The OLS aims to minimize the squared forecast error to get the best line. The Table 1 includes the equation's R-square value (0.867). It represents the squared correlation coefficient, which shows how the predicted values of the model approximate the actual EPS data. The formula for R squared is:

$$ {R}^{2}=\frac{{\left[\sum (TIMECOUNTER-\stackrel{-}{TIMECOUNTER})(EPS-\stackrel{-}{EPS})\right]}^{2}}{\sum {(TIMECOUNTER-\stackrel{-}{TIMECOUNTER})}^{2}\sum {(EPS-\stackrel{-}{EPS})}^{2}}$$

If the R^2 gets closer to 1, the better this line model fits the actual data. Therefore, with R squared value of 0.867, this linear trend explains 86.7% of the variation in our dependent variable, EPS.

3. T-value analysis

Table 2: Summary of Coefficients for the linear trend analysis

Coefficients						
Model B		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		Std. Error	Beta			
1	(Constant)	-14.522	2.513		-5.780	.000
	TIMECOUNTER	1.531	.087	.931	17.499	.000
a. Dependent Variable: ASSOCIATEDBRITFOODS_EPS						

As a crude rule-of-thumb, the t-values of the TIMECOUNTER in this model are significantly larger than 2, which means the values for the slope can be viewed as statistically significant (for a 95% confidence level).

4.1.3 Generate forecasts of EPS

Now, we use estimated models to generate forecasts of EPS for the years 2014-2018, using the time counters from 49 until 53. The result of our forecasting is shown in Table 3:

Table 3 Linear model forecasting results for the years 2014-2018

Year	Times	Actual EPS	Linear model forecasting results
2014	50	102.07	62.03
2015	51	104.40	63.56
2016	52	94.10	65.09
2017	53	120.10	66.62
2018	54	128.70	68.15

4.2 Quadratic trend model analysis

The structure of the standard quadratic trend model is as follows:

$$ {Y}_{t}=constant+{b}_{1}*t+{b}_{2}*{t}^{2}$$

In this analysis, Y means the EPS, t means the period

4.2.1 Model building and graphical

1. Graphical

In the quadratic trend model, we also use 1965-2013 EPS data to obtain the value of b_1, b_2, and constant, and the quadratic trend model generated by SPSS software is shown in Figure 2.

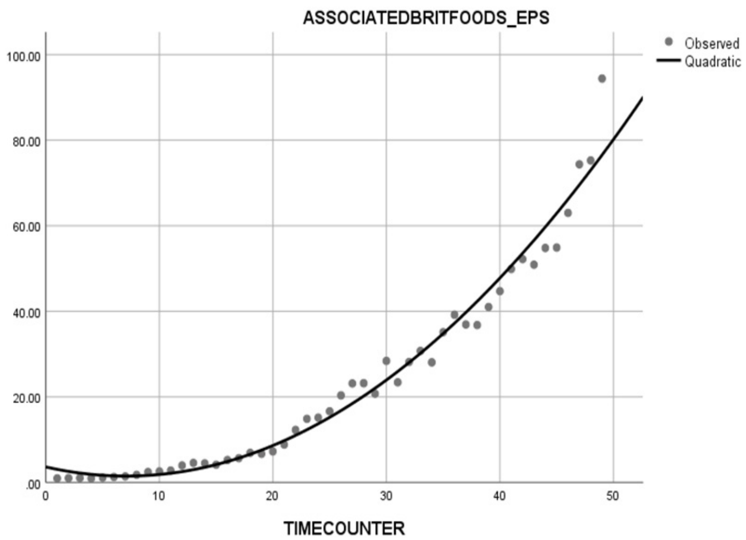


Figure 2: The quadratic trend curve obtained by SPSS

The general model in this background can be shown as the following formula:

$$EPS=constant+{b}_{1}*TIMECOUNTER+{b}_{2}*{TIMECOUNTER}^{2}$$

2. Model building

(1) the definition of St

To get the T-value by SPSS, we need to redefine the square of TIMECOUNTER. We use the function of compute variable in SPSS to replace the square of TIMECOUNTER with St. Then the model will be converted into a new formula:

$$EPS=constant+{b}_{1}*TIMECOUNTER+{b}_{2}*St$$

4.2.2 Result analysis

1. Model result analysis

Then, we obtained the Model Summary and Parameter Estimates of data from SPSS, as shown in Table 4; we can obtain the values of the constant and two slopes of the curve b_1 and b_2 from this table.

Table 4: Summary of statistics for the quadratic trend analysis

Model Summary and Parameter Estimates								
Dependent Variable: ASSOCIATEDBRITFOODS_EPS								
Equation	Model Summary					Parameter Estimates		
	R Square	F	df1	df2	Sig.	Constant	b1	b2
	.975	883.309	2	46	.000	3.616	-.603	.043
The independent variable is TIMECOUNTER.								

As shown in Table 4 above, the first slope b_1 value is -0.603, the slope b_2 value is 0.043, and the constant value is 3.616.

So, we can conclude that the model for this quadratic trend model is the following:

$EPS=3.616-0.603*TIMECOUNTER+0.043*TIMECOUNTER^2$

2. R-square value analysis

The definition, calculation formula, and the meaning of R-square have been explained above. From this table, we can see the R-square value is 0.975, which is close to 1, and that means the quadratic trend model explains 97.5% of the variation in our dependent variable, EPS.

3. T-value analysis

Table 5: Summary of Coefficients for the quadratic trend analysis

Coefficients						
Model B		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		Std. Error	Beta			
1	(Constant)	3.616	1.708		2.118	.040
	TIMECOUNTER	-.603	.158	-.367	-3.828	.000
	St	.043	.003	1.339	13.971	.000
a. Dependent Variable: ASSOCIATEDBRITFOODS_EPS						

As a crude rule-of-thumb, the absolute value of the t-value of the TIMECOUNTER in this model is greater than 2, which means the values for the slope can be viewed as statistically significant (for a 95% confidence level).

4.2.3 Generate forecasts of EPS

we use estimated models to generate forecasts of EPS for the years 2014-2018, using the time counters from 50 until 54. The result of our forecasting is shown in table 6:

Table 6: Quadratic trend model forecasting results for the years 2014-2018

	Times	Actual EPS	Quadratic model forecasting results
2014	50	102.07	80.97
2015	51	104.40	84.71
2016	52	94.10	88.53
2017	53	120.10	92.44
2018	54	128.70	96.44

4.3 S-shaped curve model analysis

The structure of the standard quadratic trend model is as follows:

$$Y_t = e^{k+(h/t)}$$

where $k > 0$ and $h < 0$

In this analysis, Y means the EPS, t means the period

4.3.1 Model building and graphical

1. Graphical

In the S-shaped curve model, 1965-2013 EPS data is also used to obtain the value of k and h, and the S-shaped model generated by SPSS software is shown in Figure 3.

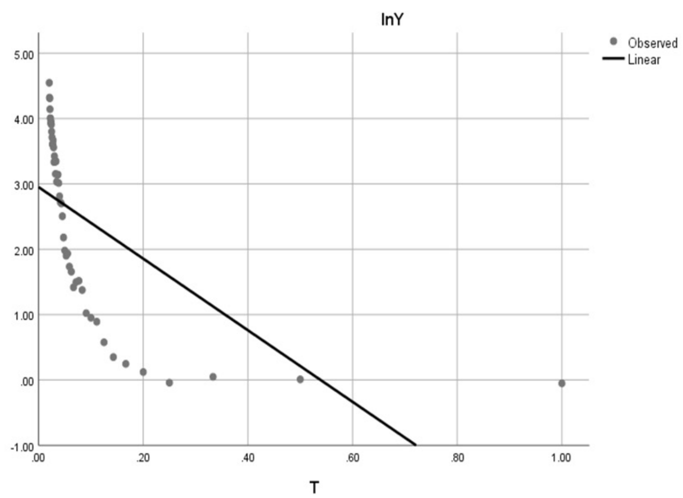


Figure 3: The S-shaped curve obtained by SPSS

The general model in this background can be shown as the following formula:

\[EPS={e}^{k+(h/TIMECOUNTER)}\]

2. Model building

(1) Formula adjustment

To make this model better appropriate for OLS, we make some adjustments and transform the formula into its log form, which is linear in its parameters, and the formula is:

\[lnYt=k+h*(1/t)\]

where k > 0 and h < 0

(2) Definition of \[lnYt\] and T

Similar to the steps of the second model, to get the T-value, we use the function of compute variable in SPSS software to replace the lny with lnY (name), replace1/t with T. In this way, the formula becomes following:

\[lnYt=k+h*T\]

Where the k is the same as the constant in a linear model, and the h is the same as b_1

4.3.2 Result analysis

1. Model result analysis

Then, we obtained the Model Summary and Parameter Estimates of data from SPSS, as shown in Table 7. We can obtain the values of constant k and h of b_1 from the table 7.

Table 7: Summary of statistics for the S-shaped curve analysis

Model Summary and Parameter Estimates							
Dependent variable: lnY							
Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.383	29.137	1	47	.000	2.951	-5.476
The independent variable is T.							

As shown in Table 7 above, the b_1 value is -5.476, and the constant value is 2.951. It means the value of h is -5,476 and k is 2.951

So, we can conclude that the model for this quadratic trend model is the following:

\[EPS={e}^{2.951+(5.476/TIMECOUNTER)}\]

$EPS=e^{2.951-(-5.476/TIMECOUNTER)}$

2. R-square value analysis

The definition, calculation formula, and the meaning of R-square have been explained above. From this table, we can see the R-square value is 0.383, which is far from 1, which means the quadratic trend model explains 38.3% of the variation in our dependent variable, EPS.

3. T-value analysis

Table 8: Summary of Coefficients for the S-shaped curve analysis

Coefficients						
Model B		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		Std. Error	Beta			
1	(Constant)	2.951	.185		15.974	.000
	T	-5.476	1.014	-.619	-5.398	.000
a. Dependent Variable: lnY						

The same absolute value of the t-value of the TIMECOUNTER in this model is larger than 2, so it also means the values for the slope can be viewed as statistically significant (for a 95% confidence level).

4.3.3 Generate forecasts of EPS

Using the TIMECOUNTER from 50 to 54. The result of our forecasting with the S-shaped curve model for EPS 2014-2018 can be shown in the table 9:

Table 9: S-shaped curve model forecasting results for the years 2014-2018

	Times	Actual EPS	S-shaped curve forecasting results
2014	50	102.07	21.34
2015	51	104.40	21.29
2016	52	94.10	21.25
2017	53	120.10	21.21
2018	54	128.70	21.17

4.4 R-square analysis—Which model has the best fit to the data?

R-squared values range from 0 to 1 and are commonly stated as percentages from 0% to 100%. It can show us how the model's predicted values approximate the actual EPS data. The closer the square value is to 1, the closer the value is to the actual value.

The formula for R squared is:

$$ {R}^{2}=\frac{{\left[\sum (TIMECOUNTER-\stackrel{-}{TIMECOUNTER})(EPS-\stackrel{-}{EPS})\right]}^{2}}{\sum {(TIMECOUNTER-\stackrel{-}{TIMECOUNTER})}^{2}\sum {(EPS-\stackrel{-}{EPS})}^{2}} $$

If the R^2 gets closer to 1, the better this line model fits the actual data.

Table 10 R-square analysis

	R-square	Analysis
Linear trend model	0.867	The Medium
Quadratic trend model	0.975	The Best
S-shaped curve model	0.383	The Worst

The R square of Quadratic trend model is closest to 1, so the forecasting data of EPS 2014-2018 with this model best matches the actual data.

4.5 Mean absolute error analysis—Which model is the most accurate?

As for the analysis of which model is the most accurate, we could use the mean absolute error (MAE) to calculate.

$$ MAE=\frac{1}{n}{\sum }_{i=1}^{n}|yi-\overline{yi}| $$

In this formula, yi means actual EPS, $\overline{andyi}$ means forecasts of EPS; the result is shown in Table 11

Table 11 The MAE and Analysis of three models

	MAE	Analysis
Linear trend model	44.784	The Medium
Quadratic trend model analysis	21.256	The Best
S-shaped curve model	92.662	The Worst

The smaller the data, the higher the accuracy, so from MAE analysis, we could conclude that Quadratic trend model analysis is the best.

4.6. The Random Walk model

The Random Walk model's format is ${Y}_{t+1}={Y}_{t}$ For the forecast ${,Y}_{t+1}$ will be the value of ${Y}_{t}$ in the previous period.

Table 12 Forecast EPS with Random Walk model error measure

Year	Actual EPS	Forecasted EPS	Absolute Error	Square Error	Absolute Percentage Forecast Error
2014	102.07	94.4	7.67	58.83	0.075
2015	104.4	102.07	2.33	5.43	0.022
2016	94.1	104.4	10.3	106.06	0.109
2017	120.1	94.1	26.0	676	0.216
2018	128.7	120.1	8.6	73.96	0.067
Sum			54.9	920.28	0.489
Mean			10.98	184.056	0.098

The mean absolute error and the mean squared error for the Random Walk model shown in Table 12 are 10.98 and 184.056. The mean absolute error is 0.098.

4.7 The money-supply-adjusted model

In articles, the money supply is usually abbreviated as Mx. In general, the larger the value of x, the larger the range of money supply involved. Chant (1980) constructed a money supply model as:

$$ {Y}_{t+1}={Y}_{t}({MS}_{t}/{MS}_{t-1}) $$

In this case, our model would be:

$$ {EPS}_{TIMECOUNTER+1}={EPS}_{TIMECOUNTER}({MS}_{TIMECOUNTER}/{MS}_{TIMECOUNTER-1}) $$

4.7.1 UK MONEY SUPPLY M0

Using the data of M_0 from the EXCEL forecasts the EPS for 2014-2018 by using the equation above. The results of forecasted EPS are shown in Table X below.

Table X Forecasted EPS with M0 model

Year	TIMECOUNTER	Actual EPS	UK_MONEY_SUPPLY_M0	Forecasted EPS
2012	48	75.26	63560	
2013	49	94.4	66671	
2014	50	102.07	70432	99.02
2015	51	104.4	74362	107.83
2016	52	94.1	80637	110.23
2017	53	120.1	81848	102.04
2018	54	128.7	81911	121.90

Then, we calculated the Absolute Error, Square Error, and Absolute Percentage Forecast Error. In Chant's articles, he used this way to measure accuracy. The results are shown in Table X.

Table X Forecasted EPS with M0 model error measure

Year	Actual EPS	Forecasted EPS	Absolute Error	Square Error	Absolute Percentage Forecast Error
2014	102.07	99.02	3.05	9.30	0.03
2015	104.4	107.83	3.43	11.75	0.03
2016	94.1	110.23	16.13	260.03	0.17
2017	120.1	102.04	18.06	326.14	0.15
2018	128.7	121.90	6.80	46.19	0.05
Sum			47.46	653.41	0.44
Mean			9.49	130.68	0.09

The mean absolute error and the mean squared error for the money supply adjusted with the M0 model shown in Table X are 9.49 and 130.68. The mean absolute error is only 0.09.

4.7.2 UK MONEY SUPPLY M3

Then, using the data of M_3 from the EXCEL forecasts the EPS for 2014-2018 by using the equation above again. The same procedures as what was done in Section 4.6.1 were carried out. The results of forecasted EPS are shown in Table X below.

Table X Forecasted EPS with M3 model

Year	TIMECOUNTER	Actual EPS	UK_MONEY_SUPPLY_M3	Forecasted EPS
2012	48	75.26	2331153	
2013	49	94.4	2372175	
2014	50	102.07	2365448	96.06
2015	51	104.4	2399466	101.78
2016	52	94.1	2634745	105.90
2017	53	120.1	2801194	103.33
2018	54	128.7	2907045	127.69

Then, we also calculated the Absolute Error, Square Error, and Absolute Percentage Forecast Error. The results are shown in Table X.

Table X Forecasted EPS with M3 model error measure

Year	Actual EPS	Forecasted EPS	Absolute Error	Square Error	Absolute Percentage Forecast Error
2014	102.07	96.06	6.01	36.12	0.06
2015	104.4	101.78	2.62	6.86	0.03
2016	94.1	105.90	11.80	139.24	0.13
2017	120.1	103.33	16.77	281.23	0.14
2018	128.7	127.69	1.01	1.02	0.01
Sum			38.21	464.48	0.36
Mean			7.64	92.90	0.07

The mean absolute and squared errors for the money supply adjusted with the M0 model shown in Table X are 7.64 and 92.9. The mean absolute error is only 0.07.

5. Discussion

The study investigates the predictive ability of models that adjust random walk forecasts of corporate earnings by incorporating past changes in economic lead indicators. The findings reveal that changes in the broad money supply measure exhibit predictive ability beyond equivalent changes in other lead indicators or an individual firm's earnings. Specifically, the forecasts generated by the broad-money model outperform those generated by financial analysts.

Interestingly, a size effect becomes evident when comparing the forecasts of the broad-money model with those of financial analysts. The superiority of analysts' forecasts becomes apparent much earlier for large firms compared to small firms. This outcome aligns with previous research highlighting a size-related differential in market participants' collection and dissemination of information.

These results shed light on the dynamics of forecast accuracy and suggest that incorporating past changes in the broad money supply can enhance the predictive ability of random walk models. Furthermore, the size effect observed in the performance of financial analysts' forecasts emphasizes the importance of considering firm size in understanding information asymmetry and market dynamics. This study highlights the importance of considering economic factors in improving EPS forecasting accuracy and advancing financial decision-making.

Reference

1. Brown, S., & Rozeff, M. S. (1978). The superiority of analysts' forecasts as measures of expectations: Evidence from earnings. Journal of Finance, 33(1), 1-16.
2. Patz, A. (1989). The relative accuracy of analysts' earnings forecasts in different European countries. European Accounting Review, 2(2), 257-275.
3. Barber, B. M., Lehavy, R., McNichols, M. F., & Trueman, B. (2001). Can Investors Profit from the Prophets? Security Analyst Recommendations and Stock Returns. Journal of Finance, 56(2), 531-563.
4. Fried, D., and DGivoly Financial Analyst's Forecast of Earnings: A Better Surrogate for Market Expectations[J].Journal of Accounting and Economics,1982 (4): 85-107.
5. Brown, L., P.Griffin, R.Hagerman, and M.Zmijewski. Security Analyst Superiority Relative to Univariance Time-Series Models in Forecasting Quarterly Earnings[J].Journal of Accounting and Economics,1987 (9): 61-87