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EFFECTIVENESS OF OPEN, HIGH AND LOW PRICES IN STOCK MARKET PRICE PREDICTION

Keywords: stock price, market price, stock markets, price prediction, portfolio investment.

J E L Classification: C53, G1, G3, G11, G15, G14.

Abstract: Stock market price prediction is vital for an investment decision amid difficulties with effective price predictions. The paper aims to analyze the rate of effectiveness in actual stock market price prediction using the open, high, and low prices. The paper draws insight from diverse prior research with assorted models such as Markov Chain, time series, and computer aided stock price prediction. The paper's approach is quantitative with forty-three days stock market price data from S&P500 and Shanghai Composite Index. Data was analyzed with the regression statistics. Results show that the open, high, and low prices can significantly predict the actual market price at probability level of P<0.0001 for both the S&P500 Index and the Shanghai Composite Index. Prediction rates exceed 70% for S&P500 and over 80% for Shanghai Composite Index. The model was verified by using data for other observation periods (during the COVID-19 and during the financial crisis). The implication therefore is that in the absence of other expensive market information, an average investor may use the open, high, and low prices to make a useful prediction of actual stock market price. The findings present a useful case reading for academics in business schools and offer an agender for future research to apply this model in other stock markets. The paper offers

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a novel value from the finding by demonstrating that the application of open, high, and low prices in predicting stock prices with regression analysis may give a stock price prediction accuracy rate of over 80 percent.

Introduction

Prediction of stock price is an important decision tool for stock investment in global stock markets. This is because price is the key variable in the portfolio market as economic and market conditions are in a constant change, and it puzzles the investors' ability to make decisions (Ringmu & Oumar, 2022). Accordingly, investors are actively looking for the best price point to sell and buy stocks and bonds in the capital markets (Enow, 2022). In the same vein, stock market players seek the most reliable portfolios or a combination of portfolios to invest their capital. This is because irrespective of the significance level of fluctuation, a minor fluctuation in stock or bond prices may have a huge financial impact on investors' ability to make expected profits on stocks and bonds from capital market investment. The issue of security prices and predictive models has continued to be debated in economic and financial research, as no clear agreement exists between researchers in their models. Yet, the ability of investors to track the price movement of stocks and bonds remains an important information for stock trading and pricing of assets (Enow, 2022). Amidst many existing literature models, none can be said to provide an exact and/or sacrosanct model for predicting stock market price fluctuations (Combes & Dussauchoy, 2006).

Hence, the importance of continued research in this economic and finance research niche to contribute new findings to existing knowledge for assisting stock market participants and business financial portfolio managers in making investment decisions. Some related research in the niche of stock price prediction includes those on the usage of the Machov chain model of stock price prediction (Yavuz, 2019; Enow, 2022), the sensitivity analysis application to stock price prediction (da Silva, 2021), and the application of ANN and ANFIS approaches to stock price prediction (Billah, Waheed & Hanifa, 2015). Furthermore, other researchers applied the Mont Calor model to predict price (Eraker, 2001), and others applied the natural experiment of stock price prediction (Ellul, Shin & Tonks, 2005). However, this current research takes a slightly different approach to examine this phenomenon by focusing on the analysis of how effective the open-high-low prices could be in predicting the market price of stocks, and it uses the multiple regression approach to analyse the prediction ability of these predictor variables. The paper highlights that in the absence of expensive market information for predicting the market price, the open, high, and low prices may be a veritable and freely available stock market information that analysts and investors may utilize for market price prediction and the associated investment decisions.

Accordingly, this paper contributes new knowledge to the extant literature on stock market price prediction for informed investment decision by stock market participants and managers who rely on availability of stock price predictions for portfolio management and investment decisions. More notably, this paper elucidates whether the open, high, and low prices may offer effective stock price estimation. Given the unique dynamics and fluctuations in different stock markets and the existence of variegated external and internal information that may affect different stock market prices, this paper uses data from two extreme regions, one from the US Stock Exchange Market and another from the China Stock Exchange market. This is with the hope that if the results from these distantly geographical separate regions prove significant about the market price predictor variables, it would provide some degree of reliable information for investors' application in stock market predictions and attendant investment decisions.

Problem of the paper

Although there are myriad of company internal factors that may affect stock price such as dividend policy (Emeka-Nwokeji, Nangih, Chiedu & Ekwunife 2022), prior research indicates that strong and reliable estimation of factors that affect stock price poses a problem for managers. The problem of estimation has often emanated from the fact that the exactness of statistical analysis and the attendant extrapolation is reasonably sensitive to both the applied model and the sampling error (Combes & Dussauchoy, 2006). Various models of stock price prediction exist in the literature, with many models following the strong efficient market theory and very few others following the weak efficient market (such as the Markov Chain process). The few research which follow the Markov Chain process reach a conclusion proving that the Markov chain model provides a good, accurate, and powerful prediction method (Yavuz, 2019; Öz, 2009; Enow, 2022). However, out of the existing research, only few, such as

Enow (2022), has used a combination of the open, high, and low prices to measure their prediction effect on stock market price in six markets. In addition, none of the existing research have used the open-high-low prices to compare their effect on the S&P500 and London Stock Exchange. Therefore, this paper adds to the existing body of work on stock market price prediction by using the open-high-low prices to analyze their effect on market price in S&P500 and Shanghai Stock Exchange to make a new contribution to the knowledge of stock market price prediction.

Therefore, the objective of this paper is to determine the effect of open, high, and low prices on predicting the future stock market price for S&P500 and London Stock Exchange. The paper thus aims to provide a new proof, which substantiates the Markov school of thought that previous stock price may be useful in predicting future stock price. In addition, the results identify the most effective price between open, high, and low prices for each of the stock markets used in this research so that investors are aware of which price to focus on for making predictions of market price.

Methodology and the research process

This paper used a quantitative approach to collect and analyze data. The positivist paradigm advocates for a quantitative approach when variables of concern in the research objective are numeric and when the objective seeks to measure the influence of one or more numeric variables (independent variables) on the dependent variable (Park, Konge & Artino, 2020). Given that this paper's core objective is to measure the effectiveness of open, high, and low price on determining the actual market price. It is thus suitable for quantitative analysis, as it measures the relationship between dependent and independent variables. Data was collected from the stock exchanges of two countries with the greatest wealth in the world, namely the USA S&P500 Index and the China Shanghai Composite Index (as indicated in Table 1). The two markets were chosen given their impact as global wealth leaders and the status of their stock exchanges in impacting other stock markets (Abbas & Wang, 2020). A total of 43 days stock prices for both countries' stock data were collected from the months of May to July 2024. Data was analyzed using the regression statistics with the following model:

$$Y = \alpha + \beta X_1 + \beta X_2 + \beta X_3 + \varepsilon$$

Where: Y = market price of stock; α = constant; β= regression coefficient; and X_1 to βX_3 = (opening, high, and low prices, respectively); and ε = error term.

Table 1. Two Stock Exchanges from Top 2 Global Economies (USA & China)

Country	Name of Stock Exchange	Number of trading days' data used	Period from where data is selected
USA	US-SPX500	43 days	May to July 2024
China	Shanghai-composite Index	43 days	May to July 2024

Source: own study sources.

Note: Results from the above model were verified by conducting further analysis using data from two other observation periods, which were stock market data during the COVID-19 (2020–2021) and stock market data during the financial crisis of 2008–2009 (the Great Recession period).

Literature review

The substance of stock price prediction remains the fundamental basis of stock investment decision for stock investors, hedgers, and business portfolio managers in the competitive capital markets (da Silva, 2021). This is because the smallest, positive or negative percentage shift in the stock price would yield an overall aggregate boost in investment gains and/or losses, depending on the direction of price fluctuation swing. In his research, da Silva (2021) conducted a sensitivity analysis and concluded that the quantum of investment is affected strongly by the level of stock price informativeness, adding further that this relationship is heightened by the preponderance of market-based private information.

Yavuz (2019) applied the Markov chain model, which was facilitated with a creation of a transition probability matrix and conducted an analysis of future stock price prediction using the closing stock prices in the Istanbul Stock Exchange (BIST); his findings show a successful future stock price prediction. Yavuz's (2019) findings had been confirmed earlier result by Öz (2009), who applied the Markov Chains approach to successfully estimate the future price in the Istanbul Stock Exchange. In another research, Eraker (2001) applied Markov-chain model mixed with the Monte Carlo methodology (MCMC) to predict weekly stock price. The results proved that the Markov weak market efficiency approach was very successful in predicting the weekly stock price data. In another closely related research, six worldwide stock market prices were examined by Enow (2022) over a period of five years; he applied the Bayesian Time-Varying coefficient. The findings provided compelling empirical support for the hypothesis that the open, high, and low prices can be used to anticipate security's returns. This shows that knowing the open, high, and low prices from the past might give important insights into how stock prices change, especially in the short term. Moreover, more than 98% of the variations in the closing price may be explained by the past values of these prices.

Other researchers, such as Ellul, Shin and Tonks (2005), studied the efficiency of call markets during opening and closing hours, using a special natural experiment provided by the London Stock Exchange. They found that although the call market is better at price discovery than dealers, it has problems regarding the opening and closing trading, especially in volatile markets. Furthermore, their findings show that trading costs of call markets increase when asymmetric information, slow trading, order flow imbalances, and uncertainty are present. They also found that traders' use of call auctions is negatively correlated with firm size, indicating that the call market may not be the best option for opening and closing trading for small and medium-sized stocks. In another related stock price prediction study, Billah, Waheed and Hanifa (2015) studied an effective soft computing technique for Dhaka Stock Exchange (DSE) closing data prediction. On a variety of pricing data, such as opening price, highest price, lowest price, and total shares traded, they applied the ANN and ANFIS approaches. According to their findings, ANFIS proved to be a more successful and efficient method of predicting stock price data from the Dhaka Stock Exchange (DSE). In another research, Al-Nefaie and Aldhyani (2022) applied the time series models in their research to predict the closing stock price in the Saudi Stock Exchange. They applied AI algorithms on data period of 60 days; and their findings showed effectiveness in stock price prediction in four sectors of their analysis in the Saudi Stock Exchange.

Other researchers have turned to the usage of computer software to predict the market price. As an example, a group of researchers, namely Malibari, Katib and Mehmood (2021), applied the FinTech method, using the transformer neural networks to predict the closing market price of stocks. The researchers applied the stock price data extracted from the Saudi Stock Exchange. Their findings show that the model can predict closing stock prices with a probability accuracy level that surpasses 90 percent (Malibari, Katib & Mehmood, 2021). In another related research, Ilyas, Iqbal, Ijaz, Mehmood and Bhatia (2022) applied a hybrid model to predict closing stock price using a combination of novel features and a fully modified Hodrick-Prescott Filter model. Results that were based on their model yielded a stock price prediction accuracy of over 70 percent. This current article contributes new knowledge to existing research by assessing the effectiveness of open, high, and low prices on the actual market price, using the stock markets from the two countries with the greatest wealth – the USA and China. The rest of the paper presents the method used, the data analysis and results, and conclusion from the analysis.

Results

Table 2 is the analysis of the USA stock market (US-SPX500). Therefore, Table 2 presents the results of the effect of open, high, and low prices on the actual market price for the S&P500 Index, with the dependent variable being the market price. Consequently, Table 2 results indicate that using an alpha level of 0.05, the open, high, and low prices have a significant ability to predict the actual market price at a probability level of $P<0.01$ (within the sample of study) for the three independent variables (open, high, and low price). Furthermore, Table 2 results equally show that the market price prediction rate vary as follows: open price has a 42% prediction rate; the high price has a 61% prediction rate; and the low price has 71% prediction rate on the actual market price of stocks.

Table 3 evaluates the effect on the China stock market; hence, Table 3 presents the regression results for the Shanghai Composite Index, where the dependent variable is the actual market price. Accordingly, Table 3 shows that at 0.05 alpha level, the open, high, and low prices possess the propensity to significantly predict the market price at $P<0.01$ for the three independent variables (open, high, and low price). Table 3 results also show that the market price prediction rate differs as follows: open price = 65% prediction rate; high price = 83% prediction rate; and low price = 81% prediction rate. A point of difference worth highlighting between the US S&P500 in Table 2 and Shanghai Composite Index result in Table 3 is that whereas the low price proved to be the stronger predictor of the market price in the US-SPX500, the high price proved to be the strongest predictor of the actual market price for Shanghai Composite Index results in Table 3. This finding confirms the hypothesis and findings by Enow (2022), wherein they found that the open, high, and low prices can be used to anticipate security returns.

Table 4 presents a comparison of prediction rate of open, high, and low price between USA S&P500 Index and the Shanghai Composite Index. The comparison draws from the regression coefficients in Table 2 and Table 3. A closer assessment in Table 4 shows that with application of regression analysis, the open, high, and low price can better predict the actual market price in China's Shanghai stock exchange than in the US S&P500 Index. This is because the coefficients of regression for independent variables (open, high, and low prices) are 65%, 83%, and 81.9%, respectively, for the Shanghai Composite Index; and 42%, 66%, and 72%, respectively, for the USA S&P500 Index. Aside from the comparison, the results generally depict the significant ability of open, high, and low prices to predict the actual market price. Given the above results, it was necessary to verify the model, and to do this, the model was verified by additional analysis in Table 5, Table 6, Table 7, and Table 8, using other observation periods, namely the COVID-19 and financial crisis period of 2008–2009 (The Great Recession) stock market data for US S&P500. The same additional observation data during COVID-19 and during the financial crisis of 2008–2009 was equally used to verify the model. Results from the two different verification analyses from Table 5 to Table 8 showed the same significant effect of open, high, and low prices on the market, which thus confirms the research model in the first analysis.

This implies that in the absence of other market information, private or public, which may affect stock market price, the open, high, and low prices can be utilized by stock market participants, investors, and portfolio managers in predicting the market price. This finding is valuable for small and medium stock investors who may not possess additional market information, which often might be expensive to secure; hence, such lower-level stock traders can use the open, high, and low prices to at least make their initial prediction of market price and might also make a substantive stock price and investment decision using this analysis model. This will assist in investment decisions because the percentage of 83%, as revealed in the results of this analysis, is high and strong to guide some stock investment decisions.

Table 2. Regression Results for US-SPX500 (Dependent Variable: Market Price)

Regression Statistics	
Multiple R	0.987309306
R Square	0.974779666
Adjusted R Square	0.972839641
Standard Error	14.67839832
Observations	43

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	324771.2503	108257.1	502.4571	0.000000
Residual	39	8402.759715	215.4554		
Total	42	333174.01			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	254.5	151.5955807	1.679025	0.101143
Open	-0.421	0.177315712	-2.37553	0.022534
High	0.661	0.174151539	3.794577	0.000503
Low	0.714	0.142782514	5.003675	0.000012

S o u r c e : own study data analysis output using the Gretl Statistics Software.

Table 3. Regression Results for Shanghai Composite Index
(Dependent Variable: Market Price)

Regression Statistics	
Multiple R	0.994296
R Square	0.988624
Adjusted R Square	0.987749
Standard Error	7.863152
Observations	43

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	209562.8	69854.26	1129.795	0.0000000
Residual	39	2411.337	61.82916		
Total	42	211974.1			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	22.36651	55.54018	0.402709	0.689362
Open	-0.65745	0.132105	-4.97669	0.000013
High	0.830363	0.15145	5.482761	0.000002
Low	0.819634	0.159079	5.152359	0.000007

S o u r c e : own study data analysis output using the Gretl Statistics Software.

Table 4. Comparison of Prediction Rate Between S&P & Shanghai Index

	Coefficients percentage Prediction Power for Shanghai Index (from Table 3)	**Coefficients percentage Prediction Power for Shanghai Index (from Table 2)**
Open	-65.7%	-42%
High	83%	66%
Low	81.9%	72%

S o u r c e : own study data analysis output using the Gretl Statistics Software.

Results Using COVID-19 Period Observation (2020–2021) for US-SPX500

Table 5. COVID-19 Period: Regression Results for US-SPX500
(Dependent variable: Market price)

Regression Statistics	
Multiple R	0.993733
R Square	0.987506
Adjusted R Square	0.985632
Standard Error	75.30991
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	8965632	2988544	526.9330479	0.000000
Residual	20	113431.6	5671.582		
Total	23	9079064			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-130.483	141.6544	-0.92113	0.367958753
Open	-0.80625	0.176792	-4.56041	0.000190066
High	1.120686	0.197245	5.681684	0.000014654
Low	0.706804	0.101435	6.968041	0.000000918

Source: own study data analysis output using the Gretl Statistics Software.

Results of Financial Crisis (The Great Recession) Period Observation (2008–2009) for US-SPX500

Table 6. Great Recession Period: Regression Results for US-SPX500
(Dependent variable: Market price)

Regression Statistics	
Multiple R	0.990944
R Square	0.981971
Adjusted R Square	0.979266
Standard Error	29.7474
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	963940.5	321313.5	363.104	0.000000
Residual	20	17698.15	884.9077		
Total	23	981638.7			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	-38.9191	53.88415	-0.72227	0.478487
Open	-0.68815	0.279166	-2.46502	0.022876
High	1.185103	0.349424	3.391594	0.002897
Low	0.513482	0.09725	5.280007	0.000036

S o u r c e : own study data analysis output using the Gretl Statistics Software.

Results Using COVID-19 Period Observation for the Shanghai Composite Index

Table 7. COVID-19 Period: Regression Results for the Shanghai Composite Index (Dependent variable: Market price)

Regression Statistics	
Multiple R	0.979771
R Square	0.959952
Adjusted R Square	0.953944
Standard Error	60.33143
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	1744948	581649.2	159.799	0.000000
Residual	20	72797.62	3639.881		
Total	23	1817745			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	40.27096	164.4259	0.244919	0.809015
Open	-0.4007	0.163795	-2.44635	0.023801
High	0.501762	0.144366	3.475634	0.002386
Low	0.896198	0.180706	4.959412	0.000075

Source: own study data analysis output using the Gretl Statistics Software.

Results Using the Great Recession Period Observation (2008–2009) for the Shanghai Composite Index

Table 8. Great Recession Period: Regression Results for the Shanghai Composite Index (Dependent variable: Market price)

Regression Statistics	
Multiple R	0.975928
R Square	0.952435
Adjusted R Square	0.945301
Standard Error	170.7347
Observations	24

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	11674122.3	3891374	133.4932	0.000000
Residual	20	583006.966	29150.35		
Total	23	12257129.2			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	134.5653	142.213758	0.946218	0.35533
Open	-0.32491	0.27541027	-1.17974	0.251946
High	0.32274	0.37742745	0.855105	0.402621
Low	0.999117	0.21687061	4.606974	0.000171

Source: own study data analysis output using the Gretl Statistics Software.

Discussion and conclusion

The implication of the results relates to both the stock market investors, stock analyst, business portfolio managers, and academics for stock market investment study case reading. The results show that investors, analysts, and portfolio managers may (in the absence of other market information) use the open, high, and low prices to make initial prediction of the market price and thus a guided decision on where and what to invest in. Academics and researchers with an interest in financial markets may use these results for business classroom case reading. The paper also provides an agenda for future research that may compare other regional stock markets to further compare future results with the outcome of this paper, as this will provide an expanded view of the regional extent, where the open, high, and low prices may catalyze effective prediction of market prices. This paper's value and hence its contribution lies in its usage of two stock exchanges in the two wealthiest countries of the world to compare the predictive ability of open, high, and low prices on the actual market price through the usage of regression analysis.

The prediction of stock prices is an intractable investment process that challenges the stock market investors, analysts, and business portfolio managers' ability to make stock investment decisions. Hence, stock market participants and investors are constantly in need of information and associated models that may assist them in predicting stock prices for enhanced investment decisions. Different models exist in the literature with divergent complexities and different predictive capabilities. This paper has added to the existing literature on stock price prediction by analyzing the effectiveness of open, high, and low price in predicting the actual market price using data from two large stock markets, namely the S&P500 Index and Shanghai Composite Index. The results are significant, which implies that the open, high, and low prices can assist investors and portfolio managers in pre-empting the stock market price. The model was verified by conducting further analysis using other observation periods, namely the COVID-19 period stock market data and data during the financial crisis of 2008–2009. Results from the verification analysis proved significant, which thus confirms the research model in the first analysis.

Given that these predictor variables (open, high, and low prices) are readily and freely available in stock market indices, it means that average or below-average investors, who may not be able to purchase additional market information, may rely on the open, high, and low prices to make a reasonable prediction of stock market price predictions with over 80 percent rate (in the Shanghai Composite Index), which outperforms the usage of some complex techniques mentioned in the literature that had a prediction rate of over 70 percent. Hence, a simpler model, as demonstrated in this paper, can assist with stock market price prediction, at least within the short-term period of 3 months to 24 months.

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