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Modelling Stock Market Prices Using the Open, High and Closes Prices. Evidence from International Financial Markets

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ABSTRACT

Purpose:
Modelling security prices seem to be an ending debate in finance literature due to no clear consensus on behavioral patterns. Knowledge of stock price movement has always been an important source of information that is much needed in asset pricing and trading strategies. The aim of this study was to model stock market prices using six international markets as a sample.

Design/methodology/approach:
This study made use of the Bayesian Time-Varying coefficient for a five-year period from January 2, 2018, to January 2, 2023.

Finding:
The findings of this study revealed that there is strong empirical evidence that the returns of a security can be modelled using the open, high and low prices.

Research limitations/implications:
This implies that the drift in stock price movement can be better explained by observing the lag values of the open, high and low prices which may be an important tool for short term traders and incorporated in volatility estimation. Also, the lag values of the open, high and low price movements explain more than 98% of changes in the closing price.

Originality/value:
As per the author's knowledge, this study is the first to model stock market prices using the open, high and low prices for multiple international markets.

1. Introduction

At the beginning of every year, analysts and academics often make gloomy forecasts about the expected performance of stock markets and economic conditions. These forecasts often cause panic and are mostly incorrect. To this end, there is no concrete approach in predicting stock market prices due to the consistent poor forecasts in stock market prices. Swedroe (2018) compiled a list of predictions made by analysts and academics for over a 7-year period, he diligently tracked these predictions and reported on their results. These forecasts were mainly 69 sure predictions from 2010 to 2018 and only 32% materialized as expected (Swedroe, 2018). The forecasted values of security prices were also studied in-depth in a paper by Bailey et al. (2018) where the authors examined 6627 forecasts made by 68 analysts. The findings revealed that 48% of those forecasts were correct and 66% had an accuracy score of less than 50% (Bailey, et al., 2018). However, there are some quantitative measures that have been very useful in forecasting future returns such as the Shiller cyclically adjusted price earnings ratio. According to this matrix, higher stock prices tend to be followed by lower stock returns. Also, prior literature (Mettle et al., 2014; Pacifico, 2021; Dar et al., 2022) still contends that stock prices follow a Markov process which is consistent with the weak form efficiency. Implying that to some extent, stock prices still encapsulate previous price history although the main driver is relevant new information (Liyanagamage and Madusanka, 2021). Many studies on modelling stock price have actively argued that the expected stock price changes in an infinitesimal time dt is constant and independent of past price movement. In essence;

$$Expected\ price\ change = E\left\{\frac{1}{d}\left[\frac{ds}{S_o}\right]\right\} = \mu \quad (1)$$

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$$\frac{ds}{S_o} = \mu dt + randomness\ with\ zero\ mean \quad (2)$$

Considering the above randomness in mean return, the expected variability in stock price changes over a period should be given by;

$$VAR\left[\frac{ds}{S_o}\right] = \sigma^2\, dt$$

(3)

Where VAR is the value at risk and σ^2 is the variance. It is therefore important to note that forecasting stock market prices can drift higher or lower than the expected value making it difficult to successfully categorize the price behaviour. Consequently, there is a large distribution of outcomes that are still not accounted for when making stock price forecasts. These distributions may be well explained when the open, high and low prices are included in the forecast of stock prices. Hence this study seeks to answer the following research question; Should the open, high and low prices be used to model stock market prices? The main aim to this study is to empirically ascertain whether the open, high and low prices can be used as good predictors of closing prices hence stock market returns. In so doing, this study makes a significant contribution on modelling stock prices and to a broader extent, modelling volatility of stock prices.

2. Literature review

Stock price modelling can be extremely difficult due to the widely accepted concept of market efficiency and weak form efficiency. In essence, stock prices are assumed to follow a Markov process and move only with new information (Enow, 2022). However, the development of stochastic processes has proven otherwise. Empirical research reveals that the distribution of stock price movements can be modelled to some extent. There is a rich literature on modelling stock prices, but almost if not all the studies used closing prices to forecast price movement. Table 1 highlights the most recent studies.

Table 1: Review of prior studies

Study (Author & year of study)	Model	Period	Variables	Findings
Ugurlu et al. (2014)	GARCH	January 8, 2001, to July 20, 2002	Logarithm of closing price relative ($\frac{p_x}{p_{x-1}}$)	GARCH model is a reliable predictor of closing prices.
Boateng et al. (2015)	ARCH/GARCH model	Not disclosed	Closing price relative ($\frac{p_x}{p_{x-1}}$)	Constant variance in closing price returns.
AL-Najjar (2016)	ARCH, GARCH, and EGARCH	Jan. 1, 2005 - Dec.31 2014.	Closing price relative ($\frac{p_x}{p_{x-1}}$)	The author forecasted persistence in volatility due to asymmetry effect.
Adewuyi (2016)	Exponential Weighted Moving Average	June 13, 2006 – December 1, 2014.	Logarithm of closing price relative ($\frac{p_x}{p_{x-1}}$)	High probability of decreasing stock prices from 2015
Kaya & Güloğlu (2017)	FIAPARCH & GARCH	January 1, 2002 – April 29, 2016	The logarithm difference in previous closing prices ($lnP_{i,t} - lnP_{i,t-1}$)	The FIAPARCH model is a good predictor of volatility than the GARCH model.
Kuhe (2018)	GARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1)	July 3, 1999 – June 12, 2017	Logarithm of closing price relative ($\frac{p_x}{p_{x-1}}$)	The EGARCH (1,1) model was a better predictor of market volatility than the other GARCH models.
Yatigammana et al. (2018)	Autoregressive Moving Average	January 16, 2014 - April 15, 2014	The logarithm difference in previous closing prices	Only 78 and 91 percent of the stock price can be

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			$(lnP_{i,t} - lnP_{i,t-1})$	estimated
Ghani & Rahim (2019)	ARMA (1,0) - GARCH	January 4, 2010 – December 29, 2017.	Daily closing prices	The ARMA (1,0) – GARCH model is the best predictor of market volatility.
Schmidt (2021)	GARCH (1,1), EGARCH (1,1) and GJR-GARCH (1,1)	February 19, 2020 – April 7, 2021.	The logarithm difference in previous closing prices $(lnP_{i,t} - lnP_{i,t-1})$	GARCH (1.1) model should not be used to forecast volatility as it had the worst performance.
Liyanagamage & Madusanka (2021)	Auto Regressive Moving Average	2009 - 2019	Past stock prices	Past stock prices can be reliably used to predict future prices

Source: Author's construct

Table 1 above provides some interesting findings. It can be observed that GARCH models and closing security prices are predominantly used to analyse and forecast market volatility. Although these studies may be relevant, daily open, high and low stock prices have not been widely used in any of these analysis. Therefore, this study is aimed at advancing the frontier of stock price behaviour forecasting by examining the effect of lag the values for the open, high and low market prices on the closing prices in international stock markets.

3. Data & methodology

In the past decade, attention has been given to many Value at Risk (VAR) models which is suitable for allowing coefficients to change over time. One of such models is the switching VAR which enables discrete occasional changes to coefficients. An alternative model to switching VAR is the Time Varying coefficient VAR (TVC VAR) which allows continuous smooth changes to coefficient with continuum of variables (Amadi et al. 2022). Whilst the large coefficients space of TVC VAR has attractive properties from a modelling perspective, it can also lead to difficulty in estimations. To this end, this study used a Bayesian Time-Varying coefficient (BTVC). A BTVC VAR has become the de factor approach to estimating time varying coefficients due to its superior forecasting technique in placing more weight in the lag values of one or more variables (Karlsson and Österholm, 2020). This model allows credible heterogeneity parameters that are suitable for modelling. In essence, the model integrates latent variables together with their probability distributions which enhances modelling inferences. As an additional benefit, the BTVC model incorporates both unconditional distribution and latent moments of the independent variables. As such, it is very useful in exploring relationships between multiple variables, hence was deemed appropriate for this study.

In its simplest form, A BTVC model is given by;

$$\ln(Close) = l_t + s_t + \sum_{t=1}^{n} \ln(open_{t,t-1})\, \beta_{t,t-1} \sum_{t=1}^{n} \ln(high_{t,t-1})\, \beta_{t,t-1} \sum_{t=1}^{n} \ln(low_{t,t-1})\, \beta_{t,t-1+\,\varepsilon}$$

(4)

Guhaniyogi et al. (2022)

Where l_t is the trend, s_t is the seasonality treated as a regression on Fourier series and $\beta_{t,t-1}$ is the time varying coefficient. The open, high, low and closing prices for six international financial markets namely, Johannesburg Stock Exchange (JSE), Nasdaq Index, the French Stock Market Index (CAC 40), the Nikkei Stock Average (Nikkei 225), the German blue-chip companies (DAX) and the Borsa Istanbul Index 100 (BIST) were sourced from Yahoo finance. The sample period was from January 2, 2018, to January 2, 2023.

4. Results and discussion

The results of the analysed data from the sampled financial markets are presented below.

Table 2: model level descriptions

		HIGH	LOW	OPEN	P-Value (F-stats)
JSE	Adjusted R-square	0.995076	0.995034	0.993669	
	F-Stats	31499.49	31231.65	24467.97	0.000*
Nasdaq	Adjusted R-square	0.980426	0.977317	0.980902	
	F-Stats	1547.438	1331.289	1586.814	0.000*
CAC 40	Adjusted R-square	0.993923	0.992438	0.995764	
	F-Stats	26106.58	20949.29	37524.85	0.000*
Nikkei 225	Adjusted R-square	0.863465	0.863975	0.908160	
	F-Stats	190.7239	191.5479	297.6551	0.000*

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DAX	Adjusted R-square	0.992476	0.990618	0.994502	
	F-Stats	20825.61	16670.50	28556.17	0.000*
BIST	Adjusted R-square	0.995326	0.995086	0.995218	
	F-Stats	32261.35	30678.13	31534.02	0.000*

Source: Author's construct

From table 2, the variability of the closing prices can be well explained by movements in the open, high and low prices. This is evident in the adjusted R square values that are close to one in all the stock markets under consideration. More specifically, all the adjusted R-square values are more than 98% indicating high levels of explanatory power. It can be suggested that the opening, high and low prices provides a meaningful explanation for the variability of the closing prices and adding additional variable may not add any value. Based on these findings, closing prices in financial markets have a high correlation with the opening, high and low prices. The F-stat test results strengthen further the explanatory effect of the opening, high and low prices on the closing prices. The p-values of the F-stats for all the financial markets under consideration are significant at 5% indicating a perfect fit of the model.

Tables 3, 4, 5,6,7 and 8 in the appendix provide the output results of the BTVC VAR estimates. From these results, the lag values of the Bayesian coefficient have positive and negative signs indicating a two-way impact. Hence, the lag values of the opening, high and low prices affect the closing prices positively and negatively. Most importantly, the 2-day lag values of the open, high and low prices are significant in all the sampled financial markets with the exception of the Nasdaq in table 4 which may signal some form of market efficiency (Enow, 2021). This means that proper analysis of the open, high and low prices for the past 2 days can be used as a guide to forecast the closing prices. In essence, todays candlestick charts of the high and low prices may provide significant information on the price movement for the next 2 days. However, the 1-day lag values of the open, high and close are insignificant with the exception of the JSE in table 3. By implication, prior information on the open, high and low price movements cannot be used as a good guide to predict the variability of the closing price distribution for the next day. These findings are supported by the regression results in tables 9, 10, 11, 12, 13 and 14 in the appendix which also revealed significant adjusted R-square values as high as 99%. The regression estimates in tables 9 to 13 portrays a significant positive relationship between the high/low prices and the closing prices. However, an inverse relationship was observed between the high/low prices and closing prices in the BIST as shown in table 14. This implies that the high and low prices move in the same direction with the closing prices in the JSE, Nasdaq Index, CAC 40, Nikkei 225 and DAX but vice versa in the BIST. In so doing, observing the price distribution of the open, high and low prices can provide a vivid understanding of the closing price returns.

5. Conclusion

Prior literature suggest that modelling stock prices is often based on observing historical returns and the concept of efficient market hypothesis where prices are assumed to follow a random pattern. The purpose of this study was to model closing prices using the open, high and low prices for a 5-year period using the BTVC VAR model. The findings of this study revealed that the closing price return in financial markets can also be modelled using the open, high and low prices. In essence, observing the market price movement for the previous 2 days' period provides a good indication of the closing market price. The shortcomings of conventional price modelling methods may be overcome by including the open, high and low price movements which may provide a more robust approach. This is in sharp contrast to a relatively outdated study by Floros (2009) who found that high and low prices overestimate future market return due to clustering effect. In this study, the lag values of these open, high and low price movements rather explained more than 98% of the changes in closing price returns. From these findings, incorporating drift in stock price movement can be better explained by observing the open, high and low prices which may be an important tool for short term traders and market speculators to predict the possible direction of the market. This study advances the frontier in forecasting stock price movements by using different variables and methods in modelling returns compared to other studies in prior literature (Ugurlu et al., 2014; Boateng et al., 2015; AL-Najjar, 2016; Adewuyi, 2016; Kaya and Güloğlu, 2017; Kuhe, 2018).

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Appendix

Table 3: JSE Bayesian VAR Hyper-parameters

	CLOSE	HIGH	LOW	OPEN
CLOSE (-1)	0.890350	0.548464	0.573229	0.609983
	(0.04178)*	(0.04113)*	(0.04156)*	(0.05612)
CLOSE (-2)	0.042413	-0.01347	-0.00969	-0.03489
	(0.03606)*	(0.03537)*	(0.03574)*	(0.04827)*
HIGH (-1)	0.000764	0.460691	0.010276	0.101939
	(0.04380)*	(0.04321)*	(0.04359)*	(0.05889)
HIGH (-2)	0.016656	0.036159	-0.05266	0.003122
	(0.03241)*	(0.03206)*	(0.03227)*	(0.04361)*
LOW (-1)	0.024428	0.057226	0.461215	0.091468
	(0.04083)*	(0.04021)*	(0.04072)*	(0.05492)
LOW (-2)	0.003379	-0.01929	0.060412	0.033337
	(0.03125)*	(0.03079)*	(0.03124)*	(0.04206)*
OPEN (-1)	0.002940	-0.07176	-0.09114	0.167827
	(0.03099)*	(0.03055)*	(0.03087)*	(0.04177)*
OPEN (-2)	0.015675	0.006452	0.038647	0.018689

Source: Author's construct

Table 4: Nasdaq Bayesian VAR Hyper-parameters:

	CLOSE	HIGH	LOW	OPEN
CLOSE (-1)	0.959637	0.239380	0.261953	0.454729

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	(0.07228)	(0.05809)	(0.06085)	(0.07239)
CLOSE (-2)	-0.00447	-0.02781	-0.02287	-0.04633
	(0.04610)*	(0.03690)*	(0.03865)*	(0.04603)*
HIGH (-1)	0.031383	0.895129	0.112579	0.035407
	(0.09338)	(0.07574)	(0.07890)	(0.09399)
HIGH (-2)	0.041898	-0.0078	-0.00932	-0.03322
	(0.05298)	(0.04308)*	(0.04480)*	(0.05336)
LOW (-1)	0.002626	0.113122	0.878964	0.055935
	(0.08937)	(0.07210)	(0.07594)	(0.08995)
LOW (-2)	-0.02268	-0.04592	-0.03908	-0.05634
	(0.05145)	(0.04154)*	(0.04384)*	(0.05183)
OPEN (-1)	-0.03308	-0.15945	-0.17793	0.603348
	(0.07846)	(0.06336)	(0.06636)	(0.07948)
OPEN (-2)	-0.00288	-0.02192	-0.02602	-0.02486
	(0.04231)*	(0.03417)*	(0.03579)*	(0.04292)*

Source: Author's construct

Table 5: CAC 40 Bayesian VAR Hyper-parameters

	CLOSE	HIGH	LOW	OPEN
CLOSE (-1)	1.045883	0.556513	0.610716	0.800806
	(0.05392)	(0.04773)*	(0.05278)	(0.05333)
CLOSE (-2)	0.052203	0.045074	0.020143	-0.01447
	(0.03990)*	(0.03518)*	(0.03890)*	(0.03933)*
HIGH (-1)	0.037950	0.658006	0.007562	-0.01025
	(0.06023)	(0.05355)	(0.05901)	(0.05973)
HIGH (-2)	-0.04094	0.027967	-0.08021	-0.01189
	(0.04097)*	(0.03653)*	(0.04017)*	(0.04066)*
LOW (-1)	-0.00241	0.003993	0.662486	0.013161
	(0.05628)	(0.04988)*	(0.05531)	(0.05580)
LOW (-2)	0.039932	0.001897	0.059591	0.003379
	(0.03808)*	(0.03377)*	(0.03754)*	(0.03778)*
OPEN (-1)	-0.13679	-0.29643	-0.29378	0.215390
	(0.05910)	(0.05244)	(0.05797)	(0.05880)
OPEN (-2)	-0.00024	1.48E-07	0.009406	0.000952
	(0.03528)*	(0.03133)*	(0.03462)*	(0.03517)*

Source: Author's construct

Table 6: Nikkei 225 Bayesian VAR Hyper-parameters

	CLOSE	HIGH	LOW	OPEN
CLOSE (-1)	0.965978	0.140210	0.132472	0.293061
	(0.07817)	(0.06885)	(0.07229)	(0.06630)
CLOSE (-2)	-0.00395	-0.015	-0.01644	-0.04405
	(0.04574)*	(0.04018)*	(0.04218)*	(0.03872)*
HIGH (-1)	-0.04395	0.877895	0.024000	0.004473
	(0.09163)	(0.08162)	(0.08515)	(0.07818)
HIGH (-2)	-0.00525	-0.0144	-0.02221	-0.04119

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	(0.05013)	(0.04474)*	(0.04661)*	(0.04279)*
LOW (-1)	-0.01385	0.073738	0.930166	0.096103
	(0.08513)	(0.07535)	(0.07958)	(0.07261)
LOW (-2)	-0.00555	-0.01949	-0.02523	-0.05181
	(0.04773)*	(0.04227)*	(0.04472)*	(0.04074)*
OPEN (-1)	0.047400	-0.09232	-0.05997	0.734024
	(0.09169)	(0.08124)	(0.08527)	(0.07871)
OPEN (-2)	-0.0317	-0.02978	-0.04092	-0.04729
	(0.04914)*	(0.04353)*	(0.04570)*	(0.04223)*

Source: Author's construct

Table 7: DAX Bayesian VAR Hyper-parameters

	CLOSE	HIGH	LOW	OPEN
CLOSE (-1)	1.050835	0.539426	0.580424	0.793156
	(0.05503)	(0.04873)*	(0.05335)	(0.05538)
CLOSE (-2)	0.060219	0.037440	0.022927	-0.0235
	(0.03999)*	(0.03527)*	(0.03861)*	(0.04011)*
HIGH (-1)	-0.02863	0.637312	0.014143	-0.01338
	(0.06232)	(0.05543)	(0.06048)	(0.06289)
HIGH (-2)	-0.00566	0.040917	-0.06607	-0.00643
	(0.04128)*	(0.03682)*	(0.04009)*	(0.04169)*
LOW (-1)	-0.00763	0.063553	0.656970	0.045978
	(0.05743)	(0.05091)	(0.05591)	(0.05794)
LOW (-2)	0.008147	-0.01633	0.031965	-0.00187
	(0.03849)*	(0.03414)*	(0.03758)*	(0.03885)*
OPEN (-1)	-0.08717	-0.31023	-0.26146	0.199959
	(0.05852)	(0.05194)	(0.05686)	(0.05925)
OPEN (-2)	0.003782	0.002168	0.016893	0.002585
	(0.03506)*	(0.03114)*	(0.03408)*	(0.03556)*

Source: Author's construct

Table 8: BIST Bayesian VAR Hyper-parameters

	CLOSE	HIGH	LOW	OPEN
CLOSE (-1)	0.973359	0.142025	0.146705	0.272355
	(0.07734)	(0.07606)	(0.07665)	(0.07722)
CLOSE (-2)	0.001777	-0.00125	-0.004	-0.00758
	(0.04264)*	(0.04188)*	(0.04219)*	(0.04253)*
HIGH (-1)	0.031811	0.948565	0.035665	-0.01041
	(0.08091)	(0.08046)	(0.08056)	(0.08129)
HIGH (-2)	0.001902	0.001383	0.006574	0.003374
	(0.04292)*	(0.04272)*	(0.04275)*	(0.04312)*
LOW (-1)	-0.01111	0.047957	0.927122	0.037829
	(0.07863)	(0.07768)	(0.07872)	(0.07894)
LOW (-2)	-0.00654	-0.01183	-0.01549	-0.01658
	(0.04264)*	(0.04215)*	(0.04276)*	(0.04282)*
OPEN (-1)	0.009129	-0.1237	-0.10211	0.720079
	(0.07689)	(0.07609)	(0.07661)	(0.07768)

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OPEN (-2)	-0.00344	-0.00479	0.002034	-0.00089
	(0.04175)*	(0.04129)*	(0.04159)*	(0.04221)*

Source: Author's construct

Table 9: Nasdaq Regression estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HIGH	0.960685	0.051355	18.70684	0.0000*
LOW	0.89575	0.049476	18.10481	0.0000*
OPEN	-0.85458	0.049463	-17.2769	0.0000*

Source: Author's construct

Table 10: JSE Regression estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HIGH	0.713558	0.0185	38.57045	0.00000*
LOW	0.538173	0.019531	27.55435	0.00000*
OPEN	-0.25663	0.017664	-14.5287	0.00000*

Source: Author's construct

Table 11: CAC 40 Regression estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HIGH	0.767979	0.019323	39.74476	0.000*
LOW	0.785461	0.017331	45.32038	0.000*
OPEN	-0.55431	0.022419	-24.7253	0.000*

Source: Author's construct

Table 12: Nikkei 225 Regression estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HIGH	0.882873	0.05072	17.40691	0.000*
LOW	0.728745	0.039944	18.24436	0.000*
OPEN	-0.60777	0.043342	-14.0228	0.000*

Source: Author's construct

Table 13: DAX Regression estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HIGH	0.794966	0.01961	40.53842	0.000*
LOW	0.788672	0.017172	45.92862	0.000*
OPEN	-0.58331	0.021591	-27.0161	0.000*

Source: Author's construct

Table 14: BIST Regression estimates

Variable	Coefficient	Std. Error	t-Statistic	Prob.
HIGH	0.00	0.00	19.18211	0.000*
LOW	0.00	0.00	33.23726	0.000*
OPEN	0.00	0.00	-20.1262	0.000*

Source: Author's construct

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