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Deep Continuous-Time Models in Nigerian Stock Exchange Sector

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Abstract

An ensemble continuous time model for predicting Nigerian stock market is proposed in this paper. The proposed technique is the integration of different continuous time models such as Stochastic Differential Equation (SDE), Geometric Brownian Motion (GBM) and Constant Elastic Variance (CEV) with Recurrent Neural Network (RNN). To validate the effectiveness and robustness of the method, it was tested using data from eleven sectors of Nigerian stock exchange which comprises of closing price stock from January 2017 to December 2019. The past returns were also tested using the aforementioned datasets, and the results show that past returns have predictive power in predicting future performance using Welch and F-statistics at 95% confidence intervals. The results indicated that Deep Continuous-time model is a promising algorithm that have the capacity to effectively predict the Nigerian stock market.

1. Introduction

Researches on stock market prediction have attracted many researchers in industries, financial sector and academia. Stock market prediction is a very laborious task because of the uncertainties in the financial market. Several researches have been conducted in the area of stock market forecasting. [1] developed a model to predict short-term stock behaviour. Simulation of the stock market was introduced by [2] using future price and different options. Many researchers have applied different techniques such as database system, continuous-time models, data mining, machine learning and artificial intelligence for predicting stock market. The authors in [3] used an ensemble machine learning technique that comprises of logistic regression, random forest, neural network, random forest and support vector machine for stock market prediction. Findings show that random forest performs better when stacked as a top layer with other algorithms than when other algorithms were stacked. [4, 5] employed non-linearities in their respective work using artificial neural network models. It was observed that their proposed systems resulted in improved stock market forecasting. A paper by [6] used a back-propagation network and obtained improved results. Also, [3] and [7] employed deep learning in their work and found out that it outperformed GARCH and random walk models. Logistic regression, support vector machine and quadratic discriminant analysis are employed by [8] which was used to predict the stock price of the following day. The result shows that their technique produced a better result than the earlier methods used for next day stock price prediction. The authors in [9] utilized One-All-One neural network (OAO-NN) and One-All-All neural network (OAA-NN) in Thailand stock exchange. It was observed that OAA-NN performed significantly better than OAO-NN with a prediction accuracy of 72.50%. Ensemble neural network was proposed by [8] to predict up and down of the North American and Brazilian stock market. [4] and [10] also propose a rough set model and artificial neural network in stock market prediction. Based on their findings, both models performed excellently well. The researchers in [11] employed an ensemble model for stock price returns using logistic regression, multi-layer perceptron and regression tree in their work. Their findings showed that when more classifiers are used, better results can be achieved. The deep neural network was employed by [1, 12] using previous stock prices and they developed a trading strategy using a deep neural network. Their findings showed good results. [13] in their paper proposed the hierarchical deep neural network for stock returns, they used five minutes returns for four years. Their findings show accuracy of 71%.

2. Methodology

The dataset used for predicting the stock return comprises of data from 11 sectors listed in the Nigerian Stock Exchange. Depicted in Table I and Figure I are the 11 sectors selected from the Nigerian Stock Exchange which all exhibited Brownian motion process. One stock was selected from each sector for our analysis and the date of incorporation and date listed were indicated. The closing stock prices are recorded at the end of every day from 03-Jan-2017 to 31-Dec-2018 and the returns are calculated using Equation (1).

The return is defined as:

$$r_t = \frac{C(t+\Delta t)-C(t)}{C(t)} = \frac{\Delta C(t)}{C(t)} \; ; \qquad (1)$$

where r_t is the return on the stock, $C(t)$ is the closing stock price at time t and $\Delta C(t)$ is the small change in closing price at time t.

The sample trading days consists of 468 trading days. All stocks returns are standardized using Equation (2). The standardized equation is given as:

$$S_r = \frac{(C_t-\mu)}{\sigma} \; ; \qquad (2)$$

where S_r is the standardized return, μ is the mean return, C_t closing price at time t and σ is the standardized return.

2.1 Continuous Time models

Price of stock market fluctuates over time and manifest what is termed stochastic process. A stochastic process can be described as behaviour of a random variable over time. The closing price of stock exhibits random variable or Brownian motion. Stock price exhibit continuous time models when price change continuously. Different researcher introduced the following:

i. Stochastic Differential Equation (SDE)

Consider an ordinary differential equation of the form

$$\frac{dC(t)}{dt} = A(t,c), \; dc(t) = A(t,c)dt \; . \qquad (3)$$

With an initial condition $c(0) = c_0$, which can be written as

$$c(t) = c_0 + \int_0^t A\big(s, c(s)\big)ds \; ; \qquad (4)$$

where $c(t) = c(t, c_0, t_0)$ is the solution with initial condition $c(t_0) = c_0$

$$\frac{dc(t)}{dt} = b(t)c(t), \qquad c(0) = c_0 \; . \qquad (5)$$

Using equation (3), we assume that $b(t)$ is a stochastic parameter and obtain a SDE given as

$$b(t) = A(t) + h(t)\xi(t) \; , \qquad (6)$$

where $\xi(t)$ is a white noise process

Then we obtain

$$\frac{dC(t)}{dt} = A(t)c(t) + h(t)c(t)\xi(t) \; . \qquad (7)$$

Writing (7) in the differential form, we use $dW(t) = \xi(t)dt$

Then, we obtain

$dC(t) = A(t)c(t)dt + h(t)c(t)dW(t)$ (8)

SDE is given as

$dc(t,\omega) = A\big(t, c(t,\omega)\big)dt + B\big(t, c(t,\omega)\big)dW(t,\omega)$; (9)

where ω which denotes that $c = c(t,\omega)$ is a random variable and possesses the initial condition $c(0,\omega) = c_0.^{00}$.

$\therefore dc(t,\omega) = \mu(t)dt + \sigma(t)dW(t,\omega)$ (10)

ii. Geometric Brownian Motion (GBM)

Recall that Equation (5) is given as

$\frac{dc(t)}{dt} = b(t)c(t), \qquad c(0) = c_0$.

Let $b_t = r_t + \sigma W_t$, assume that $r_t = r = constant$

By ito interpretation, it is equivalent to

$dc_t = rc_t dt + \sigma c_t dW_t$ (11)

or

$\frac{dc_t}{c_t} = rdt + \sigma dW_t$. (12)

We evaluate the left-hand side using its formula for the function and obtain

$d(lnc_t) = \frac{1}{c_t} \times dc_t + \frac{1}{2}\left(-\frac{1}{c_t^2}\right)(d(c_t)^2) = \frac{dc_t}{c_t} - \frac{1}{2c_t^2} \times \sigma^2 c_t^2 dt = \frac{dc_t}{c_t} - \frac{1}{2}\sigma^2 dt$ (13)

Hence,

$\frac{dc_t}{c_t} = d(lnc_t) + \frac{1}{2}\sigma^2 dt$. (14)

From (12) we have

$\ln\left(\frac{c_t}{c_0}\right) = \left(r - \frac{1}{2}\sigma^2\right)t + \sigma W_t$ (15)

Or

$c_t = c_0 exp^{\left(r - \frac{1}{2}\sigma^2\right)t + \sigma W_t}$. (16)

The general form of GBM is

$c_t = c_0 exp^{(\mu t + \sigma W_t)}$, (17)

where c_t closing price at time t, μ is the mean, σ is the variance, W_t is the wiener process and exp is the exponential.

iii. Constant Elastic Variance (CEV)

The Constant elastic variance (CEV) developed by John Cox, 1975, Cox (1975) is given as

$dc_t = \mu c_t dt + \sigma c_t^{\gamma} dW_t$ (18)

Where c_t closing price at time t, μ is the mean, σ is the variance, W_t is the wiener process and γ is the elasticity of variance with c_t.

$\mu = \frac{1}{n}\sum_{i=1}^{n} c_t$ (19)

$\sigma = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}\mu^2 - \frac{1}{n(n-1)}\left(\sum_{i=1}^{n}\mu_i\right)^2}$, (20)

where n is the number of trading days.

2.2 Proposed Deep Continuous-time Model (DCTM)

The proposed algorithm for deep continuous-time models (DCTM) were borne out of a paper by [14]. The authors opined that continuous time models (Geometric Brownian motion) cannot predict accurately the price movement of the listed stocks. DCTM is deep learning techniques incorporate that incorporates the three continuous time models as the input layer which enables us to represent the data. The DCTM consists of input layer $\hat{X}_{SDE}$, $\hat{X}_{GBM}$ and $\hat{X}_{CEV}$ as the input layer, φ is the hidden layers and Y as the output layer. Two activation functions were used; f_n is the rectified linear unit layer (RLU) and g_n is softmax layer used in this paper. RLU is given as max $(0, x)$ and softmax given as $\exp(x)\ /sum(\exp(x))$due to their ability to produce a faster learning speed than sigmoid function.

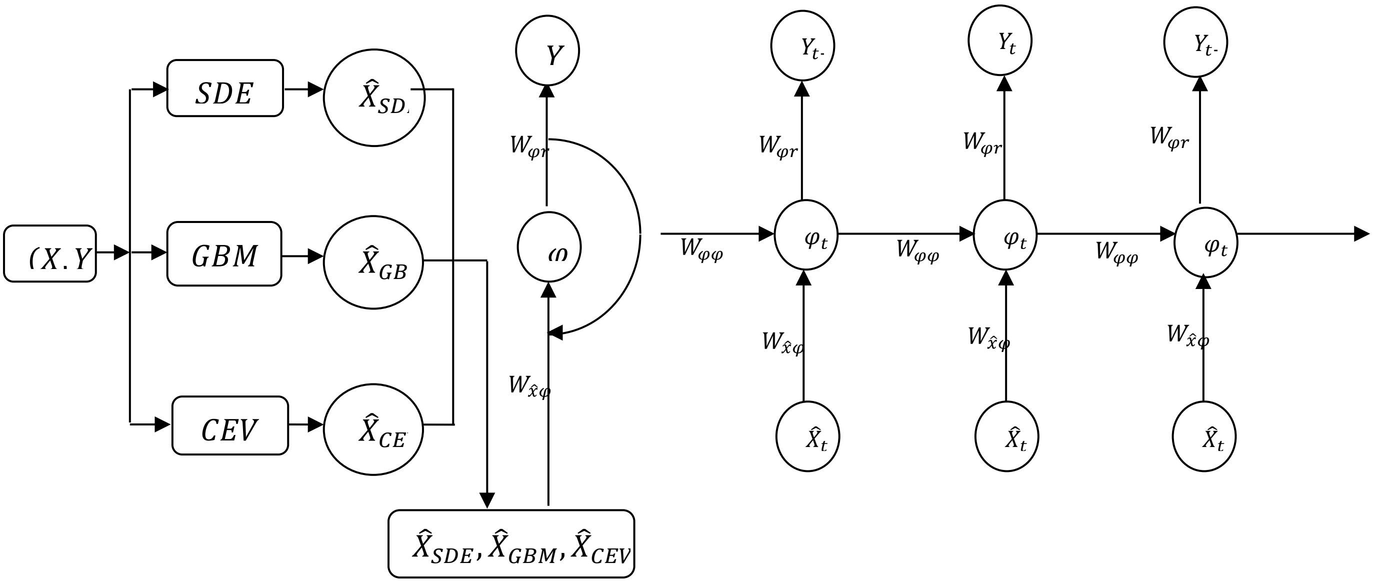

Fig. 1: Deep Continuous-Time Models (DCTM)

Input to hidden layer equation is given as:

$$\varphi_t = f_n\left(W_{\hat{x}\varphi}\hat{X}_t + W_{\varphi\varphi}\varphi_{t-1} + b_\varphi\right); \tag{21}$$

where φ_t is the hidden layer, f_n is the activation function, $W_{\hat{x}\varphi}$ is the input to hidden layer of weight matrix, $\hat{X}_t$ is the input, φ_{t-1} is the hidden layer, b_φ is the bias or threshold value.

The hidden to output layer equation is given as :

$$r_t = g_n(W_{\varphi r}\varphi_t + b_r), \tag{22}$$

where r_t is the output vector, $g_n$is the activation function, $W_{\varphi r}$ is the hidden to output layer weight matrix, b_r is the bias or threshold.

Table I: Nigerian Stock Exchange Sector

Sector	Ticker	Date Listed	Date of Incorporation
Agriculture	OKOMUOIL	March 11th 1991	December 3rd 1979
Construction/Real Estate	JBERGER	September 20th 1991	February 18th 1970
Consumer goods	DANGFLOUR	February 4th 2008	January 1st 2006
Financial Services	MANSARD	November 19th 2009	June 23rd 1989
Health Care	FIDSON	April 6th 2008	March 13th 1995
Industrial Goods	BETAGLAS	July 2nd 1986	June 2nd 1974
Information and Communication Technology	CHAMS	Invalid date	September 10th 1985
Natural Resources	BOCGAS	Invalid date	December 11th 1959
Oil and Gas	TOTAL	Invalid date	January 6th 1956
Services	ABCTRANS	Dec. 20th 2006	April 25th 1993
Conglomerates	UACN	Invalid date	April 22nd 1931

2.3 Performance Evaluation

Closing stock prices of eleven sectors in Nigerian Stock Exchange were evaluated by utilizing a four performance evaluation which are Normalized Root Mean Square Error (NRMSE), Mean Absolute Scaled Error (MASE), Normalized Mean Absolute Error (NMAE) and Normalized Mean Square Error (NMSE). R^2 help us to determine the strength of the relationship between the proposed deep continuous-time models (DCTM) and closing prices of the stock market.
Normalized Root Mean Square Error (NRMSE) is given as:

$$NRMSE = \frac{\sqrt{\frac{1}{n}\sum_{t=1}^{n}(C_t - \widehat{C_t})^2}}{\widehat{C_t}} \qquad (23)$$

Mean Absolute Scaled Error (MASE) is defined as:

$$MASE = \frac{1}{n}\sum_{t=1}^{n}\frac{|C_t - \widehat{\hat{C}_t}|}{\frac{1}{n-s}\sum_{n=s+1}^{n}|C_t - \hat{C}_{t-s}|} \quad . \qquad (24)$$

Normalized Mean Absolute Error (NMAE) is given as:

$$NMAE = \frac{\frac{1}{n}\sum_{t=1}^{n}|C_t - \widehat{C_t}|}{\max(C_t) - \min(C_t)} . \qquad (25)$$

Normalized Mean Square Error (NMSE) is defined as:

$$NMSE = \frac{\sum_{t=1}^{n}(C_t - \hat{C}_t)^2}{\sum_{t=1}^{n}(C_t - \overline{C_t})^2} \quad . \qquad (26)$$

Coefficient of Determination (R^2)

$$R^2 = 1 - NMSE \, , \qquad (27)$$

where $\overline{C_t} = \frac{1}{n}\sum_{t=1}^{n} C_t$, n is the trading days,C_t is the closing price at time t,$\widehat{C_t}$ is the predicted closing price and s is the seasonal period of C_t.

3. Results and Discussion

Statistical results of the Nigerian closing stock prices are presented in Table II. The daily mean, 1st Quarter, Median, Mean, 3rd Quartile, Maximum and Standard deviation distribution were also analyzed. Total oil Plc has the highest closing price while CHAMS has the lowest price follow by ABCTRANS. Low volatility was obtained from ABCTRANS and CHAMS which indicated that the two stock prices tend to be more stable. For an investor selecting Total and BETAGLAS stocks, the rewards can be high, but the investor also needs to consider the risk involved with high volatility. This paper also investigates the ability of past returns to have predictive power for future returns by considering five mean lagged returns of each sector in Nigerian Stock Exchange. The return is divided into two ensembles which are mean lagged returns and variance lagged returns.

Table III shows the mean lagged return is less or greater than the threshold (h) and also variance lagged returns less or greater than the threshold (h). The threshold (h) for both mean lagged returns and variance lagged return is given as $h(0,1)$ since Brownian motion is normally distributed with mean 0 and variance 1. We consider two Welch t-test for mean lagged return and F-statistics for variance lagged returns at 95% confidence intervals. The results clearly showed that mean and variance lagged returns are significant for all stocks at 95% confidence intervals. Moreover, this indicates that the past returns have predictive power on future returns.

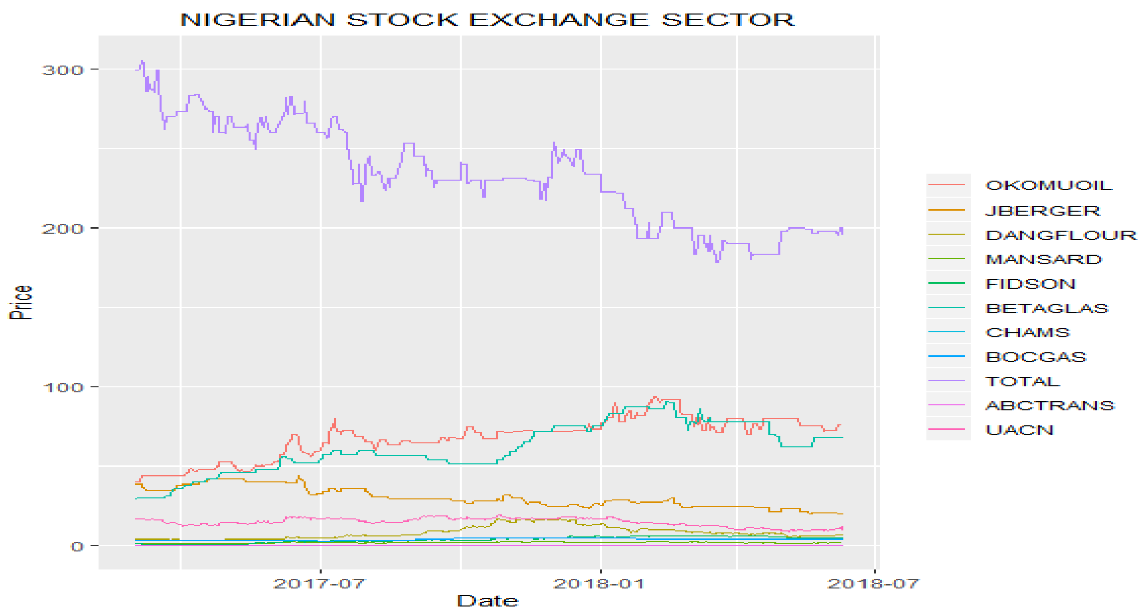

Fig. 2: Closing price of eleven sectors in the Nigerian Stock Exchange

Table II: Summary Statistics Closing price of Nigerian Stock Exchange

Stocks	Descriptive Statistics						
	Mean	1st Quartile	Median	Mean	3rd Quartile	Maximum	Standard deviation
OKOMUOIL	40.17	62.97	72.00	68.04	75.85	94.20	12.69702
JBERGER	20.10	25.00	29.00	30.19	34.83	43.84	6.190687
DANGFLOUR	3.580	5.115	7.250	8.292	10.500	16.900	3.867794
MANSARD	1.450	1.900	2.100	2.136	2.480	2.940	0.3847341
FIDSON	0.890	2.940	3.990	3.971	5.480	6.240	1.734236
BETAGLAS	29.00	51.31	59.40	61.58	75.70	90.45	15.47949
CHAMS	0.2000	0.3700	0.5000	0.4338	0.5000	0.5000	0.09628178
BOCGAS	2.990	3.520	4.210	4.017	4.580	4.630	0.4758993
TOTAL	177.6	200.0	231.0	232.6	260.0	305.0	31.33337
ABCTRANS	0.2500	0.4000	0.5000	0.4479	0.5000	0.5200	0.07529645
UACN	9.00	13.20	15.14	14.93	17.00	19.42	2.63257

Table III: Statistics of Mean lag returns of Welch two Sample t-test at 95% confidence interval

Stock	$Mlag(5) < h$	$Mlag(5) > h$	t	$p - value$
OKOMUOIL	-0.6549846	0.1726390	-11.423	2.2×10^{-16}
JBERGER	-0.6017710	0.2157233	-16.971	2.2×10^{-16}
DANGFLOUR	-0.3089682	0.3274274	-16.851	2.2×10^{-16}
MANSARD	-0.2419187	0.4167333	-18.733	2.2×10^{-16}
FIDSON	-0.2131057	0.3657223	-19.162	2.2×10^{-16}
BETAGLAS	-0.1940419	0.4917633	-23.674	2.2×10^{-16}
CHAMS	-0.8246819	0.1224312	-16.214	2.2×10^{-16}
BOCGAS	-0.1070998	0.8430296	-10.489	1.229×10^{-14}
TOTAL	-0.3596718	0.2094094	-23.688	2.2×10^{-16}
ABCTRANS	-0.6278519	0.1094666	-14.635	2.2×10^{-16}
UACN	-0.3158726	0.3075326	-23.157	2.2×10^{-16}

Table IV: Statistics of Variance lag returns of F-Statistics at 95% confidence interval

Stock	$Vlag(5) < h$	$Vlag(5) > h$	F	$p - value$
OKOMUOIL	0.02623591	2.860545	0.0026521	2.2×10^{-16}
JBERGER	0.1430126	2.836776	0.01358	2.2×10^{-16}
DANGFLOUR	0.2642619	2.908285	0.015262	2.2×10^{-16}
MANSARD	0.3042774	2.576847	0.022114	2.2×10^{-16}
FIDSON	0.2492122	3.207467	0.01428	2.2×10^{-16}
BETAGLAS	0.131519	3.424828	0.0064419	2.2×10^{-16}

CHAMS	0.008323702	8.320145	2.558×10^{-5}	2.2×10^{-16}
BOCGAS	0.007510635	6.670218	5.6129×10^{-5}	2.2×10^{-16}
TOTAL	0.2149026	2.399399	0.030787	2.2×10^{-16}
ABCTRANS	0.06185952	5.694609	0.001489	2.2×10^{-16}
UACN	0.3891462	1.953971	0.069448	2.2×10^{-16}

The performance of the actual closing price and predicted prices is measured using four performance metrics: NRMSE, MASE and NMAE and NMSE. The fitness of the prices is also calculated. Table V shows the performance evaluation of the selected stocks in this paper. In Table V, SDE and GBM performed poorly when compared to our proposed model (DCTM). However, CEV performs a bit better. Coefficient of determination shows that OKOMUOIL, JBERGER, DANGFLOUR, BETAGLAS, CHAMS, BOCGAS and FIDSON have a better fit. This shows that DCTM has better predicting power than continuous-time in predicting Nigerian Stock exchange. In all the performance evaluation used in this paper, DCTM has a very low-value which is an indication of good performance. We also compared three best stocks (BETAGLAS, CHAMS and BOCGAS) and three worst stocks (TOTAL, ABCTRANS and UACN) to verify if standardizing the closing price have the capacity to improve the accuracy as shown in Table VI. The analysis shows that standardizing a closing price cannot improve the accuracy of the stocks except in TOTAL where there is a slight improvement in the standardized data but in the remaining five selected stocks there is no indication of any improvement.

Fig. 2 shows the dendrogram of the selected stocks. The closing price of UACN is similar to DANGFLOUR, ABCTRANS closing price is also similar to CHAMS. Also, the closing price of BOCGAS is similar to FIDSON and there is also a similarity between BETAGLAS and OKOMUOIL. There is dissimilarity in TOTAL closing price. This helps an investor in determining similarity and dissimilarity price when investing in any of the stocks. The graphical representation of the proposed deep continuous-time models (DCTM) and continuous-time models are shown in Fig. 3-8. In each figure, SDE, GBM and CEV perform poorly but DCTM performs excellently well in all the figures.

Table V: Performance Evaluation

STOCK	MODELS	NRMSE	MASE	NMAE	NMSE	R^2(%)
OKOMUOIL	SDE	115.6	5.983941	0.2500277	1.5076	0.5076
	GBM	117.1	8.541656	0.2933561	2.7581	1.754
	CEV	64.1	3.894912	0.1041518	0.7951	20.49
	DCTM	33.5	1.396017	0.06664947	0.0998	90.02
JBERGER	SDE	58.4	6.029814	0.1334732	1.0296	2.9566
	GBM	198.7	7.347906	0.295357	1.4359	0.4359
	CEV	99.4	4.878949	0.2179521	0.4993	50.07
	DCTM	25.4	1.553744	0.05443239	0.0613	93.87
DANGFLOUR	SDE	305.5	9.942853	0.5489648	1.9505	0.9505
	GBM	301	9.33677	0.5931288	1.8904	0.8904
	CEV	208.5	6.151065	0.2897485	0.9035	9.6536
	DCTM	20.4	1.326854	0.04112533	0.0398	96.02
MANSARD	SDE	132.4	7.456786	0.2668246	4.2791	3.2791
	GBM	210.1	7.364465	0.4652081	4.1477	3.1477
	CEV	104.6	3.032031	0.1587756	0.8260	17.40
	DCTM	46.8	1.373566	0.09891307	0.1818	81.82
FIDSON	SDE	150.6	10.54291	0.3078555	0.9675	3.2490
	GBM	121.1	11.59823	0.3017717	1.1589	0.1589
	CEV	67.4	6.332254	0.1132136	0.4286	57.14
	DCTM	24.8	2.112718	0.05573585	0.0722	92.78
BETAGLAS	SDE	148.7	10.52053	0.279374	1.2000	0.2000
	GBM	138.3	15.78154	0.375254	2.0396	1.0396

	CEV	91.3	9.687158	0.1824478	0.8724	12.76
	DCTM	14.2	1.30523	0.02821009	0.0196	98.04*
CHAMS	SDE	92.7	35.41255	0.2421847	1.7650	0.7650
	GBM	251.9	49.52352	0.4947922	2.8375	1.8375
	CEV	118.6	27.39653	0.2844234	0.8779	12.21
	DCTM	19.6	3.623774	0.03636656	0.0380	96.20*
BOCGAS	SDE	213.7	23.76678	0.4183456	2.0835	1.0835
	GBM	128	17.13626	0.259244	1.2704	0.2704
	CEV	96.8	12.68505	0.1792287	0.5142	48.58
	DCTM	13	1.551824	0.02526198	0.0164	98.36*
TOTAL	SDE	93.6	9.933649	0.2012432	4.9299	3.9299
	GBM	156.8	6.077427	0.2548629	1.3792	0.3792
	CEV	198.8	8.248073	0.3910695	2.3658	1.3658
	DCTM	51.3	2.195249	0.101194	0.2347	76.53**
ABCTRANS	SDE	83.6	17.06382	0.1997224	2.9369	1.9369
	GBM	303.8	20.21471	0.5096617	3.4747	2.4747
	CEV	117.3	7.669992	0.2136057	0.6147	38.53
	DCTM	56.8	3.884652	0.09731257	0.2488	75.12**
UACN	SDE	101.1	8.739132	0.2375154	5.1243	4.1243
	GBM	307.2	7.796265	0.4979018	3.8516	2.8516
	CEV	113.9	2.789908	0.1883988	0.5968	40.32
	DCTM	59.6	1.734548	0.108429	0.2665	73.35**

Table VI: Differences between unstandardized and standardized data of DCTM

STOCK	DCTM	NMSE	R^2
BETAGLAS	UNSTANDARDIZED	0.0196	98.04
	STANDARDIZED	0.0333	96.67
CHAMS	UNSTANDARDIZED	0.0380	96.20
	STANDARDIZED	0.0781	92.19
BOCGAS	UNSTANDARDIZED	0.0164	98.36
	STANDARDIZED	0.0118	98.02
TOTAL	UNSTANDARDIZED	0.2347	76.53
	STANDARDIZED	0.1982	80.18
ABCTRANS	UNSTANDARDIZED	0.2488	75.12
	STANDARDIZED	0.3876	61.24
UACN	UNSTANDARDIZED	0.2665	73.35
	STANDARDIZED	0.3914	60.86

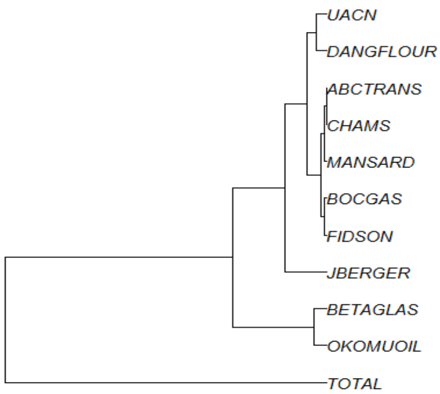

Fig. 3: Dendrogram of Nigerian Stock Sector

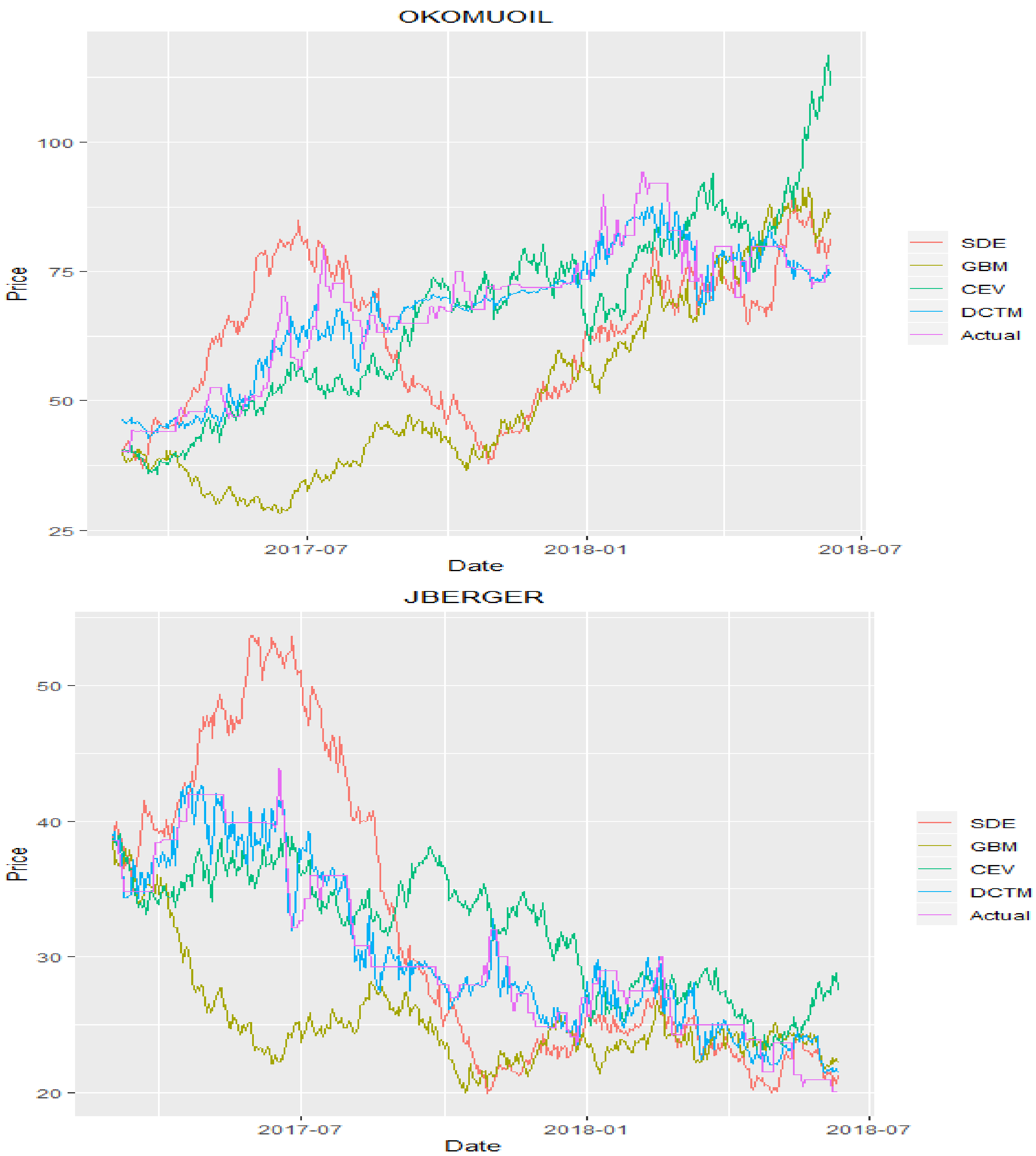

Fig. 4: Closing price of SDE, GBM, CEV, DCTM, Actual in OKOMUOIL and JBERGER

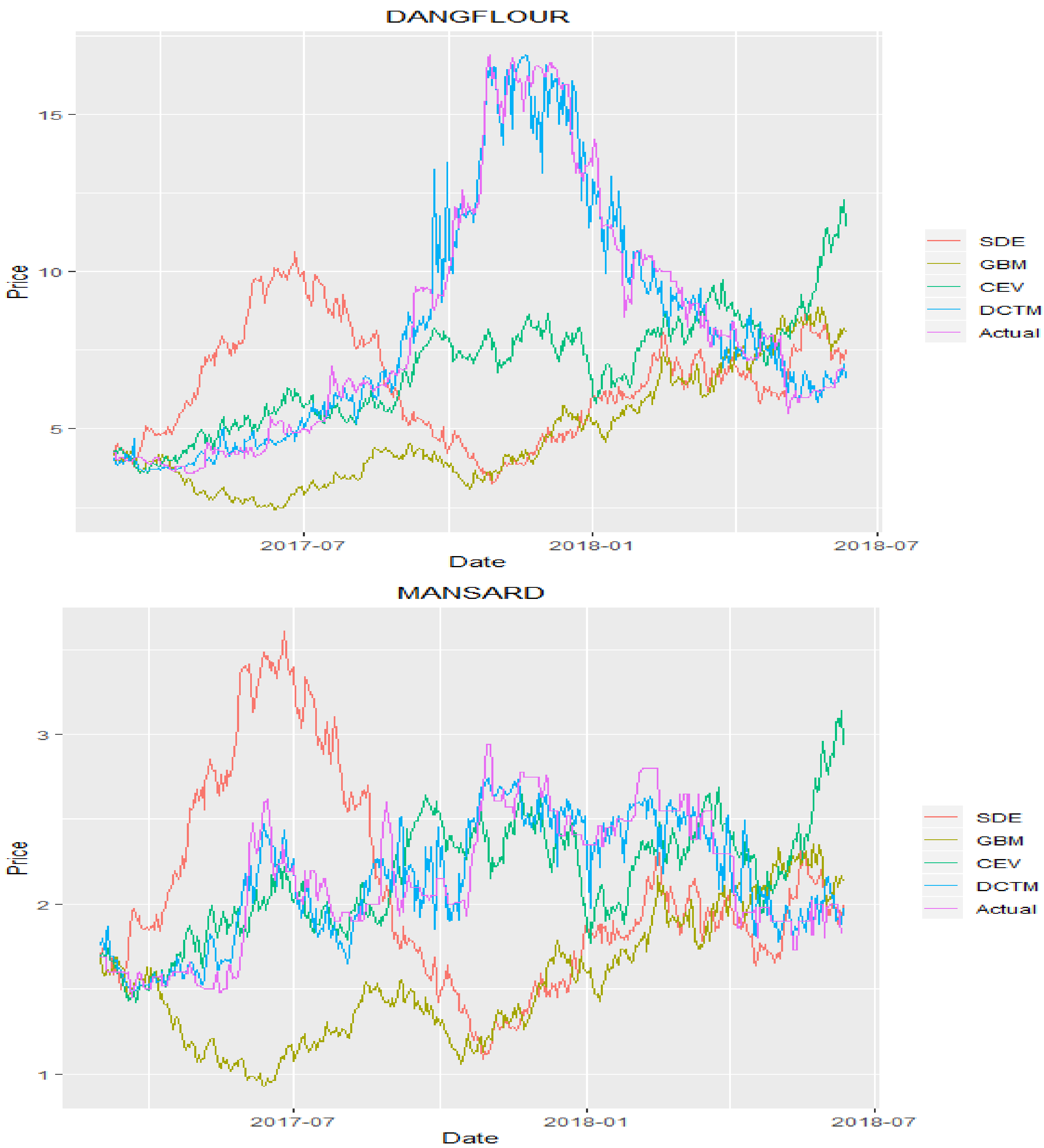

Fig. 5: Closing price of SDE, GBM, CEV, DCTM, Actual in DANGFLOUR and MANSARD

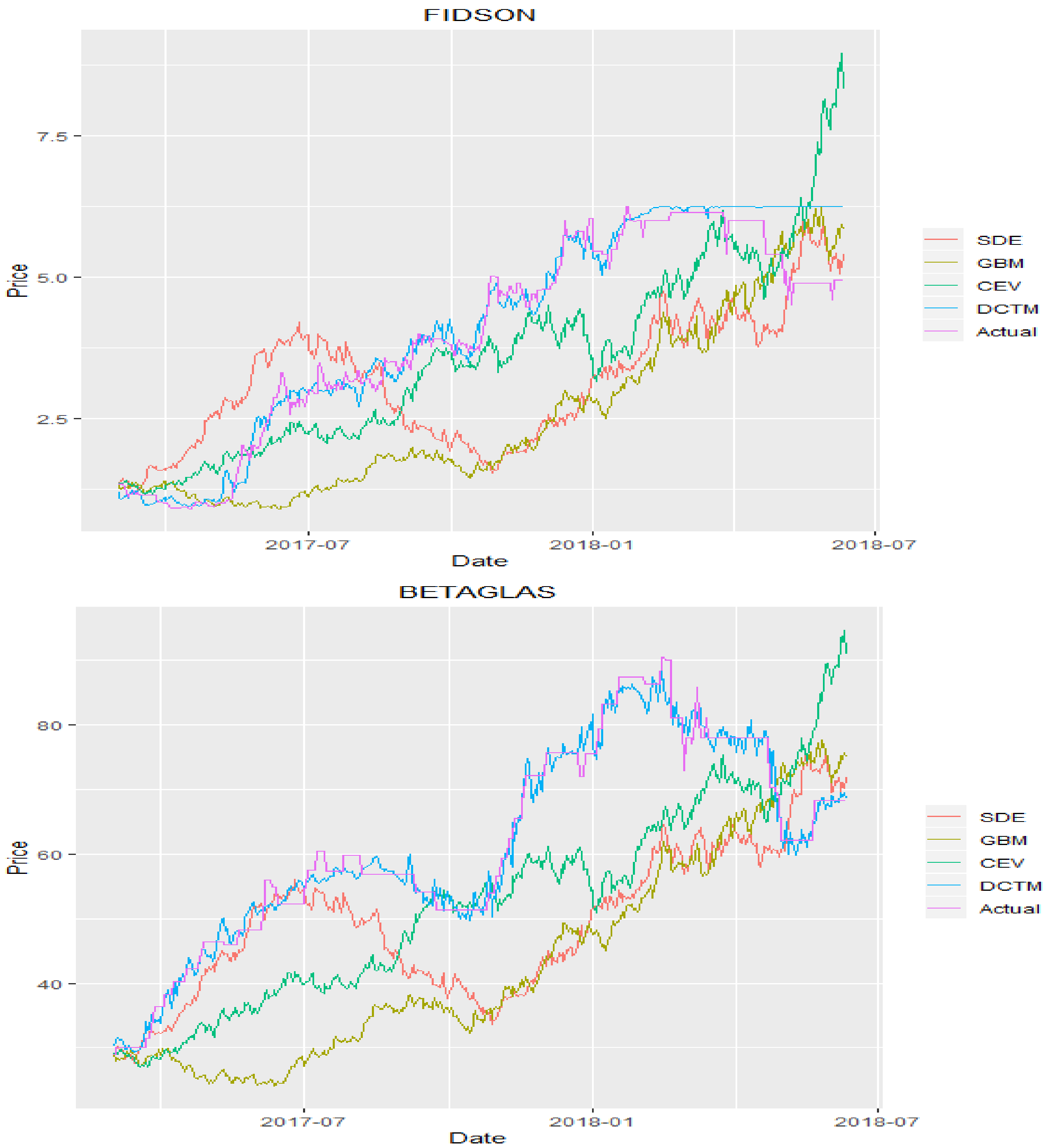

Fig. 6: Closing price of SDE, GBM, CEV, DCTM, Actual in FIDSON and BETAGLAS

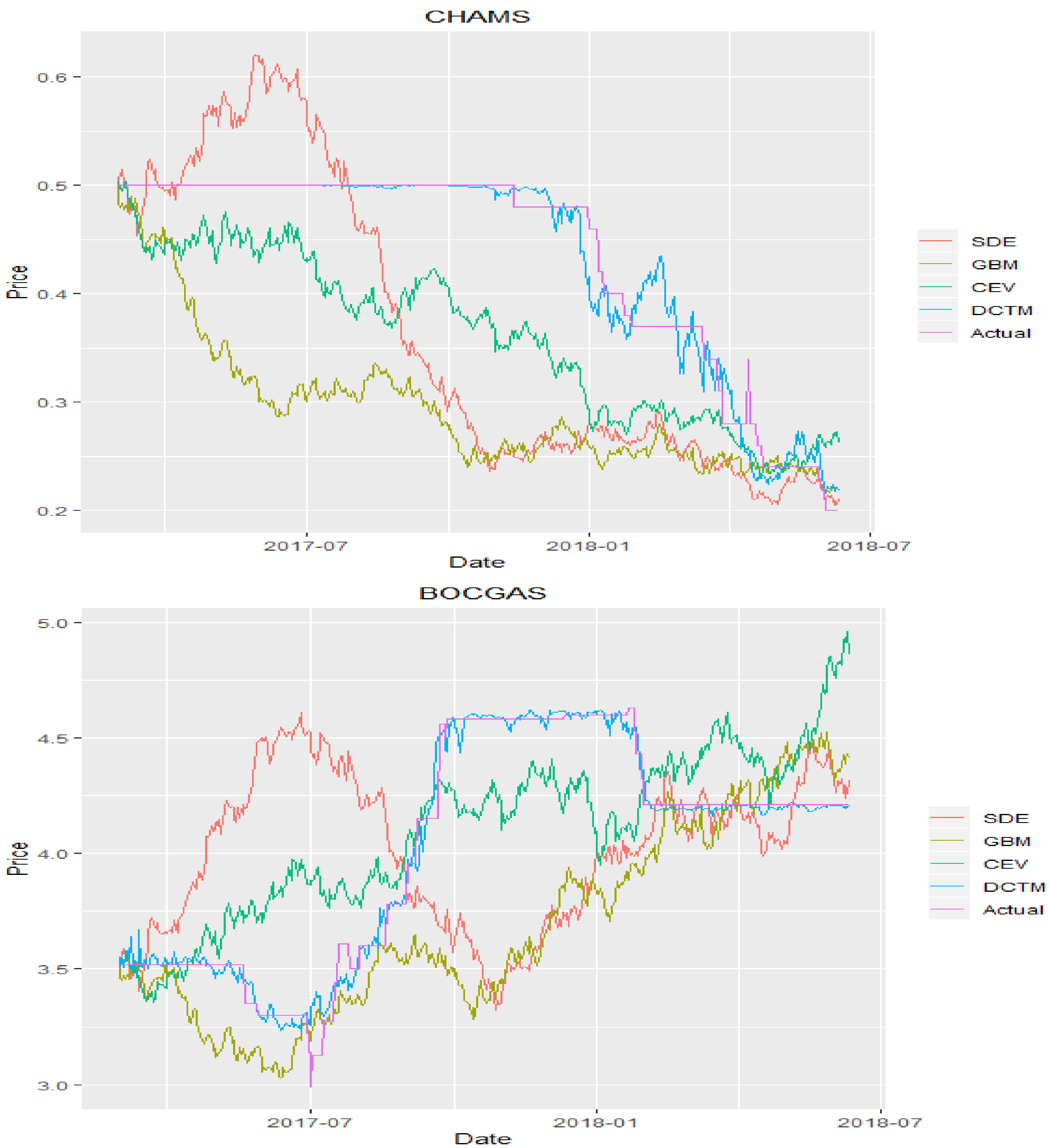

Fig. 7: Closing price of SDE, GBM, CEV, DCTM, Actual in CHAMS and BOCGAS

Fig. 8: Closing price of SDE, GBM, CEV, DCTM, Actual in TOTAL and ABCTRANS

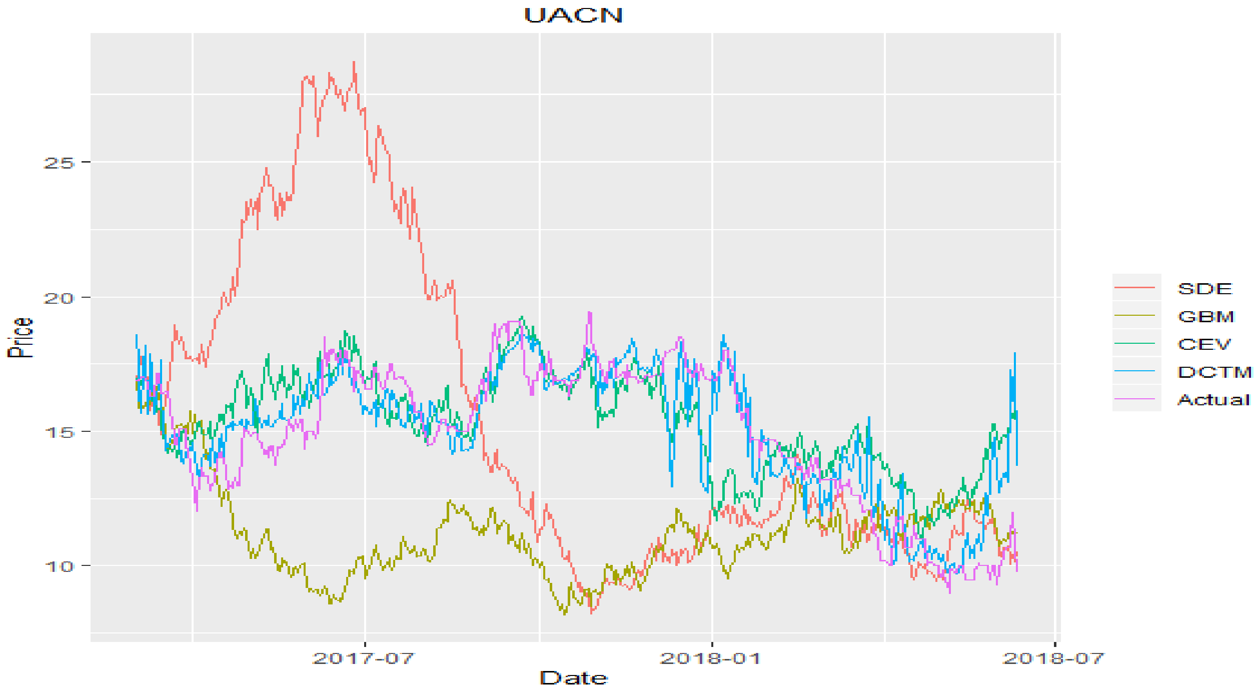

Fig. 9: Closing price of SDE, GBM, CEV, DCTM, Actual in UACN

4. Conclusion

This paper proposed a novel deep continuous-time models (DCTM) model for stock market forecasting. The findings showed that the proposed a deep continuous-time models (DCTM) stock market prediction model can significantly improve the predictive performance of the stock markets based on the performance evaluation of NRMSE, MASE, NMAE and NMSE. We integrated continuous-time models and a deep neural network to predict the stocks market. The overall results indicate that deep continuous time models predictive power surpasses continuous-time models and it also has a better fit. Our experiments also demonstrate that past return can have predictive power on future returns. Many researchers standardized their data, in our experimental results it shows that unstandardized data can perform significantly better than standardized data. This shows that standardized data can reduce the accuracy of the models. Thus, DCTM will help investor who is willing to make gains in the stock market.

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