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Modelling Monthly Volatility of the Muscat Securities Market (MSM) Index Using Auto Regressive Integrated Moving Average (ARIMA)

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Abstract: The Stock market is eyewitness's responsive activities and is gradually more gaining importance. The purpose of the study is to measure the volatility of selected emerging indices Muscat Securities Market (MSM). Time series analysis techniques were used including Auto Regressive Integrated Moving Average (ARIMA) models. The time series data considered of this study taken MSM 30. The study period has taken from January 2013 to December 2018 except Sharia-compliant index would be June 2013 to December 2018. Tools used for the study is Unit Toot Test (Augmented Dickey–Fuller and Phillips-Perron), ARIMA models and for performance model using Theil's U-Statistic. The study made a few observations which may help the investors and model builders to understand better about the stock market.

Key words: muscat securities market (MSM) index; stock market; ARIMA; forecasting; AIC; MAPE
JEL codes: G00

1. Introduction

The pivotal role of the economy in the contemporary world is the how best and industrious the stock market is operational globally, regionally and specific at the micro level. Stock market in general and investments in particular gives an indication and confidence to all the stakeholders how effective and sustainable the movement and trend can be predicted and growth of investments over a period of times both historical as well as the progressive. The aim of this research is to study the trend exists in MSM with reference to the conventional index and the impact of Sharia-compliant Index as it has been started trading from the year 2013 onwards. The micro-analysis will elucidate the trend pattern from the year 2013 to 2018. The diversified of investment behaviour among the investors institutional investors and the retail investors, the perception and the reflection between the conventional index and the Sharia-compliant Index, its correlation and its regressive impact will be looked into.

The Sultanate's economy is witnessing (CBO 2017) a structural transformation with increased diversification leading to accelerated non-oil economic activities and reduced dependence on hydrocarbon sector over the last few years. The nominal gross domestic product (GDP) grew by 8.7 percent in 2017 as against a contraction of

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15.0 percent and 3.0 percent in 2015 and 2016.The fluctuations in the MSM over a period of time qualified to various explanations which includes global fluctuations in oil prices, economical changes in MENA region and regional economic factors. MSM (2017), MSM-30 index dropped by 11.82% compared to 2016. Meanwhile, Sharia-compliant index dropped by 17.88 % compared to at the end of 2017.

2. Literature Review

Stock indices forecasting is very tricky to estimate future values in particularly time series data. The existing econometric model has been developed on applications (Zotteri et al., 2005). The capable and robust econometric models are Auto Regressive Integrated Moving Average (ARIMA) models, which are used to forecast the financial time series data for short term than the other techniques such as Artificial Neural Networks, etc. (L.C. K Yung Joo et al., 2007; N. Merh et al., 2010; J. Sterba, 2010).

Several researchers worked in ARIMA forecasting models to predict the future returns (M. Khasel et al., 2009; C. Lee & C. Ho, 2011; M. Khashei et al., 2012). In ARIMA model, stationary, invariability and parsimony are the three important parameters are used to identification, estimation and diagnostic checking respectively (Asteriou D. & S. G. Hall, 2015).

Al-Loughani and Moosa (1997) test the efficiency of the market by using a set of moving averages of different lengths. The results obtained by the authors indicate market inefficiency.

Gjerde et al. (1999) in their study examined the relation between stock returns and macroeconomic variables in Norway. Evidence from their results, shows a positive relationship between oil price and stock returns and real economic activity and stock returns. Although, this study fails to show the significant relationship between stock returns and inflation. Malkiell (2003) research shows that investors strongly focus on growth stocks while making investment decisions and are much les concerned about value stocks. This is partly due to the fact that the analysts rarely monitor stocks which have performed poorly in the recent past (value). It is argued that such lack of interest in value stocks leads their prices to depreciate to a value far below their true value, thereby giving investors the chance to benefit from the mispricing errors.

Firmansyah (2006) fluctuations in stock price are indicated by volatility to statistical measure of price fluctuation over a given period. Duca (2007) employs Granger causality test to examine direction of causality among stock prices and GDP in developed market economies. But the result points out a unidirectional causality which runs from stock prices to DGP and that no causality was found in the reverse direction in the developed economies market.

Wan Ismail et al. (2015) investigates the quality of report earnings in the corporate reports of shariah-complaint companies. They found that the Shariah-complaint companies have significantly higher earnings quality compared to other companies. The results provide support for the arguments that shariah-complaint companies supply a higher quality of report earnings in order to attract foreign investment.

Itimi et al. (2018) concludes the result follow the theory of a positive risk premium on stock indices which states that the higher returns are expected for asset with higher level of risk. This confirms that the Nigerian stock market prices are reactive to the changes in macroeconomic variables eventually regardless of high volatility and immaturity.

Onuoha (2018) make insights into the predictability of GCC stock returns using crude oil prices using the approach of Wasteland et al. (2012, 2015) that account of salient features of the predictor. The results show superior performance of the oil based stock model over time-series models (namely, AR, MA, ARMA and ARIMA) for both in-sample and out-of-sample forecasts. The results are robust to different oil prices series (Brent and WTI prices) and forecast horizons (30 and 60 days). Mohammed Nafie, Alkesh (2019), The Sultanate economy is projected to achieve a positive growth of 3 percent at constant prices. The International Monetary Fund (IMF) expects Oman to have the highest growth rate among all GCC countries in 2019, which is reflective of positive potential opportunities for local and international invests.

Qamruzzaman (2015) examined a wide variety of popular volatility models for Chittagong stock return index from 04 January 2004 to14 September 2014 and found that there has been empirical evidence of volatility clustering. The study confirmed that these five models GARCH-z, EGARCH-z, IGARCH-z, GJR-GARCH-z and EGARCH-can capture the main characteristics of Chittagong stock exchange (CSE).

Qiang Zhang (2015) explored the influence of the global financial crisis on the volatility spill over between the Mainland China and Hong Kong stock markets from January 04, 2002 to December 31, 2013. The results indicated that while there is no volatility spill over in the pre-crisis period, strong bi-directional volatility spill over exists in the crisis period.

Prashant Joshi (2014) used three different models: GARCH (1,1), EGARCH(1,1) and GJR-GARCH(1,1) to forecast daily volatility of Sensex of Bombay Stock Exchange of India from January 1, 2010 to July 4, 2014 and confirmed the persistence of volatility, mean reverting behavior and volatility clustering and the presence of leverage effect.

Neha Saini (2014) examined and compared the forecasting ability of Autoregressive Moving Average (ARMA) and Stochastic Volatility models applied in the context of Indian stock market using daily values of Sensex from Bombay Stock Exchange (BSE). The results of the study confirmed that the volatility forecasting capabilities of both the models.

Potharla Srikanth (2014) modeled the asymmetric nature of volatility by applying two popularly used asymmetric GARCH models, i.e., GJR-GARH model and PGARCH model in. BSE-Sensex between 1st July, 1997 to 30th march, 2013. The results revealed that the presence of leverage effect in Indian stock market and it also confirmed the effect of periodic cycles on the conditional volatility in the market.

Amitabh Joshi (2014) tried to analyze the volatility of BSE Small cap index using 3 years data from 1st July 2011 to 1st July 2013 suggested that ARCH and GARCH terms are significant.

Mohandass (2013) attempted to study the best fit volatility model using Bombay stock exchange daily sectoral indices for the period of January, 2001 to June, 2012. The findings concluded that the non-linear model is fit to model the volatility of the return series and recommended GARCH (1,1) model is the best one.

Naliniprava (2013) forecasted the stock market volatility of six emerging countries by using daily observations of indices over the period of January 1999 to May 2010 by using ARCH, GARCH, GARCH-M, EGARCH and TGARCH models. The study revealed that the positive relationship between stock return and risk only in Brazilian stock market. The analysis exhibits that the volatility shocks are quite persistent in all country's stock market. Further the asymmetric GARCH models find a significant evidence of asymmetry in stock returns in all six country's stock markets. This study confirmed the presence of leverage effect in the returns series.

Fereshteh, Hossein (2013) applied GARCH (1-1), and GARCH (2-2) to investigate the volatility using daily index from 2006 to 2010 for selected pharmaceutical group, vehicle group and oil industry respectively. The result showed volatilities feedback in pharmaceutical and oil industry. Positive effects of volatilities reign on output in pharmaceutical group, when this effect was negative in oil group. Also it was not confirmed in vehicle group.

Ung-Shi Liau et al. (2013) studied the stock index returns from seven Asian markets to test asymmetric volatility during Asian financial crisis. The empirical results showed that both volatility components have displayed an increasing sensitivity to bad news after the crisis, especially the transitory part.

Ming Jing Yang (2012) explored the predictive power of the volatility index (VIX) in Taiwan market from December 2006 to March 2010. The results shown that the predictive power of the models is improved by 88% in explaining the future volatility of stock markets.

Rakesh Gupta (2012) aimed to forecast the volatility of stock markets belonging to the five founder members of the Association of South-East Asian Nations, referred to as the ASEAN-5 by using Asymmetric-PARCH (APARCH) models with two different distributions (Student-t and GED). The result showed that APARCH models with t-distribution usually perform better.

Praveen (2011) investigated BSE SENSEX, BSE 100, BSE 200, BSE 500, CNX NIFTY, CNX 100, CNX 200 and CNX 500 by employing ARCH/GARCH time series models to examine the volatility in the Indian financial market during 2000-14. The study concluded that extreme volatility during the crisis period has affected the volatility in the Indian financial market for a long duration.

Srinivasan et al. (2010) attempted to forecast the volatility (conditional variance) of the SENSEX Index returns using daily data, covering a period from 1st January 1996 to 29th January 2010. The result showed that the symmetric GARCH model do perform better in forecasting conditional variance of the SENSEX Index return rather than the asymmetric GARCH models.

Jibendu Kumar Mantri et al. (2010) applied different methods i.e. GARCH, EGARCH, GJR-GARCH, IGARCH & ANN for calculating the volatilities of Indian stock markets using fourteen years of data of BSE Sensex & NSE Nifty. The result showed that, there is no difference in the volatilities of Sensex, & Nifty estimated under the GARCH, EGARCH, GJR GARCH, IGARCH & ANN models.

Amit Kumar Jha (2009) investigated to forecast the volatility of Nifty and Sensex with the help from Autoregressive Conditional Heteroskedastic models (ARCH). The study found that EGARCH method emerged as the best forecasting tool available, among others.

Dima Alberg and Haim Shalit (2008) analyzed the mean return and conditional variance of Tel Aviv Stock Exchange (TASE) indicesusing various GARCH models. The results showed that the asymmetric GARCH model with fat-tailed densities improves overall estimation for measuring conditional variance. The EGARCH model using a skewed Student-t distribution is the most successful for forecasting TASE indices.

Floros, Christos (2008) examined the use of GARCH-type models for modelling volatility and explaining financial market risk using daily data from Egypt (CMA General Index) and Israel (TASE-100 index). The study found the strong evidence that daily returns can be characterized by the above models and concluded that increased risk will not necessarily lead to a rise in the returns.

Banerjee A. and Sarkar S. (2006), predicted the volatility using five-minute intervals daily return to model the volatility of a very popular stock market in India, called the National Stock Exchange. This result emphasized that the Indian stock market experiences volatility clustering and hence GARCH-type models predict the market volatility better than simple volatility models, like historical average, moving average etc. It is also observed that the asymmetric GARCH models provide better fit than the symmetric GARCH model, confirming the presence of leverage effect.

Kumar S. S. S. (2006) attempted to evaluate the ability of ten different statistical and econometric volatility forecasting models to the context of Indian stock and forex markets. The findings confirmed that G.-I RCH 11. I, and EW.1 L4 methods will lead to Netter volatility forecasts in the Indian stock market and G.4RCH (5, I) will achieve the same in the forex market.

Glen R. (2005) investigated the role of trading volume and improving volatility forecasts produced by ARCH and option models and combinations of models. The findings revealed an important switching role for trading volume between a volatility forecast that reflects relatively stale information (the historical ARCH estimate) and the option-implied forward-looking estimate.

Hock Guan Ng (2004) estimated the asymmetric volatility of daily returns in Standard and Poor's 500 Composite Index and the Nikkei 225 Index in the presence of extreme observations, or significant spikes in the volatility of daily returns. The study concluded that both the GARCH(1,1) and GJR(1,1) models show superior forecasting performance to the Risk Metrics model. In choosing between the two models, however, superiority in forecasting performance depends on the data set used.

Philip (1996) studied the predictive power of GARCH model and two of its nonlinear modification to forecast weekly stock market volatility for the German stock market, Netherland, Spain, Italy and Sweden for 9 years from 1986 to 1994. The study found that the QGARCH model is the best when the estimation sample does not contain extreme observations such as the 1987 stock market crash.

3. Research Methodology

The present study based on the monthly closing market index for the Muscat Securities Market (MSM). Actively performing indices from MSM index such as All MSS data (Jan 2013-Dec 2018), Financial index (Jan. 2013-Dec. 2018), Industrial index (Jan. 2013-Dec. 2018), Services index (Jan. 2013-Dec. 2018) and Sharia-compliant Index (Jun. 2013-Dec. 2017) used for forecasting modes. In this study, Statistical software's E views 9 and R- language were used for the forecasting model building. The use of the data indices has substantial limitations for analysing and modelling of the forecasting both in terms of internal and external environment variables, economic conditions and investment behaviour.

3.1 Results and Discussion

Table 1 Descriptive Statistics of Monthly MSM Indices

	All MSM	Financial	Industrial	Services	Sharia-compliant
Mean	5838.18	7592.14	7683.99	3109.60	878.20
Median	5793.74	7519.50	7494.45	3140.36	874.46
Standard Deviation	831.26	601.28	1848.11	442.56	155.35
Standard Error	97.97	70.86	217.80	52.16	18.98
Kurtosis	-0.90	-0.10	-0.64	-1.14	-1.05
Skewness	-0.06	0.30	-0.19	-0.25	-0.22
Minimum	4323.74	6336.52	4323.74	2290.34	591.90
Maximum	7484.17	9305.60	11086.00	3810.54	1131.75
Jarque-Bera	2.59	5.12	6.79	4.67	3.65
p-value	0.01	0	0	0	0
Count	72	72	72	72	67

Data source: E views 9

All assumptions used in the study will be presented. Detailed descriptive analysis and specifics analysis will be provided if necessary. In Jarque-Bera normality test used in this analysis for data normality. The null hypothesis for the test is that the data is normally distributed; the alternate hypothesis is that the data does not come from a normal distribution. A small probability value leads to the rejection of the null hypothesis of a normal distribution. The Jarque-Bera test values of indices indicated significant departures from normality for the indices.

3.2 ARIMA Methodology

3.2.1 Stationary Test

(A) Augmented Dickey–Fuller (ADF) test

One of the assumptions on time series is non-stationary. To make sure existence of stationary relationship, the following stationary test Augmented Dickey–Fuller test (ADF) tests are employed in the study.

$$\Delta\lambda_t = \alpha_0 + \alpha_2 t + \sum_{i=1}^{k} \beta\Delta\lambda_{t-1} + \varepsilon_t$$

Where λ_t denotes the monthly index of the individual stock at time t, β is the coefficient to be estimates, k is the number of lagged terms, t is the trend term, α_2 is the estimated coefficient for the trend, α_0 is the constant and ε is white noise.

(B) Phillips-Perron (PP) test

The Phillips-Perron (PP) test figures out if a time series is stationary around a mean or is non-stationary due to a unit root. A stationary time series is one where statistical properties like the mean and variance are constant over time.

$$\prod \alpha = t_\alpha \left(\frac{\gamma_0}{f_0}\right)^{1/2} - \mathrm{T}\ \frac{(f_0-\gamma_0)\varepsilon_t(\alpha)}{2\, f_0^{1/2}\varepsilon}$$

Where α is the estimate, t_α is the ratio of α and $\varepsilon_t(\alpha)$ is coefficient standard error and ε is the standard error of the test regression.

The present study employs the Augmented Dickey Fuller test and Phillips-Perron test to examine whether the time series data are stationary or not using p-values. The results show the test statistics all four indices is

Table 2 ADF and PP test for Unit Roots

Index	Augmented Dickey Fuller test (p-value)	Phillips-Perron (p-value)
All MSS	-3.2587(0.0817)	-3.2416(0.08)
Financial	-3.2414(0.0848)	-3.2978(0.07)
Industrial	-3.0965(0.1151)	-3.1045(0.12)
Services	-3.0871 (0.1174)	-3.5534(0.04)
Sharia-compliant	-3.7083 (0.0207)	-3.7368.026)

Note: Alternative hypothesis: stationary for ADF test
Alternative hypothesis: Non-stationary for PP test
Data source: E views 9

The unit root test performed the major indices that all are shows non-stationary in their levels form, which is foremost step in time series modelling it helps to data stationary or not.

3.3 ARIMA Model

One of the dominant time series forecasting model Box and Jenkins methodology used in this study. This methodology collection of set of activities for identifying, estimating and diagnosing of ARIMA models with particularly time series data. The model is most well-known methods in financial forecasting. An ARIMA model describes efficient capability to forecast short term data. The multiplicative seasonal ARIMA model is

$$\Phi_P(B^s)\varphi_p(B)\nabla^D{}_s\,\nabla^d{}_{zt} = \theta_q(B)\Theta_Q(B^s)a_t$$

Where

- $\Phi^P (B^s) = 1 - \Phi_1 B^s - ... - \Phi_P B^{sP}$ is the seasonal AR operator of order P;
- $\varphi_p = 1 - \varphi_1 B - ... - \varphi_p B^P$ is the regular AR operator of order p;
- $\nabla^D{}_s = (1 - B^s)^D$ represents the seasonal differences and $\nabla^d = (1 - B)^d$ the regular differences;
- $\Theta_Q (B^s) = 1 - \Theta_1 B^s - ... - \Theta_Q B^{sQ}$ is the seasonal moving average operator of order Q;
- $\theta_q (B) = (1 - \theta_1 B - ... - \theta_q B^q)$ is the regular moving average operator of order q;
- a_t is a white noise process

The method used in this current study to develop ARIMA models for MSM indices explained in below table. The tool used for performance is E views 9 software and R-language five emerging stock indices monthly data were used in this model. In this study the closing index is chosen to represent the index to be predicted.

To determine the fitting best ARIMA model among the several combinations performed, the following criteria used in this modelling

- Relatively small of Akaike Information Criterion (AIC)
- Relatively high of the R-Square
- Relatively low MAPE value
- Q-Statistics and correlgram refer that there is no significant pattern auto correlation function (ACF) and partially auto correlation function (PACF), it means the residual of the selected model are white noise.

3.4 Akaike.s Information Criterion (AIC)

A way of selecting the order of the AR process is to find an order that balances the reduction of estimated error variance with the number of parameters being fit. One such measure is Akaike.s Information Criterion (AIC). The AIC is a tool for determining the order of the fitted autoregressive model. For an order k model, this criterion can be written as:

$$AIC(k) = n \log \hat{\sigma}^2_{\epsilon,k} + 2k$$

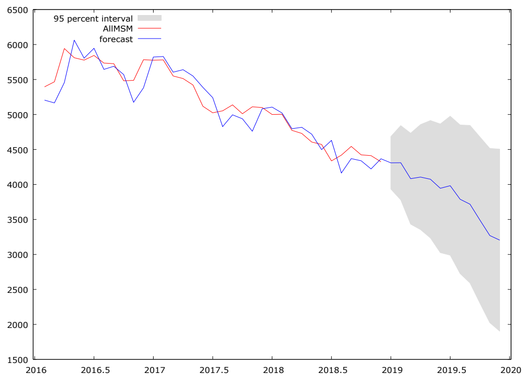
If the series is an AR process, then the value of k that minimizes is an estimate of the order of the auto regression.

Table 3 Automatic ARIMA (p d q) (P D Q) (S) with AIC Values of Indices

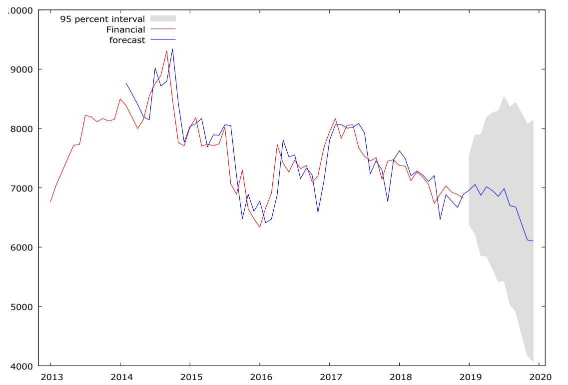
Indices	ARIMA (p d q) (P D Q) (S)	AIC-value	R-Square	MAPE (%)
All MSS	**(0 1 1) (0 1 1) (12)**	**814.15**	**0.925**	**3.132**
	(0 1 0) (0 1 1) (12)	815.24	0.921	3.186
	(0 1 0) (0 1 2) (12)	816.83	0.922	3.155
Financial	**(0 1 0) (0 1 1) (12)**	**866.52**	**0.634**	**3.691**
	(0 1 1) (0 1 1) (12)	867.64	0.639	3.622
	(0 1 0) (0 1 2) (12)	868.46	0.634	3.699
Industrial	(0 1 0) (0 1 2) (12)	891.09	0.938	4.476
	(0 1 0) (0 1 1) (12)	**891.74**	**0.937**	**4.424**
	(0 1 0) (0 1 3) (12)	891.86	0.938	4.567
Services	**(0 2 1) (0 2 3) (12)**	**606.09**	**0.802**	**4.201**
	(0 2 1) (0 2 2) (12)	606.94	0.802	4.236
	(0 2 1) (0 2 1) (12)	607.31	0.792	4.255
Sharia compliant	**(0 1 0) (0 1 3) (12)**	**517.74**	**0.957**	**2.569**
	(0 1 0) (0 1 1) (12)	518.31	0.956	2.637
	(0 1 1) (0 1 1) (12)	518.62	0.957	2.618

Data source: R-language

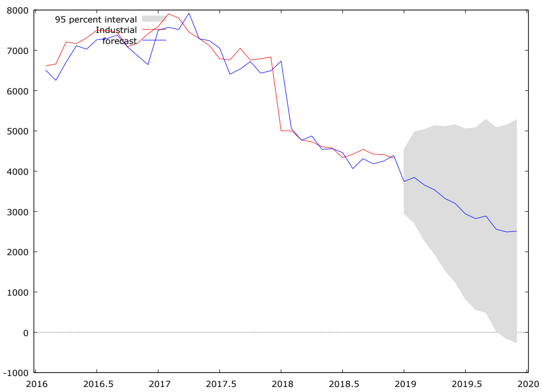
Table 3 shows the results of Automatic ARIMA forecasting used R-language, compared with best three forecasting models for five indices of MSM. In which All MSM index lowest AIC value is 814.15, ARIMA (0 1 1) (0 1 1) (12) model is best estimation and its MAPE is 3.132 and also the coefficient of determination is 0.925. Regarding Financial index the lowest AIC value is 866.52 and its MAPE is 3.691. The values obtained from Industrial index the ARIMA (0 1 0) (0 1 1) (12) shows MAPE is 4.424 it is best estimation model for future values. In Services index compared all best three models for forecasting the R-squares values vary close to same each other except ARIMA (0 2 1) (0 2 1) (12) finally lowest AIC value index is 606.09 and lowest MAPE is 4.201 considered as a best model. Lastly, the Sharia-compliant index best model obtained by ARIMA (0 1 0) (0 1 3) (12) the R-square is 0.957 and its MAPE is 2.569.



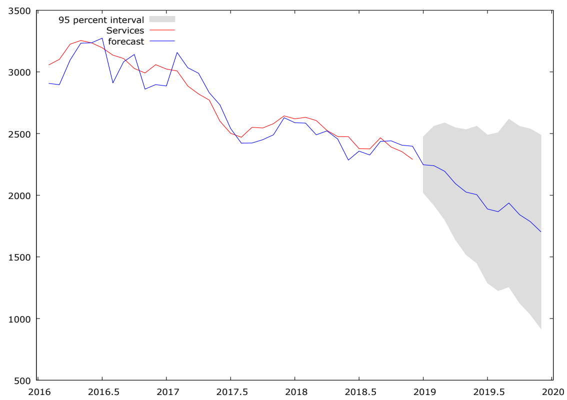
(1) Trend for all MSM index



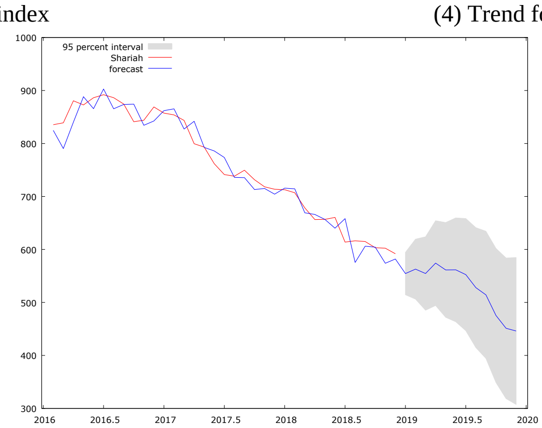
(2) Trend for financial index



(3) Trend for Industrial index



(4) Trend for Services index



(5) Trend for Sharia compliant index

Figure1 Forecasting trend for all five MSM Indices

Table 4 appropriate ARIMA model was selected using Box Jenkins's methodology. Forecasted value of All MSS index, Industrial index, Services index and Sharia compliant index are shows decline over the time period. The Financial index shows fluctuate the over the time period.

Table 4 Forecasted Values of All MSM Indices (Jan. 2019 to Dec. 2019)

Year	Month	All MSS	Financial	Industrial	Services	Sharia compliant
2019	Jan	4309	6958	3793	2247	554
	Feb	4310	7056	3783	2239	562
	Mar	4082	6875	3460	2194	554
	Apr	4105	7018	3386	2094	574
	May	4074	6952	3188	2025	561
	Jun	3845	6855	3002	2004	561
	Jul	3982	6986	2773	1888	552
	Aug	3788	6699	2574	1866	527
	Sep	3717	6675	2500	1936	514
	Oct	3491	6396	2150	1841	475
	Nov	3270	6120	1980	1786	451
	Dec	3204	6104	1758	1703	446

4. Forecast Evaluation

In order to assess the prediction performance, it is necessary to introduce a forecasting evaluation criterion. In this study, the Theil's U Statistics were used for performance of the models

4.1 Theil's U Statistic

Theils suggested one of the performances of the forecasting model. The Theils U Statistics falls between 0 and 1. The value U = 0 it indicates the predictive performances of the model is excellent, When U = 1 then it mean that the forecasting performance is not better than just using the actual values as a forecast. The following formulae is given by

$$U=\sqrt{\frac{\sum_{t=1}^{n-1}\left(\frac{\hat{Y}_{t+1}-Y_{t+1}}{Y_t}\right)^2}{\sum_{t=1}^{n-1}\left(\frac{Y_{t+1}-Y_t}{Y_t}\right)^2}}$$

Where U is Theil's statistic and t is time period.

Table 5 shows the results of performance of ARIMA models, in which every model has been, tested that model performing in future. The model plays a important role in outlook. Used Theils U-Statistics for all indices, in which all the five indices performing is superior the Theils values obtained all indices less than one or close to zero, which indicates that the error percentage is very less and the values of actual and forecast showing the almost same results. Therefore, the estimation ARIMA could be acceptable and forecasted values are accurate.

Table 5 Performance of the Forecasting ARIMA Model

Indices	ARIMA (p d q) (P D Q) (S)	Thei's U-Statistic
All MSS	(0 1 1) (0 1 1) (12)	0.0632
Financial	(0 1 1) (0 1 1) (12)	0.0018
Industrial	(0 1 0) (0 1 1) (12)	0.0836
Services	(0 2 1) (0 2 3) (12)	0.0100
Sharia compliant	(0 1 0) (0 1 3) (12)	0.1126

Data source: R-language

5. Conclusion

Difficult to building of forecasting models in predominantly in time series data. Mainly in stock market data very oscillating within time. Forecasting with Auto ARIMA models provides a prediction based on historical data, in which data has been tested stationary and employed first and second order differences to remove white noise problems. In this analysis Auto ARIMA estimated AIC, MAPE and Theil's which yielded the more accurate forecast over the time period and performance of the models.

Thus, the study shows that ARIMA model outperforms in forecasting MSM indices in terms of forecasting accuracy and in generating upcoming index. Probably this type of time series model could be used by policy makers in forecasting financial and economic data, apart from trader, borrowers and arbitrageurs developing trading models that leads to better investment decision and returns.

Its only a very short term forecast subject to measurement error, optimistically the stock markets will definitely rebound and recover either within the forecasted period and even in the long term it will have a very optimistic growth trends to be seen based on global and regional economic investment environment.

This research is to be carried forward further, on two different aspects first a similar a pre sharia-compliant index and post sharia complaint index to identify and explore the impact of sharia-compliant index investment behaviour and a comparison with a similar stock exchanges with the other stock exchanges where sharia-complaint index is traded, which will give us a comprehensive results and conclusion to think about.

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