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Forecasting Stock Prices Through Exponential Smoothing Techniques in The Creative Industry of The UK Stock Market

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ABSTRACT

The purpose of this study is to thoroughly and critically evaluate the predictive ability of exponential smoothing approaches in the UK stock market's creative industry. Because of this, weekly closing price data were gathered for the sample period spanning October 13, 2003, to February 2, 2024, as determined by the FTSE-350 General Industrial Index and the five creative industry enterprises. Using the multiple breakpoints test of Bai-Perron's L + 1 vs. L sequentially determined breaks, the plain data of the sub-sample period for each selected series has been determined. The weekly closing prices are not normally distributed, as can be shown by looking at the descriptive statistics table, histograms, and kernel density graphs from each series. verifies, through the use of test papers, that the weekly closing prices of each series are not random. Furthermore, the Chow-Denning joint test's variance ratio establishes the martingale model's applicability to all series. Additionally, according to the great majority of the programs, serial auto-correlation is not present at the first difference. Test of serial correlation for LB. Moreover, it seems that none of the series have a unit root at the first difference, according to the results of the Augmented Dickey Fuller unit root test. As a result, statistical research showed that the creative sector's home, the London Stock Exchange (LSE), was weak-form inefficient and had consistent stock values across the testing period. Holt's double exponential smoothing technique has helped to enhance the short-term forecastability of stock prices for the FTSE 350 General Industrial Index and most creative industry series

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INTRODUCTION

For any investor, predicting the price of stocks is a difficulty. Every investor wants to experience the least amount of loss and the highest return. It's not an easy calculation, though. In order to accurately predict stock values, numerous academics have created a variety of prediction models. In time series analysis, exponential smoothing approaches are popular models that are straightforward to employ. Due to their simplicity, objectivity, robustness, and efficacy, this study will use The creative industry's stock values are predicted using industries that use double (Holt) and triple (Holt-Winters) exponential smoothing techniques (such as publishing, games, music, fashion, IT, advertising, architecture, and crafts). In essence, the Holt–Winters approach is a way to fit suitable values to historical time series data (Gujarati et al., 2015). Holt's 1957 study made the pattern in the data obvious by employing the double exponential blending approach. The Holt technique, sometimes referred to as Holt–Winters' forecasts, became well-liked after Winters' (1960) experimentation with a few exponential moving approaches.

LITERATURE REVIEW

Funde and Damani (2023) used exponential smoothing and ARIMA algorithms to forecast Nifty 50 stock prices (the Indian stock market). They discovered that, in certain circumstances, exponential smoothing methods outperformed ARIMA. Rahman (2023) reported a similar outcome in his analysis of the London Stock Exchange. Comparably, Holt-Winters' model was used in a study by Liu et al. (2020), and the findings of that study demonstrate that Holt-Winters' model outperformed other used models in the prediction of electricity consumption. But according to Almazrouee et al. (2020), the Holt-Winters model did a terrible job of projecting Kuwait's electricity consumption. A comparative analysis of prediction models was also conducted by Awajan et al. (2018) in the US-S&P 50, Malaysia, the Netherlands, France, Australia, and Sri Lankan stock markets and shown that the Holt-Winters model performs better in terms of estimation accuracy and performance when compared to the alternative time series models. Furthermore, Kotsialos (2005) discovered that the Holt-Winters model performs better and is more effective than other forecasting models. The triple exponential smoothing approach, according to Agustina et al. (2021), improves prediction accuracy (MAPE), which brings in money for investors. According to Suwanvijit and associates (2011), the Holt-Winters model with additive seasonality is produced the best fit, excellent estimates, and 95% accuracy when used to predict beverage sales in Thailand. But according to Chawla and Jha's (2009) analysis, Winters's model fared better than Holt's approach when they used both double and triple exponential smoothing techniques. Furthermore, According to Octiva et al. (2024), Holt-Winters' exponential smoothing approaches work exceptionally well for forecasting the supply of medicine. Furthermore, the double exponential smoothing (Holt) approach has been demonstrated by Andreyanto and Wahyuni (2024) to outperform the moving average. Muliawati (2024) discovered, however, that because the data included seasonality, the triple exponential smoothing method produced a trustworthy rainfall estimate for the upcoming year. Atoyebi et al.

(2023) state that the multiplicative model performs better than the additive model. in Nigeria when it comes to forecasting currency circulation, a sign of increased predictability. Rahman (2023) studied the UK stock market's predictability based on technical analysis for a variety of industries, such as primary, secondary, or quaternary, as well as manufacturing and services. Additionally, a study on the use of technical analysis for stock price forecasting in China's manufacturing sector was carried out by Tsai et al. (2018). In addition, Tang and colleagues (2020) employed artificial intelligence (ARIMA, MA) to predict stock values in China's logistics industry.

But the research' failure to include the degree of predictability of the stock prices in the creative sector. The results of the aforementioned research show that exponential smoothing methods have a high degree of prediction accuracy. These methods haven't been applied to forecast stock values in the creative sector, though.

METHODOLOGY

The study would select weekly data from October 13, 2003, to February 2, 2024, a period of about 20 years. These 1061 observations come from five different creative sector companies that are part of the The FTSE-350 General Industrial Index and the FTSE All Share Index. Still, it takes a while to get data from the FTSE-350 General Industrial Index. This means that the data in this series spans the period from May 31, 2009, to February 11, 2024. Considering the forecasting principles outlined by Hyndman and Athanasopoulos (2018), the estimating period will only have 204 observations, the shorter data period will not effect prediction. One may wonder why the study used the data it did for such a long time. This is because technical analysis requires data for an extended amount of time in order to determine the features of information and patterns. The information will be gathered via investing.com and Yahoo Finance.

Runs Test:

Tests will be carried out to ascertain whether stock prices fluctuate at random. Gujarati (2004) provides the expected runs (v) formula, which is as follows:

$$Mean: \mu_v(expected\ runs) = \frac{2W_1W_2}{W} + 1$$

$$Variance: \sigma_v^2 = \frac{2W_1W_2\,(2W_1W_2 - W)}{W^2(W-1)}$$

Where, W1 and W2 = the number of individual observations above and below the mean,

W = total number of observations {i.e. (W1 +W2) = W}

v = expected run.

The The The difference between the actual and anticipated number of runs is represented by the Z statistic. Reject the hypothesis that stock prices vary randomly if Z ≥ ±1.96 (i.e., if projected runs are bigger); reject weak-form market efficiency and the hypothesis that share prices fluctuate randomly if 9≥Z≤20 (i.e., if stock prices are foreseeable). Sharma and Kennedy's (1977) research outlines these steps at the 5% significant level. Check the unit root of ADF:

It's assumed that STK is a series of stocks. The following could be used to construct a random walk model for STK:

$$\Delta STK_t = \beta_1 + \beta_2 t + \delta\ STK_{t-1} + \Sigma\alpha_i\ \Delta\ STK_{t-i} + \varepsilon_t\text{, (Gujarati, 2004)}$$

Where,
STK_t = Share price at time period t
α = Drift,
β_t = time trend
t = time period
ε_t = Error term or white noise in time period t.
If α > 0, the process will show an upward trend.

$$STK_t = \rho STK_{t-1} + \varepsilon_t \qquad \text{where } -1 \leq \rho \leq 1$$

When ρ = 1, there is no drift or nonstationarity in the unit root or random walk model of the data or STKt.

The time series STKt is stationary if |ρ|≤ 1(ρ is less than 1), meaning that the first and second difference are not required. The data are stationary since ε_t is a white noise error term, indicating that the first difference of a time series based on random walks is also stationary.

$$\Delta\ STK_{t-1} = (STK_{t-1} - STK_{t-2}),\ \Delta\ STK_{t-2} = (STK_{t-2} - STK_{t-3}),\text{ etc. (Gujarati, 2004)}$$

Autocorrelation: Ljung-Box test:
The formula of Ljung-Box Q* test is given below:

$$Q^* = n(n+2)\sum_{k=1}^{m}\frac{\rho^2 K}{n-K} \sim x_m^2 \text{ , Gujarati (2004)}$$

Where,
x_m^2= chi-square distribution with m degree of freedom (df).
n = sample size
m = lag length,
k = lag, k = 1,2,………………..
ρ_k = sample autocorrelation co-efficient

Variance Ratio Test

This test is used to determine whether the series has any homoskedastic or heteroskedastic random walks. The variance ratio (VR) calculation looks like this:

$$VR(q) = \frac{\sigma_q^2}{q*\sigma^2}\text{, (Lo and MacKinlay, 1988)}$$

Where,
σ_q^2 = The variance for the qth difference in stock prices
and σ^2 = The variance of the one-period difference in stock prices.

Double Exponential Smoothing

This study will use the linear trend method, which takes into account levels and trends in the time series data to forecast future values, to determine whether or not stock prices are predictable. The following is the technique's equation:

$$L_t = \alpha VSTK_t + (1 - \alpha)(L_{t-1} + T_{t-1})$$
$$T_t = \theta (L_t - L_{t-1}) + (1 - \theta) T_{t-1}$$
$$\widehat{VSTK}_t = L_{t-1} + T_{t-1}$$

Where,
L_t is the level at time t, α is the weight for the level
T_t is the trend at time t, θ is the weight for the trend
$VSTK_t$ is the stock price at time t,
$\widehat{VSTK}_t$ is the predicted price at time t Source: Hyndman and Athanasopoulos (2018)

Holt-Winters' Multiplicative Model

This method takes into consideration not only the trend and level of the data, but also its seasonality. To obtain the forecast fit, the seasonality component in this model is multiplied by the sum of the base-case level and trend. Since data will be collected weekly, the seasonal duration of the study is 52 weeks (Hyndman and Athanasopoulos, 2018). The next is the formula:

$$L_t = \alpha (VSTK_t - C_{t-p}) + (1 - \alpha)(L_{t-1} + T_{t-1})$$
$$T_t = \theta [L_t - L_{t-1}] + (1 - \theta) T_{t-1}$$
$$S_t = \delta (VSTK_t - L_t) + (1 - \delta) C_{t-p}$$
$$\widehat{VSTK}_t = (L_{t-1} + T_{t-1}) C_{t-p}$$

Where, is the weight of the seasonal component; P is the seasonal period; and Ct is the seasonal component at time t. According to Hyndman and Athanasopoulos (2018), source.

Holt-Winters' Additive Model

This model will be used in the investigation to determine whether Holt's model predicts anything differently. Since weekly data will be gathered, the seasonal length is 52 (Hyndman and Athanasopoulos, 2018). The following are the equations for Winters' additive model:

$$L_t = \alpha (VSTK_t - C_{t-p}) + (1 - \alpha)(L_{t-1} + T_{t-1})$$
$$T_t = \theta [L_t - L_{t-1}] + (1 - \theta) T_{t-1}$$
$$S_t = \delta (VSTK_t - L_t) + (1 - \delta) C_{t-p}$$
$$\widehat{VSTK}_t = L_{t-1} + T_{t-1} + C_{t-p}$$

Source: Hyndman and Athanasopoulos (2018)

Forecasting Errors

According to According to Rahman (2023), some forecasting errors—such as mean absolute error (MAE) and root mean square error (RMSE)—are inappropriate for use as benchmarks. In relation to the other hand, U_(1) and U_(2) Theil inequality coefficients and MAPE serve as benchmarks. As a result, only the analysis in this study will take these inaccuracies into account.The benchmark is the MAPE, or mean absolute percentage error. However, it may become unclear what proportion of MAPE is appropriate for a prediction to be deemed trustworthy. According to Chen et al. (2017) and Gilliland (2010), there isn't a best MAPE value to use as a predictor. The following is the MAPE: formula:

$$MAPE = \frac{\sum \left| \frac{X_{obs,t} - X_{model,t}}{X_{obs,t}} \right|}{n} \times 100$$

Source: Minitab, Version-17

- Theil inequality coefficient U1:

It takes values between 0 and 1. The formula of U_1 is provided below:

$$U_1 = \frac{\left[\frac{1}{n}\sum_{i=1}^{n}(A_i - F_i)^2\right]^{\frac{1}{2}}}{\left[\frac{1}{n}\sum_{i=1}^{n}A_i^2\right]^{1/2} + \left[\frac{1}{n}\sum_{i=1}^{n}F_i^2\right]^{1/2}}$$

Where, A_i = The actual values and

F_i = The corresponding forecasted values

Source: Omnia (2016)

Nevertheless, U_1 has a number of serious flaws, the main one being that it consistently produces values that are nearly zero regardless of how well the model performs. On the other hand, U_2 is flawless. It provides precise information regarding the effectiveness of the model that is being used. U_2 thus functions as a benchmark, according to Bliemel (1973). As a result, in order to determine the predictability of the applied model, this study will place greater attention on U2.

- Theil inequality coefficient U2:

When the value of U2 equals 1, According to Omnia (2016), the naïve method or random walk, where Ft represents the most recent observation, performs as well as the forecasting strategy under consideration. It makes no sense to use a prediction model as a result. The prediction approach employed is superior to the naïve method when Theil U2 is less than one (U2 <1). Since the most recent observed value in the data produces a superior prediction (the price from yesterday is the best predictor for today), using a prediction model is pointless if Theil U2 is more than one (U2>1). The formula for U2 is as follows:

$$U_2 = \frac{\left[\sum_{i=1}^{n}(F_i - A_i)^2\right]^{1/2}}{\left[\sum_{i=1}^{n}A_i^2\right]^{1/2}}$$

Where, A_i = The actual values and

F_i = The corresponding forecasted values

Source: Omnia (2016)

Additionally, Ahlburg (1984), Granger and Newbold (1973), and Bliemel (1973) discovered that U2 was more reliable than U1.

RESULT

A market is weak-form efficient if a series exhibits a random walk, which means that past prices cannot be used to predict future values. A series is non-stationary, or independently and identically distributed, when the starting differences are -i.i.d., when they exhibit a random walk. A series without heteroscedasticity (at level), serial correlation (at first difference), or unit root (at first difference) is said to exhibit weak-form inefficiency., Rahman (2023).

According to Wooldridge (2019), a market is weak-form inefficient when data demonstrates that Future prices are predictable based on past prices; there is no unit root at the first difference of the ADF and no serial autocorrelation at the first difference from the LB test.

Each series shows that none of the series follow the random walk model after conducting experiments at that level. The ADF-unit root test shows that none of the series have a unit root at the beginning. Moreover, all of the series—apart from APTD.L—show no serial autocorrelation, according to the correlogram at first difference. Moreover, a level combination test shows that every series behaves like a martingale instead of a random walk.

In light of the four distinct test results (which are presented below), statistical inference can be made indicating that the LSE's creative sector is not weak-form efficient, implying future pricing stability. These are the outcomes of four distinct tests:

Table 1. Statistical Inference Regarding Weak-Form Market Efficiency for All Series

Series	**Runs test at level**	**ADF – unit root test at first difference**	**LB's serial autocorrelation at first difference**	**Variance ratio test at level**	**Statistical inference**
ACC.L	Does not follow a random walk	Rejects null of unit root	Rejects presence of autocorrelation up to 19 lags	The joint test accepts the null of martingale	Weak-form inefficient
JD.L	Does not follow a random walk	Rejects null of unit root	Rejects presence of autocorrelation for all 24 lags	The joint test accepts the null of martingale	Weak-form inefficient
APTD.L	Does not follow a random walk	Rejects null of unit root	Supports presence of autocorrelation for all 24 lags	The joint test accepts the null of martingale	Weak-form inefficient
BRBY.L	Does not follow a random walk	Rejects null of unit root	Rejects presence of autocorrelation for all 24 lags	The joint test accepts the null of martingale	Weak-form inefficient
PSON.L	Does not follow a random walk	Rejects null of unit root	Rejects presence of autocorrelation for all 24 lags	The joint test accepts the null of martingale	Weak-form inefficient
FTSE 350	Does not follow a random walk	Rejects null of unit root	Rejects presence of autocorrelation for all 24 lags	The joint test accepts the null of martingale	Weak-form inefficient

Source: Results of a Weak-Form Efficiency Test Using SV-12 and Eviews

Note: The following creative industry businesses' weekly closing prices are analyzed in the above table: Pearson PLC (PSON.L), Burberry Group PLC (BRBY.L), JD plc (JD.L), Aptitude Software Group plc (APTD.L), and Access Intelligence plc (ACC.L).

The following table presents the comparative forecast evaluation statistics using the multiplicative and additive triple exponential smoothing methods developed by Holt-Winters (which take seasonality in the data into consideration) and Holt's double exponential smoothing methodology. Since they are not useful as benchmarks, RMSE and MAE have not been included in the table. The chart also includes MAPE, Theil U1 and U2 in their respective roles as benchmarks. Moreover, a better model has a lower error.

Double exponential smoothing techniques outperform triple exponential smoothing techniques (additive and multiplicative), according to ACC.L data. This is because, although if MAPE indicates the reverse, the Theil inequality coefficient of U2 from this method is smaller than 1, indicating that double exponential smoothing techniques have stronger forecastability than triple exponential smoothing techniques. MAPE internal There is no set standard for determining what proportion of MAPE is deemed suitable for prediction, hence this situation would not be taken into account. Because its U2 value is bigger than 1, the naïve approach surpasses triple exponential smoothing approaches in forecasting the future value based on the last value in the observations. One could argue that the multiplicative technique is the second-best predictor based on the analysis of MAPE.

It is evident from the JD.L evaluation data that no forecasting model outperforms naïve forecasting. This is due to the fact that Theil U2 is greater than 1 in all applied models. In addition, the MAPE of JD.L is somewhat greater than that of the other series in our analysis.

The APTD.L results show that every model used has a greater capacity for prediction. All of the applied models have U2 values smaller than 1, which suggests that forecasting models are more predictive than the naive approach. Furthermore, the results show that compared to double exponential smoothing approaches, triple exponential smoothing techniques are less forecastable. This is because, in contrast to what MAPE suggests, When employing double exponential smoothing, theil U1 and U2 are lower than with multiplicative and additive exponential smoothing approaches. There is no seasonality in the data, as shown by line graphs, correlograms, and triple exponential smoothing, which takes seasonality into consideration. Based on the data, the additive model is likewise the second-best APTD.L predictor.

Another clothing firm, BRBY.L, demonstrates how none of the methods could accurately forecast stock values. The fact that each applied model produced a Theil U2 value greater than 1, suggesting that the naïve technique could forecast future prices, justifies this. more accurately than all applied models combined. merged.

Holt's model was able to predict better than the Holt-Winters models., according to PSON.L predictive metrics, because U2 is smaller than 1. The lack of seasonality in the data may be the cause of this. U2 is bigger than 1 in the other two models, which use multiplicative and additive techniques. As a result, the naïve method may yield more predictable results than triple exponential smoothing methods. Despite the fact that Compared to APTD.L, MAPE is lower in this series.

The The FTSE-350 General Industrial Index (GII) shows that every model that has been used can predict future stock values with accuracy. For any model that pertains to this series, the Theil U2 is less than 1. U1 and MAPE are also lower for this series. Furthermore, Holt's model (double) is the best predictor, and the multiplicative technique is the second-best, because the better the model, the less the error. as proved by Theil U1, U2, and the MAPE.

Table 2. Comparison of Forecast Evaluation Statistics from All Applied Models

Series	**Model**	**MAPE**	**Theil U_1**	**Theil U_2**	**2 Best predictors sequentially**
ACC.L	Double	3.18	0.023	0.79	**Double**
	Multiplicative	2.66	0.014	6.13	**Multiplicative**
	Additive	2.95	0.019	9.26	
JD.L	Double	31.07	0.1345	7.31	**None**
	Multiplicative	31.54	0.1376	7.42	
	Additive	32.56	0.1416	7.71	
APTD.L	Double	18.22	0.091	0.70	**Double**
	Multiplicative	15.71	0.109	0.86	**Additive**
	Additive	16.74	0.093	0.73	
BRBY.L	Double	4.30	0.028	1.54	**None**
	Multiplicative	7.70	0.040	2.14	
	Additive	7.43	0.039	2.07	
PSON.L	Double	1.33	0.009	0.63	**Double**
	Multiplicative	3.13	0.018	1.31	
	Additive	3.75	0.022	1.62	
FTSE-350 GII	Double	2.68	0.017	0.66	**Double**
	Multiplicative	4.86	0.027	0.77	**Multiplicative**
	Additive	5.49	0.030	0.80	

Note: The firms in the creative industry that are analyzed in the above table are: Pearson PLC (PSON.L), Burberry Group PLC (BRBY.L), JD plc (JD.L), Access Intelligence plc (ACC.L), and Aptitude Software Group plc (APTD.L).

DISCUSSION

The following topics are highlighted in regard to the study's primary findings:

1. Inadequate market effectiveness
2. The creative sector's predictability
3. Forecast accuracy of the models used

LB's correlogram at the first difference, the heteroscedasticity test through the variance ratio at the level, the ADF-unit root test at the data level, and the test outcomes from runs, a Based on statistical evidence, the London Stock Exchange (LSC) was determined not to be weak-form efficient. These research demonstrated the non-random behavior and serial autocorrelation of LSE stock values, particularly in the creative industry. The test results suggest that stock prices in the creative industry may be predictable and support the weak-form market inefficiency noted during the examined sub-sample period. However, predictability depends on how reliable the applied model is.

This study looked at the FTSE-350 General Industrial Index and the stock prices of several creative industry companies. Tests of weak-form efficiency suggest that stock The creative industry has predictable prices. Moreover, the majority based on the relevant predictions, the enterprises in the creative industry are predictable methods. Gaining a general understanding of the predictability of all other LSE businesses is the aim of FTSE-350 GII assessment. The findings proved that every other industry is just as predictable as the creative sector. It is therefore possible to argue that stock values in other businesses, including the creative sector, are predictable.

With the exception of The different relevant Models of triple exponential smoothing techniques, like the additive and multiplicative models, show how unpredictable a series can be. Seasonality is allowed for in triple exponential smoothing (Holt-Winters') models, therefore its absence in the data could be the reason. Additionally, it has been demonstrated by line graphs and correlograms that there is no seasonality in the data.

The different relevant The limited predictability of the series is demonstrated by models of triple exponential smoothing techniques, such as the multiplicative and additive models. Given that triple exponential smoothing (Holt-Winters') models allow for seasonality, the lack of it in the data may be the cause. Furthermore, line graphs and correlograms have shown that the data do not exhibit seasonality.

The FTSE-350 General Industrial Index and the stock prices of the creative industry are not normally distributed, according to the results of descriptive statistics. The The selected series are either platykurtic or leptokurtic. According to studies by Al-Jafari (2013), Camellia (2013), and Rahman (2023), the stock markets in Turkey, Romania, Hungary, the Czech Republic, Slovakia, Estonia, and the BRIC (Brazil, Russia, India, and China) countries, as well as the UK, are predictable and not normally distributed. These results are consistent with those findings.

The LSE, which includes the creative industry and other industries (as assessed by the FTSE-350 General Industrial Index), is not weak-form efficient, according to the study's weak-form efficiency test results, which also show that future prices are predictable. This outcome is in line with the research conducted by Chakraborty (2006), Mollah (2007), Abedini (2009), Mishra (2013), Mobarek and Keasey (2000), and Rahman (2023) who discovered that stock markets are return patterns are predictable in Bangladesh, Sri Lanka, Botswana, Bahrain, Kuwait, Dubai, India, and the UK, respectively, and the model is not weak-form efficient.

The results of the analysis indicate that, for the majority of the series, stock prices may be accurately predicted using the double exponential smoothing method. The outcomes of Andreyanto and Wahyuni (2024), Funde and Damani (2023), and Rahman (2023), who contended that the double exponential smoothing (Holt) model could precisely predict future values, corroborate this conclusion. Results from the following studies: Agustina et al. (2021), Liu et al. (2020), Awajan et al. (2018), Chawla and Jha (2009) and others are not compatible with this result. researchers Muliawati (2024), who discovered that triple exponential smoothing approaches yield more accurate forecasts than double exponential smoothing methods.

The results of this investigation are consistent with those according to Almazrouee et al. (2020), the triple exponential smoothing model of Holt-Winters performed badly in predicting power consumption.

The literature review in the appendix of this work shows that several scholars have conducted multiple experiments on the predictability of double and triple exponential smoothing approaches. Additionally, a few of them used exponential smoothing techniques in conjunction with more complex models like ARIMA and artificial neural networks (ANN) in a few research. A number of these investigations have been carried out in various sectors, such as the manufacturing, logistics, and service industries. Nevertheless, no one has expanded or taken into account the creative industry's study breadth yet. Each industry has unique traits that cause it to behave differently, meaning that some may be predictable while others may not be. This is due to the fact that certain sectors exhibit trends in their data and other industries' stock values. vary suddenly and erratically. To date, no one has used Using exponential smoothing techniques, examine how predictable creative industry stocks are values. This idea has been generally ignored in the literature that currently exists.

This study investigated the predictability of creative industry stock values. The London Stock Exchange's creative industry stock price patterns and movements are observably predictable, according to this study's empirical findings. By taking into account the predictability of stock prices in the creative business, this research has added to the body of knowledge already in existence.

CONCLUSION AND RECOMMENDATION

The initial goal was to use a variety of exponential smoothing approaches to investigate whether or not The creative sector of the London Stock Exchange (LSE) is weak-form efficient. This was accomplished by using a range of statistical tools and techniques while examining graphs and figures from specific series. First, we looked at the histogram, line graphs, kernel density graphs, and descriptive statistics. Second, in order to make statistical inferences on weak-form efficiency, the runs test, autocorrelation test, variance ratio test, and ADF-unit root test were conducted. Thirdly, the FTSE-350 General Industrial Index and the creative industry's weak-form efficiency were investigated using exponential smoothing approaches. Finally, conclusions on the predictability and weak-form efficiency of the models were drawn by comparing the assessment statistics of the benchmarks with those from the anticipated results. The weekly closing values of the FTSE-350 General Industrial Index and theDescriptive statistics, histograms, and kernel density graphs show that the five creative industry enterprises are not dispersed randomly. The non-normal distribution of the data indicates that historical prices can be utilized to forecast future stock values.

The runs test at level indicates that there is no random fluctuation in the stock prices of any series, including the FTSE-350 General Industrial Index and five creative enterprises. The correlogram's initial differential results show inconsistent outcomes. With the exception of the APTD series, it is discovered that none of these series exhibit serial autocorrelation.L. ADF-unit root tests on the first difference document show that none of the series have a unit root. Additionally, the multiple variance ratio test demonstrates that fluctuations in stock prices arenot at random. They adhere to the template of the martingale.

In conclusion, none of the series pass the requirements for weak-form market efficiency substantially during the plain period—that is, during which there is no structural break. Consequently, it was statistically concluded that the London Stock Trade, which includes the creative sector, is not inefficient in any way.

The forecast assessment statistics of MAPEs, Theil U1 and U2, show how well Holt's double exponential smoothing technique could predict stock prices for much of the period.

Thus, one may contend that the London Stock Exchange, and more specifically the creative industry, is not weak-form efficient at the moment under investigation.

The second goal was to assess the forecasting ability of the econometric models by estimating them using exponential smoothing techniques. In order to accomplish this goal, the most popular and easily understood econometric models of exponential smoothing have been selected for this study. By examining the forecast errors of the six series—including the FTSE-350 General Industrial Index—applied to the models and five creative industry businesses, this goal was accomplished.

The two The exponential smoothing technique (Holt model) indicates that most of the series are predictable as the forecasting error parameter of U2 is less than 1 and MAPE is smaller.

However, the Holt-Winters models, which use triple exponential smoothing techniques, reveal that just two of the six series are predictable. This is because the study's data series do not exhibit any seasonality that might be identified using a correlogram or line graph, despite the fact that additive and multiplicative models (Holt-Winters) take seasonality in data into consideration. Consequently, even though the market is not weak-form efficient, it might be argued that exponential smoothing approaches have modest forecasting ability because they are unable to accurately predict all series.

This is not where the research ends. It creates a new avenue for investigation into various businesses and the predictability of the London Stock Exchange over a range of sample lengths

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