European Journal of Business and Management
ISSN 2222-1905 (Paper) ISSN 2222-2839 (Online)
Vol.11, No.36, 2019
www.iiste.org

Short Term Predicting Volatility Service Jordanian Sector

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Abstract

Stock market volatility have added an important section in risk scholarship and it is actual problem particularly in emerging markets. Earlier, it is measured by standard deviation of the return. Consequently, in this research the volatility data will be predicted based on ARIMA model (Autoregressive Integrated Moving Average model) of the service sector in Amman Stock Exchange (ASE) from January 2019 to December 2019. Consequently this article shows that the ARIMA model has important results in prediction. Therefore, These outcomes will be helpful for the investments.

Keywords: ARIMA model, forecasting, Service sector.

DOI: 10.7176/EJBM/11-36-14
Publication date: December 31st 2019

1. Introduction

Volatility is important point for many scholars in financial institutions specially in emerging markets. Therefore, numerous scholars have focus in this field such as detecting and modeling and forecasting volatility since the volatility is used to assess the risk in the market for more details refer to (Bollersley, et al. 2016). Newly, many models of volatility have been recommend in order to make testing of the major trade-off between return and risk of financial assets such as GARCH model. This model is implemented for modeling and predicting volatility data (Babu & Reddy, 2015).

As we stated before, several scientists have focused on the volatility data since all the financial data are extremely volatile. Therefore, the data trend and accuracy stores can be happened simultaneously (Babu & Reddy, 2015). Consequently, this reason encourage the researchers to expand many approaches for modeling the forecasting volatility data. (Joukar & Nahmens, 2015) employed ARCH and GARCH models to calculate the volatility. The mathematical definition of volatility can be defined (Al Wadi, 2017). The volatility data hardly forecasting since the data are non-stationary and non-linear with high heteroscedasticity [Wang, et. al., 2012]. This reason encourage the scientists to recover many predicting models such as artificial neural network model, ARIMA model and others. ARIMA model is an traditional model with widely application in stock market data application [Awajan, et. al., 2017, Awajan, et. al., 2017, Al Wadi, 2013].

thousands of articles have available using ARIMA model in many fields. Therefore, in order to highpoint the gap and the differences between this work and previous works the a critically review should be presented. Numerous scientists have been emerging predicting models such as exponential, regression, GARCH models. However, only some linked works that has used ARIMA model in predicting financial data such as [Khashei, et. al., 2012; Wang, 2011; Al-Khazaleh et al, 2015]. Whereas, rarely to find any article that utilize Amman Stock Exchange using ARIMA model in forecasting such as (Al Wadi, 2015; Al Wadi, 2017; Al Wadi, et al., 2011). Especially the volatility of service sector in ASE recently.

3.Autoregressive Integrated Moving-Average Model (ARIMA (p,d,q))

The auto-regressive moving average is signified by (ARMA) model is implemented for stationary data only, it contains three combination models. An addition of the ordinary ARMA model is the auto-regressive integrated moving-average model (ARIMA(p,d,q)) given by :

$$\phi_p(B)(1-B)^d Y_t = \grave{e}_0 + \grave{e}_q(B)\, e_t$$

Where p, d and q denote orders of auto-regression, integration (differencing) and moving average, respectively. When d=0, the ARIMA model reduces to the ordinary ARMA model [Awajan, et. al., 2017].

4. Result and discussion

MINTAB software is applied to create the results. The daily service data from ASE for a specific period of time has been designated as the statistical population. There are many ARIMA model can be predictable for one column of dataset based on using different values of p,d and q. Therefore, the fitted ARIMA model which has less MSE (Mean Square Error) which is ARIMA (1,1,0)

```
Final Estimates of Parameters

Type              Coef     SE Coef      T      P
AR   1         -0.4479      0.0583  -7.68  0.000
Constant  -0.00002137  0.00009330  -0.23  0.0419


Differencing: 1 regular difference
Number of observations:  Original series 238, after differencing 237
Residuals:    SS =  0.000484823 (backforecasts excluded)
              MS =  0.000002063  DF = 235
```

It is noticeable here is that MS is very small which indicate that the forecasting accuracy is very high.

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Modified Box-Pierce (Ljung-Box) Chi-Square statistic

Lag             12     24     36     48
Chi-Square    47.0   68.6   83.5  105.5
DF              10     22     34     46
P-Value      0.000  0.000  0.000  0.000
```

Also here the P-value is significant at all the lages since it is less than 0.05. Therefore, the predicted 50 values (next 50 days) is

```
Forecasts from period 238

                     95 Percent Limits
Period   Forecast       Lower      Upper  Actual
   239  0.0010440  -0.0017718  0.0038598
   240  0.0008769  -0.0023395  0.0040933
   241  0.0009304  -0.0029216  0.0047823
   242  0.0008851  -0.0033953  0.0051654
   243  0.0008840  -0.0038320  0.0056000
   244  0.0008631  -0.0042322  0.0059584
   245  0.0008511  -0.0046052  0.0063074
   246  0.0008351  -0.0049564  0.0066266
   247  0.0008209  -0.0052888  0.0069306
   248  0.0008059  -0.0056057  0.0072175
   249  0.0007912  -0.0059088  0.0074913
   250  0.0007764  -0.0062001  0.0077530
   251  0.0007617  -0.0064809  0.0080043
   252  0.0007469  -0.0067522  0.0082461
   253  0.0007322  -0.0070150  0.0084794
   254  0.0007174  -0.0072701  0.0087050
   255  0.0007027  -0.0075182  0.0089235
   256  0.0006879  -0.0077599  0.0091357
   257  0.0006731  -0.0079956  0.0093419
   258  0.0006584  -0.0082258  0.0095426
   259  0.0006436  -0.0084509  0.0097382
   260  0.0006289  -0.0086713  0.0099290
   261  0.0006141  -0.0088872  0.0101154
   262  0.0005994  -0.0090989  0.0102976
```


263	0.0005846	-0.0093067	0.0104759
264	0.0005698	-0.0095109	0.0106505
265	0.0005551	-0.0097115	0.0108217
266	0.0005403	-0.0099088	0.0109895
267	0.0005256	-0.0101030	0.0111541
268	0.0005108	-0.0102942	0.0113158
269	0.0004960	-0.0104826	0.0114747
270	0.0004813	-0.0106683	0.0116308
271	0.0004665	-0.0108513	0.0117844
272	0.0004518	-0.0110320	0.0119355
273	0.0004370	-0.0112102	0.0120843
274	0.0004223	-0.0113862	0.0122307
275	0.0004075	-0.0115601	0.0123750
276	0.0003927	-0.0117318	0.0125173
277	0.0003780	-0.0119015	0.0126575
278	0.0003632	-0.0120693	0.0127958
279	0.0003485	-0.0122353	0.0129322
280	0.0003337	-0.0123994	0.0130668
281	0.0003189	-0.0125618	0.0131997
282	0.0003042	-0.0127226	0.0133309
283	0.0002894	-0.0128817	0.0134605
284	0.0002747	-0.0130392	0.0135886
285	0.0002599	-0.0131953	0.0137151
286	0.0002452	-0.0133498	0.0138402
287	0.0002304	-0.0135030	0.0139638
288	0.0002156	-0.0136548	0.0140860

5. Conclusion

This article presented a important model that carries a good predicting model of the new high technology procedure. Consequently, collecting enough data to predict service data in ASE, an ARIMA model are applied over the dataset performed to improve the prediction.. Around 250 observations were collected to appliance the forecasts of this and the best ARIMA model were selected based on the most famous criteria which is MSE (Mean Square Error). Then the 50 future values will be presented. Forthcoming research in this topic includes other stock market data such as industrial data also the future values can be found using the suggested model.

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