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Project Title: Forecasting Stock Prices Through Exponential Smoothing Techniques in The Creative Industry of The UK Stock Market	
Course: Business and Management	**Unit Leader: Teresa Havvas**
Year of Study (e.g. 1st/2nd etc.): 3rd and Final year	**Submission Date: 18 April, 2024**

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

By
Md Aminur Rahman

Student ID number: 2116142

April 2024

Critical Self Reflection: My journey to my career

I have already set up my goal or aim in my life which inspire me to perform my degree project in a creative and smart way. My aim is to be a lecturer at a university in the United Kingdom after accomplishing my bachelor, masters, and PhD in a specific area of interest. Thus, I must achieve these qualifications to be in my preferred area of interest. This intension keeps me busy each and every day to be a lecturer. I hope my dream would turn into a reality after a long journey of my education life.

I work in a team although degree project is an individual task. I try to contribute significantly in the team to accomplish tasks, meet goals. I listen to my co-workers, respect their opinion and ideas. I try to collaborate with other members to achieve target or complete tasks. I understand my role and its impact on the team performance. I appreciate the performance from other team members.

I have completed ACCA part 1. Thus, I would like to have my career in finance. I have determined my area of research would be in the area of finance in PhD. I have got an opportunity to learn statistical analysis including descriptive analysis, correlation, regression, correlogram, different charts and different forecasting models, tools, and techniques through LinkedIn, YouTube videos and from instructors to predict future values based on historical values and make investment decisions. I have uploaded some videos on finance in YouTube. The YouTube videos are on weak-form market efficiency and structural breakpoints analysis. Thus, how I connect my accomplishments to the area of interest. I have got a publication in the area of finance. It is available in google scholar. The international journal of business and management has published my work. This is a huge work on technical analysis of time series data. I have applied sophisticated forecasting models of ARIMA (Autoregressive Integrated Moving Average) and GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model. This degree project is just a part of this article due to word limit and shorter period. In this degree project, I have just applied simple and easy to understand methods of exponential smoothing techniques, as UCA is a fashion and music related university. I hope to publish this work as well after achieving my grade from the submission. This degree project is in the area of finance. Therefore, I could claim that it will help me to reach in my aim.

Abstract:

This study aims to assess the prediction power of exponential smoothing techniques critically and rigorously in the creative industry of the UK stock market. For this reason, weekly closing price data were collected from the five companies of the creative industry and FTSE-350 General Industrial Index, for the sample period from 13 October 2003 to 2 February 2024. Bai-Perron's multiple breakpoints test of L + 1 vs. L sequentially determined breaks has been applied for the purpose of identifying plain data of sub-sample period for all selected series. The descriptive statistics table, histograms, and kernel density graphs from all series exhibit that the weekly closing prices are not normally distributed. Runs test documents that weekly closing prices of all the series do not move randomly. Additionally, variance ratio of Chow-Denning joint test evidences that all series follow a martingale model. Furthermore, LB's serial correlation test documents that most of the series do not have serial auto-correlation at the first difference. Moreover, the Augmented Dickey Fuller - unit root test suggests none of the series have got unit root at the first difference. Consequently, the statistical inference was made that the London Stock Exchange (LSE) including the creative industry is weak-form inefficient in the period of the tests and its stock prices are predictable. Holt's double exponential smoothing technique contributes to demonstrate better short-term forecastability of stock prices for most of the series in the creative industry and the FTSE 350 General Industrial Index. Therefore, this study does not find any support for weak-form efficiency over the periods tested in the LSE. This research extends the current literature by studying the existence of weak-form inefficiency in the creative industry.

KEYWORDS: Forecasting stock price, creative industry, exponential smoothing techniques, random walk model, structural breakpoints.

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Chapter Four: Research and development

Part -C: Research Methodology-Non-prediction related research methods

[1]This part explains the applied statistical tools and techniques in this study which are not related with forecasting. They are Bai-Perron's multiple breakpoints test, weak-form market efficiency tests of runs test, variance ratio test, ADF-unit root test, correlogram or auto-correlation test and descriptive statistics.

a) Bai-Perron's structural breakpoint test:

Structural breaks in the data take place when a big change occur in the micro and macro-economic variables, for example, launching a highly demanding product by a company such as COVID vaccine (micro variable), changes in the inflation rate (macro variable) etc. When a forecasting will be made based on data that have structural breaks in it, forecasting accuracy will not be achieved as data is not smooth. Therefore, it is required to consider a data period that has no structural breaks for achieving better forecasting accuracy. One approach is to determine the number of breaks sequentially by testing for L + 1 against L breaks developed by by Bai (1997) and Bai and Perron (1998). The formula is as follows:

$\text{Sup } F_T(L+1|L) = \{S_T(T\hat{}_1,\ldots,T\hat{}_L) - \min \inf_{1\leq i\leq L T \varepsilon I,\ L} S_T(T\hat{}_1,\ldots,T\hat{}_{i-1,T},T\hat{}_{I,\ldots},T\hat{}_L)\}/\sigma\hat{}2$

b) Runs test:

This test will be applied to see whether stock prices change randomly or not. The formula of expected runs (v) is provided by Gujarati (2004) 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, W_1 and W_2 = the number of individual observations above and below the mean,

W = total number of observations {i.e. (W_1 +W_2) = W}

v = expected run.

Z statistic is the distinction between expected and actual number of runs. Sharma and Kennedy (1977) claimed that if Z ≥ ±1.96; reject that stock prices change randomly (predicted runs are

[1] PLEASE NOTE THAT CHAPTER ONE, TWO, THREE AND FIRST TWO PARTS OF CHAPTER FOUR ARE SHOWN IN APPENDIX DUE TO WORD LIMIT RESTRICTIONS.

higher) at 5% level of significance and if 9≥Z≤20; reject that share prices are random and reject weak-form market efficiency (i.e., stock prices are foreseeable).

c) **ADF- Unit Root test**:

STK is assumed as a series of stock. A random walk model for STK could be written as follows:

$\Delta STK_t = \beta_1 + \beta_2 t + \delta\ STK_{t-1} + \Sigma\alpha_i\ \Delta\ STK_{t-i} + \varepsilon_t$, (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 $\alpha > 0$, the process will show an upward trend.

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

If ρ = 1, data or STK_t has unit root or random walk model without drift or nonstationarity.

If |ρ|≤ 1(ρ is less than 1), time series STK_t is stationary, or series does not need to use first or second difference. As ε_t is a white noise error term, data are stationary which suggests that first difference of a random walk time series is stationary.

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

d) **Autocorrelation: Ljung-Box test:**

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

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

e) Variance ratio test:

Variance ratio test is applied to see any homoskedastic and heteroskedastic random walks in the series. The formula of variance ratio (VR) is as follows:

VR(q) = $\frac{\sigma_q^2}{q*\sigma^2}$, (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.

f) Descriptive statistics:

Descriptive statistics will be applied to examine whether share prices are normally distributed or not. If historical prices are normally distributed, future prices are unpredictable. If they are not normally distributed, future prices might be predicable (Mollah, 2007). Descriptive statistics would help achieve the third objective in the lists. It consists of several measures.

The equation of the mean has been provided under run test. To uncover the median, this research would follow the procedures explained by Anderson et al. (2002) which is to place the observations of a sample from the smallest to the largest and pick the middle value from an odd number of data and compute the mean of the two middle values for an even number of data. To calculate the mode of a sample, this study would follow the guidance delivered by Anderson et. al. (2002): the mode is the value that takes place most frequently. The standard error (SE) of the mean will be computed based on the formula given by Berenson et al. (2006), given below:

SE of mean = $\frac{\sigma}{\sqrt{n}}$

Where, σ = standard deviation,

n = sample size

The equation of σ for a sample is given by Berenson et al. (2006) as follows:

$$\sigma = \sqrt{\frac{\sum(y - \bar{y})^2}{n-1}}$$

Where, y = each value in the sample,

$\bar{y}$ = mean,

Smaller the range, lower the volatility in the stock market. The formula of range is provided by Anderson et al. (2002) as follows:

Range = $X_{\text{largest value in the sample}} - X_{\text{smallest value in the sample}}$

The formula of Pearson's co-efficient of skewness is provided by Kazmier (2004) as follows:

SK_p (population skewness) = $\frac{3(Mean - Median)}{Standard\ deviation} = \frac{3(\mu - Median)}{\sigma}$

Sample skewness = $\frac{3(Mean - Median)}{Standard\ deviation} = \frac{3(\bar{m} - Median)}{s}$

The equation of kurtosis (K) is explained by Gujarati (2004) provided below:

K = fourth moment about mean / square of the second moment.

$K = m_4 / m_2^2 = m_4 / (\sigma^2)^2$

Chapter Four: Research and development

Part -D: Research Methodology-prediction related research methods

The forecasting models - Holt' double exponential smoothing, and Holt-Winters's triple exponential smoothing techniques will be applied to predict stock prices. Their results will be evaluated through prediction evaluation statistics of errors including root mean squared errors (RMSEs), mean absolute percentage error (MAPE) and Theil inequality co-efficients of U_1 and U_2. However, RMSE does not work as a benchmark as it generates values based on the size of the number. The bigger the value, the bigger the RMSE and vice-versa. Thus, MAPE and Theil U_1 and U_2 will be used to determine and decide the performance of the applied models.

(1) Double exponential smoothing technique:

This is a linear trend method that considers trends and level in the time series data for future value prediction and will be applied in this study to examine whether stock prices are predictable or not. The equation of this technique is provided below:

$L_t = \alpha VSTK_t + (1 - \alpha)(L_{t-1} + T_{t-1})$

$T_t = \theta (L_t - L_{t-1}) + (1 - \theta) T_{t-1}$

$\widehat{VSTK}_t = L_{t-1} + T_{t-1}$

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)

(2) Holt-Winters' multiplicative model

This technique considers seasonality in the data in addition to trend and level. In this model, the base-case level and trend are added together and multiplied by the seasonality factor to obtain the forecast fit. The seasonal length is 52 in this study as weekly data will be collected (Hyndman and Athanasopoulos, 2018). The formula is as follows:

$$L_t = \alpha\ (VSTK_t - C_{t-p}) + (1-\alpha)\ (L_{t-1} + T_{t-1})$$

$$T_t = \theta\ [L_t - L_{t-1}] + (1 - \theta)T_{t-1}$$

$$S_t = \delta\ (VSTK_t - L_t) + (1 - \delta)\ C_{t-p}$$

$$\widehat{VSTK}_t = (L_{t-1} + T_{t-1})\ C_{t-p}$$

Where,

C_t is the seasonal component at time t,

δ is the weight for the seasonal component,

p is the seasonal period

Source: Hyndman and Athanasopoulos (2018)

(3) Holt-Winters' additive model of triple exponential smoothing:

This model will be applied in this study to see any difference in prediction from Holt's model. The seasonal length is 52 as weekly data will be collected (Hyndman and Athanasopoulos, 2018). The equations of Winters' additive model are as follows:

$$L_t = \alpha\ (VSTK_t - C_{t-p}) + (1-\alpha)\ (L_{t-1} + T_{t-1})$$

$$T_t = \theta\ [L_t - L_{t-1}] + (1 - \theta)T_{t-1}$$

$$S_t = \delta\ (VSTK_t - L_t) + (1 - \delta)\ C_{t-p}$$

$$\widehat{VSTK}_t = L_{t-1} + T_{t-1} + C_{t-p}$$

Source: Hyndman and Athanasopoulos (2018)

Forecasting errors:

Rahman (2023) claimed that all the forecasting errors do not work as benchmarks, for example, root mean squared error (RMSE), mean absolute error (MAE) and many more. However, MAPE, Theil inequality coefficients of U_1 and U_2 work as benchmark. Therefore, this study will consider these errors only in the analysis.

1. Mean absolute percentage error (MAPE)

MAPE works as benchmark. However, the question might come that what percentage of MAPE is acceptable a prediction to be reliable. Gilliland (2010) and Chen et al. (2017) found there is no rule concerning the value of MAPE to be considered as the best predictor. The equation of MAPE is as follows:

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

Source: minitab, version-17

2. Theil inequality coefficient U1:

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

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

Where, A_i = The actual values and
F_i = The corresponding forecasted values

Source: Omnia (2016)

However, U_1 has some severe drawbacks and the key problem is that it always creates values close to zero irrespective the performance of the model. Conversely, U_2 has not got faults. It delivers the accurate information about the performance of the applied model. Therefore, U_2 works as a benchmark, Bliemel (1973). Thus, this study would give more emphasis on U_2 to decide about the predictability of the applied model.

3. Theil inequality coefficient U₂:

Omnia (2016) recommended that when the value of U_2 is 1, the random walk or naïve method (where F_t is equal to the last observation) is as good as the forecasting technique being assessed. Therefore, there is no rationality to apply a prediction model. When the value of Theil U_2 is less than one (U_2 <1), the prediction method being applied is better than the naïve method. If the value of Theil U_2 is greater than one (U_2>1), the application of prediction model is useless as the last observed value in the data provides better prediction (the price that was yesterday is the best predictor for today). The equation of U_2 is given below:

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

Where, A_i = The actual values and

F_i = The corresponding forecasted values

Source: Omnia (2016)

Furthermore, Bliemel (1973), Granger and Newbold (1973) and Ahlburg (1984) found the reliability of U_2 over U_1.

Chapter Five: Data Analysis and Findings

Part A: An illustration of a series

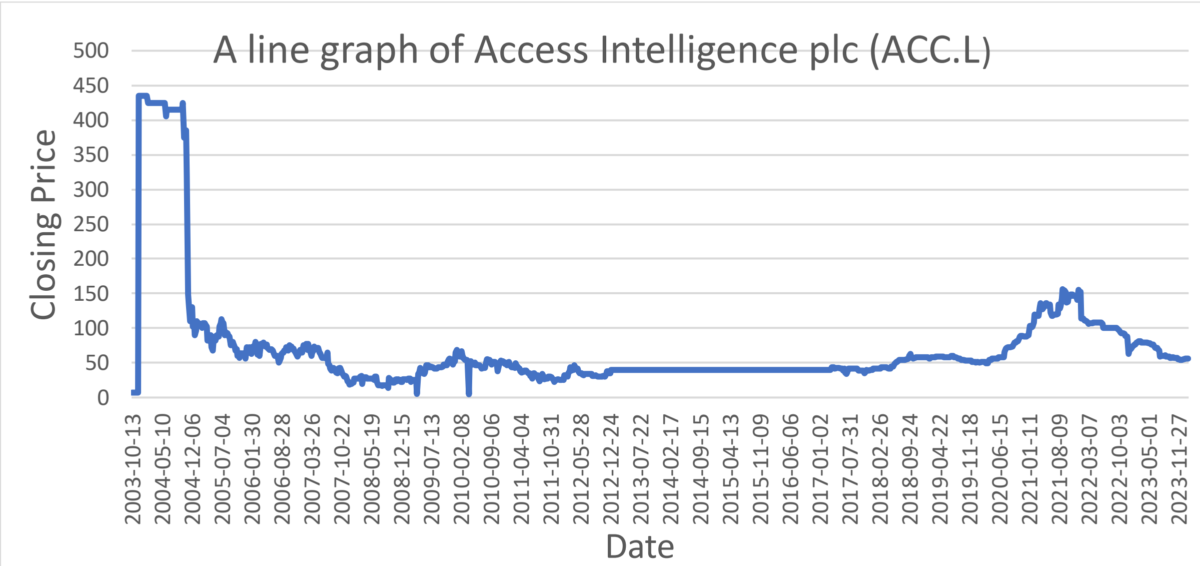
In this chapter, part-A shows an example of the first series, ACC.L in detail, while the detailed tests following the same sequence for all remaining series are attached in the appendix from part- B. Thus, the summarised results for all remaining series will be shown in the next part, B.

(i) **Visual Inspection of Series**:

1(a): A line graph for ACC.L

The line graph below shows a significant jump of price on 1 December 2003, and it was remained stable until 1 November 2004. Stock prices then decreased sharply and remained steady until 20 July 2020. Stock prices increased a bit again for a short period and then declined.

Figure 1: A line graph for ACC.L for period from 13 October 2003 to 2 February 2024

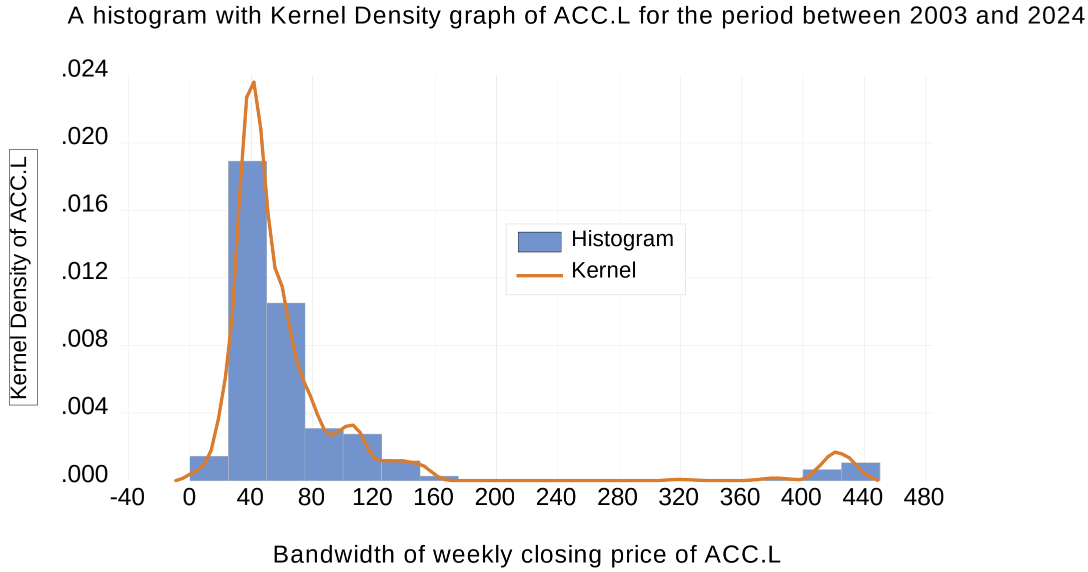


Source: Diagram generated by author with database for the period of 13 October 2003 to 2 February 2024.

1(b): A histogram with Kernel Density graph for ACC.L

As stock price moved from lower to higher and higher to downward trend, the Kernel density line created two peaks in the histogram for ACC plc. Therefore, it is a bimodal distribution. The distributions are not normally distributed.

Figure 2: A histogram with Kernel Density graph for ACC.L for the period between 13 October 2003 and 2 February 2024



Source: Diagram generated by author with database for the period of 13 October 2003 to 2 February 2024.

(ii) Descriptive statistics for ACC.L:

The table below shows there are 1061 observations for the above series. As the kurtosis more than 3, the distribution is leptokurtic (peaked) compared to normal distribution. The series has got positive skewness, which is 3.608, indicating a higher possibility of positive returns from the investment of this company.

Descriptive Statistics

	N	Minimum	Maximum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
Price	1061	4.63	435.00	72.6956	2.486	80.979	6557.681	3.608	.075	12.723	.150
Valid N (listwise)	1061										

Source: Output of descriptive statistics found from applying SPSS

(iii) Structural break test through Bai-Perron test:

The following table explains that there are two structural breaks in the series including 10/30/2006 and 8/03/2020. These structural breaks would not produce a good forecast. Therefore, it is required to choose a plain period of data for a better forecasting. Hyndman and Athanasopoulos (2018) explain that 204 continuous data are sufficient for predicting through any models. The estimation period of the selected sub-sample is chosen from 10/13/2003 and 2/02/2024, which includes 204 observations. The validation period has been chosen 4 more observations after that period, which include from 29/06/2020 to 20/07/2020 for out-of-sample forecasts.

Table: Bai-Perron's multiple breakpoints test for the period between 10/13/2003 and 2/02/2024

Series	Break date	Clean period	Obser-vation	Co-efficient	Standard error	t-statistic	P value
ACC.L	10/30/2006	10/13/2003 –	159	181.91	5.05	36.00	0.00***
	8/03/2020	10/23/2006		42.45	2.38	17.85	0.00***
		10/30/2006 –	718				
		7/27/2020					
		8/03/2020 –	184	96.32	4.70	20.50	0.00***
		2/02/2024					

Source: Output of Bai-Perron's multiple breakpoints test found from applying Eviews, SV-12

Full Bai-Perron's multiple breakpoints test:

Dependent Variable: CLOSE
Method: Least Squares with Breaks
Date: 02/10/24 Time: 08:20
Sample: 10/13/2003 2/02/2024
Included observations: 1061
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 10/30/2006, 8/03/2020
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
10/13/2003 - 10/23/2006 -- 159 obs				
C	181.9126	5.053038	36.00063	0.0000
10/30/2006 - 7/27/2020 -- 718 obs				
C	42.45534	2.377874	17.85433	0.0000
8/03/2020 - 2/02/2024 -- 184 obs				
C	96.32065	4.697234	20.50582	0.0000

R-squared	0.382081	Mean dependent var	72.69560
Adjusted R-squared	0.380913	S.D. dependent var	80.97951
S.E. of regression	63.71638	Akaike info criterion	11.14958
Sum squared resid	4295245.	Schwarz criterion	11.16363
Log likelihood	-5911.854	Hannan-Quinn criter.	11.15491
F-statistic	327.0988	Durbin-Watson stat	0.061025
Prob(F-statistic)	0.000000		

Selected clean period: 10/30/2006 – 7/27/2020 = 718 observations

Data for testing = 204 observations

Data for validity = 4, thus 208 observations

Thus, testing period = 01/08/2016 to 22/06/2020

Validity period 29/06/2020 to 20/07/2020

Testing weak-form efficiency on selected Sub-sample period for ACC.L:

i) Runs test

Hypothesis:
Null: Prices are random
Alternative: Prices are not random

As the p-value (level of significance) is less than 5% (0.000<0.05), stock prices are not random. Furthermore, as the Z statistic is greater than 1.96, the alternative hypothesis (of prices are not random) is accepted at 5% level of significance, Sharma and Kennedy (1977).

Runs test on ACC.L for the selected sub-sample period of 01/08/2016 – 22/06/2020 (204 observations)

Series	Total number of runs	Z statistic	P value
ACC.L	4	-13.90	0.00

Source: Output of runs test found from applying SPSS

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
Close	204	48.5032	7.94212	33.75	63.00

Runs Test

	Close
Test Value[a]	50.00
Cases < Test Value	102
Cases >= Test Value	102
Total Cases	204
Number of Runs	4
Z	-13.897
Asymp. Sig. (2-tailed)	<.001

a. Median

ii) Unit root test

Augmented Dickey-Fuller (ADF) unit root test has been applied using Schwarz Information Criterion (SIC). As test statistics is less than 5% at first difference, there is no unit root at first difference. Furthermore, the null hypothesis of data (closing price) has a unit root can be rejected at first difference as test statistic is significantly bigger than critical values.

ADF-Unit Root test on ACC.L for the selected sub-sample period of 01/08/2016 – 22/06/2020 (204 observations)

Series	t-statistic at level	t-statistic at first difference
ACC.L P value	-1.804875 (0.699)	-11.53155 (0.000)***

Note 1: Their critical values for ADF at 1% level of significance are -4.003902 (at level) and -4.004365 (at first difference). p-value < 1% = ***

Source: Outcome of ADF-unit root test from sub-sample period of ACC.L using Eviews, SV-12

At level:

Null Hypothesis: CLOSE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.804857	0.6990
Test critical values:	1% level	-4.003902	
	5% level	-3.432115	
	10% level	-3.139793	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE)
Method: Least Squares
Date: 12/02/24 Time: 21:25
Sample (adjusted): 8/08/2016 22/06/2020
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLOSE(-1)	-0.031618	0.017518	-1.804857	0.0726
C	1.257634	0.676841	1.858093	0.0646
@TREND("1/08/2016")	0.003560	0.002366	1.504812	0.1339

R-squared	0.016077	Mean dependent var	0.088670
Adjusted R-squared	0.006238	S.D. dependent var	1.189659
S.E. of regression	1.185942	Akaike info criterion	3.193620
Sum squared resid	281.2918	Schwarz criterion	3.242584
Log likelihood	-321.1525	Hannan-Quinn criter.	3.213429
F-statistic	1.633992	Durbin-Watson stat	1.889890
Prob(F-statistic)	0.197743		

At First Difference:

Null Hypothesis: D(CLOSE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-11.53155	0.0000
Test critical values:	1% level	-4.004365	
	5% level	-3.432339	
	10% level	-3.139924	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE,2)
Method: Least Squares
Date: 12/02/24 Time: 21:27
Sample (adjusted): 22/08/2016 22/06/2020
Included observations: 201 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CLOSE(-1))	-1.125445	0.097597	-11.53155	0.0000
D(CLOSE(-1),2)	0.172865	0.070779	2.442327	0.0155
C	0.089737	0.170616	0.525958	0.5995
@TREND("1/08/2016")	8.85E-05	0.001442	0.061383	0.9511

R-squared	0.495127	Mean dependent var	0.000000
Adjusted R-squared	0.487439	S.D. dependent var	1.656310
S.E. of regression	1.185808	Akaike info criterion	3.198426
Sum squared resid	277.0099	Schwarz criterion	3.264164
Log likelihood	-317.4418	Hannan-Quinn criter.	3.225026
F-statistic	64.39909	Durbin-Watson stat	2.015391
Prob(F-statistic)	0.000000		

iii) Autocorrelation : Ljung-Box test

Null hypothesis: Time series is not auto-correlated (no serial auto-correlation)

Alternative hypothesis: Time series is auto-correlated

As p value is more than 5% at first difference except the second and twentieth lag, the null hypothesis is accepted that the series does not have any serial autocorrelation.

Autocorrelation test at first difference on ACC.L for the selected sub-sample period of 01/08/2016 – 22/06/2020 (204 observations)

Series	P value
ACC.L	More than 5% for up to 19 lags

Source: output of autocorrelation test for sub-sample period of FTSE-all share index in Eviews, SV-12

Correlogram at first difference D(close):

Correlogram of D(CLOSE)

Date: 09/04/24 Time: 10:23
Sample (adjusted): 8/08/2016 22/06/2020
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.040	0.040	0.3359	0.562
		2	-0.168	-0.170	6.1874	0.045
		3	-0.059	-0.045	6.9058	0.075
		4	0.073	0.051	8.0244	0.091
		5	-0.000	-0.023	8.0244	0.155
		6	0.011	0.031	8.0520	0.234
		7	0.025	0.027	8.1885	0.316
		8	-0.010	-0.011	8.2086	0.413
		9	-0.043	-0.031	8.6069	0.474
		10	-0.006	-0.006	8.6142	0.569
		11	0.091	0.079	10.427	0.492
		12	0.052	0.043	11.025	0.527
		13	0.018	0.046	11.098	0.603
		14	-0.100	-0.083	13.306	0.503
		15	0.069	0.087	14.366	0.498
		16	0.015	-0.020	14.417	0.568
		17	-0.046	-0.041	14.899	0.603
		18	0.197	0.229	23.649	0.167
		19	0.034	-0.018	23.910	0.200
		20	-0.189	-0.134	31.998	0.043
		21	0.021	0.090	32.095	0.057
		22	0.064	-0.033	33.027	0.061
		23	-0.065	-0.095	34.014	0.065
		24	0.036	0.095	34.320	0.079

iv) Single and multiple variance ratio (VR) tests at level:

The following tests consider variance ratio test, homoscedasticity test statistic Z(q), heteroscedasticity test statistic Z*(q) and joint test for weekly observations of the series of ACC.L. As p value is more than 5%, for both individual test developed by Lo and MacKinlay (1988) and maximum |Z| multiple statistics formulated by Chow-Denning (1993), it reveals that weekly closing price follows a martingale and null hypothesis is accepted. Therefore, stock prices do not follow a random walk model. Furthermore, VRs are less than 1 for individual test except period 2, which indicate, it does not follow a random walk model and there is a negative or mean reverting relationship in the prices of this series.

Series		q = 2	q = 4	q = 8	q = 16	Chow-Denning joint test (max |Z|) and p value
ACC.L	VR Z Z*	1.050704 0.465391 0.108948	0.881705 -0.564937 0.209395	0.880360 -0.387573 0.308692	0.938914 -0.156621 0.390025	0.587154 and p value = 0.9830

Source: Output of heteroscedasticity test found from applying Eviews, SV-12

Hypothesis:

Null: PRICE is a martingale
Alternative: PRICE is not a martingale

Null Hypothesis: CLOSE is a martingale
Date: 12/02/24 Time: 21:34
Sample: 1/08/2016 22/06/2020
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16 32

Joint Tests	Value	df	Probability
Max |z| (at period 32)*	0.587154	203	0.9830

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.050704	0.108948	0.465391	0.6417
4	0.881705	0.209395	-0.564937	0.5721
8	0.880360	0.308692	-0.387573	0.6983
16	0.938914	0.390025	-0.156621	0.8755
32	1.304737	0.519007	0.587154	0.5571

*Probability approximation using studentized maximum modulus with parameter value 5 and infinite degrees of freedom

Test Details (Mean = 0.0886699507389)

Period	Variance	Var. Ratio	Obs.
1	1.41529	--	203
2	1.48705	1.05070	202
4	1.24787	0.88170	200
8	1.24596	0.88036	196
16	1.32883	0.93891	188
32	1.84658	1.30474	172

Inference on Weak-form efficiency:

On the basis of the tests conducted, the statistical inference is that the series is not weak-form efficient in the period of the tests. The level data has a unit root, but the number of runs is not random although the data shows that there is no autocorrelation and heteroscedasticity at the first difference (at the 5% level). Furthermore, variance ratio tests at level explain that stock prices do not move randomly. Therefore, results support the inference of weak-form inefficiency over the period tested.

Application of prediction models:

Prediction on ACC.L by applying double and triple exponential smoothing techniques:

Series	Selected sub-sample period of 204 observations from clean period for estimation	Forecasted/evaluation period of 4 observations after the estimation period
ACC.L	01/08/2016 – 22/06/2020	29/06/2020 – 20/07/2020

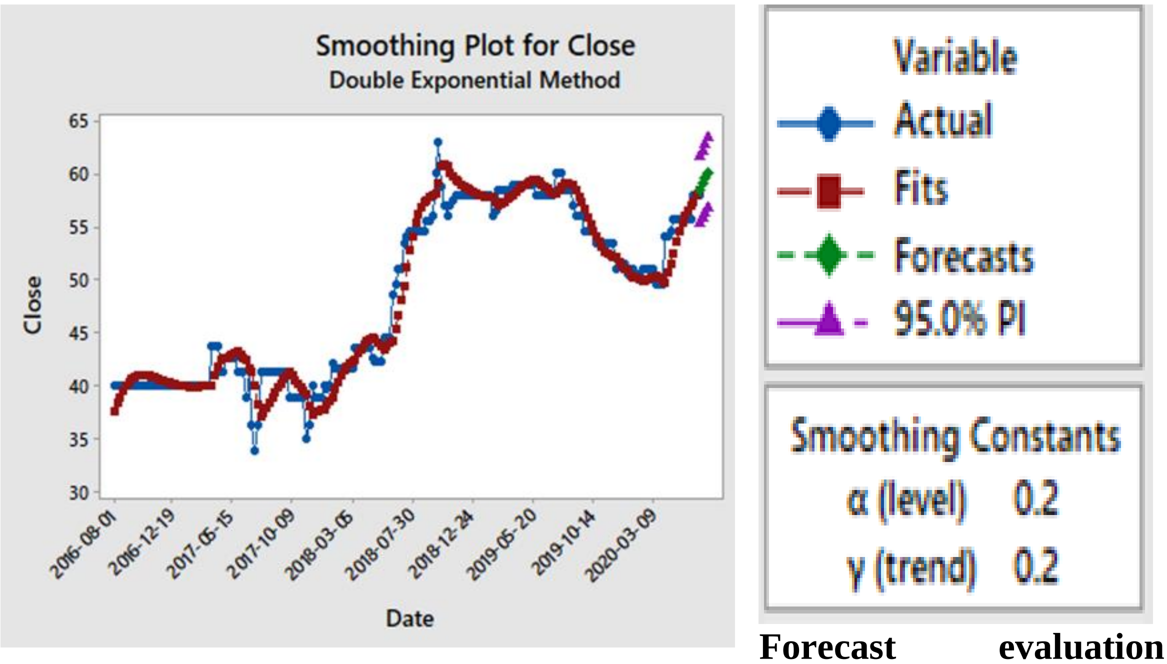
Double exponential smoothing technique:

Smoothing Constants
α (level) 0.2
γ (trend) 0.2

Forecasts

Period	Forecast	Lower	Upper
2020-06-29	58.4928	55.3370	61.6486
206	59.0363	55.8147	62.2578
207	59.5798	56.2874	62.8722
208	60.1233	56.7554	63.4912

Figure 3: Forecasting from Double exponential smoothing technique for ACC.L



Forecast evaluation statistics:

Forecast Evaluation
Date: 02/12/24 Time: 11:04
Sample: 7/06/2020 7/27/2020
Included observations: 4
Evaluation sample: 7/06/2020 7/27/2020
Training sample: 7/06/2020 7/27/2020
Number of forecasts: 6

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	2.805178	2.002500	3.183003	3.261697	0.023494	0.796858
Simple mean	2.805178	2.002500	3.183003	3.261697	0.023494	0.796858
Simple median	2.805178	2.002500	3.183003	3.261697	0.023494	0.796858
Least-squares	2.805178	2.002500	3.183003	3.261697	0.023494	0.796858
Mean square error	2.805178	2.002500	3.183003	3.261697	0.023494	0.796858
MSE ranks	2.805178	2.002500	3.183003	3.261697	0.023494	0.796858

*Trimmed mean could not be calculated due to insufficient data

Triple exponential smoothing- Multiplicative Method:

Smoothing Constants

α (level) 0.2
γ (trend) 0.2
δ (seasonal) 0.2

Forecasts

Period	Forecast	Lower	Upper
205	56.5385	53.3752	59.7018
206	56.5826	53.3697	59.7954
207	58.6874	55.4193	61.9555
208	61.1284	57.7996	64.4572

Forecast Evaluation
Date: 18/03/24 Time: 10:05
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	7.387255	0.1129

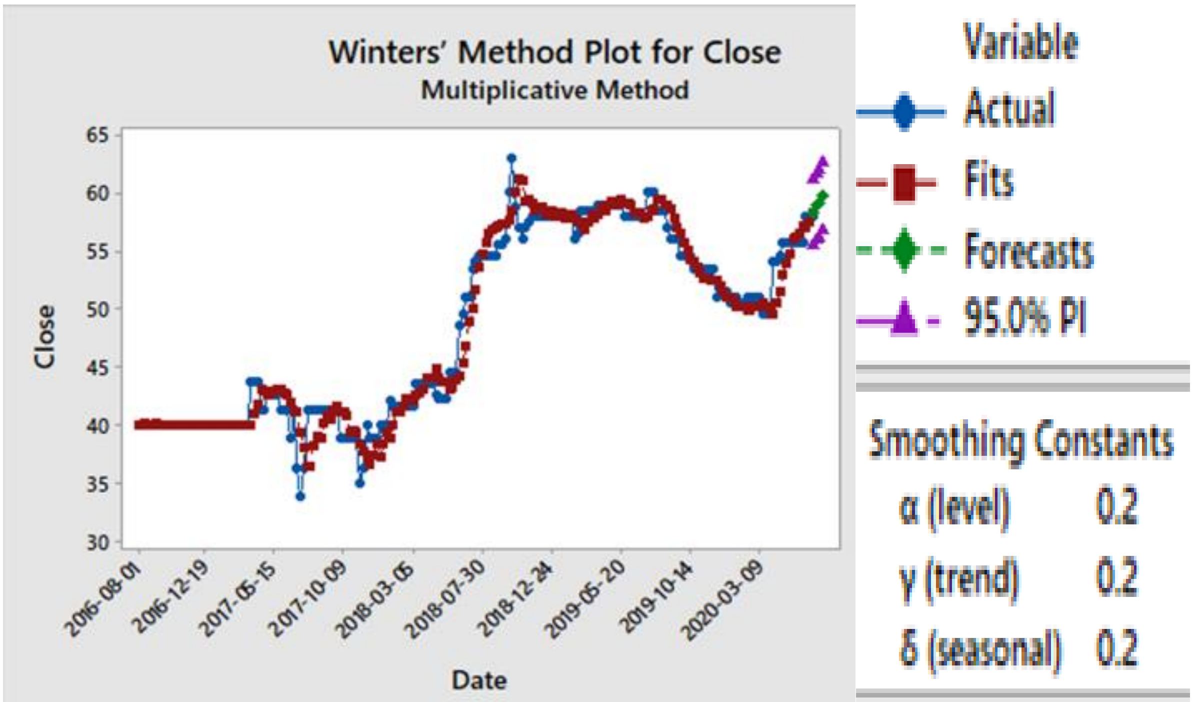
Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-188.9152	0.0000	0.0000	1.0000
Sq Error	-251.3027	0.0000	0.0000	1.0000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	1.698602	1.550000	2.662725	2.651864	0.014594	6.134949
C	57.12541	57.12500	98.27955	193.2346	0.966174	198.0328
Simple mean	28.51754	28.50750	49.04979	65.01243	0.324957	97.95116
Simple median	28.51754	28.50750	49.04979	65.01243	0.324957	97.95116
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	1.694418	1.548520	2.660369	2.651825	0.014564	6.068590
MSE ranks	18.99842	18.96833	32.63987	39.03741	0.195252	64.64751

Figure 4: Forecasting from multiplicative method for ACC.L



Holt-Winters’ additive method:

Forecasts

Winters’ Method for Close

Additive Method
Data Close
Length 205

Smoothing Constants

α (level) 0.2
γ (trend) 0.2
δ (seasonal) 0.2

Forecasts

Period	Forecast	Lower	Upper
205	58.0831	54.9767	61.1895
206	58.4594	55.3044	61.6145
207	60.4129	57.2036	63.6223
208	62.4317	59.1628	65.7006

Forecast Evaluation
Date: 18/03/24 Time: 10:32
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	5.701679	0.1396

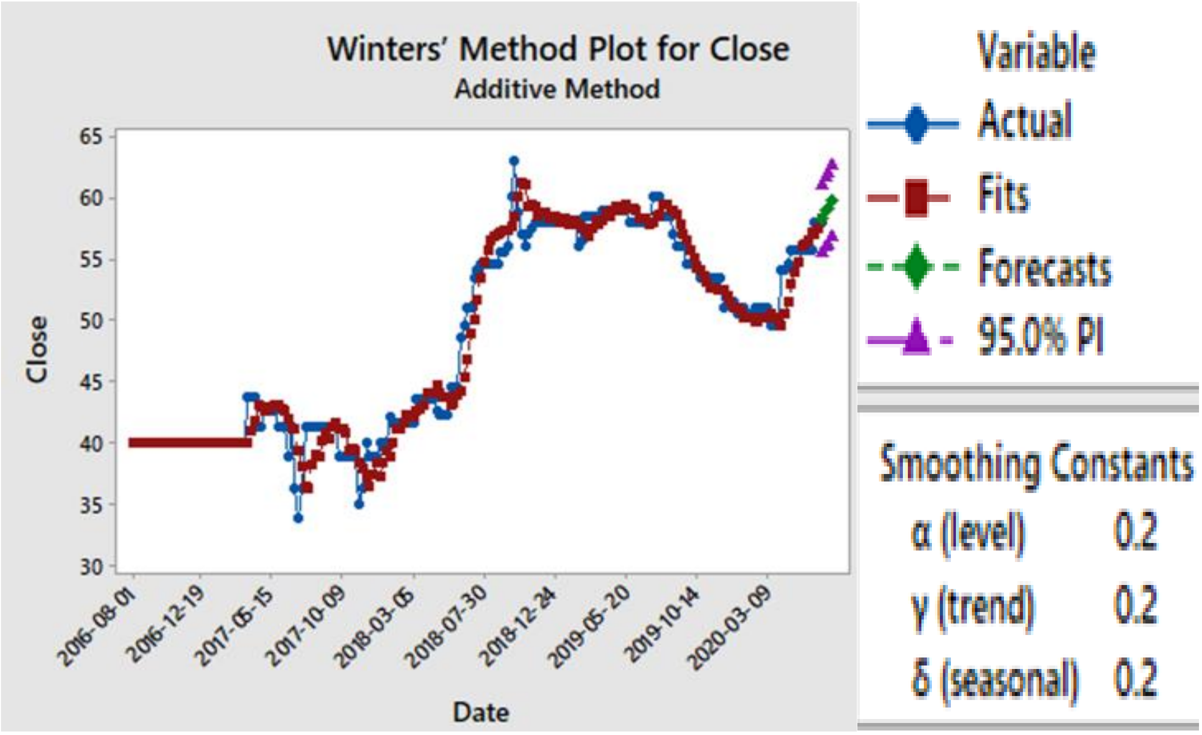
Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-69.55166	0.0000	0.0000	1.0000
Sq Error	-295.2216	0.0000	0.0000	1.0000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	2.316841	1.720000	2.951039	2.874509	0.019635	9.265981
C	57.12541	57.12500	98.27955	193.2346	0.966174	198.0328
Simple mean	27.71109	27.70250	47.66425	62.59772	0.312907	95.11354
Simple median	27.71109	27.70250	47.66425	62.59772	0.312907	95.11354
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	2.244071	1.630234	2.796641	2.724808	0.019034	8.976242
MSE ranks	17.92161	17.89500	30.79249	36.42188	0.182182	60.85264

Figure 5: Forecasting from additive method for ACC.L



Comparison of evaluation statistics from all three applied models:

The table below shows that double exponential smoothing technique performs better than triple exponential smoothing techniques (additive and multiplicative). This is because, Theil U_2 is less than 1 from this method, which indicates double exponential smoothing technique has higher forecastability than triple exponential smoothing techniques (Omnia, 2016), although MAPE documents the opposite. MAPE in this case would not be taken into consideration as there is no specific guideline about what the percentage of MAPE would be considered reliable for forecasting (Gilliland, 2010 and Chen et al. 2017). Naïve method (the last value in the observations for predicting the next value) performs better than triple exponential smoothing methods as their U_2 is greater than 1.

Models	MAPE	Theil U_1	Theil U_2
Holt's Double exponential smoothing	3.18	0.023	0.79
Holt-Winters' Multiplicative model	2.66	0.014	6.13
Holt-Winters' Additive model	2.95	0.019	9.26

Chapter Five: Data Analysis and Findings

Part B: Summarised Analysis of all series and their findings

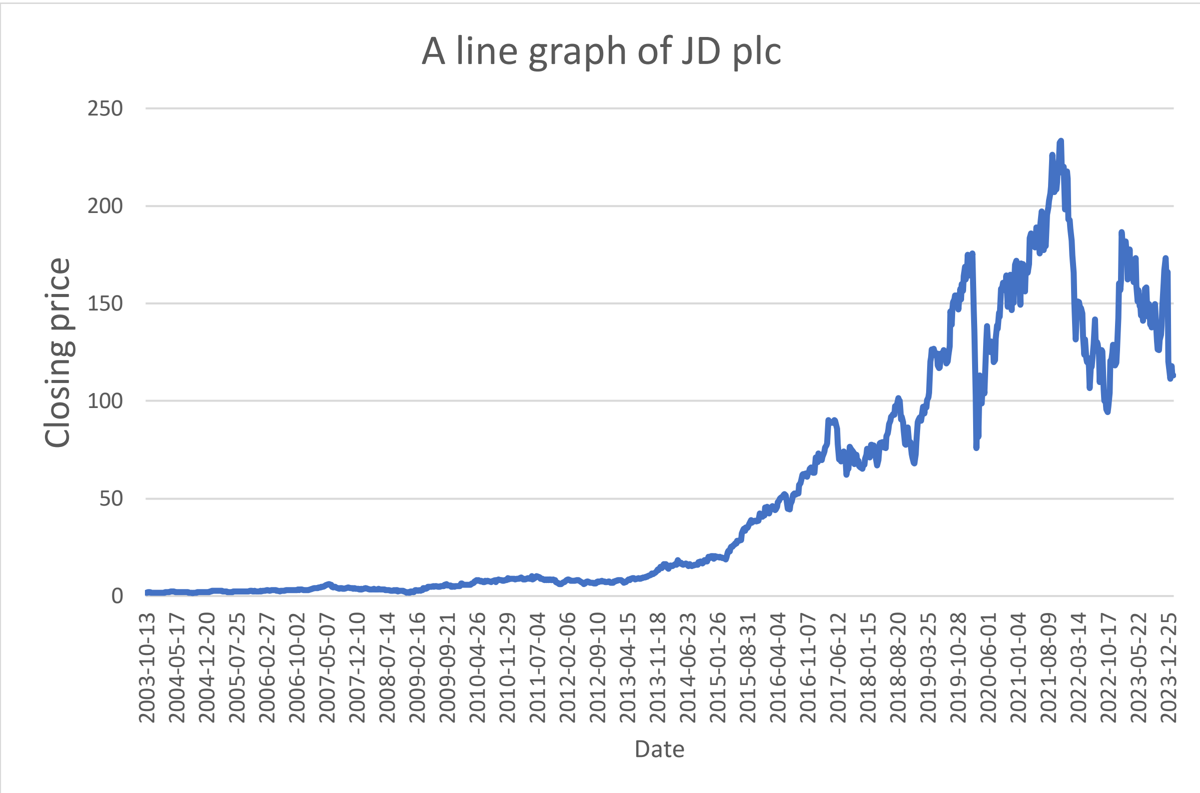
In this chapter, part B summarises and compares the results in a table and analyse the findings, following the same stages as completed in the earlier part of chapter five. The next section draws and analyse line graphs and histogram with kernel density line to find out the characteristics of data.

Line graphs and Histogram with Kernel Density line:

2(a): A line graph for JD.L

Figure 7 below details that stock prices were very low at the beginning of the sample period. It began to increase gradually with little fluctuations. It is apparent that there are some structural breakpoints in the period between 18 November 2013 and 25 December 2023.

Figure 6: A line graph for JD.L for the period between 13 October 2003 and 2 February 2024

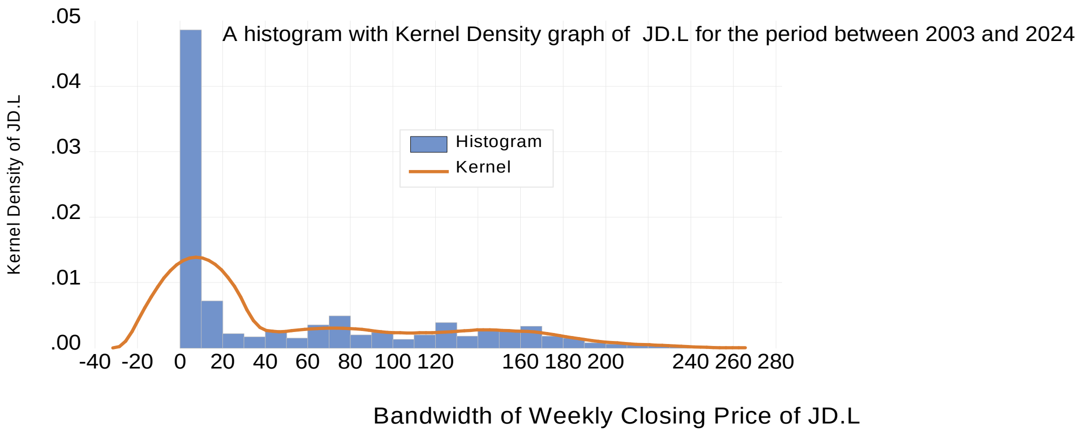


Source: Diagram generated by author with database for the period of 13 October 2003 to 2 February 2024.

2(b): A histogram with Kernel Density graph for JD.L

The graph 8 below shows that it has got several peaks. As the stock prices frequently increase and decrease, the diagram takes a multimodal shape. Furthermore, the distribution is skewed to the right and it is positively skewed.

Figure 7: A histogram with Kernel Density graph for JD.L for period from 13 October 2003 to 2 February 2024

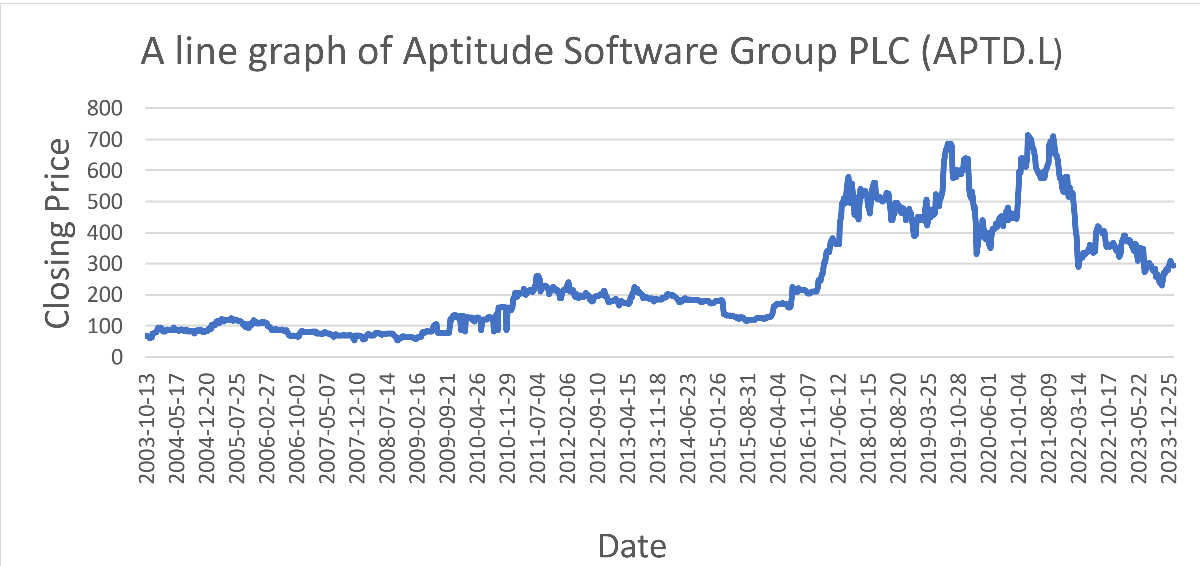


Source: Diagram generated by author with database for the period of 13 October 2003 to 2 February 2024.

3(a): A line graph for APTD.L

The figure 9 below illustrates that stock prices of APTD.L were low and steady at the beginning of the sample period. However, the prices fluctuated very frequently at the end of the sample period.

Figure 8: A line graph for APTD.L for the period between 13 October 2003 and 2 February 2024

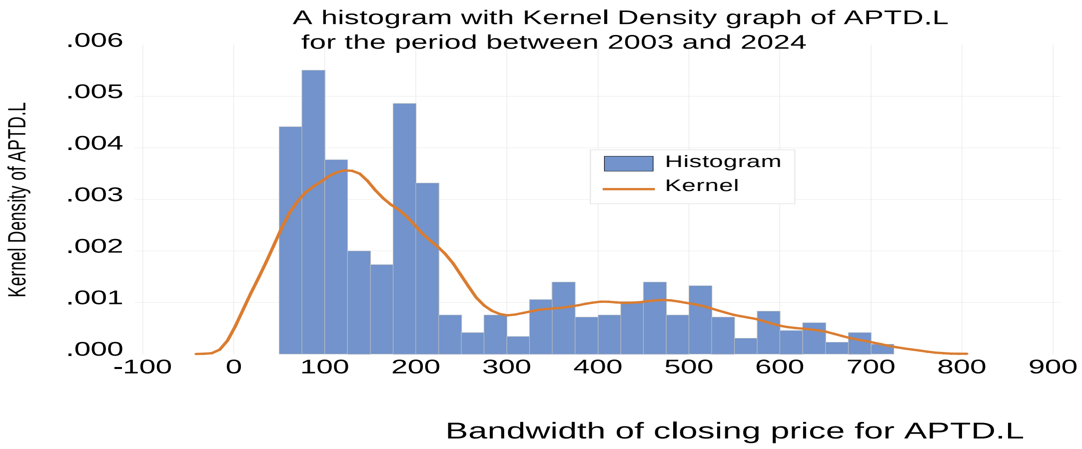


Source: Diagram generated by author with database for the period of 13 October 2003 to 2 February 2024.

3 (b): A histogram with Kernel Density graph for APTD.L

As the stock prices changed frequently from low to high and high to low, the kernel density line created two peaks in the histogram. Neither of the peaks are normally distributed. As the prices constantly rise and fall, the figure takes a bimodal shape.

Figure 9: A histogram with Kernel Density graph for APTD.L for the period between 13 October 2003 and 2 February 2024

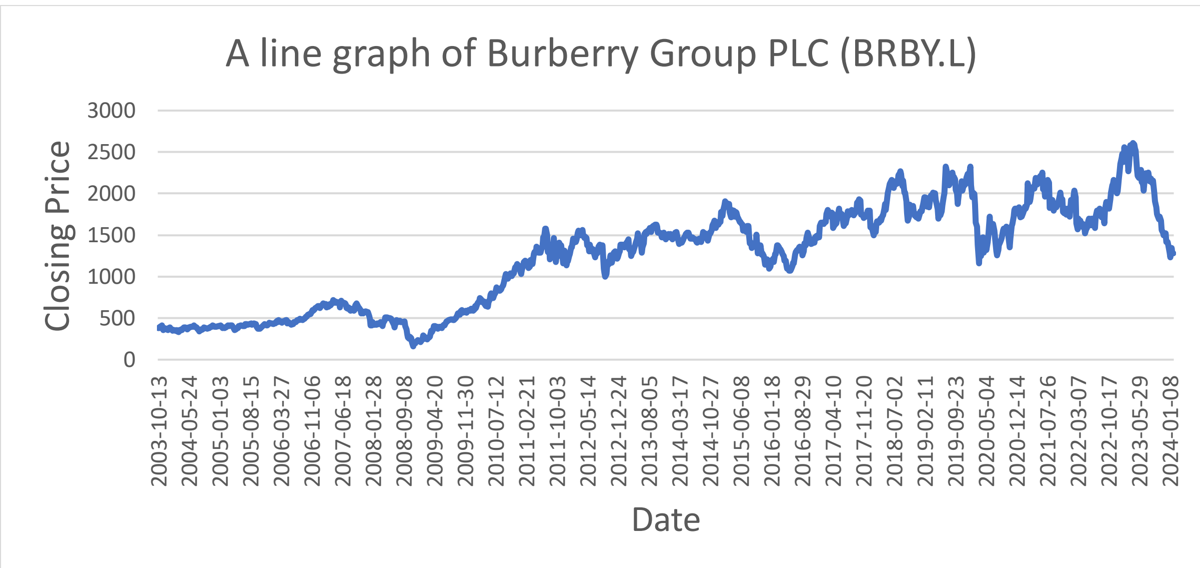


Source: Diagram generated by author with database for the period of 13 October 2003 to 2 February 2024.

4(a): A line graph of BRBY.L

The line graph 11 below shows the behaviour of the stock price of BRBY plc. The stock prices move up and down very frequently and rapidly. Thus, the trend is challenging to identify, and the future price of this company seems to be unpredictable.

Figure 10: A line graph for BRBY.L for the period between 13 October 2003 and 2 February 2024

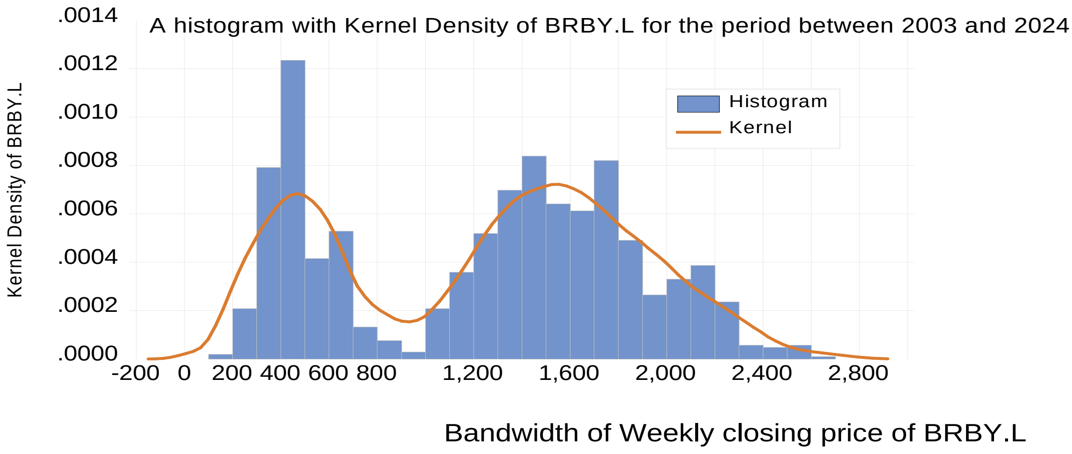


Source: Diagram generated by author with database for the period of 13 October 2003 to 2 February 2024.

4(b): A histogram with Kernel Density for BRBY.L

The kernel density line below explains whether data is normally distributed or not. The graph 12 below shows the histogram is not normally distributed and it has got two peaks. As the stock prices move up and down constantly, the graph takes a bimodal shape.

Figure 11: A histogram with Kernel Density graph for BRBY.L for the period between 13 October 2003 and 2 February 2024

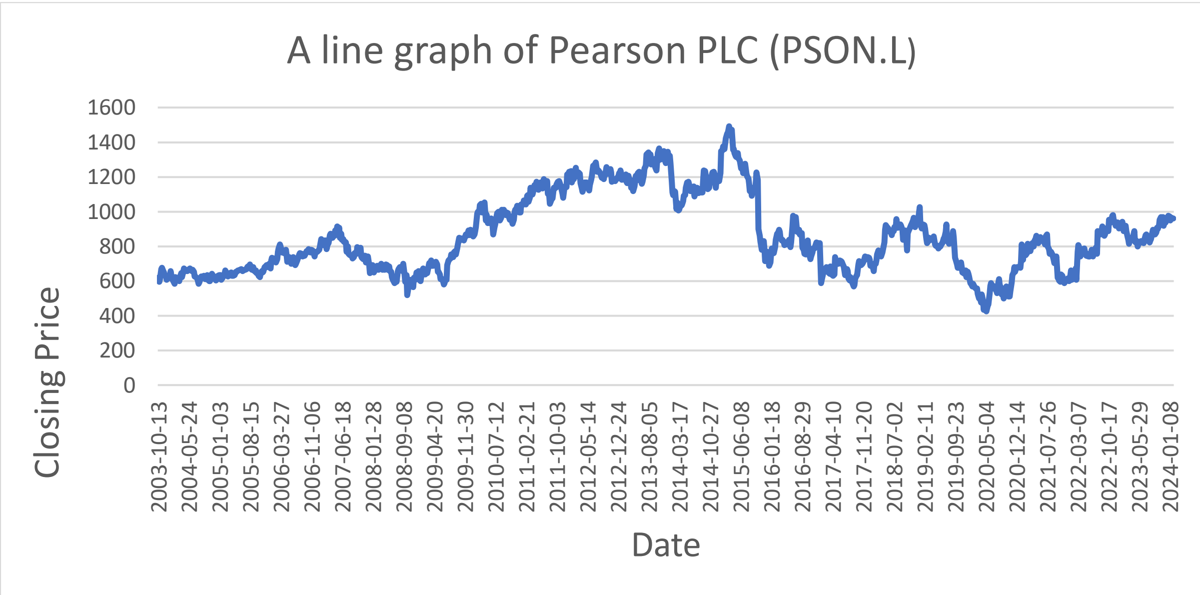


Source: Diagram generated by author with database for the period of 13 October 2003 to 2 February 2024.

5(a): A line graph for PSON.L

The figure 13 below depicts that the stock prices altered up and down very repeatedly throughout the whole sample period.

Figure 12: A line graph for PSON.L for the period between 13 October 2003 and 2 February 2024

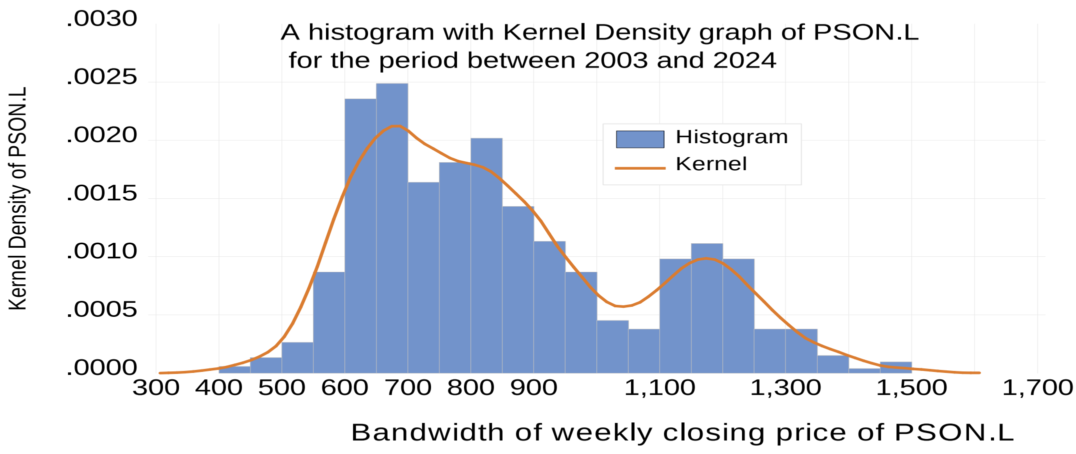


Source: Diagram generated by author with database for the period of 13 October 2003 to 2 February 2024.

5(b): A histogram with Kernel Density graph for PSON.L

As the stock prices moved up and down repeatedly, the kernel density line created two peaks in the histogram and graph is bimodal shape. The figure details it is not normally distributed.

Figure 13: A histogram with Kernel Density graph for PSON.L for the period between 13 October 2003 and 2 February 2024

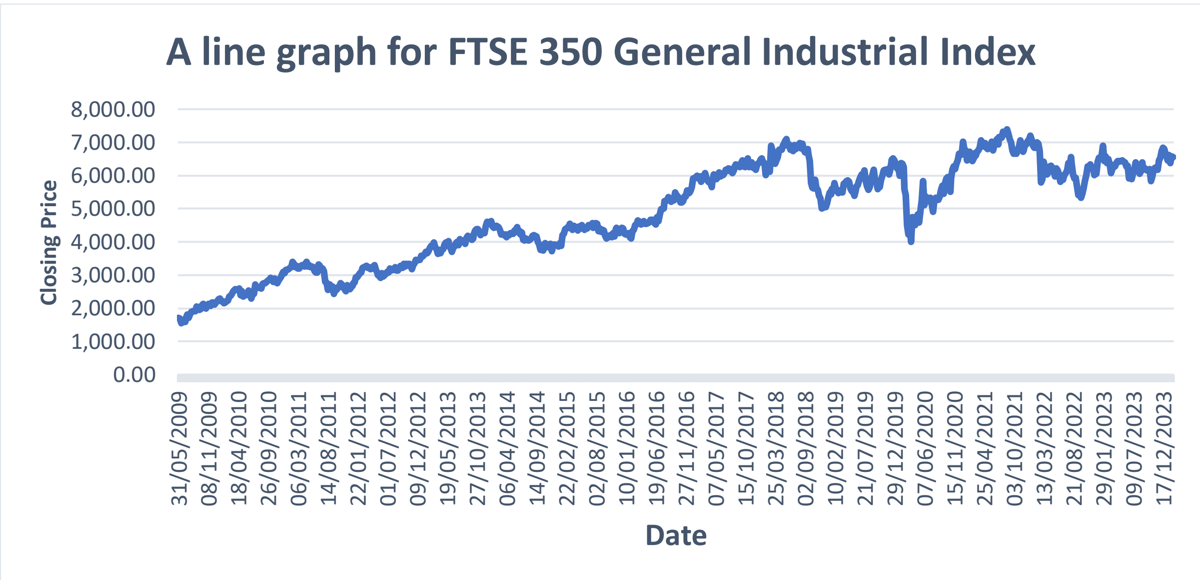


Source: Diagram generated by author with database for the period of 13 October 2003 to 2 February 2024.

6(a): A line graph for FTSE-350 General Industrial Index

The figure 15 below illustrates that the trend line is upward with frequent fluctuations. At the starting of the sample period, the prices were low. However, they begun to rise steadily and gradually from beginning to end of the sample period.

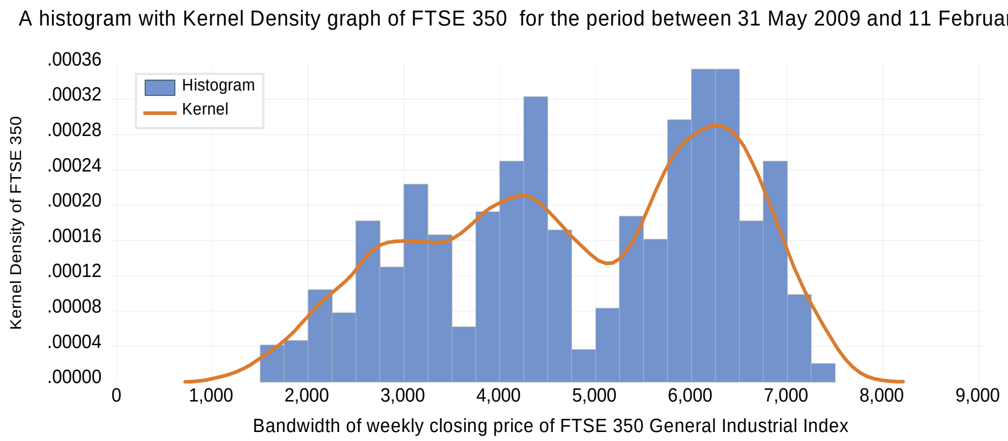
Figure 14: A line graph for FTSE 350 General Industrial Index for the period between 31 May 2009 and 11 February 2024



Source: Diagram generated by author with database for the period of 31 May 2009 to 11 February 2024.

The kernel density line with histogram in figure 16, explains histogram is not normally distributed. As stock prices shifted from downward to uptrend and upward to downward trend repeatedly, the Kernel density line created multimodal shape in the histogram for FTSE-350 General Industrial Index.

Figure 15: A histogram with Kernel Density graph for FTSE 350 General Industrial Index for the period between 31 May 2003 and 11 February 2024



Source: Diagram generated by author with database for the period of 31 May 2009 to 11 February 2024.

(i) Descriptive statistics:

The table -1 below shows descriptive statistics of five different companies in the creative industry and FTSE 350 General Industrial Index. There are 1061 weekly observations for each company in the creative industry (n = 1061). However, FTSE-350 has got 768 observations due to unavailability.

The table below shows that BRBY.L has got the highest mean of 1240.65 in the creative industry, indicating the weekly stock price of BRBY.L is 1240.65 on average. Contrary to that, FTSE 350 General Industrial Index has got average share price of 4840.11. This result indicates there is a significant difference in price between other industry and the creative industry. Furthermore, JD.L has got the lowest average stock price of 52.21. Thus, JD.L has got the lowest standard error of mean of 1.90 and standard deviation of 62.14 and variance of 3861.95 in the creative industry. Moreover, FTSE 350 has got the highest standard error of mean of 54.43 and standard deviation of 1508.60 and variance of 2275898.88.

Similarly, BRBY.L has got the highest standard error of mean of 18.92 and standard deviation of 616.41 and variance of 379966.29 in the creative industry. All the series have got kurtosis less than 3 except ACC.L. This indicates all these series are flat or platykurtic (Eviews, version 8). Carmody (2013) suggests that platykurtic distribution provides an indication of a greater chance of extreme outcomes (either loss or profit). However, ACC.L has got kurtosis more than 3, indicating distribution is peaked (leptokurtic) relative to the normal. These leptokurtic and platykurtic distributions suggest that stock prices are not normally distributed (Killam, 2014).

On the other hand, BRBY.L and FTSE 350 have got negative skewness and the remaining other series have got positive skewness. Carmody (2013) claims that a negatively skewed distribution has frequent small gains and a few extreme losses while a positively skewed distribution indicates frequent small losses and a few extreme gains. Killam (2014) argues that negative and positive skewness confirm that stock prices are not normally distributed. These results of non-normal frequency distribution of the stock price confirm that the market does not follow a random-walk model (prices do not move randomly) and stock prices are predictable.

Table 1: Descriptive Statistics of all series for the full-sample period

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
ACC.L	1061	430.38	4.63	435.00	72.6956	2.48609	80.979	6557.681	3.608	.075	12.723	.150
JD.L	1061	231.92	1.48	233.40	52.2090	1.90785	62.144	3861.936	1.032	.075	-.279	.150
APTD.L	1061	661.10	52.90	714.00	245.0842	5.34294	174.035	30288.347	.915	.075	-.353	.150
BRBY.L	1061	2449.00	160.00	2609.00	1240.6566	18.92408	616.414	379966.296	-.110	.075	-1.202	.150
PSON.L	1061	1067.00	425.00	1492.00	856.6878	6.79163	221.224	48939.899	.631	.075	-.571	.150
FTSE350	768	5843.53	1548.76	7392.29	4840.1154	54.43721	1508.608	2275898.882	-.279	.088	-1.134	.176
Valid N (listwise)	768											

Note: The above table analyses the weekly closing price of the following companies in the creative industry: Access Intelligence plc (ACC.L), JD plc (JD.L), Aptitude Software Group plc (APTD.L), Burberry Group PLC (BRBY.L), Pearson PLC (PSON.L).

Source: Output of descriptive statistics using spss

(ii) Bai-Perron’s multiple breakpoints test

STATA (2024) details that structural breaks take place when a time series sharply changes at a point of time due to heteroskedasticity or volatility influenced by micro (e.g. launching a highly demanding product) or macroeconomic variables (e.g. recession, inflation).
Visual examination of each series at the beginning of this chapter documents that there could be a few breakpoints. Therefore, the Bai-Perron’s multiple breakpoints test of sequential L+1 breaks vs. L has been applied to determine breaks for each series.

The table below shows all the p values are significant at 1% level. The full test for each series is shown in the appendix. The table below shows a several breakpoints at different point of time for each series. Furthermore, table shows clean periods where there are no breaks, and these clean periods will be considered for prediction and validation of the predictability of models rather than the periods with structural breaks. This is because, predictions would not achieve accuracy during the volatile periods.

Table 2: Bai-Perron's multiple breakpoints test for the full-sample period

Series	Break date	Clean period	Obser-vation	Co-efficient	Standard error	t-statistic	P value
ACC.L	10/30/2006 8/03/2020	10/13/2003 – 10/23/2006	159	181.91	5.05	36.00	0.00***
		10/30/2006 – 7/27/2020	718	42.45	2.38	17.85	0.00***
		8/03/2020 – 2/02/2024	184	96.32	4.70	20.50	0.00***
JD.L	12/04/2010 18/05/2015 15/04/2019	13/10/2003 – 5/04/2010	339	3.23	0.96	3.37	0.00***
		12/04/2010 – 11/05/2015	266	10.92	1.08	10.09	0.00***
		18/05/2015 – 8/04/2019	204	65.30	1.23	52.89	0.00***
		15/04/2019 – 2/02/2024	252	151.08	1.11	135.99	0.00***
APTD.L	4/10/2010 17/02/2014 6/03/2017 23/03/2020	**13/10/2003 – 27/09/2010**	364	88.10	3.54	24.90	0.00***
		4/10/2010 – 10/02/2014	176	196.44	5.09	38.61	0.00***
		17/02/2014 – 27/02/2017	159	169.98	5.35	31.75	0.00***
		6/03/2017 – 16/03/2020	159	495.05	5.35	92.48	0.00***

		23/03/2020 – 2/02/2024	203	431.79	4.74	91.14	0.00***
BRBY.L	30/10/2006	13/10/2003 – 23/10/2006	159	410.42	15.93	25.76	0.00***
	13/09/2010	30/10/2006 – 6/09/2010	202	534.63	14.13	37.82	0.00***
	16/12/2013	13/09/2010 – 9/12/2013	170	1318.40	15.41	85.56	0.00***
	16/01/2017	16/12/2013 – 9/01/2017	161	1452.56	15.83	91.74	0.00***
	25/01/2021	**16/01/2017 – 18/01/2021**	210	1798.78	13.86	129.75	0.00***
		25/01/2021 – 2/02/2024	159	1933.02	15.93	121.33	0.00***
PSON.L	1/03/2010	13/10/2003 – 22/02/2010	333	700.85	5.99	117.02	0.00***
	19/10/2015	1/03/2010 – 12/10/2015	294	1161.48	6.38	182.22	0.00***
	25/01/2021	**19/10/2015 – 18/01/2021**	275	742.13	6.59	112.60	0.00***
		25/01/2021 – 2/02/2024	159	817.62	8.67	94.33	0.00***
FTSE350	30/12/2012	31/05/2009- 23/12/2012	187	2748.54	38.49	71.40	0.00***
	7/08/2016	30/12/2012 – 31/07/2016	188	4221.31	38.39	109.96	0.00***
	8/11/2020	**7/08/2016 – 1/11/2020**	222	5877.21	35.32	166.37	0.00***
		8/11/2020 – 11/02/2024	171	6464.46	40.25	160.60	0.00***

Note: The above table analyses the weekly closing price of the following companies in the creative industry: Access Intelligence plc (ACC.L), JD plc (JD.L), Aptitude Software Group plc (APTD.L), Burberry Group PLC (BRBY.L), Pearson PLC (PSON.L).

Source: Output of Bai-Perron's multiple breakpoints test using Eviews, SV-12

The forecasting principles explain that estimation period should not include a large number of observations and it should be around 200 observations. This is because, most time series do not work for very long period (Hyndman and Athanasopoulos, 2018). Therefore, the estimation period in this study includes 204 observations and validation period includes 4 more observations after the estimation period for out-of-sample forecasts. These 204 observations will be selected from the latest clean period where there is no breakpoint and 4 more observations after the estimation period to evaluate forecast accuracy and model's predictability.

Table 3: Selection of sub-sample period for data analysis and evaluation period based on forecasting principles

Series	Selected sub-sample period of 204 observations from clean period for estimation	Forecasted/evaluation period of 4 observations after the estimation period
ACC.L	01/08/2016 – 22/06/2020	29/06/2020 – 20/07/2020
JD. L	17/02/2020 – 08/01/2024	15/01/2024 – 02/02/2024
APTD.L	09/10/2006 – 30/08/2010	06/09/2010 – 27/09/2010
BRBY.L	30/01/2017 – 21/12/2020	28/12/2020 – 18/01/2021
PSON.L	30/01/2017 – 21/12/2020	28/12/2020 – 18/01/2021
FTSE 350	13/11/2016 – 04/10/2020	11/10/2020 – 01/11/2020

Note: The above table analyses the weekly closing price of the following companies in the creative industry: Access Intelligence plc (ACC.L), JD plc (JD.L), Aptitude Software Group plc (APTD.L), Burberry Group PLC (BRBY.L), Pearson PLC (PSON.L).

Source: Output of selected sub-sample period based on forecasting principles

Testing weak-form efficiency on selected Sub-sample period:

(i) Runs test at level:

The results of runs test are shown below and full tests are shown in the appendix. The table - 4 below shows that p values from all series are less than 5% (0.00<0.05). These results indicate that stock prices of all series listed below are not random. Thus, stock prices of LSE do not move randomly.

Furthermore, Z value is more than 1.96 (Z > ±1.96), indicating null hypothesis of random is rejected at 5% level of significance (Sharma and Kennedy, 1977).

Therefore, it could be claimed on the basis of runs test that share prices do not move randomly, and they are predictable.

Hypothesis:
Null: Stock prices change randomly
Alternative: Stock prices do not change randomly

Table 4: Runs test on all series for the selected sub-sample period of 204 observations

Series	**Total number of runs**	**Z statistic**	**P value**
ACC.L	4	-13.90	0.00***
JD.L	20	-11.65	0.00***
APTD.L	12	-12.773	0.00***
BRBY.L	29	-10.388	0.00***
PSON.L	13	-12.634	0.00**
FTSE 350	17	-12.072	0.00**

Note: The above table analyses the weekly closing price of the following companies in the creative industry: Access Intelligence plc (ACC.L), JD plc (JD.L), Aptitude Software Group plc (APTD.L), Burberry Group PLC (BRBY.L), Pearson PLC (PSON.L).

Source: Output of runs test found from applying SPSS

(ii) Unit Root Test:

Augmented Dickey Fuller (ADF)- unit root test is run using Schwarz Information Criterion (SIC). Furthermore, it is run under trend and intercept. The table 5 below shows that all series data have unit root at level. This is because, critical values are bigger than test statistics and their p values are more than 5% (p values > 0.05). Thus, data are non-stationary at level.

Furthermore, when first difference of data is applied for all series, it is found that their test statistics are significantly bigger than critical values and all the p-values are 0.000 at the 1% level of significance. Therefore, the null hypothesis of data has a unit root could be rejected at first difference and it can be decided that the weekly closing prices of all series are stationary (no unit root) at first difference.

Hypothesis:

Null hypothesis: Closing price/D(Closing price) has a unit root
Alternative hypothesis: Closing price/D(Closing price) has no unit root

Table 5: ADF-Unit Root test on all series for the selected sub-sample period of 204 observations

Series	t-statistic at level (close)	t-statistic at first difference, D(close)
ACC.L	-1.804875	-11.53155
P value	(0.699)	(0.000)***
JD.L	-2.119137	-14.65411

P value	(0.5316)	(0.000)***
APTD.L	-2.804189	-18.83524
P value	(0.19750)	(0.000)***
BRBY.L	-2.469356	-13.38918
P value	(0.3431)	(0.000)***
PSON.L	-1.820433	-13.94706
P value	(0.6914)	(0.000)***
FTSE 350 Gen. Indus. Index	-3.069342	-15.71041
P value	(0.1166)	(0.000)***

Note 1: Their critical values for ADF at 1% level of significance are -4.003902 (at level) and -4.004365 (at first difference). p-value < 1% = ***

Note 2: The above table analyses the weekly closing price of the following companies in the creative industry: Access Intelligence plc (ACC.L), JD plc (JD.L), Aptitude Software Group plc (APTD.L), Burberry Group PLC (BRBY.L), Pearson PLC (PSON.L).

Source: Outcome of ADF-unit root test from sub-sample period of different series using Eviews, SV-12

(ii) Autocorrelation : Ljung-Box (LB) test

The table below shows Ljung-Box's serial autocorrelation at the first difference to detect whether the time series data is serially auto correlated or not. They have been measured up to 24 lags and shown in the appendix. As all the series have got p values more than 5% at first difference except APTD.L, the null hypothesis is accepted that all these series do not have any serial autocorrelation, indicating there is no correlation between past values and current values of data.

These results evidence that all these series follow a random walk model, and their future prices are not predictable. Conversely, APTD.L shows that p-value is less than 5% for all 24 lags. This result argues that data of APTD.L are strongly auto correlated. Thus, this series does not follow a random walk model and its future values are predictable.

Null hypothesis: Time series is not auto-correlated (no serial auto-correlation)

Alternative hypothesis: Time series is auto-correlated

Table 6: Autocorrelation test at first difference on all series for the selected sub-sample period of 204 observations

Series	P value
ACC.L	More than 5% for up to 19 lags
JD.L	More than 5% for all 24 lags

APTD.L	Less than 5% for all 24 lags
BRBY.L	More than 5% for all 24 lags
PSON.L	More than 5% for all 24 lags
FTSE 350 General Industrial Index	More than 5% for all 24 lags

Note: The above table analyses the weekly closing price of the following companies in the creative industry: Access Intelligence plc (ACC.L), JD plc (JD.L), Aptitude Software Group plc (APTD.L), Burberry Group PLC (BRBY.L), Pearson PLC (PSON.L).

Source: output of autocorrelation test for sub-sample period is performed using Eviews, SV-12

(iii) Heteroscedasticity test through Single and multiple variance ratio (VR) tests at level:

The table -7 below explains two types of variance ratio tests including individual test of Lo and MacKinlay (1988) and the other one is the Chow and Denning (1993) multiple VR test. The tests consider variance ratio test (VR), homoscedasticity test statistic Z(q), heteroscedasticity test statistic Z*(q) and Chow-Denning's joint test for weekly observations of the following series.

In the Chow-Denning joint test, the p values are greater than 5% for all series including the creative industry and FTSE-350 General Industrial Index. This result indicates that the acceptance of null hypothesis that weekly closing prices of all series follow a martingale (a probability that next value in the sequence is equal to the present value, regardless of all prior values) rather than a random walk model.

VRs are less than 1 for JD.L, APTD.L and FTSE-350 General Industrial Index in all periods including 2,4, 8 and 16, which indicate, these series do not follow a random walk model at all and there is a negative or mean reverting relationship in the stock prices of these series. Furthermore, the null hypothesis is accepted that these series follow a martingale.

VR is more than 1 for the series of BRBY.L in all periods including 2,4,8 and 16, indicating a strong positive relationship in the prices.

Conversely, ACC.L and PSON.L show VRs is 1 in period 2, indicating they follow a random walk model. However, these series have got VRs less than 1 the in periods of 4, 8 and 16, indicating they follow a martingale rather than a random walk model.

It could be concluded on the basis of above findings that multiple variance ratio tests show all the series follow a martingale rather than a random walk model. Furthermore, single variance ratios evidence that most of the series follow a martingale. Thus, weekly closing prices do not move randomly.

Hypotheses:
Null hypothesis: Stock price follows a martingale
Alternative hypothesis: Stock price does not follow a martingale

Table 7: Single and multiple variance ratio (VR) tests on the selected sub-sample period for all series

Series		**q = 2**	**q = 4**	**q = 8**	**q = 16**	**Chow-Denning joint test (Max |Z|) and p value**
ACC.L	VR	1.050704	0.881705	0.880360	0.938914	0.587154
	Z	0.465391	-0.564937	-0.387573	-0.156621	and p value
	Z*	0.108948	0.209395	0.308692	0.390025	= 0.9830
JD.L	VR	0.971814	0.914747	0.750945	0.820564	1.048867
	Z	-0.340526	-0.551760	-1.048867	-0.547863	and p value
	Z*	0.082773	0.154511	0.0.237451	0.327520	= 0.7519
APTD.L	VR	0.649465	0.422502	0.354527	0.245486	2.051900
	Z	-1.940362	-2.051900	-1.588220	-1.447746	and p value
	Z*	0.180655	0.281446	0.406413	0.521164	= 0.1513
BRBY.L	VR	1.060158	1.211523	1.141263	1.021023	1.371749
	Z	0.734302	1.371749	0.576209	0.058281	and p value
	Z*	0.081925	0.154199	0.245160	0.360727	= 0.5257
PSON.L	VR	1.022252	0.970805	0.866699	0.874092	0.632354
	Z	0.261897	-0.199972	-0.632354	-0.410459	and p value
	Z*	0.084963	0.145994	0.210802	0.306748	= 0.9500
FTSE 350	VR	0.899964	0.947457	0.906395	0.844477	0.974677
	Z	-0.974677	-0.272180	-0.312821	-0.367434	and p value
	Z*	0.102635	0.193046	0.299228	0.423266	= 0.7982

Note: The above table analyses the weekly closing price of the following companies in the creative industry: Access Intelligence plc (ACC.L), JD plc (JD.L), Aptitude Software Group plc (APTD.L), Burberry Group PLC (BRBY.L), Pearson PLC (PSON.L).

Source: Output of heteroscedasticity test found from applying Eviews, SV-12

Statistical inference regarding weak-form market efficiency:

A market is weak-form efficient (i.e. a market is not predictable based on historical prices) if a series follows a random walk (i.e. future prices are not predictable). The meaning of a random walk is that the first differences of series are non-stationary (independent and identically distributed, -i.i.d). Weak-form inefficiency indicates that a series does not have a unit root (at first difference) or serial correlation (at first difference) or heteroscedasticity (at level), Rahman, 2023.

Wooldridge, (2019) explains that when data shows there is no unit root at the first difference of ADF and no serial autocorrelation at first difference from LB test, a market is weak-form inefficient (future prices are predictable based on historical prices).

All the series from runs test at level show that none of the series follows a random walk model. None of the series has got unit root at first difference from ADF- unit root test. Furthermore, correlogram at first difference shows that there is no serial autocorrelation for all series except APTD.L. Moreover, joint test at level shows that all the series follow a martingale rather than random walk.

On the basis of results from four different tests (shown below), statistical inference could be drawn that the creative industry of LSE is not weak-form efficient, indicating future prices are predictable. The results of four different tests are as follows:

Table 8: 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

Note: The above table analyses the weekly closing price of the following companies in the creative industry: Access Intelligence plc (ACC.L), JD plc (JD.L), Aptitude Software Group plc (APTD.L), Burberry Group PLC (BRBY.L), Pearson PLC (PSON.L).

Source: Output of weak-form efficiency test applying Eviews, SV-12

The application of forecasting models and techniques:

This study has applied all proposed models which are shown in the appendix for more details. The forecast evaluation statistics from applied models are explained below.

Forecast evaluation statistics of double exponential smoothing technique:

The table 9 below shows forecast evaluation statistics of MAPE, Theil U_1 and U_2 from Holt's double exponential smoothing technique. Rahman (2023) argued that root mean squared error (RMSE) and mean absolute error (MAE) do not work as benchmark and thus, they have been ignored from the table. Furthermore, Theil inequality coefficient of U_1 does not provide prediction accuracy of a model as it always provides values close to zero, Omnia (2016). Therefore, MAPE and Theil U_2 will be considered with greater importance to evaluate forecast accuracy of the model in this study. Moreover, Gilliland (2010) and Chen et al. (2017) claimed that there is no any guidelines regarding what percentage of MAPE is considered a prediction to be reliable. However, Omnia (2016) argued that if the value of Theil U_2 is less than one (U_2 <1), the prediction method being applied is better than the naïve method. Therefore, this study would evaluate forecasting accuracy based on Theil U_2 mainly.

The following table explains that the lowest MAPE is achieved from PSON.L, which is 1.33. Furthermore, Theil U_1 and U_2 confirm that PSON.L has got the lowest values of 0.009 and 0.63 respectively. Therefore, it could be claimed that PSON.L is highly predictable in the creative industry. The highest MAPE has been calculated from JD.L, which is 31.07. The consistent results have been obtained from Theil inequality coefficients of U_1 and U_2. Furthermore, Theil U_2 confirms that there is point to apply double exponential smoothing technique for JD.L. This forecasting model fails to predict future stock prices of JD.L. Furthermore, Theil U_2 shows that double exponential smoothing technique could not predict future stock prices of BRBY.L. Therefore, it might be claimed that apparel sector in the creative industry is not predictable on the basis of double exponential smoothing model. A higher predictive model, such as, autoregressive integrated moving average (ARIMA) model might be able to forecast the future prices of apparel sector as the market efficiency test explains that creative industry including apparel sector is not weak-form efficient.

Theil U_2 in the table below shows that all the companies as well as FTSE 350 are predictable except apparel sector (JD.L and BRBY.L) from the application of double exponential smoothing technique. Moreover, the results indicate most of the series (4 out of 6) are predictable using double exponential smoothing technique.

Thus, it might be claimed that double exponential smoothing technique has got moderate predictive power.

Table 9: Forecast evaluation statistics of double exponential smoothing technique

Series	MAPE	Theil U1	Theil U2
ACC.L	3.18	0.023	0.79
JD.L	31.07	0.1345	7.31
APTD.L	18.22	0.091	0.70
BRBY.L	4.30	0.028	1.54
PSON.L	1.33	0.009	0.63
FTSE-350	2.68	0.017	0.66

Note: The above table analyses the weekly closing price of the following companies in the creative industry: Access Intelligence plc (ACC.L), JD plc (JD.L), Aptitude Software Group plc (APTD.L), Burberry Group PLC (BRBY.L), Pearson PLC (PSON.L).

A comparison table of forecast evaluation statistics from all 3 applied model:

The table below explains the comparative forecast evaluation statistics from Holt's double exponential smoothing method and Holt-Winters' multiplicative and additive methods of triple exponential smoothing (that consider seasonality in the data). RMSE and MAE have not been considered in the table as they do not work as benchmarks. Moreover, the table considers MAPE, Theil U_1 and U_2 as they work as benchmarks. Furthermore, lower the error, better the model.

The results from ACC.L show that double exponential smoothing technique performs better than triple exponential smoothing techniques (additive and multiplicative). This is because, Theil inequality coefficient of U_2 is less than 1 from this method, which indicates double exponential smoothing technique has higher forecastability than triple exponential smoothing techniques, although MAPE documents the opposite. MAPE in this case would not be taken into consideration as there is no specific guideline about what percentage of MAPE would be considered to be reliable for forecasting. Naïve method (the last value in the observations for predicting the next value) performs better than triple exponential smoothing methods as their U_2 is greater than 1. From the consideration of MAPE, it could be claimed that multiplicative method is the second-best predictor.

The evaluation statistics from JD.L document that none of the forecasting models is better than naïve forecasting. This is because, Theil U_2 is greater than 1 from all applied models. Furthermore, MAPE from JD.L is comparatively higher than other series in this study.

The outcomes from APTD.L evidence that all the applied models have higher predictive ability. The values of U_2 from all applied models are less than 1, indicating forecasting models have higher predictiveability than naïve method. Furthermore, the results show that double exponential smoothing has better forecastability than triple exponential smoothing methods. This is because, Theil U_1 and U_2 are lower from double exponential smoothing compared to multiplicative and additive methods of exponential smoothing techniques, although MAPE shows the opposite. The reason is that data do not have any seasonality evidenced from line graphs and correlogram and triple exponential smoothing considers seasonality in the data. Moreover, the results show additive model is the second-best predictor for APTD.L.

Another apparel company BRBY.L shows that none of the applied methods could predict stock prices precisely. This is because, all applied models generated Theil U_2 greater than 1, which indicate naïve method could predict future prices more precisely than all applied models.

Predictive measures from PSON.L show that Holt's model could predict more accurately than Holt-Winters's models as U_2 is less than 1. This could be due to absence of seasonality in the data. The other two models including multiplicative and additive methods generate U_2 greater than 1. Thus, naïve method could produce better predictability than triple exponential smoothing techniques. Although MAPE is lower from this series compared to APTD.L.

FTSE-350 General Industrial Index (GII) exhibits all applied models could predict future stock prices accurately. Theil U_2 is less than 1 from all applied models for this series. Additionally, U_1 and MAPE are lower for this series. Moreover, the MAPE, Theil $U_1$and U_2 evidenced that Holt's model (double) is the best predictor and multiplicative method is the second-best predictor as lower the error better the model.

Table 10: 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	Double	2.68	0.017	0.66	**Double**
GII	Multiplicative	4.86	0.027	0.77	**Multiplicative**
	Additive	5.49	0.030	0.80	

Note: The above table analyses the weekly closing price of the following companies in the creative industry: Access Intelligence plc (ACC.L), JD plc (JD.L), Aptitude Software Group plc (APTD.L), Burberry Group PLC (BRBY.L), Pearson PLC (PSON.L).

Summary of findings:

The key findings of the study are discussed below in relation to the following issues:

1. Weak-form market efficiency
2. Forecastability of the creative industry
3. Forecastability of the applied models

The statistical inference was made that London Stock Exchange (LSC) is not weak-form efficient based on test results from runs test at level of data, ADF-unit root test at the first difference of data, LB's correlogram at first difference, heteroscedasticity test through variance ratio at level. These tests evidenced that stock prices of LSE, especially the creative industry do not move randomly, and they have serial autocorrelation. Test results support weak-form market inefficiency on the tested sub-sample period and therefore, stock prices of the creative industry could be predictable. However, predictability depends on the robustness of the applied model.

This study examined stock prices of different companies from the creative industry as well as FTSE-350 General Industrial Index. Weak-form efficiency tests draw inference that stock prices of the creative industry are predictable. Furthermore, the applied forecasting models evidence that most of the companies in the creative industry are predictable. The purpose of examination of FTSE-350 GII is to gain general idea about predictability of all other industries in the LSE. The results documented that all other industries are equally predictable same as the creative industry. Therefore, it could be claimed that stock prices of the creative industry as well as other industries are predictable.

Double exponential smoothing technique (Holt model) that does not consider seasonality in the data documented that all the companies in the creative industry as well as the FTSE-350 General Industrial Index are predictable except the apparel sector that included JD plc and Burberry Group plc. A stronger predictive model, for example, ARIMA model could predict the stock prices of apparel sector precisely as weak-form efficiency test shows stock prices are predictable.

The other applied models of triple exponential smoothing techniques including multiplicative and additive models show the limited predictiveability of the series. The reason could be due to absence of seasonality in the data, as triple exponential smoothing (Holt-Winters's) models consider seasonality in the data. Furthermore, it has been documented that data do not have any seasonality which is found through correlogram, and line graphs.

Chapter Six: Discussion

This chapter addresses the synthesised results from the previous chapter (data analysis and findings), links these findings with previous empirical findings from other research papers and finally uncovers the originality of this study.

6.1 A comparison and linking the findings of this study with literature review:

The results from descriptive statistics show that stock prices of the creative industry as well as FTSE-350 General Industrial Index are not normally distributed. The selected series are either platykurtic or leptokurtic. These outcomes are similar to the findings of Al-Jafari (2013), Camellia (2013) and Rahman (2023) who studied stock markets in Turkey, Romania, Hungary, the Czech Republic, Slovakia, Estonia and Brazil, Russia, India and China (BRIC countries), and UK respectively and found that stock prices are not normally distributed, and they are predictable.

The results from the weak-form efficiency test evidence in this study that the LSE including the creative industry and other industry (achieved through FTSE-350 General Industrial Index) is not weak-form efficient and future prices are predictable. This outcome is in the line with Mobarek and Keasey (2000), Chakraborty (2006), Mollah (2007), Abedini (2009), Mishra (2013), Rahman (2023) who documented that stock prices do not behave randomly, returns are predictable and stock markets are not weak-form efficient in Bangladesh, Sri Lanka, Botswana, Bahrain, Kuwait and Dubai, India and UK respectively.

The findings of this study show that double exponential smoothing technique could predict stock prices precisely for most of the series. This result is consistent with the findings of Andreyanto and Wahyuni (2024), Funde and Damani (2023) and Rahman (2023) who argued that double exponential smoothing (Holt) model could predict future values accurately. This outcome is inconsistent with the findings of Agustina et al. (2021), Liu et al. (2020), Awajan et al. (2018), Chawla and Jha (2009), and Muliawati (2024) who found that triple exponential smoothing methods provide better forecast accuracy compared to double exponential smoothing techniques.

The finding of this study is in line with the findings of Almazrouee, et al. (2020) who argued that Holt-Winters’ model (triple exponential smoothing) performed poorly in the prediction of electricity consumption.

6.2 The contributions of this study:

This study has gone through significant number of studies (shown through literature review in appendix) performed by different scholars in relation to predictability of double and triple exponential smoothing techniques. Furthermore, some of them applied more sophisticated models including ARIMA and artificial neural network (ANN) in few studies along with exponential smoothing techniques. Some of these studies have been performed in different industries including service industry, manufacturing industry and logistic industry. However, no one has yet considered or extended the scope of study in the creative industry. Every industry has got specific characteristics to behave differently, indicating some industries might be predictable and some other might not be. This is because, some industries show trend in the data and stock prices of some other industries fluctuate randomly and abruptly. Nobody has yet applied exponential smoothing techniques to uncover the predictability of stock prices of the creative industry. The existing literature has largely neglected this idea.

This study explored whether stock prices of the creative industry could be predicted or not. This research empirically found that stock price movements and trends of the creative industry are predictable in the London Stock Exchange. This paper has contributed to the existing body of knowledge by considering the predictability of stock prices in the creative industry.

Chapter Seven: Conclusion and Further Research

This chapter draws the conclusion, recommends for further study, answers the research questions, and assesses whether research aim and objectives that are outlined in chapter one have been achieved or not.

7.1 Answers to research questions:

Research question 1:

In relation to the research question regarding stock prices of the creative industry of the UK stock market are weak-form efficient or not, this study applied different statistical tools and methods to answer this question. The descriptive statistics show that stock prices of all series are not normally distributed. Furthermore, histograms and kernel density graphs explain that none of the series is normally distributed. Thus, the weekly closing prices in the creative industry do not follow the random-walk model.

The results from runs test show that p values from all 6 series are less than 5%, which indicate stock prices of LSE do not move randomly. Additionally, ADF -unit root test evidences that weekly closing prices do not have unit root at the first difference. Furthermore, multiple variance ratio tests claim that all the series follow a martingale model. Moreover, heteroscedasticity tests evidence that most of the series do not have serial autocorrelation.

Based on above findings, statistical inference was made that the LSE including the creative industry is not weak-form efficient, indicating stock prices are predictable.

The double exponential smoothing technique (Holt model) evidences through forecast evaluation statistics of MAPE, U_1 and U_2 that stock prices of most of the series are predictable. Therefore, it could be claimed that the LSE (especially, the creative industry) is not weak-form efficient.

Research question 2:

Referring to the research question concerning the forecasting power of different econometric models of exponential smoothing techniques (Holt and Holt-Winters' models), this study explored the prediction power of these models following the forecasting principles. Hyndman and Athanasopoulos (2018) explain that estimation period should include data around 200 observations, as most time series data do not work for very long period. This study has considered 204 observations for estimation period and 4 more observations after that period for out-of-sample prediction (validation period).

The benchmark parameters of MAPE, Theil inequality co-efficient of U_1 and U_2 evidence that no applied model could forecast stock prices that are exactly same as the actual prices. However, the double exponential smoothing technique evidences that most of the series are predictable as their Theil inequality co-efficient of U_2 are less than 1 and MAPE is lower. The additive and multiplicative models show that a few series (2 out of 6 series) are predictable documented by MAPE and Theil inequality co-efficient of U_2. This is because, additive and multiplicative models (Holt-Winters) consider the seasonality in data and data series in this study have not revealed any seasonality found through correlogram and line graphs.

On the basis of above analysis, it could be claimed that exponential smoothing techniques have moderate forecasting power. This is because, future prices for all the series should be predictable as the market is not weak-form efficient. However, the applied models could not predict all series precisely.

7.2 Objectives of the research:

All the research objectives listed in chapter one have been achieved. These are explained below how the objectives have been obtained.

7.2.1Objective 1:

The first objective of this study was to perform a critical review of existing literature on the predictability of exponential smoothing techniques. This objective is achieved in chapter two, which is literature review and it is shown in the appendix. In relation to this objective, the latest and key scholars written journal articles in the area of the predictability of exponential smoothing techniques were examined. The scholars are Funde and Damani (2023), Liu et al. (2020), Awajan et al. (2018), Almazrouee, et al. (2020), Agustina et al. (2021), Octiva et al (2024), Andreyanto and Wahyuni (2024), Muliawati (2024), Atoyebi et al. (2023) and so on. Some of the scholars have documented that exponential smoothing techniques could predict stock prices and some of them found contradictory results. Some of them have shown that double exponential smoothing technique could predict better than triple exponential smoothing technique and some of them found the opposite results.

The collection of the prominent articles for the concepts of exponential smoothing techniques were made possible using keywords put into search engines of peer-reviewed databases. Notable amongst them were Emerald, Ebscohost, Science Direct, JSTOR, Ethos, Google and Google scholar.

7.2.2 Objective 2:

The second objective was to examine whether the creative industry in the London Stock Exchange (LSE) is weak-form efficient or not using a range of exponential smoothing techniques. This objective was attained by applying different statistical tools and techniques and analysing graphs and figures of selected series. At first, the descriptive statistics and line graphs, histogram and kernel density graphs were examined. Secondly, runs test, ADF-unit root test, variance ratio test and autocorrelation test were performed to draw statistical inference regarding weak-form efficiency. Thirdly, exponential smoothing techniques were applied to test weak-form efficiency for the creative industry, and FTSE-350 General Industrial Index. Finally, evaluation statistics of benchmarks were compared with those from the forecasted results to draw conclusion regarding weak-form efficiency and predictability of models.

Descriptive statistics, histogram and kernel density graphs have shown that weekly closing prices of five companies in the creative industry and FTSE-350 General Industrial Index are not normally distributed. Non-normal distribution of data suggests that future stock prices are predictable from the analysis of historical prices.

The runs test at level evidences that stock prices of all series including FTSE-350 General Industrial Index and five companies in the creative industry do not move randomly. The results of the correlogram at first difference are mixed. It is found that all these series do not have any serial autocorrelation except one series, which is APTD.L. ADF - unit root tests at first difference document that all the series do not have unit root. Furthermore, multiple variance ratio test shows that stock prices do not move randomly. They follow a martingale model.

In summary, none of the series, in the period without a structural break (plain period) robustly passes the criteria required for weak-form market efficiency. Thus, statistical inference was made that the London Stock Exchange including the creative industry is not weak-form efficient.

The forecast evaluation statistics of MAPEs, Theil U_1 and U_2 evidence that Holt' double exponential smoothing technique could predict stock prices for the most of the series precisely.

Therefore, it could be claimed that the London Stock Exchange, especially the creative industry is not weak-form efficient for the period tested.

7.2.3 Objective 3:

The third objective was to estimate econometric models using exponential smoothing techniques and test their forecasting power. To achieve this objective, this study has chosen most commonly used and easy to understand econometric models of exponential smoothing. This objective was achieved by analysing the forecast errors from the applied models to all 6 series including five companies in the creative industry and FTSE-350 General Industrial Index.

The double exponential smoothing technique (Holt model) shows that most of the series are predictable as forecasting error parameter of U_2 is less than 1 and MAPE is lower.

On the other hand, triple exponential smoothing techniques (Holt-Winters' models) show that only 2 series out of 6 are predictable. This is because, additive and multiplicative models (Holt-Winters) consider seasonality in data and data series in this study do not reveal any seasonality found through correlogram and line graphs. Therefore, it could be claimed that exponential smoothing techniques have moderate forecasting power as they could not predict all the series precisely although the market is not weak-form efficient.

7.2.4 Objective 4:

In relation to the fifth objective, to compare and contrast the outcomes from this research with key takeaways from previous studies and synthesize the entire research towards assessing the capability of forecastability of exponential smoothing techniques.
This study found that weekly closing prices of stocks in the LSE, especially the creative industry do not move randomly over the period tested. Therefore, the double exponential smoothing technique revealed that most of series are predictable. The results of this research are similar with the findings from studies conducted by Andreyanto and Wahyuni (2024), Funde and Damani (2023), Rahman (2023) and Awajan et al. (2018). They argued that Holt's model has got an exceptional performance in prediction.

However, contradictory results found from the studies conducted by Almazrouee, et al. (2020) who claimed that exponential smoothing models do not perform well in prediction. Furthermore, this study exhibited that triple exponential smoothing techniques do not perform effectively in the prediction of stock prices.

Therefore, it could be claimed that a stock market goes through different states of efficiency, which is relevant with adaptive market hypothesis. Ito and Sugiyama (2009) and Lim et al. (2013) showed that stock markets usually go through different periods of efficiency and inefficiency due to macroeconomic and industry specific factors.

7.3 Limitation of this study:

The limitations of this study are as follows:

i. This study analysed only the stock prices of the creative industry. The results of this study are limited to the creative industry.
ii. This study did not take into account the transaction costs. Thus, the calculation of the returns from forecasting was ignored.

7.4 Recommendations for further study:

This study will not stop here. It opens a new window for further research that will consider many industries to see the predictability of the London Stock Exchange in different sample period.

Data source:

https://nz.finance.yahoo.com/quote/ACC.L/history?period1=1066348800&period2=1707004800&interval=1wk&filter=history&frequency=1wk&includeAdjustedClose=true

https://finance.yahoo.com/quote/JD.L/history?period1=1675544400&period2=1707080400&interval=1wk&filter=history&frequency=1wk&includeAdjustedClose=true

https://uk.finance.yahoo.com/quote/APTD.L/history?period1=1675544553&period2=1707080553&interval=1wk&filter=history&frequency=1wk&includeAdjustedClose=true

https://uk.finance.yahoo.com/quote/BRBY.L/history?period1=1675544635&period2=1707080635&interval=1wk&filter=history&frequency=1wk&includeAdjustedClose=true

https://uk.finance.yahoo.com/quote/PSON.L/history?period1=1675544716&period2=1707080716&interval=1wk&filter=history&frequency=1wk&includeAdjustedClose=true

https://uk.investing.com/indices/ftse-350-general-industrials-historical-data

London South East (2024), available at: https://www.lse.co.uk/SharePrice.html?shareprice=ACC&share=Access-intelligence#:~:text=Over%20the%20last%20year%2C%20Access,%2C%20reputation%20management%2C%20and%20compliance.

London South East (2024), available at: https://www.lse.co.uk/SharePrice.html?shareprice=JD.&share=Jd-sports.

London South East (2024), available at https://www.lse.co.uk/SharePrice.html?shareprice=APTD&share=aptitude

London South East (2024), available at: https://www.lse.co.uk/SharePrice.html?shareprice=BRBY&share=Burberry.

London South East, (2024), available at: https://www.lse.co.uk/SharePrice.html?shareprice=PSON&share=PEARSON.

References:

Abedini, B. (2009) “Weak-form efficiency: stock market in the Gulf co-operation council countries,” *SCMS Journal of Indian Management*, pp. 15–29.

Agustina, C., Asfihani, T., Ginting, R., and Subchan, S. (2021) “Model predictive control in optimizing stock portfolio based on stock prediction data using Holt–Winters exponential smoothing” *Journal of Physics*, 1821:12030. doi:10.1088/1742-6596/1821/1/012030.

Ahlburg D. (1984) “Forecast evaluation and improvement using Theil’s decomposition” *Journal of Forecasting*, 3, 345-351.

Al-Jafari M. K. (2013) “The random walk behaviour and weak form efficiency of the Istanbul stock market 1997-2011: Empirical evidence”, *International Journal of Management*, 30(3), 169-185.

Almazrouee, A. I., Almeshal A. M., Almutairi A.S., Alenezi M. R. and Alhajeri S. N. (2020) “Long-term forecasting of electrical loads in Kuwait using Prophet and Holt–Winters models,” *Applied sciences (Basel, Switzerland)*, 10(16), p. 5627, doi: 10.3390/app10165627.

Anderson D. R., Sweeney D. J. and Williams T. A. (2002) “Statistics for business and economics” 8th edition, USA, Thomson Learning.

Andreyanto M. F. and Wahyuni H. C. (2024) “Comparison of Forecasting Techniques Moving Average and Double Exponential Smoothing in Sugar Production for Enhanced Maintenance Preparedness Ahead of Milling Season” *Procedia of Engineering and Life Science*, Vol. 7.

Atoyebi, S. B., Olayiwola M. F., Oladapo J. O. and Oladapo D. I. (2023) “Forecasting currency in circulation in Nigeria using Holt-Winters exponential smoothing method,” *South Asian Journal of Social Studies and Economics*, 20(1), pp. 25–41. doi: 10.9734/sajsse/2023/v20i1689.

Awajan, A., Ismail, M., and Wadi, S. (2018) “Improving forecasting accuracy for stock market data using EMD-HW bagging” PLoS One 13:e0199582, doi:10.1371/journal.pone.0199582.

Bai, J. (1997) “Estimating Multiple Breaks One at a Time,” *Econometric Theory*, 13, 315–352.

Bai, J. and Perron P. (1998) “Estimating and Testing Linear Models with Multiple Structural Changes,” *Econometrica*, 66, 47–78.

Berenson M. L., Levine D. M. and Krehbiel T. C. (2006) "Basic business statistics: concepts and applications" 9th edition, USA, Pearson education international.

Bliemel F. (1973) "Theil's forecast accuracy coefficient: a clarification" *journal of marketing research*, 10, 444-446.

Bryman A. (2008), "Social Research Methods" page number 12, 14 and 24, Third Edition, Oxford University press, United Kingdom.

Camellia O. (2013) "Testing informational efficiency: The case of U.E. and BRIC emergent markets" *Studies in business and economics*, 94-112.

Carmody, M. (2013) "*Skewness and kurtosis in return distribution*" [Online Video].

Chakraborty M. (2006) "On the validity of random walk hypothesis in the Colombo Stock Exchange, Sri Lanka" *Decision*, 33(1), 135-162.

Chawla, D., and Jha, V. S. (2009) "Forecasting production of natural rubber in India" *Paradigm*, 13, 39–55, doi:10.1177/0971890720090107

Chen C., Twycross J. and Garibaldi J. (2017) "A new accuracy measure based on bounded relative error for time series forecasting" *Journal of Plos One*, 12(3), 1-23.

Chow K. and Denning K. (1993) "A Simple Multiple Variance Ratio Test" *Journal of Econometrics*, 58, 385-401.

Collis, J. and, Hussey R. (2009), "Business Research: A Practical Guide for Undergraduate and postgraduate Students" Page Number 56, Third Edition, Palgrave Macmillan, United States.

Gilliland M. (2010) "The Business Forecasting Deal: Exposing Myths, Eliminating Bad Practices, Providing Practical Solutions" SAS Institute, Inc, UK.

Gujarati D. N. (2004) "Basic Econometrics" 4th edition, Chicago, The McGraw-Hill companies.

Gujarati D., Porter D., and Gunasekar S. (2015) "Basic Econometrics" Fifth Edition, New York, NY: Mc Graw Hill Higher Education.

Granger C. and Newbold P. (1973) "Some comments on the evaluation of economic forecasts" *Applied Economics*, 5, 35-47.

Holt, C. C. (1957) "*Forecasting seasonals and trends by exponentially weighted averages* (O.N.R. Memorandum No. 52)" Carnegie Institute of Technology, Pittsburgh USA. [DOI]

Hyndman R. J. and Athanasopoulos G. (2018) "*Forecasting: Principles and Practice"* second edition, online textbook, Australia.

Ito, M. and Sugiyama, S. (2009) "Measuring the degree of time varying market inefficiency," *Economics letters*, 103(1), pp. 62–64. doi: 10.1016/j.econlet.2009.01.028.

Jankowicz A. D. (2005) "Business Research Projects", page number 109- 110, Fourth Edition, Thomson Learning, United Kingdom.

Kazmier L. J. (2004) "Business Statistics" 4th edition, New York, McGraw-Hill Companies.

Killam, N. (2014) *Normal distribution, standard deviations, modality, skewness and kurtosis: understanding concepts*.

Kotsialos, A., Papageorgiou, M., and Poulimenos, A. (2005). Long-term sales forecasting using holt-winters and neural network methods. *Journal of Forecasting*, 24(5), 353–368, doi: 10.1002/for.943

Lim, K. P., Luo, W. and Kim, J. H. (2013) "Are US stock index returns predictable? Evidence from automatic autocorrelation-based tests"," *Applied Economics*, 45, pp. 953–962.

Liu, C., Sun, B., Zhang, C. and Li, F. (2020) "A hybrid prediction model for residential electricity consumption using holt-winters and extreme learning machine," *Applied energy*, 275(115383), 115-383. doi: 10.1016/j.apenergy.2020.115383.

Lo A. W. and MacKinlay A. C. (1988) "Stock market prices do not follow random walks: evidence from a simple specification test" *The Review of Financial Studies*, 1(1), 41-66.

Malhotra N. K. And Birks D. F. (2003) "Marketing Research: An Applied Approach" Page Number 69-70, 362-372 and 519, Second Edition, Prentice Hall, United Kingdom.

Mishra P. K. (2013) "Random walk behaviour: Indian equity market" *SCMS Journal of Indian Management*, 55-63.

Mollah A. S. (2007) "Testing weak-form market efficiency in emerging market: evidence from Botswana stock exchange" *International Journal of Theoretical and Applied Finance*, 10(6), 1077-1094.

Mobarek A. and Keasey K. (2000) "Weak-form market efficiency of an emerging market: evidence from Dhaka Stock Market of Bangladesh" *Journal of ENBS*, 1-30.

Mollah A. S. (2007) "Testing weak-form market efficiency in emerging market: evidence from Botswana stock exchange" *International Journal of Theoretical and Applied Finance*, 10(6), 1077-1094.

Monette, D. R.; Sullivan, T. J. and Dejong C. R (2005) "Applied Social Research- A Tool for the Human Services" page number 34, Sixth Edition, Thomson, USA.

Muliawati, T. (2024) "Analysis of rainfall prediction in Lampung Province using the Exponential Smoothing method," *International journal of scientific research in science, engineering and technology*, pp. 232–240. doi: 10.32628/ijsrset2411127.

Octiva, C. S., Israkwaty, Nuryanto U. W., Eldo H. and Tahir A. (2024) "Application of Holt-Winter Exponential Smoothing method to design a drug inventory prediction application in private health units," *Jurnal Informasi dan Teknologi*, pp. 1–6. doi: 10.60083/jidt.v6i1.464.

Omnia O. H. (2016) "Theil's U statistics" youtube.

Rahman, M. A. (2023) "Forecasting stock prices on the basis of technical analysis in the industrial sectors of the UK stock market," *International Journal of Asian Business and Management*, 2(1), pp. 11–32. doi: 10.55927/ijabm.v2i1.2901.

Robson Colin (2002) "Real World Research", page number 20, 88-90, 178 and 263-265, Second Edition, Blackwell Publishing, United Kingdom.

Saunders, Lewis, Thornhill (2007), "Research Methods for Business Students", page number 104-108, 110, 232-234 and 613, fourth edition, Prentice Hall, United Kingdom.

Sharma J. L. and Kennedy R. E. (1977) "A comparative analysis of stock price behaviour on Bombay, London and New York Stock Exchanges" *Journal of Financial and Quantitative analysis*, 391-413.

Suwanvijit, W., Lumley, T., Choonpradub, C., and McNeil, N. (2011) "Longterm sales forecasting using Lee–Carter and Holt–Winters methods" *Journal of Applied Business Research*, 27(1), 87–102. doi: 10.19030/jabr.v27i1.913

STATA (2024) "Tests for structural breaks in time-series data" available at: https://www.stata.com/features/overview/structural-breaks/

Tang, Y. M., Chau K. Y., Li W. and Wan T. W. (2020) “Forecasting economic recession through share price in the logistics industry with artificial intelligence (AI),” *Computation (Basel, Switzerland)*, 8(3), p. 70. doi: 10.3390/computation8030070.

Tsai, M.-C., Cheng C. H., Tsai M. I. and Shiu H. Y. (2018) “Forecasting leading industry stock prices based on a hybrid time-series forecast model,” *PloS one*, 13(12), p. e0209922. doi: 10.1371/journal.pone.0209922.

Winters P. (1960) “Forecasting sales by exponentially Weighted moving averages” *Management Science*, 6(3), 324–342. doi: 10.1287/mnsc.6.3.324.

Appendices:

Chapter One: Introduction

Forecasting stock price is a challenge for every investor. All the investors would like to have maximum return and minimum loss. However, this is not a simple calculation. Many scholars have developed different prediction models to predict stock prices precisely. Exponential smoothing techniques are simple but widely used models in the time series analysis. This study would apply double (Holt) and triple (Holt-Winters) exponential smoothing techniques to predict stock prices of the creative industry (companies in the area of music, fashion, IT, publishing, architecture, games, film, advertising and crafts) due to their easiness, objectiveness, robustness, and effectiveness. The Holt–Winters' method is basically a technique to fit appropriate values to historical data of time series (Gujarati et al., 2015). In 1957, Holt experimented the double exponential smoothing technique that revealed trend in the data. This method become popular after Winters (1960) experimented a few exponential moving techniques and Holt method was one of them, which is now known as Holt–Winters' forecasts.

1.1 Research questions:

1. Is the creative industry of the UK stock market weak-form efficient?
2. Are smoothing techniques strong enough to predict the movements of stocks of the creative industry, if the London Stock Exchange (LSE) is not weak-form efficient?

1.2 Research aim:

After a comprehensive review of the existing knowledge (through literature review) about predictability of exponential smoothing, it was decided that the aim of this study is to fill the gaps in the existing literature. Therefore, the aim of this research is to assess the prediction power of exponential smoothing techniques critically and rigorously in the creative industry of the UK stock market.

1.3 Research objectives:

This study has some objectives and hypothesis that help attain the research aim. The objectives of this research are:

1. To perform a critical review of existing literature on the predictability of exponential smoothing techniques

2. To assess whether stocks in the creative industry in the London Stock Exchange (LSE) are weak-form efficient using a range of econometric tests.
3. To estimate econometric models using exponential smoothing techniques and test their forecasting power.
4. To compare and contrast the outcomes from this research with key takeaways from previous studies and synthesize the entire research towards assessing the capability of forecasting models of exponential smoothing techniques.

The above objectives and research questions are closely connected with historical data of stock prices that will be obtained through yahoo finance and examined thoroughly and rigorously through several statistical methods, and techniques to achieve the aim of this study. Thus, the aim will be achieved through research questions and objectives and they are closely linked with historical prices of stocks in the creative industry. The reason is the aim has been broken down into a few objectives and research questions. The combination of all objectives and research questions above will assist to attain the research aim. Therefore, they are essential to be considered in this research to fulfil the research aim.

Chapter Two: Literature Review

Literature review explains recently found empirical evidence on exponential smoothing techniques and their predictability. Furthermore, it uncovers research gap in the existing study.

2.1 Findings from the early literature regarding exponential smoothing techniques:

Funde and Damani (2023) applied ARIMA and exponential smoothing techniques to predict stock prices of Nifty 50 (stock market in India). They found that exponential smoothing techniques performed better than ARIMA in some cases. Similar result was documented by Rahman (2023) in the study of London Stock Exchange. Similarly, Liu et al. (2020) performed a study using Holt-Winters's model and their results explain that Holt-Winters's model resulted an exceptional performance in the prediction of electricity consumption than other applied models. However, Almazrouee, et al. (2020) claimed a poor performance of Holt-Winters's model in the prediction of electricity consumption in Kuwait. Furthermore, Awajan et al. (2018) performed a comparative study of prediction models in six stock market markets, including Sri Lanka, France, Australia, Netherlands, Malaysia, and US- S&P 50 and evidenced that Holt–Winters model performs better and provides more accurate estimations than the other time series models. Moreover, Kotsialos (2005) found effectiveness of Holt–Winters' model that documents marginally better performance than other forecasting models. Agustina et al. (2021) revealed that triple exponential smoothing technique provides a better prediction accuracy (MAPE) which generated wealth for the investors. Suwanvijit et al. (2011) evidenced that the Holt-Winters model with additive seasonality resulted excellent estimates, 95% accuracy, and the best fit in prediction of beverage sales in Thailand. However, Chawla and Jha (2009) applied both double and triple exponential smoothing techniques and their findings detail that Winters's model outperformed Holt's method. Moreover, Octiva et al (2024) claimed Holt-Winters' exponential smoothing methods show an outstanding performance in the drug supply prediction. Additionally, Andreyanto and Wahyuni (2024) showed that double exponential smoothing (Holt) method performs better than moving average. However, Muliawati (2024) found that triple exponential smoothing method generated a reliable forecasting for next year rainfall as data contains seasonality. To measure better predictability, Atoyebi et al. (2023) found multiplicative model outperforms the additive model for forecasting currency circulation in Nigeria. Rahman (2023) performed a study on the predictability of stock prices in the UK based on technical analysis in the different industries including primary, secondary or manufacturing, service and quaternary industries. Furthermore, Tsai et al. (2018) conducted a study to predict stock prices in the manufacturing industry in China by applying technical analysis. Moreover, Tang et al. (2020) applied artificial intelligence (ARIMA, MA) in the logistics industry in China to predict stock prices.

However, none of studies have not considered the predictability of stock prices in the creative industry. All the above findings detail that exponential smoothing techniques have a significant predictive power. However, these techniques have not been used to predict stock prices in the creative industry.

2.2 Research gap:

A significant number of studies have been conducted on exponential smoothing to predict future stock prices found through literature review. However, no studies have been yet performed to predict stock prices of the creative industry using exponential smoothing techniques or other sophisticated models.

This study assumes that every industry has got its specific nature to behave. Some industries might be predictable based on their trends. These industries absorb market information very slowly and thus, they might be predictable. Some other industries might not be predictable as they absorb all available information instantly and promptly. The behaviour of the creative industry is still unknown as no one has yet tested the predictability of this industry. Therefore, this study would like to perform a technical analysis of exponential smoothing techniques to see whether the creative industry is predictable or not.

Chapter Three: Conceptual Framework

3.1 Variables in this study:

The dependent and independent variables of this study are as follows.

Dependent variables: Forecasted stock prices

Independent variables: Weekly historical prices of five companies in the creative industry and FTSE-350 General Industrial Index (GII).

3.2 Designing the conceptual framework:

The conceptual framework of this study is as follows:

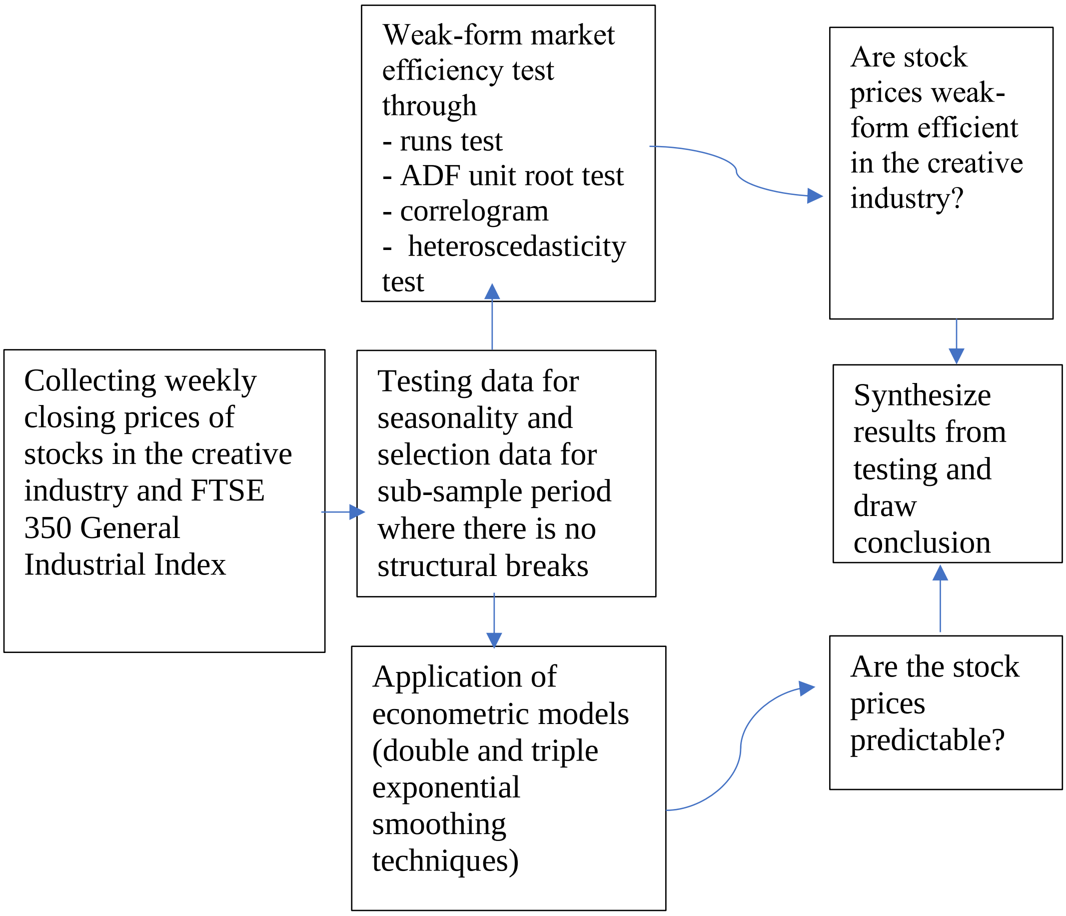


Figure 16: The conceptual framework of this study

Data will be collected through yahoo finance and market efficiency will be tested through runs test, ADF-unit root test, variance ratio (heteroscedasticity) test and serial correlation test (correlogram). If the results show the London Stock Exchange (LSE) is not weak-form efficient, exponential smoothing techniques will be applied to see their predictability.

Chapter Four: Research and development

This chapter has been divided into four different parts. Part-A narrates research ethics, philosophy, approach, and design. Part- B details the data collection, sample period and sampling technique in this study. Part-C clarifies the adopted statistical tools and techniques which are not related with forecasting such as breakpoint test, efficiency tests etc. The final part – D explains forecasting related statistical models that this study will apply to predict future stock prices of the LSE as well as the creative industry and forecasting errors.

Part -A: Research ethics, philosophy, approach, and design

Ethical Approval

This study would collect secondary (published) data. The collection of published data for this study will not influence the rights of any person, group, or organization. Consequently, it could be claimed that it is ethically sound and does not need any approval from anyone to collect data.

Research philosophy:

The research philosophy of this study is positivism. This is because, it deals with answering questions which are closely related with quantitative data ((Jankowicz, 2005, and Robson, 2002). Saunders et al. (2007) explain that positivism philosophy mostly deals with quantifiable observations. Quantitative data of stock price have been collected for the purpose of answering questions whether stock prices are predictable or not through exponential smoothing techniques. Therefore, it could be claimed that this study follows positivism philosophy.

Research approach:

The adopted research approach of this study is deductive approach. This is because, related theories in relation to exponential smoothing techniques and prediction of the creative industry have been explored first through literature review to find a research gap, and then research questions have been designed. These questions will be answered in the data analysis chapter and research findings and similarity will be explored to relate to the existing theory. Thus, this approach moves from theory to research questions and hypothesis (Monette et al, 2005). It is not inductive approach as theory has not been developed from observations and research findings first (Bryman, 2008 and Collis, Hussey, 2009).

Research design:

The adopted research design for this research is conclusive research**.** More specifically, causal research design has been adopted in this study. This is because, this study involves with determining dependent and independent variables, and finding relationship between historical stock prices and future prices of stocks (Malhotra and Birks, 2003). It is not exploratory research design as exploratory research mostly depends on qualitative data (Malhotra and Birks, 2003).

Chapter Four: Research and development
Part – B: Sampling and Data collection

Adopted sampling technique:

This study would apply non-probability judgemental sampling. This study would select five companies from the creative industry that are related with fashion, craft, publication, IT, software and computer services. On the top of that, this study would take FTSE 350 General Industrial Index into consideration to get idea of other industries whether they are predictable and compare the outcomes with creative industry from prediction. The next section would explain about the source of data.

Data source, sample period and listed companies in FTSE in the creative industry:

This study would select approximately 20 years' weekly data from 13 October 2003 to 2 February 2024. They include 1061observations from five different companies in the creative industry listed in FTSE all share index as well as FTSE-350 General Industrial Index. However, data from FTSE-350 General Industrial Index are not available for that long period. Thus, this series includes data from 31 May 2009 to 11 February 2024. This shorter period of data will not affect prediction as estimation period would include only 204 observations based on the forecasting principles mentioned by Hyndman and Athanasopoulos (2018). The question might come why this study has chosen data for long period. This is because, technical analysis needs data for a long period to identify the characteristics of data and trends. The data will be collected through yahoo finance and investing.com and corresponding links will be provided in the reference to verify the source of data.

However, only a few companies in the creative industry are listed in the London Stock Exchange (LSE). The selected companies in the creative industry listed in FTSE are explained below:

Access Intelligence plc (ACC.L):

Access Intelligence plc is a British technology company specialising in the Software and Computing sector listed in the FTSE AIM All-Share index (London South East, 2024).

JD plc (JD.L):

JD Sports fashion plc is a British multinational sportswear and fashion retailer, listed on the London Stock Exchange trading with ticker code JD.L. (London South East, 2024).

Aptitude Software Group plc (APTD.L):

Aptitude Software Group Plc is listed in FTSE all share index trading with ticker code APTD.L (London South East, 2024).

Burberry Group PLC (BRBY.L):

Burberry PLC, a British luxury fashion house, listed in the London Stock Exchange, is renowned for its distinctive designs, craftsmanship, and innovation in the area of luxury apparel, accessories, and beauty products (London South East, 2024).

Pearson PLC (PSON.L):

Pearson is listed in the Media sector of LSE. It is a prominent multinational education company operating in various segments, including global assessments, educational services, and publishing (London South East, 2024).

1. **Bai-Perron's multiple breakpoints test**

JD.L:

Dependent Variable: CLOSE
Method: Least Squares with Breaks
Date: 15/02/24 Time: 07:55
Sample: 13/10/2003 2/02/2024
Included observations: 1061
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 12/04/2010, 18/05/2015, 15/04/2019
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
13/10/2003 - 5/04/2010 -- 339 obs				
C	3.231888	0.957807	3.374257	0.0008
12/04/2010 - 11/05/2015 -- 266 obs				
C	10.91881	1.081277	10.09806	0.0000
18/05/2015 - 8/04/2019 -- 204 obs				
C	65.30590	1.234704	52.89195	0.0000
15/04/2019 - 2/02/2024 -- 252 obs				
C	151.0768	1.110907	135.9941	0.0000

R-squared	0.919699	Mean dependent var	52.20902
Adjusted R-squared	0.919471	S.D. dependent var	62.14447
S.E. of regression	17.63510	Akaike info criterion	8.581423
Sum squared resid	328723.6	Schwarz criterion	8.600148
Log likelihood	-4548.445	Hannan-Quinn criter.	8.588519
F-statistic	4035.334	Durbin-Watson stat	0.096308
Prob(F-statistic)	0.000000		

APTD.L:

Dependent Variable: CLOSE
Method: Least Squares with Breaks
Date: 15/02/24 Time: 08:03
Sample: 13/10/2003 2/02/2024
Included observations: 1061
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 4/10/2010, 17/02/2014, 6/03/2017, 23/03/2020
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
13/10/2003 - 27/09/2010 -- 364 obs				
C	88.10019	3.537930	24.90162	0.0000
4/10/2010 - 10/02/2014 -- 176 obs				
C	196.4397	5.087960	38.60873	0.0000
17/02/2014 - 27/02/2017 -- 159 obs				
C	169.9837	5.353051	31.75454	0.0000
6/03/2017 - 16/03/2020 -- 159 obs				
C	495.0479	5.353051	92.47958	0.0000
23/03/2020 - 2/02/2024 -- 203 obs				
C	431.7857	4.737530	91.14153	0.0000

R-squared	0.850141	Mean dependent var	245.0842
Adjusted R-squared	0.849573	S.D. dependent var	174.0355
S.E. of regression	67.49941	Akaike info criterion	11.26682
Sum squared resid	4811316.	Schwarz criterion	11.29022
Log likelihood	-5972.046	Hannan-Quinn criter.	11.27569
F-statistic	1497.658	Durbin-Watson stat	0.073933
Prob(F-statistic)	0.000000		

BRBY.L:

Dependent Variable: CLOSE
Method: Least Squares with Breaks
Date: 15/02/24 Time: 08:12
Sample: 13/10/2003 2/02/2024
Included observations: 1061
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 30/10/2006, 13/09/2010, 16/12/2013, 16/01/2017, 25/01/2021
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
13/10/2003 - 23/10/2006 -- 159 obs				
C	410.4182	15.93249	25.75983	0.0000
30/10/2006 - 6/09/2010 -- 202 obs				
C	534.6270	14.13535	37.82199	0.0000
13/09/2010 - 9/12/2013 -- 170 obs				
C	1318.400	15.40841	85.56368	0.0000
16/12/2013 - 9/01/2017 -- 161 obs				
C	1452.565	15.83322	91.74161	0.0000
16/01/2017 - 18/01/2021 -- 210 obs				
C	1798.781	13.86349	129.7495	0.0000
25/01/2021 - 2/02/2024 -- 159 obs				
C	1933.022	15.93249	121.3258	0.0000

R-squared	0.894278	Mean dependent var	1240.657
Adjusted R-squared	0.893777	S.D. dependent var	616.4141
S.E. of regression	200.9011	Akaike info criterion	13.44914
Sum squared resid	42581103	Schwarz criterion	13.47723
Log likelihood	-7128.769	Hannan-Quinn criter.	13.45979
F-statistic	1784.798	Durbin-Watson stat	0.107999
Prob(F-statistic)	0.000000		

PSON.L:

Dependent Variable: CLOSE
Method: Least Squares with Breaks
Date: 15/02/24 Time: 08:15
Sample: 13/10/2003 2/02/2024
Included observations: 1061
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 1/03/2010, 19/10/2015, 25/01/2021
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
13/10/2003 - 22/02/2010 -- 333 obs				
C	700.8491	5.989077	117.0212	0.0000
1/03/2010 - 12/10/2015 -- 294 obs				
C	1161.481	6.373946	182.2233	0.0000
19/10/2015 - 18/01/2021 -- 275 obs				
C	742.1305	6.590459	112.6068	0.0000
25/01/2021 - 2/02/2024 -- 159 obs				
C	817.6201	8.667293	94.33397	0.0000

R-squared	0.756628	Mean dependent var	856.6878
Adjusted R-squared	0.755938	S.D. dependent var	221.2236
S.E. of regression	109.2904	Akaike info criterion	12.22966
Sum squared resid	12625223	Schwarz criterion	12.24838
Log likelihood	-6483.833	Hannan-Quinn criter.	12.23675
F-statistic	1095.383	Durbin-Watson stat	0.088217
Prob(F-statistic)	0.000000		

FTSE 350 General Industrial Index:

Dependent Variable: PRICE
Method: Least Squares with Breaks
Date: 15/02/24 Time: 08:18
Sample: 31/05/2009 11/02/2024
Included observations: 768
Break type: Bai-Perron tests of L+1 vs. L sequentially determined breaks
Breaks: 30/12/2012, 7/08/2016, 8/11/2020
Selection: Trimming 0.15, Max. breaks 5, Sig. level 0.05

Variable	Coefficient	Std. Error	t-Statistic	Prob.
31/05/2009 - 23/12/2012 -- 187 obs				
C	2748.540	38.49032	71.40862	0.0000
30/12/2012 - 31/07/2016 -- 188 obs				
C	4221.314	38.38781	109.9650	0.0000
7/08/2016 - 1/11/2020 -- 222 obs				
C	5877.214	35.32611	166.3703	0.0000
8/11/2020 - 11/02/2024 -- 171 obs				
C	6464.464	40.25077	160.6047	0.0000

R-squared	0.878748	Mean dependent var	4840.115
Adjusted R-squared	0.878272	S.D. dependent var	1508.608
S.E. of regression	526.3472	Akaike info criterion	15.37499
Sum squared resid	2.12E+08	Schwarz criterion	15.39918
Log likelihood	-5899.998	Hannan-Quinn criter.	15.38430
F-statistic	1845.639	Durbin-Watson stat	0.544627
Prob(F-statistic)	0.000000		

2. **Runs test**

Descriptive Statistics

	N	Mean	Std. Deviation	Minimum	Maximum
BRBY.L	204	1800.7034	247.13889	1159.00	2329.00
PSON.L	204	719.8765	139.12743	425.00	1027.50
FTSE350	204	5915.4381	590.38743	3999.61	7095.23
APTD.L	204	83.5735	22.82786	52.90	134.45
JD.L	204	153.9615	32.47511	75.84	233.40

Runs Test

	BRBY.L	PSON.L	FTSE350	APTD.L	JD.L
Test Value[a]	1777.25	698.50	5952.84	75.67	150.88
Cases < Test Value	102	102	102	100	102

Cases >= Test Value	102	102	102	104	102
Total Cases	204	204	204	204	204
Number of Runs	29	13	17	12	20
Z	-10.388	-12.634	-12.072	-12.773	-11.651
Asymp. Sig. (2-tailed)	<.001	<.001	<.001	<.001	<.001

a. Median

3. Unit Root Test

(i) JD.L

At Level:

Augmented Dickey-Fuller test statistic		-2.119137	0.5316
Test critical values:	1% level	-4.003902	
	5% level	-3.432115	
	10% level	-3.139793	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE)
Method: Least Squares
Date: 19/02/24 Time: 21:28
Sample (adjusted): 24/02/2020 8/01/2024
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLOSE(-1)	-0.046230	0.021816	-2.119137	0.0353
C	7.159974	3.680007	1.945641	0.0531
@TREND("17/02/2020")	-0.003287	0.012045	-0.272921	0.7852

R-squared	0.022182	Mean dependent var	-0.302020
Adjusted R-squared	0.012404	S.D. dependent var	10.11621
S.E. of regression	10.05327	Akaike info criterion	7.468341
Sum squared resid	20213.66	Schwarz criterion	7.517305
Log likelihood	-755.0367	Hannan-Quinn criter.	7.488150
F-statistic	2.268535	Durbin-Watson stat	1.947911
Prob(F-statistic)	0.106120		

At first difference:

Null Hypothesis: D(CLOSE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-14.65411	0.0000
Test critical values:	1% level	-4.004132	
	5% level	-3.432226	
	10% level	-3.139858	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE,2)
Method: Least Squares
Date: 19/02/24 Time: 21:45
Sample (adjusted): 2/03/2020 8/01/2024
Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CLOSE(-1))	-1.018506	0.069503	-14.65411	0.0000
C	0.529888	1.420865	0.372933	0.7096
@TREND("17/02/2020")	-0.006811	0.012049	-0.565240	0.5725

R-squared	0.519220	Mean dependent var	0.112426
Adjusted R-squared	0.514388	S.D. dependent var	14.32935
S.E. of regression	9.985530	Akaike info criterion	7.454891
Sum squared resid	19842.45	Schwarz criterion	7.504024
Log likelihood	-749.9440	Hannan-Quinn criter.	7.474770
F-statistic	107.4553	Durbin-Watson stat	2.024758
Prob(F-statistic)	0.000000		

APTD.L at level:

Null Hypothesis: CLOSE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 1 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.804189	0.1975
Test critical values:	1% level	-4.004132	
	5% level	-3.432226	
	10% level	-3.139858	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE)
Method: Least Squares
Date: 05/03/24 Time: 11:02
Sample (adjusted): 23/10/2006 30/08/2010
Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLOSE(-1)	-0.105361	0.037573	-2.804189	0.0055
D(CLOSE(-1))	-0.286094	0.072435	-3.949671	0.0001
C	6.415195	2.487758	2.578706	0.0106
@TREND("9/10/2006")	0.025044	0.014395	1.739848	0.0834

R-squared	0.137298	Mean dependent var	0.084563
Adjusted R-squared	0.124226	S.D. dependent var	9.438932
S.E. of regression	8.833215	Akaike info criterion	7.214518
Sum squared resid	15449.09	Schwarz criterion	7.280029
Log likelihood	-724.6664	Hannan-Quinn criter.	7.241024
F-statistic	10.50379	Durbin-Watson stat	1.925150
Prob(F-statistic)	0.000002		

APTD.L at first difference:

Null Hypothesis: D(CLOSE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-18.83524	0.0000
Test critical values:	1% level	-4.004132	
	5% level	-3.432226	
	10% level	-3.139858	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE,2)
Method: Least Squares
Date: 05/03/24 Time: 11:07
Sample (adjusted): 23/10/2006 30/08/2010
Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CLOSE(-1))	-1.339267	0.071104	-18.83524	0.0000
C	0.394910	1.278394	0.308911	0.7577
@TREND("9/10/2006")	-0.002077	0.010844	-0.191517	0.8483

R-squared	0.640909	Mean dependent var	-0.202768
Adjusted R-squared	0.637300	S.D. dependent var	14.91791
S.E. of regression	8.984252	Akaike info criterion	7.243564
Sum squared resid	16062.64	Schwarz criterion	7.292696
Log likelihood	-728.5999	Hannan-Quinn criter.	7.263443
F-statistic	177.5882	Durbin-Watson stat	1.950704
Prob(F-statistic)	0.000000		

BRBY.L at level:

Augmented Dickey-Fuller Unit Root Test on CLOSE

Null Hypothesis: CLOSE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.469356	0.3431
Test critical values:	1% level	-4.003902	
	5% level	-3.432115	
	10% level	-3.139793	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE)
Method: Least Squares
Date: 08/03/24 Time: 07:54
Sample (adjusted): 6/02/2017 21/12/2020
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLOSE(-1)	-0.057287	0.023199	-2.469356	0.0144
C	109.6551	44.45932	2.466414	0.0145
@TREND("30/01/2017")	-0.057894	0.097833	-0.591768	0.5547

R-squared	0.030011	Mean dependent var	0.581281
Adjusted R-squared	0.020311	S.D. dependent var	81.94055
S.E. of regression	81.10413	Akaike info criterion	11.64401
Sum squared resid	1315576.	Schwarz criterion	11.69298
Log likelihood	-1178.867	Hannan-Quinn criter.	11.66382
F-statistic	3.093969	Durbin-Watson stat	1.845150
Prob(F-statistic)	0.047498		

BRBY.L at first difference:

Augmented Dickey-Fuller Unit Root Test on D(CLOSE)

Null Hypothesis: D(CLOSE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.38918	0.0000
Test critical values:	1% level	-4.004132	
	5% level	-3.432226	
	10% level	-3.139858	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE,2)
Method: Least Squares
Date: 08/03/24 Time: 08:01
Sample (adjusted): 13/02/2017 21/12/2020
Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CLOSE(-1))	-0.949046	0.070882	-13.38918	0.0000
C	3.676697	11.73029	0.313436	0.7543
@TREND("30/01/2017")	-0.030127	0.099466	-0.302891	0.7623

R-squared	0.473937	Mean dependent var	-0.250000
Adjusted R-squared	0.468650	S.D. dependent var	113.0758
S.E. of regression	82.42519	Akaike info criterion	11.67640
Sum squared resid	1351988.	Schwarz criterion	11.72553
Log likelihood	-1176.316	Hannan-Quinn criter.	11.69628
F-statistic	89.64078	Durbin-Watson stat	2.003190
Prob(F-statistic)	0.000000		

PSON.L at level:

Augmented Dickey-Fuller Unit Root Test on CLOSE

Null Hypothesis: CLOSE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.820433	0.6914
Test critical values:	1% level	-4.003902	
	5% level	-3.432115	
	10% level	-3.139793	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE)
Method: Least Squares
Date: 08/03/24 Time: 08:22
Sample (adjusted): 6/02/2017 21/12/2020
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLOSE(-1)	-0.029123	0.015998	-1.820433	0.0702
C	25.08120	13.42144	1.868742	0.0631
@TREND("30/01/2017")	-0.038472	0.037974	-1.013120	0.3122

R-squared	0.017349	Mean dependent var	0.186700
Adjusted R-squared	0.007523	S.D. dependent var	30.22196
S.E. of regression	30.10806	Akaike info criterion	9.662131
Sum squared resid	181299.1	Schwarz criterion	9.711095
Log likelihood	-977.7063	Hannan-Quinn criter.	9.681940
F-statistic	1.765579	Durbin-Watson stat	1.951204
Prob(F-statistic)	0.173744		

PSON.L at first difference:

Augmented Dickey-Fuller Unit Root Test on D(CLOSE)

Null Hypothesis: D(CLOSE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-13.94706	0.0000
Test critical values:	1% level	-4.004132	
	5% level	-3.432226	
	10% level	-3.139858	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE,2)
Method: Least Squares
Date: 08/03/24 Time: 08:28
Sample (adjusted): 13/02/2017 21/12/2020
Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CLOSE(-1))	-0.988400	0.070868	-13.94706	0.0000
C	1.674707	4.331025	0.386677	0.6994
@TREND("30/01/2017")	-0.015107	0.036729	-0.411314	0.6813

R-squared	0.494313	Mean dependent var	-0.042574
Adjusted R-squared	0.489231	S.D. dependent var	42.56722
S.E. of regression	30.42199	Akaike info criterion	9.682949
Sum squared resid	184174.0	Schwarz criterion	9.732081
Log likelihood	-974.9778	Hannan-Quinn criter.	9.702828
F-statistic	97.26202	Durbin-Watson stat	1.999266
Prob(F-statistic)	0.000000		

FTSE 350 General Industrial Index at level:

Augmented Dickey-Fuller Unit Root Test on CLOSE

Null Hypothesis: CLOSE has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.069342	0.1166
Test critical values:	1% level	-4.003902	
	5% level	-3.432115	
	10% level	-3.139793	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE)
Method: Least Squares
Date: 08/03/24 Time: 08:54
Sample (adjusted): 20/11/2016 4/10/2020
Included observations: 203 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CLOSE(-1)	-0.079759	0.025986	-3.069342	0.0024
C	519.4435	167.1818	3.107058	0.0022
@TREND("13/11/2016")	-0.433922	0.261802	-1.657442	0.0990

R-squared	0.045787	Mean dependent var	3.372562
Adjusted R-squared	0.036245	S.D. dependent var	202.5051
S.E. of regression	198.8013	Akaike info criterion	13.43716
Sum squared resid	7904393.	Schwarz criterion	13.48612
Log likelihood	-1360.871	Hannan-Quinn criter.	13.45697
F-statistic	4.798378	Durbin-Watson stat	2.136600
Prob(F-statistic)	0.009216		

FTSE 350 General Industrial Index at first difference:

Augmented Dickey-Fuller Unit Root Test on D(CLOSE)

Null Hypothesis: D(CLOSE) has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 0 (Automatic - based on SIC, maxlag=14)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-15.71041	0.0000
Test critical values:	1% level	-4.004132	
	5% level	-3.432226	
	10% level	-3.139858	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(CLOSE,2)
Method: Least Squares
Date: 08/03/24 Time: 09:00
Sample (adjusted): 27/11/2016 4/10/2020
Included observations: 202 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(CLOSE(-1))	-1.107841	0.070516	-15.71041	0.0000
C	12.76306	28.84368	0.442491	0.6586
@TREND("13/11/2016")	-0.095173	0.244575	-0.389135	0.6976

R-squared	0.553657	Mean dependent var	0.069059
Adjusted R-squared	0.549171	S.D. dependent var	301.6928
S.E. of regression	202.5681	Akaike info criterion	13.47477
Sum squared resid	8165731.	Schwarz criterion	13.52390
Log likelihood	-1357.952	Hannan-Quinn criter.	13.49465
F-statistic	123.4225	Durbin-Watson stat	1.974965
Prob(F-statistic)	0.000000		

4. **Correlogram or Autocorrelation test at first difference: Ljung-Box test**

JD.L:

Correlogram of D(CLOSE)

Date: 19/02/24 Time: 21:55
Sample (adjusted): 24/02/2020 8/01/2024
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.018	-0.018	0.0670	0.796
		2	0.065	0.065	0.9462	0.623
		3	0.006	0.008	0.9527	0.813
		4	0.009	0.005	0.9689	0.914
		5	-0.092	-0.093	2.7415	0.740
		6	-0.023	-0.028	2.8579	0.826
		7	-0.004	0.007	2.8612	0.898
		8	-0.008	-0.003	2.8741	0.942
		9	0.003	0.004	2.8760	0.969
		10	-0.009	-0.016	2.8922	0.984
		11	0.033	0.028	3.1250	0.989
		12	0.061	0.065	3.9480	0.984
		13	-0.105	-0.109	6.3468	0.933
		14	0.051	0.041	6.9281	0.937
		15	-0.024	-0.013	7.0586	0.956
		16	-0.019	-0.019	7.1360	0.971
		17	0.020	0.038	7.2295	0.980
		18	-0.007	-0.023	7.2400	0.988
		19	-0.011	-0.010	7.2670	0.993
		20	0.071	0.076	8.4250	0.989
		21	-0.029	-0.035	8.6157	0.992
		22	0.035	0.034	8.8998	0.994
		23	-0.140	-0.152	13.423	0.942
		24	-0.006	-0.012	13.432	0.958

APTD.L:

Correlogram of D(CLOSE)

Date: 06/03/24 Time: 09:02
Sample (adjusted): 16/10/2006 30/08/2010
Included observations: 203 after adjustments

	AC	PAC	Q-Stat	Prob
1	-0.303	-0.303	18.881	0.000
2	0.004	-0.096	18.884	0.000
3	-0.110	-0.153	21.410	0.000
4	0.229	0.165	32.351	0.000
5	-0.139	-0.033	36.400	0.000
6	-0.066	-0.120	37.317	0.000
7	0.018	-0.016	37.383	0.000
8	-0.011	-0.085	37.409	0.000
9	-0.002	-0.014	37.410	0.000
10	0.069	0.107	38.428	0.000
11	-0.145	-0.147	42.970	0.000
12	0.035	-0.042	43.236	0.000
13	-0.032	-0.054	43.456	0.000
14	0.078	-0.010	44.795	0.000
15	-0.137	-0.057	48.970	0.000
16	-0.016	-0.112	49.024	0.000
17	0.219	0.195	59.723	0.000
18	-0.098	-0.023	61.898	0.000
19	-0.003	-0.011	61.900	0.000
20	-0.067	-0.037	62.907	0.000
21	0.176	0.047	70.010	0.000
22	-0.095	0.012	72.106	0.000
23	-0.009	-0.005	72.125	0.000
24	0.092	0.114	74.075	0.000

BRBY.L:

Correlogram of D(CLOSE)

Date: 08/03/24 Time: 08:06
Sample (adjusted): 6/02/2017 21/12/2020
Included observations: 203 after adjustments

	AC	PAC	Q-Stat	Prob
1	0.051	0.051	0.5386	0.463
2	0.068	0.066	1.5011	0.472
3	0.065	0.059	2.3937	0.495
4	-0.128	-0.139	5.7999	0.215
5	0.017	0.022	5.8622	0.320
6	-0.144	-0.136	10.257	0.114
7	-0.016	0.015	10.314	0.171
8	0.013	0.010	10.348	0.241
9	-0.028	-0.004	10.513	0.311
10	0.035	-0.001	10.771	0.376
11	-0.088	-0.088	12.454	0.330
12	0.024	0.019	12.579	0.400
13	0.001	0.000	12.579	0.481
14	-0.039	-0.021	12.914	0.533
15	-0.071	-0.104	14.042	0.522
16	0.004	0.033	14.046	0.595
17	-0.099	-0.120	16.237	0.507
18	-0.146	-0.135	21.007	0.279
19	0.045	0.056	21.461	0.312
20	0.023	0.047	21.587	0.363
21	0.036	-0.002	21.883	0.406
22	0.179	0.143	29.238	0.138
23	0.046	0.021	29.732	0.157
24	0.065	0.003	30.713	0.162

PSON.L:

Correlogram of D(CLOSE)

Date: 08/03/24 Time: 08:32
Sample (adjusted): 6/02/2017 21/12/2020
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.013	0.013	0.0326	0.857
		2	-0.050	-0.050	0.5564	0.757
		3	-0.048	-0.047	1.0354	0.793
		4	-0.004	-0.005	1.0389	0.904
		5	-0.062	-0.067	1.8530	0.869
		6	0.012	0.010	1.8823	0.930
		7	-0.042	-0.050	2.2592	0.944
		8	0.148	0.146	6.9440	0.543
		9	0.081	0.075	8.3681	0.498
		10	-0.034	-0.029	8.6203	0.568
		11	-0.127	-0.107	12.105	0.356
		12	0.064	0.068	13.004	0.369
		13	-0.149	-0.152	17.849	0.163
		14	-0.023	-0.019	17.970	0.208
		15	0.058	0.059	18.717	0.227
		16	0.007	-0.037	18.728	0.283
		17	-0.027	-0.041	18.887	0.335
		18	0.013	-0.006	18.924	0.397
		19	-0.099	-0.064	21.148	0.329
		20	0.022	0.014	21.258	0.382
		21	0.059	0.078	22.065	0.396
		22	0.047	0.065	22.566	0.427
		23	0.004	0.003	22.569	0.486
		24	0.160	0.128	28.498	0.240

FTSE 350 General Industrial Index:

Series: CLOSE Workfile: SUB FTSE350::Untitled\
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Correlogram of D(CLOSE)

Date: 08/03/24 Time: 09:04
Sample (adjusted): 20/11/2016 4/10/2020
Included observations: 203 after adjustments

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.107	-0.107	2.3403	0.126
		2	0.108	0.097	4.7418	0.093
		3	-0.031	-0.011	4.9472	0.176
		4	-0.023	-0.038	5.0561	0.282
		5	-0.087	-0.091	6.6632	0.247
		6	0.020	0.009	6.7443	0.345
		7	0.067	0.090	7.7064	0.359
		8	0.064	0.075	8.5857	0.378
		9	-0.012	-0.021	8.6145	0.474
		10	-0.024	-0.050	8.7420	0.557
		11	-0.073	-0.070	9.8879	0.540
		12	-0.122	-0.115	13.129	0.360
		13	-0.031	-0.034	13.335	0.422
		14	-0.088	-0.089	15.026	0.376
		15	0.108	0.077	17.607	0.284
		16	-0.018	-0.000	17.676	0.343
		17	0.040	0.006	18.041	0.386
		18	-0.136	-0.131	22.201	0.223
		19	0.075	0.065	23.471	0.217
		20	-0.060	0.017	24.295	0.230
		21	-0.014	-0.027	24.337	0.277
		22	0.073	0.055	25.573	0.270
		23	0.089	0.063	27.415	0.239
		24	-0.006	-0.014	27.424	0.285

5. Variance ratio tests:

JD.L:

Variance Ratio Test on CLOSE

Null Hypothesis: CLOSE is a martingale
Date: 06/03/24 Time: 09:38
Sample: 17/02/2020 8/01/2024
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 8)*	1.048867	203	0.7519

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.971814	0.082773	-0.340526	0.7335
4	0.914747	0.154511	-0.551760	0.5811
8	0.750945	0.237451	-1.048867	0.2942
16	0.820564	0.327520	-0.547863	0.5838

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = -0.302019704433)

Period	Variance	Var. Ratio	Obs.
1	102.338	--	203
2	99.4531	0.97181	202
4	93.6131	0.91475	200
8	76.8500	0.75095	196
16	83.9746	0.82056	188

APTD.L:

Variance Ratio Test on CLOSE

Null Hypothesis: CLOSE is a martingale
Date: 06/03/24 Time: 09:09
Sample: 9/10/2006 30/08/2010
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 4)*	2.051900	203	0.1513

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.649465	0.180655	-1.940362	0.0523
4	0.422502	0.281446	-2.051900	0.0402
8	0.354527	0.406413	-1.588220	0.1122
16	0.245486	0.521164	-1.447746	0.1477

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 0.0696694581281)

Period	Variance	Var. Ratio	Obs.
1	88.6974	--	203
2	57.6059	0.64946	202
4	37.4748	0.42250	200
8	31.4457	0.35453	196
16	21.7740	0.24549	188

BRBY.L:

Variance Ratio Test on CLOSE

Null Hypothesis: CLOSE is a martingale
Date: 08/03/24 Time: 08:12
Sample: 30/01/2017 21/12/2020
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 4)*	1.371749	203	0.5257

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.060158	0.081925	0.734302	0.4628
4	1.211523	0.154199	1.371749	0.1701
8	1.141263	0.245160	0.576209	0.5645
16	1.021023	0.360727	0.058281	0.9535

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 0.581280788177)

Period	Variance	Var. Ratio	Obs.
1	6714.25	--	203
2	7118.17	1.06016	202
4	8134.47	1.21152	200
8	7662.73	1.14126	196
16	6855.41	1.02102	188

PSON.L:

Variance Ratio Test on CLOSE

Null Hypothesis: CLOSE is a martingale
Date: 08/03/24 Time: 08:39
Sample: 30/01/2017 21/12/2020
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 8)*	0.632354	203	0.9500

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	1.022252	0.084963	0.261897	0.7934
4	0.970805	0.145994	-0.199972	0.8415
8	0.866699	0.210802	-0.632354	0.5272
16	0.874092	0.306748	-0.410459	0.6815

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 0.186699605911)

Period	Variance	Var. Ratio	Obs.
1	913.367	--	203
2	933.691	1.02225	202
4	886.701	0.97081	200
8	791.614	0.86670	196
16	798.367	0.87409	188

FTSE 350 General Industrial Index:

Series: CLOSE Workfile: SUB FTSE350::Untitled\
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Variance Ratio Test on CLOSE

Null Hypothesis: CLOSE is a martingale
Date: 08/03/24 Time: 09:09
Sample: 13/11/2016 4/10/2020
Included observations: 203 (after adjustments)
Heteroskedasticity robust standard error estimates
User-specified lags: 2 4 8 16

Joint Tests	Value	df	Probability
Max |z| (at period 2)*	0.974677	203	0.7982

Individual Tests

Period	Var. Ratio	Std. Error	z-Statistic	Probability
2	0.899964	0.102635	-0.974677	0.3297
4	0.947457	0.193046	-0.272180	0.7855
8	0.906395	0.299228	-0.312821	0.7544
16	0.844477	0.423266	-0.367434	0.7133

*Probability approximation using studentized maximum modulus with parameter value 4 and infinite degrees of freedom

Test Details (Mean = 3.37256157635)

Period	Variance	Var. Ratio	Obs.
1	41008.3	--	203
2	36906.0	0.89996	202
4	38853.6	0.94746	200
8	37169.7	0.90639	196
16	34630.6	0.84448	188

6. Application of the forecasting models

JD. L:

Double exponential smoothing:

Forecasts

Period	Forecast	Lower	Upper
205	149.105	119.492	178.719
206	149.064	118.834	179.294
207	149.022	118.127	179.917
208	148.981	117.377	180.584

Forecast Evaluation
Date: 21/03/24 Time: 08:54
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	0.000582	0.9829

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-27.51655	0.0001	0.0001	0.9999
Sq Error	-27.51440	0.0001	0.0001	0.9999

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	35.36473	35.28050	31.07158	26.86850	0.134553	7.308891
C	112.7889	112.7625	99.12058	196.5130	0.982579	24.14417
Simple mean	38.81767	38.74100	34.02450	41.01644	0.205591	8.436893
Simple median	38.81767	38.74100	34.02450	41.01644	0.205591	8.436893
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	22.16347	22.02884	19.41779	17.67518	0.088803	4.505216
MSE ranks	14.27701	14.06717	12.32580	13.15614	0.066876	3.220565

Triple exponential smoothing technique:

Multiplicative method:

Forecasts

Period	Forecast	Lower	Upper
205	150.321	121.635	179.008
206	144.893	115.757	174.029
207	155.615	125.978	185.252
208	147.252	117.064	177.439

Forecast Evaluation
Date: 21/03/24 Time: 09:07
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	1.145884	0.3965

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-16.73615	0.0005	0.0002	0.9998
Sq Error	-21.68046	0.0002	0.0001	0.9999

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	36.22796	35.75750	31.53556	27.13798	0.137559	7.417387
C	112.7889	112.7625	99.12058	196.5130	0.982579	24.14417
Simple mean	38.70814	38.50250	33.79251	40.73235	0.204723	8.468145
Simple median	38.70814	38.50250	33.79251	40.73235	0.204723	8.468145
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	22.54070	21.86765	19.31637	17.51609	0.090355	4.532143
MSE ranks	14.49201	13.74917	12.01648	12.86968	0.067771	3.346147

Additive method:

Forecasts

Period	Forecast	Lower	Upper
205	151.070	122.633	179.507
206	145.317	116.435	174.200
207	157.764	128.385	187.143
208	148.575	118.650	178.499

Forecast Evaluation
Date: 21/03/24 Time: 09:21
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	1.084016	0.4071

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-15.58468	0.0006	0.0003	0.9997
Sq Error	-20.60312	0.0003	0.0001	0.9999

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	37.45552	36.91750	32.56085	27.88447	0.141589	7.708693
C	112.7889	112.7625	99.12058	196.5130	0.982579	24.14417
Simple mean	38.15598	37.92250	33.27987	40.00287	0.201178	8.342759
Simple median	38.15598	37.92250	33.27987	40.00287	0.201178	8.342759
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	22.82494	22.05026	19.48135	17.63875	0.091423	4.625640
MSE ranks	13.87059	12.97583	11.33296	12.11157	0.064628	3.209710

APTD.L:

Double exponential smoothing:

Forecasts

Period	Forecast	Lower	Upper
205	116.763	101.125	132.400
206	115.897	99.933	131.861
207	115.031	98.717	131.346
208	114.166	97.477	130.855

Forecast Evaluation
Date: 21/03/24 Time: 09:41
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	0.231624	0.6778

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-6.779365	0.0066	0.0033	0.9967
Sq Error	-4.691626	0.0183	0.0092	0.9908

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	21.34565	19.89250	18.21679	17.52588	0.091278	0.701450
C	117.3999	115.3925	99.10731	196.4621	0.983389	3.752478
Simple mean	61.99508	58.16000	48.05486	64.43830	0.351013	2.065321
Simple median	61.99508	58.16000	48.05486	64.43830	0.351013	2.065321
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	21.82248	19.89250	17.63892	17.52860	0.094802	0.743349
MSE ranks	44.56663	39.08250	31.03738	38.25183	0.227734	1.528521

Triple exponential smoothing technique:

Multiplicative method:

Forecasts

Period	Forecast	Lower	Upper
205	106.853	91.5396	122.165
206	104.335	88.7819	119.888
207	102.184	86.3637	118.004
208	96.431	80.3171	112.545

Forecast Evaluation
Date: 21/03/24 Time: 09:52
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	0.789439	0.4680

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-12.30561	0.0012	0.0006	0.9994
Sq Error	-5.270203	0.0133	0.0067	0.9933

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	24.25025	19.66000	15.71410	17.19070	0.109778	0.864747
C	117.3999	115.3925	99.10731	196.4621	0.983389	3.752478
Simple mean	67.88815	64.66875	54.04894	74.91188	0.399008	2.250977
Simple median	67.88815	64.66875	54.04894	74.91188	0.399008	2.250977
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	26.89842	21.85881	17.10467	19.21697	0.124100	0.961702
MSE ranks	51.92284	47.76083	39.02948	49.60242	0.277570	1.762248

Additive method:

Forecasts

Period	Forecast	Lower	Upper
205	112.932	96.6305	129.234
206	111.396	94.8386	127.952
207	110.053	93.2118	126.895
208	106.264	89.1099	123.419

Forecast Evaluation
Date: 21/03/24 Time: 09:59
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	0.860287	0.4516

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-8.533584	0.0034	0.0017	0.9983
Sq Error	-4.949124	0.0158	0.0079	0.9921

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	21.29906	19.32750	16.74164	17.00539	0.093184	0.733731
C	117.3999	115.3925	99.10731	196.4621	0.983389	3.752478
Simple mean	64.32484	60.81250	50.53033	68.61799	0.369733	2.138698
Simple median	64.32484	60.81250	50.53033	68.61799	0.369733	2.138698
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	22.59630	19.34550	16.21321	16.99405	0.100387	0.795187
MSE ranks	47.40611	42.61917	34.33800	42.75198	0.246682	1.618911

BRBY.L:
Double exponential smoothing technique:

Forecasts

Period	Forecast	Lower	Upper
205	1803.05	1505.49	2100.61
206	1834.04	1530.28	2137.80
207	1865.03	1554.60	2175.47
208	1896.02	1578.46	2213.58

Forecast Evaluation
Date: 21/03/24 Time: 10:13
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	0.820529	0.4606

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-27.04302	0.0001	0.0001	0.9999
Sq Error	-33.42083	0.0001	0.0000	1.0000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	101.2811	74.89000	4.306506	4.142993	0.027938	1.540572
C	1774.401	1773.875	99.94362	199.7746	0.998874	23.36488
Simple mean	851.3569	849.6075	47.82483	62.89930	0.315220	11.07444
Simple median	851.3569	849.6075	47.82483	62.89930	0.315220	11.07444
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	96.87365	71.86334	4.130244	3.980689	0.026766	1.475433
MSE ranks	544.7205	541.5183	30.45190	35.97822	0.181032	6.991860

Triple exponential smoothing technique:

Multiplicative method:

Forecasts

Period	Forecast	Lower	Upper
205	1869.95	1591.20	2148.70
206	1923.60	1640.48	2206.71
207	1945.63	1657.65	2233.62
208	1901.56	1608.23	2194.89

Forecast Evaluation
Date: 21/03/24 Time: 10:21
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	0.298567	0.6396

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-28.38524	0.0001	0.0000	1.0000
Sq Error	-31.85849	0.0001	0.0000	1.0000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	147.7515	135.3100	7.702041	7.360422	0.040087	2.142290
C	1774.401	1773.875	99.94362	199.7746	0.998874	23.36488
Simple mean	820.8063	819.2825	46.12079	59.97874	0.300541	10.69659
Simple median	820.8063	819.2825	46.12079	59.97874	0.300541	10.69659
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	135.7531	122.1636	6.960807	6.670851	0.036963	1.979250
MSE ranks	503.8678	501.0850	28.17985	32.84565	0.165239	6.485862

Additive method:

Forecasts

Period	Forecast	Lower	Upper
205	1869.90	1588.60	2151.21
206	1919.06	1633.34	2204.77
207	1941.83	1651.20	2232.46
208	1891.11	1595.08	2187.13

Forecast Evaluation
Date: 21/03/24 Time: 10:29
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	0.271111	0.6545

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-28.68401	0.0001	0.0000	1.0000
Sq Error	-31.97927	0.0001	0.0000	1.0000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	143.1214	130.6000	7.435632	7.114453	0.038880	2.066766
C	1774.401	1773.875	99.94362	199.7746	0.998874	23.36488
Simple mean	823.1341	821.6375	46.25400	60.20308	0.301654	10.73903
Simple median	823.1341	821.6375	46.25400	60.20308	0.301654	10.73903
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	131.9280	118.2898	6.741552	6.467231	0.035960	1.915329
MSE ranks	506.9368	504.2250	28.35745	33.08544	0.166417	6.542503

PSON.L:

Double exponential smoothing technique:

Forecasts

Period	Forecast	Lower	Upper
205	672.799	572.838	772.760
206	686.833	584.789	788.876
207	700.867	596.580	805.153
208	714.901	608.221	821.580

Forecast Evaluation
Date: 21/03/24 Time: 19:27
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	2.378974	0.2629

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-53.82562	0.0000	0.0000	1.0000
Sq Error	-38.36329	0.0000	0.0000	1.0000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	12.37441	9.050000	1.332654	1.319385	0.008949	0.631140
C	687.8193	687.6500	99.85472	199.4197	0.997101	32.11698
Simple mean	341.3977	341.2250	49.54378	65.86609	0.329429	15.84501
Simple median	341.3977	341.2250	49.54378	65.86609	0.329429	15.84501
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	12.28005	9.050000	1.332223	1.319387	0.008882	0.623897
MSE ranks	225.9868	225.7500	32.77346	39.20686	0.196197	10.42333

Multiplicative method:

Forecasts

Period	Forecast	Lower	Upper
205	697.321	613.527	781.115
206	719.283	634.176	804.390
207	679.332	592.762	765.903
208	684.536	596.358	772.714

Forecast Evaluation
Date: 21/03/24 Time: 19:35
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	0.241586	0.6717

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-73.54977	0.0000	0.0000	1.0000
Sq Error	-38.83156	0.0000	0.0000	1.0000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	25.81644	21.69750	3.133303	3.110800	0.018652	1.310442
C	687.8193	687.6500	99.85472	199.4197	0.997101	32.11698
Simple mean	341.1331	340.5913	49.42574	65.68762	0.328973	16.01693
Simple median	341.1331	340.5913	49.42574	65.68762	0.328973	16.01693
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	25.57198	21.20182	3.058661	3.040523	0.018488	1.305591
MSE ranks	225.8839	224.9050	32.61608	39.02071	0.195964	10.66808

Additive method:

Forecasts

Period	Forecast	Lower	Upper
205	689.922	604.285	775.560
206	712.317	625.337	799.296
207	663.600	575.124	752.075
208	665.573	575.455	755.692

Forecast Evaluation
Date: 21/03/24 Time: 19:43
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	0.465144	0.5656

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-149.4531	0.0000	0.0000	1.0000
Sq Error	-40.16081	0.0000	0.0000	1.0000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	30.45394	26.11750	3.751192	3.790836	0.022197	1.617601
C	687.8193	687.6500	99.85472	199.4197	0.997101	32.11698
Simple mean	347.3924	346.7238	50.31106	67.27532	0.336983	16.34630
Simple median	347.3924	346.7238	50.31106	67.27532	0.336983	16.34630
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	30.70216	26.08176	3.743855	3.790783	0.022400	1.636487
MSE ranks	234.3339	233.0817	33.79651	40.73964	0.204733	11.11228

FTSE-350 General Industrial Index:

Double exponential smoothing technique:

Forecasts

Period	Forecast	Lower	Upper
205	5775.07	5183.69	6366.44
206	5826.57	5222.88	6430.27
207	5878.08	5261.11	6495.05
208	5929.59	5298.46	6560.71

Forecast Evaluation
Date: 21/03/24 Time: 19:58
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	0.238481	0.6736

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-33.50938	0.0001	0.0000	1.0000
Sq Error	-28.89745	0.0001	0.0000	1.0000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	203.0285	152.3875	2.682486	2.642912	0.017402	0.663136
C	5813.648	5811.085	99.98278	199.9311	0.999656	18.52110
Simple mean	2891.284	2885.421	49.59442	65.98404	0.330756	9.094702
Simple median	2891.284	2885.421	49.59442	65.98404	0.330756	9.094702
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	201.6972	152.3248	2.679219	2.642933	0.017298	0.651028
MSE ranks	1919.495	1910.200	32.79830	39.27912	0.197546	5.958720

Multiplicative method:

Forecasts

Period	Forecast	Lower	Upper
205	5485.02	4932.66	6037.38
206	5645.47	5084.46	6206.48
207	5871.87	5301.21	6442.53
208	5827.87	5246.62	6409.12

Forecast Evaluation
Date: 21/03/24 Time: 20:09
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	1.754961	0.3164

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-39.22301	0.0000	0.0000	1.0000
Sq Error	-29.49537	0.0001	0.0000	1.0000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	317.4565	281.6475	4.863780	4.915847	0.027547	0.776221
C	5813.648	5811.085	99.98278	199.9311	0.999656	18.52110
Simple mean	2966.903	2957.806	50.81824	68.21076	0.342205	9.254904
Simple median	2966.903	2957.806	50.81824	68.21076	0.342205	9.254904
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	323.0545	289.8857	4.997941	5.064589	0.028074	0.773917
MSE ranks	2022.736	2006.713	34.43006	41.69552	0.210233	6.177017

Additive method:

Forecasts

Period	Forecast	Lower	Upper
205	5411.70	4859.27	5964.12
206	5575.39	5014.31	6136.47
207	5805.45	5234.72	6376.18
208	5751.50	5170.18	6332.83

Forecast Evaluation
Date: 21/03/24 Time: 20:17
Sample: 1 4
Included observations: 4
Evaluation sample: 1 4
Training sample: 1 4
Number of forecasts: 7

Combination tests
Null hypothesis: Forecast i includes all information contained in others

Forecast	F-stat	F-prob
FORECAST	NA	NA
C	1.913643	0.3007

Diebold-Mariano test (HLN adjusted)
Null hypothesis: Both forecasts have the same accuracy

Accuracy	Statistic	<> prob	> prob	< prob
Abs Error	-49.19829	0.0000	0.0000	1.0000
Sq Error	-30.05963	0.0001	0.0000	1.0000

Evaluation statistics

Forecast	RMSE	MAE	MAPE	SMAPE	Theil U1	Theil U2
FORECAST	349.5904	319.9850	5.492404	5.609302	0.030524	0.802999
C	5813.648	5811.085	99.98278	199.9311	0.999656	18.52110
Simple mean	3002.669	2993.580	51.43350	69.32234	0.347764	9.369198
Simple median	3002.669	2993.580	51.43350	69.32234	0.347764	9.369198
Least-squares	NA	NA	NA	NA	NA	NA
Mean square error	359.8162	329.8310	5.652731	5.789498	0.031473	0.819374
MSE ranks	2070.268	2054.412	35.25041	42.90027	0.216244	6.329065