International Journal of Asian Business and Management (IJABM)
Vol.2, No.1, 2023: 11-32

Forecasting Stock Prices on the Basis of Technical Analysis in the Industrial Sectors of the UK Stock Market

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A R T I C L E I N F O

Keywords: Forecasting, Industrial Price Behaviour, Random Walk Model, Structural Breakpoint, Technical Analysis, Time Series Analysis

Received : 3 January
Revised : 16 January
Accepted: 18 February

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A B S T R A C T

This study aims to evaluate, critically and rigorously the weak-form market efficiency and forecasting power of technical analysis in different industries in the London Stock Exchange. Weekly data were collected from the FTSE-all share index, FTSE-350 general industrial index and twenty companies of four different industries, for the period between 1997 and 2017. Bai-Perron's multiple breaks test was applied to diagnose plain data period for the purpose of forecasting. The statistical inference was made from the application of the runs test, variance ratio tests, Ljung-Box's test and ADF-unit root test that the market is not weak-form efficient and stock prices are predictable. This study extends the current literature by considering the existence of weak-form inefficiency in different industrial sectors. The findings do not support for weak-form efficiency over the periods tested from the application of the ARIMA and GARCH (1, 1) models and double and triple exponential smoothing techniques

DOI: https://doi.org/10.55927/ijabm.v2i1.2901
ISSN-E: 2964-3651
https://journal.formosapublisher.org/index.php/ijabm

INTRODUCTION

The idea of technical analysis is against the efficient-market hypothesis (EMH). The relationship between technical analysis and EMH is so contradictory that technical analysis refutes the existence of market efficiency. More specifically, technical analysts rebut weak-form market efficiency, which is one of the forms of market efficiency. They believe that future performance can be seen as a reflection of past performance. Therefore, the future prices of selected stocks can be estimated from their historical performance

Structure of This Paper

First, books and journals were reviewed as part of this research to identify the existing knowledge gaps. This led to some interesting research questions and helped to derive an aim and objectives from the research problem in introduction and literature review. Data and methodology section explains the line graphs, histograms and kernel density graphs from data collected from twenty individual companies listed in FTSE100 in four different industries to diagnose the impacts of regulation based announcements and disclosures on stock price movements.

Then, in results section this research applies forecasting related statistical techniques and non-forecasting and forecasting related statistical methods and evaluation techniques to justify, rigorously and critically, the predictability of different industries and technical analysis. Next sections interpret research findings and draw conclusion.

Research Gap

Many scholars argue that developed stock markets are usually weak-form efficient. This study believes that a developed market could be weak-form efficient. However, all industries in the developed market could not be sufficiently efficient to embed all relevant new information into stock prices at the same time. The speed in the incorporation of stock price might differ from industry to industry in the same market. Therefore, this study is conducted using a developed stock market, the London Stock Exchange to test this hypothesis.

This study assumes that all industries, even in a developed market, are not equally capable of incorporating all relevant information into stock prices at the same time. All industries might not have the same performance level. Some industries could be weaker and other industries could be strong enough to adjust this information into prices. Therefore, all industries in a developed market could not be weak-form efficient.

It was observed in the review of literature that no one ever investigated this assumption so far especially in the London Stock Exchange. This research will investigate all industrial sectors to see the predictability of those sectors. Therefore, the aim of this research is to evaluate weak-form market efficiency and the forecasting power of technical analysis critically and rigorously in different industrial sectors in the UK.

LITERATURE REVIEW

Most early research on investigating weak-form efficiency, initiated on the developed stock markets, support the weak-form efficiency of the stock markets considering transaction cost and a low degree of auto correlation (Kendall 1953, Cootner 1962, Osborne 1962 and Fama 1965). All these researchers found that stock prices change randomly, frequently, and independently. Therefore, future prices are not possible to predict on the basis of past performance of stocks especially when transaction costs are considered.

Some researchers found that the forecastability of stock price alters in developed markets, however, they did not conclude regarding profitable trading rules (Fama and French 1988, Poterba and Summers, 1988). Poterba and Summers (1988) claimed that noise trading and demand for stocks are measured by several factors other than desired returns of investors. They claimed that serial autocorrelation in stock prices take place when researchers try to construct and examine the theory of noise trading. Fama and French (1988) surmised that stock market inefficiency could happen due to serial correlation. However, none of the studies consider serial correlation in stock prices that could take place when a long historical data is taken even in a developed market. Hudson, Dempsey, and Keasey (1996) claimed that the technical analysis could have forecasting power but not adequate to satisfy an additional return in the UK stock market.

Mills (1997) evidenced that technical analysis generated profits in the London Stock Exchange until 1979. However, the application of technical trading rules could not beat the buy-and-hold strategy after 1980. The reason that Mills suggested was that the predictability in the period between 1935 and 1979 was driftless (stationary). Contrary to these findings, Brock et al. (1992) applied the same trading rules to the American stock market and found that they worked successfully throughout the sample period. However, Mills (1997) found a discrepancy in the last sub-sample period, which is doubtable. Furthermore, if the specified period was driftless, the market would have collapsed. Therefore, the findings of the research are confusing and seem to be invalid. Summers, Griffiths, and Hudson (2004) investigated the validity of technical analysis of the London Stock Exchange and confirmed their assumption that returns are predictable.

McMillan, Speight, and Apgwilym (2000) found that the FTSE 100 index and FTA All-Share Index in the UK provide returns. Similarly, Maris et al. (2004) evidenced that the FTSE (UK)/the ASE (Greece) 20 stock index provide prediction more precisely for short-term investment, especially for one week.

Lee (1992) investigated weak-form efficiency in ten developed countries including Japan, Australia, Belgium, France, Italy, Netherlands, Canada, Switzerland, United Kingdom, and West Germany. His applied variance ratio test showed that all markets are weak-form efficient and prices move randomly. Consistent with the study of Lee (1992), Choudhry (1994) found that the stock prices of developed countries including United Kingdom, France, Italy, Japan, German, Canada, and United States of America are not predictable. However, Al-Loughani and Chappel (1997) examined the London Stock Exchange and claimed that stock prices do not behave randomly and they are predictable.

Similarly, Du and Wong (2018) found that the forecastability of technical analysis in the Singapore Stock Market.

Groenewold (1997) examined Australia and New Zealand for the periods between 1975 and 1992 and obtained mixed results. Furthermore, Chan et al. (1997) studied eighteen stock markets from developed and developing countries including the UK, the USA, Canada, Germany, France, Italy, Spain, Denmark, Finland, Netherlands, Norway, Sweden, Switzerland, Australia, Belgium, Japan, India, and Pakistan and documented that all the developed markets are weak-form efficient.

Lee et al. (1999) explored the Spanish future market and found that the market is weak-form efficient and prices change very frequently. In relation to the findings of Lee et al. (1999) and Groenewold (1997), Worthington and Higgs (2006) studied sixteen developed and four developing stock markets in Europe. They claimed that only Germany, Ireland, Portugal, Sweden, and the United Kingdom of developed countries strictly follow a random walk hypothesis. Consistent results were found from the study conducted by Andrews and Hellen (2010) who found that the European markets of Germany, Ireland, Portugal, Sweden, and the UK follow a random walk fashion.

Similarly, Adebayo (2013) confirmed the weak-form market efficiency for the UK for the period between 2006 and 2011. Moreover, Konak and Seker (2014) reconfirmed the existence of weak-form efficiency for the UK stock market. The developed markets, such as the US and UK markets, are perceived as being weak-form efficient, but other studies found support for the inefficiency of these markets. For example, Otilia (2011) studied the US, UK, and the Japanese market, Shynkevich (2012), Arevalo et. al. (2017) and Lin (2018) in US market. All the researchers claimed that these markets do not follow a random walk hypothesis over the inquiry period and returns are predictable. Furthermore, Ghimire et al. (2016) investigated the validity of weak-form market efficiency for six developed and underdeveloped agricultural markets. The findings show that all the markets are weak-form inefficient.

Smith (2012) tested martingale behaviour of stock prices for fifteen developing markets in Europe including Croatia, the Czech Republic, Estonia, Hungary, Iceland, Latvia, Lithuania, Malta, Poland, Romania, Russia, the Slovak Republic, Slovenia, Turkey, and the Ukraine, and three developed stock markets including Greece, Portugal, and the UK. The variance ratio tests evidenced the mixed results that developed markets are not always weak-form efficient. The results detail that the Turkish, UK, Hungarian, and Polish stock markets are highly weak-form efficient. The consistent results were documented by Ahmad et al. (2017) who studied the London Stock Exchange and documented that moving average strategy substantially outperforms a buy-and-hold strategy. However, the market is weak-form efficient as actual transaction costs are considerably lower than breakeven transaction costs. Groenewold (1997) also demanded that long historical prices have forecasting power in the Australian stock market, but the degree of forecastability is not significant.

Gan et al. (2005) claimed stock markets in Japan, New Zealand, Australia, and United States are weak-form efficient. Furthermore, Fang et al. (2014)

reconfirmed weak-form efficiency of the US market. Similarly, Torun and Kurt (2008) evidenced that eleven European markets are weak-form efficient. Hasanov (2009) re-investigated the stock markets from Australia and New Zealand using the work of Narayan (2005). The application of unit root test documented that none of the markets are weak-form efficient, opposing the findings of Narayan (2005). Kim and Shamsuddin (2008) claimed that stock prices of highly developed markets move very frequently and randomly. Consequently, stock prices of these markets are unpredictable. Conversely, stock prices of under developing markets are mean reverting and predictable.

Early studies used traditional unit root tests to examine weak-form efficiency. Scholars have not considered structural breaks in the data set even in the developed markets. However, traditional unit root tests (ADF, PP, KPSS and so on) have low power to reject the null hypothesis of series have unit root in the presence of one or multiple structural breaks (Perron, 1989). Wu et al. (2019) found from the from the application of Bai-Perron test that structural breaks take place in stock market due to an event which impact fall on mean or variance or both level. As a consequence, Parab and Reddy (2020) found significant impact of multiple structural breakpoints on returns in the stock market of India caused by macroeconomic variables from the application of Bai-Perron test. Barari et al. (2014) found structural breaks in the housing prices from the application of Bai-Perron's multiple breakpoints test in U.S. Furthermore, Stylianou (2014) found a significant impact of multiple breakpoints in the relationship of growth, foreign direct investment and exports in the U.S.

Narayan and Liu (2013) identified one possible reason for that is not to consider structural breaks of dataset in the analysis. The early studies have largely ignored the presence of heteroskedasticity in the data series. Lim and Brooks (2011) revealed that when return series contains a unit root, they show a random walk and shock in that series and resulted in unpredictability of future return series based on past series. When return series are stationary, they exhibit a mean reverting and make it possible to predict future movement of returns using past data series

METHODOLOGY

Twenty years' weekly closing data from 3 March 1997 to 16 July 2017 were collected through London South East (LSE) stock prices. These data include the weekly closing prices of FTSE-all share index, FTSE-350 general industrial index, 20 individual companies from 4 different industries for the purpose of evaluating the discrepancies between the actual price and the predicted price. Thus, there are 22 series, each of which contains 1064 observations except FTSE-350 general industrial index. This is because, data of FTSE-350 general industrial index is not available for this time span. This series includes period from 07/06/2009 to 16/07/2017, which is 424 observations.

However, this study has chosen an estimation period of 204 observations. Hyndman and Athanasopoulos (2018) explain that the number of observations should not be large especially for stock market as most time series do not work for very long time series. The number of observations should be around 200.

Therefore, the short period of observations for FTSE-350 general industrial index will not affect significantly.

At first, all the series will be visually inspected for the whole sample period to see whether there are any seasonality and structural breaks in the data. Furthermore, the Friedman test of Chi-Square statistics will be applied to detect seasonality. Secondly, structural breaks will be investigated if there is any from the application of Bai-Perron's multiple breakpoints test for the whole sample period.

If there are any breakpoints at different point of time, a clean period of data will be selected for each series where there is no any structural break for statistical analysis and forecasting purposes. As a consequence, the clean period will be a sub-sample period. However, this sub-sample period might not be the same for all series. This is because, all the series might have specific shocks or events caused by microeconomic factors.

Statistical inferences regarding market efficiency will be made from four different statistical tests (ADF-unit root test at the first difference, runs test at level, Ljung Box's serial autocorrelation at first difference and variance ratio test at level). Weak-form efficiency inference is made if there is no unit root and serial-autocorrelation at the first difference and there is no heteroscedasticity (variance is constant) at the level.

ADF-unit root test:

To apply the augmented Dickey–Fuller (ADF) unit root test, it is assumed that STK is the stock index series. The formula of a random walk model for STK could be written as follows:

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

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

If $|\rho| \leq 1$(ρ is less than 1), time series STK_t is stationary or series does not need to use first or second difference. As u_t is a white noise error term, data are stationary which suggests that first difference of a random walk time series are stationary (Gujarati, 2004).

Variance Ratio test:

The variance ratio (VR) is written as follows:

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

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.

Source: Gujarati (2004)

Run test:

The formula of expected runs (v) is given by Gujarati (2004) as follows:

$$Mean: \mu_v(expected\ runs) = \frac{2M_1M_2}{M} + 1$$

$$Variance: \sigma_v^2 = \frac{2M_1M_2\,(2M_1M_2 - M)}{M^2(M-1)}$$

Where, M_1 and M_2 = The number of individual observations above and below the mean,

M = Total observations (i.e. $M_1 + M_2$ = M)

v = Expected run.

The total number of runs is explained by two tailed Z statistic. Z statistic provides the distinction between expected and observed number of runs. Sharma and Kennedy (1977) detailed that if $Z \geq \pm 1.96$; reject that returns are random (expected runs are higher) at 5% level of significance or if $9 \geq Z \leq 20$; reject that stock prices are random or reject weak-form efficiency (i.e. returns are predictable).

Ljung Box's serial autocorrelation:

For a large sample, the Ljung—Box (LB) statistic follows the chi-square distribution with m degrees of freedom. Furthermore, the formula of Box-Pierce statistic will be applied to test whether a time series is white noise. The formula is as follows:

$$Q = n \sum_{k=1}^{m} \rho^2\, k$$

Where,

n = Sample size

m = Lag length

ρ_k = Sample autocorrelation co-efficient

Source: Gujarati (2004), p. 813

The formula for the Ljung-Box Q* test is as follows:

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

Where,

x_m^2= chi-square distribution with m (degree of freedom) df.

ρ_k^2 (Rho squared k) = Auto-correlation coefficients at lag k;

n = sample size

Source: Gujarati (2004, p. 813)

After drawing the statistical inference, statistical models and techniques (ARIMA; GARCH-1, 1; exponential smoothing techniques) will be applied to predict the market for each sub-sample period. This study will choose a sub-sample period of 204 observations for each series to estimate the model. A few observations just before the breakpoint have been excluded from the estimation period to evaluate the forecastability of the model.

The validation period is taken up to 4 observations. This is because, most time series models could not forecast for a very long period or do not provide accurate prediction for multi-step forecasts. There is another reason for considering a short estimation period. Afterwards, a conclusion will be drawn on predictability or market efficiency based on evaluation statistics including MAPE, Theil U_1 and U_2 from each model and technique. The forecast encompassing tests will be applied to determine which model performs better than the other. If the forecast encompassing tests fail to decide a better model, this study will go one step further back and rely on three parameters of forecast benchmarks including MAPE, Theil U_1 and U_2.

RESULT

weak-form market efficiency tests (runs test, unit root tests, correlogram, variance ratio tests), are conducted in a period of clear 204 observations, as required for forecasting using any models (Hyndman and Athanasopoulos, 2018).

The runs test shows that all the series including FTSE-all share index, FTSE-350 general industrial index and 20 companies from four different industries do not follow a random walk model as the p values are less than 5%. The ADF unit root tests show that all the series do not have unit root at first difference. The results of the Ljung-Box’s autocorrelation test are mixed: it seems some of the series do have autocorrelations up to 24 lags and others do not. The Chow Denning statistic joint test shows that the variance is constant at different lags.

In summary, except for the Variance ratio test, none of the series, in a period without a structural break (where ARIMA models will be estimated) robustly passes the criteria required for weak-form market efficiency. Four tests are applied and the results are as below:

Table 1. The Tests of Weak-Form Efficiency on 204 Observations from Each of 22 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
FTSE-ALL SHARE INDEX	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
FTSE-350 General Industrial Index	Not consistent with random walk	rejects the null of a unit root	Supports presence of autocorrelation up to first 2 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
The primary industry					
ANTO.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 2 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
BP.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 6 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
CNA.L	Not consistent with random walk	rejects the null of a unit root	Supports presence of autocorrelation up to first lag	The joint test of constant variance accepts the null of martingale	weak-form inefficient
SVT.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 5 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
JMAT.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient

The manufacturing industry					
ABF.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
BATS.L	Not consistent with random walk	rejects the null of a unit root	Supports presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
BDEV.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 3 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
BKG.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
DGE.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to 9 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
The service industry					
ADN.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
AHT.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to 15 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
AV.L	Not consistent with random walk	rejects the null of a unit root	Supports presence of autocorrelation for all 24 lags	The joint test of constant variance rejects the null of martingale	weak-form inefficient
BAB.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constants variance accept the null of martingale	weak-form inefficient

BARC.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 5 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
The quaternary industry					
AZN.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
GSK.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
SHP.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 13 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
SGE.L	Not consistent with random walk	rejects the null of a unit root	Supports presence of autocorrelation for all 24 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient
SN.L	Not consistent with random walk	rejects the null of a unit root	Rejects presence of autocorrelation up to first 3 lags	The joint test of constant variance accepts the null of martingale	weak-form inefficient

The ARIMA (p,d,q) models are estimated (after examining the ADF-unit root test, the ACF and PACF). The best ARIMA model is identified and the forecast accuracy is evaluated with a corresponding GARCH (1, 1) model with the same mean equation as the best identified ARIMA model.

The FTSE-all share index shows that double and triple exponential smoothing techniques are significantly inferior to ARIMA and GARCH (1, 1) models based on the forecast parameters of MAPE, Theil U_1 and U_2. The results also document that the ARIMA model performs better than all other applied models for this series. Furthermore, the GARCH (1, 1) model produces the second-best results for the same series. Therefore, the forecast encompassing test will be performed between ARIMA and GARCH (1, 1) models for this series in the next section. However, the values of Theil U_2 argue that none of the models is better than the naive method.

Similar results have been documented from FTSE-350 general industrial index. This series explains that exponential smoothing techniques fail to predict the prices. This is because, their values of MAPE, Theil U_1 and U_2 are considerably higher. Moreover, their values from exponential smoothing techniques are significantly higher than those from ARIMA and GARCH (1, 1) models. On the other hand, the ARIMA model shows its better predictability than GARCH (1, 1) model. Thus, the forecast encompassing test will be conducted between ARIMA and GARCH (1, 1) models for this series. Both ARIMA and GARCH (1, 1) models perform better than the naive method. However, the naive method performs better than exponential smoothing techniques.

ANTO.L, SVT.L and JMAT.L in the primary industry argue that the ARIMA model performs better than all other models. Furthermore, ARIMA model shows better forecastability than naive method for SVT.L. However, naive method beats ARIMA model for ANTO.L and JMAT.L. Contrary to that, GARCH (1, 1) model shows that it is the second-best performer for these series. However, the naive method shows better predictability than GARCH (1, 1) model for ANTO.L, SVT.L and JMAT.L. On the other hand, BP.L and CNA.L in the same industry show that GARCH (1, 1) model is the best predictor for those series among all applied models. Furthermore, both ARIMA and GARCH (1, 1) models beat the naive method for these series. Additionally, double and triple exponential smoothing techniques document poorer forecasting outcomes for all series in the primary industry compared to ARIMA and GARCH (1, 1) models. Moreover, the naive method shows better predictability than exponential smoothing techniques for all series in the primary industry.

ABF.L and DGE.L in the manufacturing industry evidence that ARIMA model generates significantly better prediction compared to all other applied models. Furthermore, the GARCH (1, 1) model claims that it is the second-best model for those series. Consequently, the forecast encompassing test will be done between these two models for those series in the next section. Contrary to that, GARCH (1, 1) model exhibits as the best performer for BDEV.L in the same industry. Hence, it will be examined in the next section whether ARIMA and GARCH (1, 1) models contain similar information or not. Furthermore, exponential smoothing techniques recorded as the best performers for BATS.L and BKG.L in the same industry. As a result, forecast encompassing tests will be run to examine whether double exponential smoothing technique contains additional information than triple exponential smoothing technique. ARIMA and GARCH (1, 1) models claim that all the series in the manufacturing industry are predictable as all the values of Theil U_2 are less than 1 and they both beat the naïve method, Bliemel (1973) and Omnia (2016). This result indicates that the manufacturing industry is predictable.

GARCH (1, 1) model shows better predictability than ARIMA model for ADN.L, AHT.L and BARC.L in the service industry. On the other hand, ARIMA model exhibits higher forecastability than GARCH (1, 1) model for BAB.L in the same industry Therefore, an encompassing test will be run between these two models for these series to see whether their forecast accuracy is equal or not. However, the results explain that naive model shows more precise predictability than ARIMA and GARCH (1, 1) models for ADN.L, AV.L, BAB.L and BARC.L. Contrary to that, both ARIMA and GARCH (1, 1) models beat the naive method for AHT.L. Double and triple exponential smoothing techniques confirm more precise forecasting for AV.L in the same industry than ARIMA and GARCH (1, 1) models and they beat the naive method.

ARIMA and GARCH (1, 1) models claim their more accurate forecasting power for AZN.L, GSK.L and SN.L in the quaternary industry respectively. However, GARCH (1, 1) and ARIMA models argue their better predictability than other applied forecasting techniques in this study for SHP.L and SN.L in the same industry respectively. Therefore, their encompassing tests will be conducted in the next section to see whether the two best models have similar forecast errors. However, the naive method beats GARCH (1, 1) model for AZN.L, GSK.L and SHP.L. Furthermore, the naive method evidences higher predictability than ARIMA model for AZN.L and SHP.L. Contrarily, both ARIMA and GARCH (1, 1) models beat naive method for SGE.L and SN.L in the same industry.

It is observed in the above analysis that ARIMA model performs better prediction for 11 series out of 22 series than all other applied models. In comparison with ARIMA, GARCH (1, 1) model shows better predictability for 8 series. Furthermore, double and triple exponential smoothing techniques document more forecast accuracy for the remaining 3 series than ARIMA and GARCH (1, 1) models. Additionally, it is found from Theil U_2 that all the series in the manufacturing industry are predictable. Therefore, it could be claimed that the market is predictable based on the industrial category. However, there is a contradiction regarding the forecast accuracy of Theil U_1 and U_2.

Table 2. A Comparison Table of Forecast Evaluation Statistics from All 4 Applied Models

Series	Model	MAPE	Theil U1	Theil U2	Two best predictors out of 4 models sequentially
FTSE- ALL SHARE INDEX	ARIMA	1.145679	0.007547	1.060459	ARIMA, GARCH
	GARCH	1.155130	0.007598	1.067716	
	Double	2.582081	0.014297	2.034027	
	Triple	2.197367	0.012453	1.777845	
FTSE-350 GENERAL INDUSTRIAL INDEX (GII)	ARIMA	1.562584	0.009604	0.892477	ARIMA, GARCH
	GARCH	1.618699	0.009764	0.903659	
	Double	4.514366	0.025168	2.070696	
	Triple	4.087236	0.022388	1.836150	
The primary industry					
ANTO.L	ARIMA	4.122849	0.021844	1.206746	ARIMA, GARCH
	GARCH	4.122595	0.021872	1.204551	
	Double	4.514366	0.025168	2.070696	
	Triple	4.087236	0.022388	1.836150	
BP.L	ARIMA	2.815959	0.019119	0.986113	GARCH, ARIMA
	GARCH	2.819547	0.019070	0.982496	
	Double	5.823316	0.032658	1.544930	
	Triple	6.028173	0.035157	1.675553	
CNA.L	ARIMA	2.118351	0.011514	0.922690	GARCH, ARIMA
	GARCH	2.022766	0.010851	0.935223	
	Double	5.834100	0.029684	3.929118	
	Triple	5.085861	0.026222	3.483295	
SVT.L	ARIMA	3.009562	0.015341	0.949282	ARIMA, GARCH
	GARCH	2.897015	0.015389	1.010646	
	Double	4.471125	0.024401	1.820317	
	Triple	3.961760	0.021343	1.581641	
JMAT.L	ARIMA	2.923678	0.023505	1.873953	ARIMA, GARCH
	GARCH	2.699760	0.021583	2.086932	
	Double	9.807355	0.051586	19.89782	
	Triple	9.662958	0.050834	19.35932	
The manufacturing industry					
ABF.L	ARIMA	0.583392	0.003866	0.797084	ARIMA, GARCH
	GARCH	0.667737	0.004153	0.830336	
	Double	2.728067	0.013985	2.528351	
	Triple	2.624046	0.013262	2.314116	
BATS.L	ARIMA	4.521327	0.024935	0.719096	Triple, Double
	GARCH	4.538673	0.025077	0.731332	
	Double	2.337800	0.014848	0.250096	
	Triple	2.206778	0.016285	0.128392	

BDEV.L	ARIMA	1.220913	0.007012	0.896468	
	GARCH	1.056305	0.006257	0.759193	GARCH,
	Double	1.988697	0.010243	1.503635	ARIMA
	Triple	2.124924	0.011350	1.672187	
BKG.L	ARIMA	1.903508	0.010949	0.901504	
	GARCH	1.906488	0.011356	0.949258	Double, Triple
	Double	0.745590	0.004668	0.469225	
	Triple	0.761496	0.004881	0.499641	
DGE.L	ARIMA	1.791252	0.010605	0.918546	
	GARCH	1.798614	0.010560	0.913910	ARIMA,
	Double	5.415759	0.027610	2.458514	GARCH
	Triple	4.362744	0.022663	2.015039	
The service industry					
ADN.L	ARIMA	2.928772	0.017792	1.124075	
	GARCH	2.869895	0.017451	1.104559	GARCH,
	Double	3.352904	0.020443	1.111195	ARIMA
	Triple	3.643779	0.021992	1.255875	
AHT.L	ARIMA	2.870944	0.019088	0.962709	
	GARCH	2.335542	0.015878	0.804961	GARCH,
	Double	14.71910	0.088603	3.928435	ARIMA
	Triple	14.66936	0.087368	3.853282	
AV.L	ARIMA	1.413938	0.009176	1.129999	
	GARCH	1.325929	0.009044	1.121699	Double, Triple
	Double	1.059147	0.005514	0.715380	
	Triple	1.118708	00.007388	0.994948	
BAB.L	ARIMA	1.168331	0.007604	1.119051	
	GARCH	1.296876	0.008070	1.187320	ARIMA,
	Double	2.195635	0.013136	1.907208	GARCH
	Triple	2.207764	0.012513	1.812073	
BARC.L	ARIMA	1.487715	0.008628	1.362048	
	GARCH	1.211768	0.006894	1.149752	GARCH,
	Double	7.466937	0.038807	8.907646	ARIMA
	Triple	5.869521	0.030436	7.089522	
The quaternary industry					
AZN.L	ARIMA	1.100702	0.006214	1.064539	
	GARCH	1.310470	0.006950	1.092987	ARIMA,
	Double	4.005783	0.020693	3.349079	GARCH
	Triple	3.255487	0.017000	2.772819	
GSK.L	ARIMA	1.764622	0.010188	0.963569	
	GARCH	1.972891	0.011390	1.033593	ARIMA,
	Double	5.947575	0.031527	2.933498	GARCH
	Triple	5.898024	0.031174	2.903220	
SHP.L	ARIMA	2.246899	0.013001	1.043464	
	GARCH	2.241766	0.012955	1.044898	

	Double	2.744445	0.015210	1.511719	GARCH,
	Triple	2.494744	0.013829	1.378084	ARIMA
SGE.L	ARIMA	2.527741	0.022065	0.763353	
	GARCH	2.856003	0.025231	0.872170	ARIMA,
	Double	15.26865	0.089994	2.705754	GARCH
	Triple	15.37389	0.093975	2.802137	
SN.L	ARIMA	1.965597	0.010802	0.969098	
	GARCH	1.923406	0.010788	0.942978	GARCH,
	Double	4.240883	0.022222	2.756107	ARIMA
	Triple	3.902053	0.020361	2.553244	

DISCUSSION

It is crucial to outline the key findings of the entire thesis. This study has reached about three major decisions based on findings. These are related to the followings

1. Weak-form efficiency
2. Forecastability of an industry
3. Better predictive model

The statistical inference was made that the London Stock Exchange (LSE) is not weak-form efficient on the basis of results found from runs test at level, ADF-unit root test at first difference, LB's serial autocorrelation at first difference and variance ratio test at level. These tests documented that stock prices of LSE have serial autocorrelation and they do not move randomly. The results support the weak-form inefficiency of the LSE over the period tested and thus, stock prices of this market should be predictable. The four statistical models and techniques have been applied to predict the prices of 22 series. The series are FTSE-All Share Index, FTSE-350 General Industrial Index and 5 companies from each of four industry sectors including the primary, secondary or manufacturing, service and quaternary industries.

The applied models and techniques are ARIMA and GARCH (1, 1) models and double and triple exponential smoothing techniques. The forecast evaluation statistics of mean absolute percentage error (MAPE), Theil inequality coefficient of U_1 and U_2 explain that a few series from different industrial sectors are predictable. However, the manufacturing industry exhibits that all the series or companies are predictable. On the other hand, most of the series in the service industry are unpredictable.

An assumption was made at beginning of thesis that stock prices could be predictable even in the developed market (the LSE), if the entire market is divided into different industry sectors based on their functions and characteristics. This is because, when new information comes into market, all the industries in that market might not be able to absorb all relevant information into stock prices instantly. All the industries might not be equally capable to update the information into prices instantly. Some industries might absorb all information into prices immediately. However, other industries might delay to embed all relevant information into prices. This advantage of delaying could be taken from these industries and stock prices could be predicted for short period. Thus, a short period of observations (4) has taken into consideration to evaluate forecasts rather than a long period of observations.

Consequently, it was found that the stock prices of the manufacturing industry are predictable. The probable reasons could be that the industry is laggard to embed all relevant information into prices. Furthermore, it could be due to industry characteristics. Moreover, it could be due to other reasons mentioned by Lo and MacKinlay (1988); Lo (2004); Rosini and Shenai (2020) who claimed that a stock market goes through different states of performance all the time, like a circle.

Therefore, documents support that the London Stock Exchange is weak-form inefficient and stock prices are predictable on the basis of industry sectors. In relation to better predictive model, this study has applied two forecast encompassing tests to decide.

The forecast encompassing tests of Fair-Shiller and Chong-Hendry have been applied to identify better predictive model among 4 models and techniques. However, the results from them show that the encompassing tests are not applicable in stock markets as the models do not encompass each other. This could be due to selecting a short forecast evaluation period. However, a long period of data could not be predicted in stock market as stock prices change rapidly and randomly.

Therefore, this study has relied on forecast benchmarks including MAPE, Theil U_1 and U_2 to decide a better predictive model. These parameters (in table 6.18) show that ARIMA model performs better for 11 series out of 22 than other models and techniques. The GARCH (1, 1) model performs better for 8 series out of 22 than other models and techniques. The exponential smoothing techniques perform better for 3 series out of 22 than ARIMA and GARCH (1, 1) models. Therefore, it could be concluded that ARIMA model performs better, on average, than all other models and techniques in this study.

These are three major findings of this study. However, this study extends current literature by showing the existence of weak-form inefficiency in industry sector in the developed market, the LSE. It is found that industry sectors impact the market efficiency.

CONCLUSION AND RECOMMENDATION

This study has evidenced that all industries do not perform equally in adjusting the effects of all relevant new information into prices. No researchers have considered in their analysis whether industry-based analysis of historical prices might not lead to weak-form efficiency in a developed market. The empirical evidence supports this study that a developed stock market is not always weak-form efficient when the whole market is divided into different industry sectors. This study also documents that certain econometric models are better in certain sectors.

This research does not stop here. This research is a new and ongoing research. It opens a new avenue for further research that more research will be undertaken in the future by considering other sectors of the LSE and other stock markets in different periods.

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