Quantitative Analyst Test

1. We assume that the best prediction of the volatility of an FX rate over the next 60 minutes is the historic volatility of that FX rate over the previous 60 minutes.

We now wish to enhance that volatility prediction by incorporating what is known about upcoming economic events (from the dataset provided by www.forexfactory.com).

Please propose, in as much detail as you can, a method for incorporating the economic events information into the volatility prediction. Kindly include your explanation of the model and code if you have any.

Answer:

Volatility is a statistical measure of the dispersion of returns for a given security or market index. In most cases, the higher the volatility, the riskier the security. Volatility is often measured as either the standard deviation or variance between returns from that same security or market index.

In the securities markets, volatility is often associated with big swings in either direction. For example, when the stock market rises and falls more than one percent over a sustained period of time, it is called a "volatile" market. An asset's volatility is a key factor when pricing options contracts.

Difference between risk and volatility:

- Risk is the probability that an investment will result in permanent or long-lasting loss of value.
- Volatility is merely how rapidly or significantly an investment tends to change in prices over a period of time. (fluctuations in price)

The reason this is important is because volatility doesn’t necessarily address how sturdy an investment’s *value* is. Price is what you pay for an investment, while value is what you get.

Although price and value are related, they are not identical. An investment could fluctuate wildly in price even though its value remains fairly steady over the long term. In that case, what’s changing is merely the market perception of the value, especially over the short term. Volatility is therefore something that must be managed if you need to withdraw your money within a specified timeframe.

Value investing is the original investment strategy to take advantage of the difference between price and value, and it relies on buying shares of companies for which the stock price is mistakenly below the real value of the company.

High Volatility & Low Risk

It’s a situation when the investment opportunity come. People sometimes been confused with risk and volatility because of 2 main reasons:

- The market’s obsession with financial models.
- The market’s horizon obsession with short-term investment horizon.

Risks are difficult to calculates and volatility are a bit easy to calculate through standard deviation calculation. If the financial models that falsely represent calculations of volatility it can represent risk to the investors. The problem is volatility are not necessarily equal to risk.

In the short-term, there is less distinction between volatility and risk. Volatility can cause permanent capital loss wherever it forces investors into a situation under which they are forced to sell an investment following a temporary drop in price, crystallizing losses.

Generally, the volatility is more likely to cause permanent capital loss for investments with short-term horizons, and investments that are heavily leveraged. The longer the holding period of an investment, the less consequential of the effects of volatility, and the greater the distinction between volatility and risk. So, high volatility does not necessarily equate to high risk.

ARCH Model

An ARCH Model is a model for the variance of a time series. ARCH model could possibly be used to describe a gradually increasing variance over time, often used in situations in which there may be short periods of increased variation.

The ARCH(1) variance model

$$Var(y_t|y_{t-1}) = \sigma_t^{\,2} = a_0 + a_1 y_{t-1}^{\,2}$$

#Note: The variance at time t is connected to the value of the series at time t-1. A relatively larger value of $y_{t-1}^{\,2}$ gives relatively large value of the variance at time t. This means that the value of y_t is less predictable at time t-1 than at times after a relatively small value of $y_{t-1}^{\,2}$.

If we assume the series mean = 0, the simplify version of ARCH Model is:

$y_t = \sigma_t \epsilon_t$ with $\sigma_t = \sqrt{a_0 + a_1 y_{t-1}^{\,2}}$ and $\epsilon_t \sim (\mu = 0, \sigma^2 = 1)$

GARCH Model

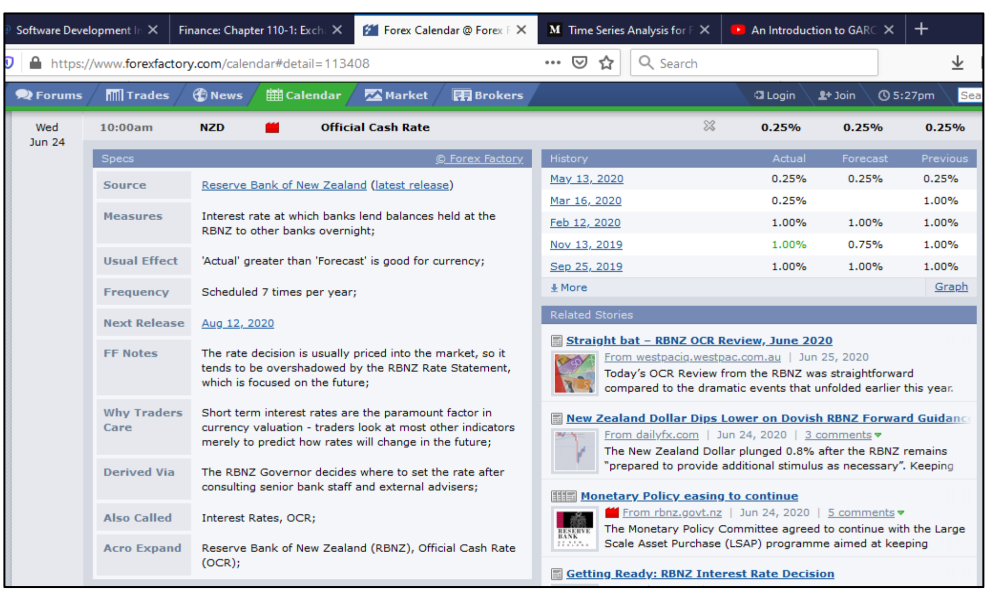
This model uses values of the past squared observations and past variances to model the variance at time t. Example GARCH(1,1):

$$\sigma_t^{\,2} = a_0 + a_1 y_{t-1}^{\,2} + \beta_1 \sigma_{t-1}^{\,2}$$

The first subscript in GARCH(1,1) indicates the order of y^2-terms and the second one refer to the order of σ^2-terms.

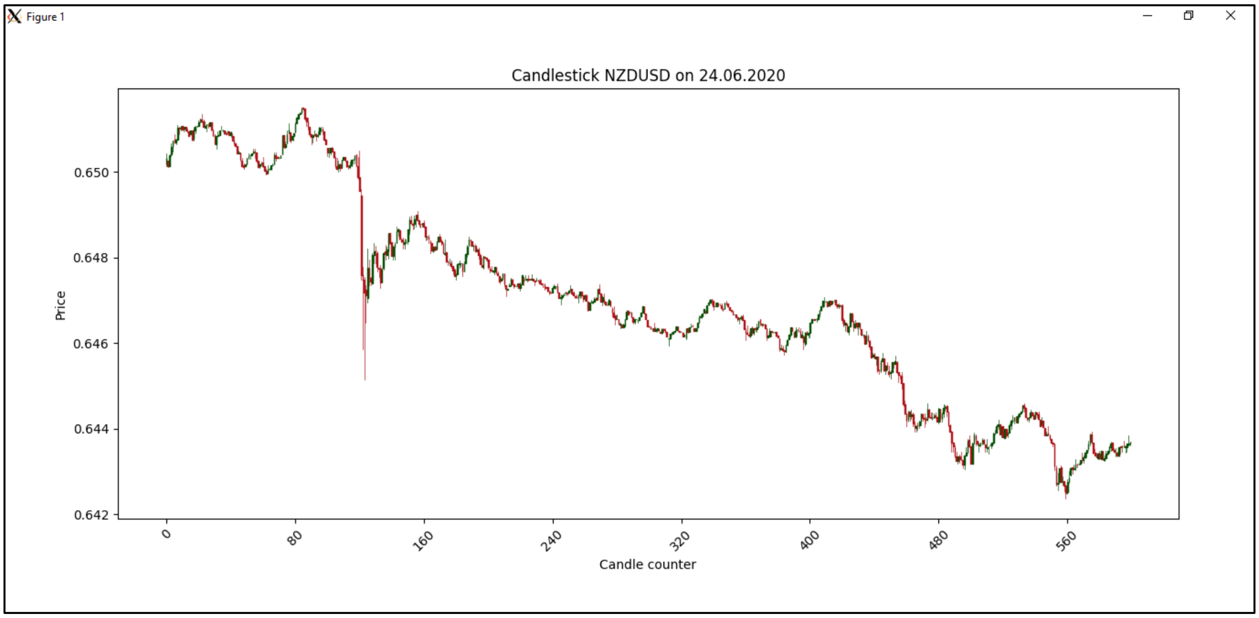
How can news from forex factory give impacts on volatility prediction?

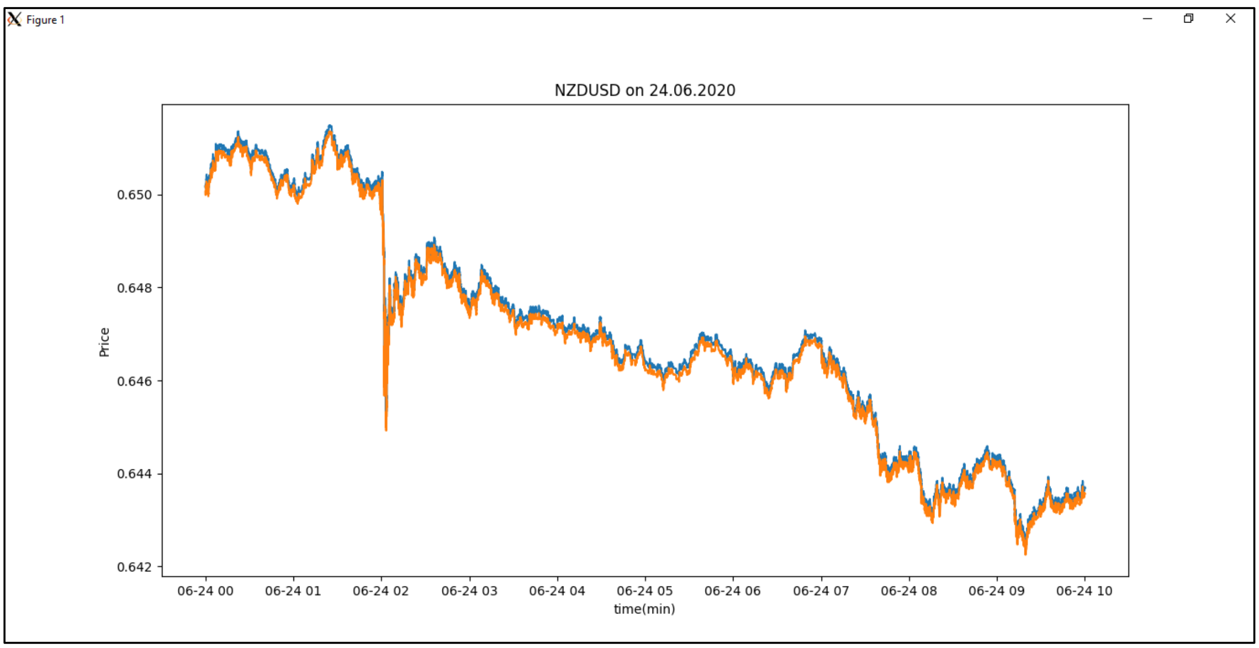
(Date: 24.6.2020 Currency Exchange =NZDUSD)



PART A (Methodology)

The event will occurred at 10 a.m, the candlestick chart before 10 a.m is as follow:





In order to determine whether dataset is stationary or non-stationary the test must be done:

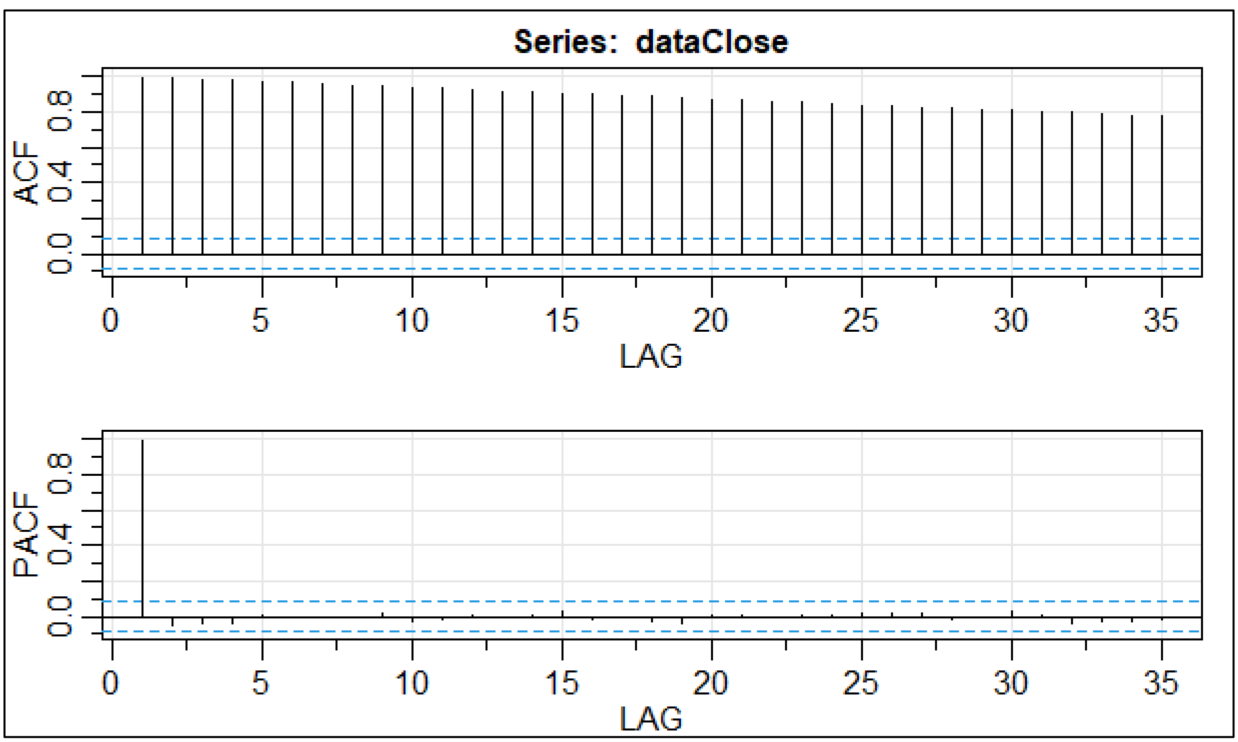
```
	Augmented Dickey-Fuller Test

data:  dataClose
Dickey-Fuller = -2.8716, Lag order = 8, p-value = 0.2094
alternative hypothesis: stationary
```

(Before Diffing)

The p-value are greater than 0.05, which indicates data is non-stationary. So, the diffing process must be done:

```
	Augmented Dickey-Fuller Test

data:  diffdata
Dickey-Fuller = -8.5004, Lag order = 8, p-value = 0.01
alternative hypothesis: stationary
```

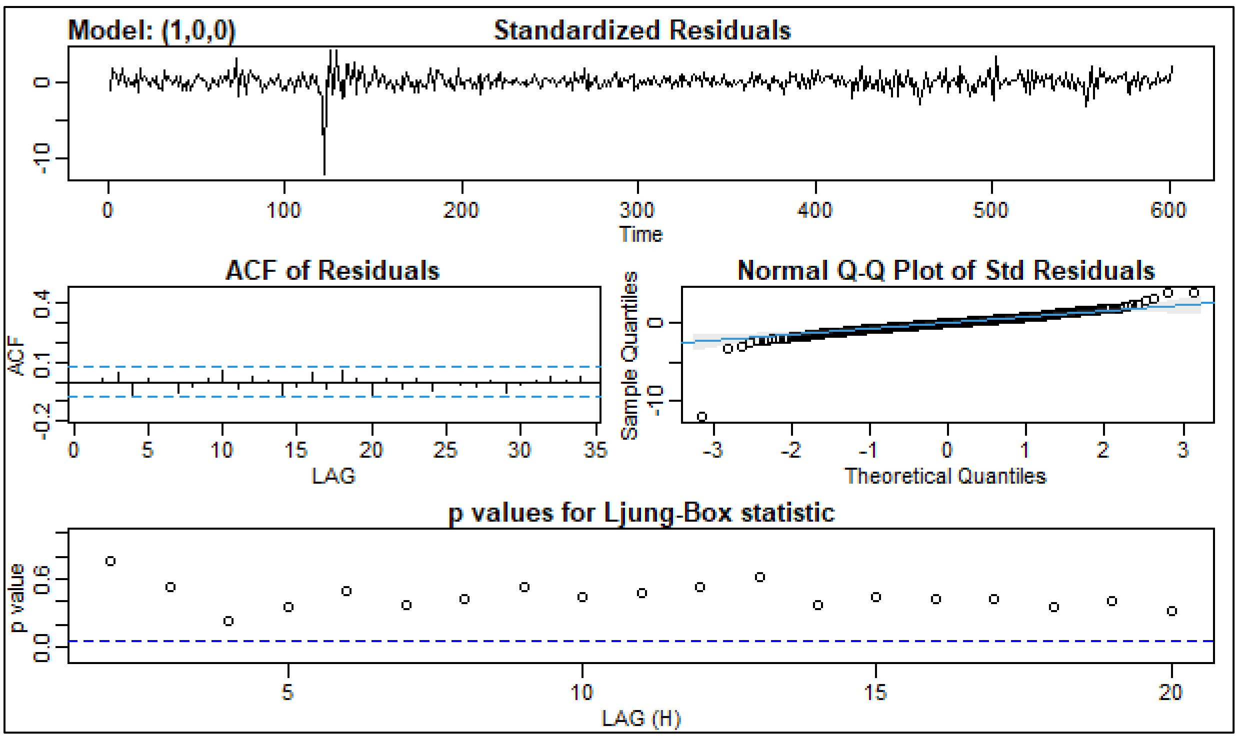
Next, in order to determine which model should recommended be used, the ACF and PACF tests must be done. From figure below, the AR(1) model is recommended.



Now, let's compare all possible models for the data series:

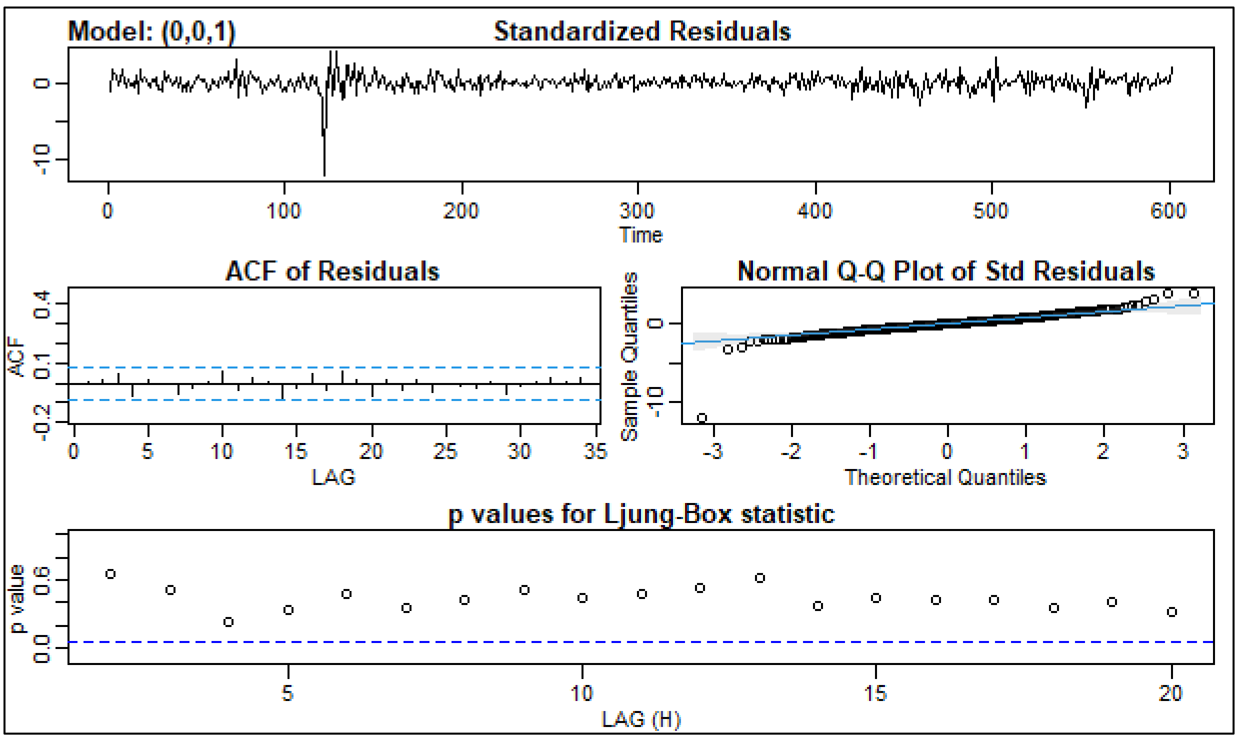
AR(1) model:

```
Call:
stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
    Q), period = S), xreg = xmean, include.mean = FALSE, transform.pars = trans,
    fixed = fixed, optim.control = list(trace = trc, REPORT = 1, reltol = tol))

Coefficients:
         ar1  xmean
      0.0783      0
s.e.  0.0408      0

sigma^2 estimated as 2.575e-08:  log likelihood = 4391.11,  aic = -8776.22

$degrees_of_freedom
[1] 598

$ttable
      Estimate     SE t.value p.value
ar1     0.0783 0.0408  1.9174  0.0557
xmean   0.0000 0.0000 -0.2537  0.7998

$AIC
[1] -14.62703

$AICc
[1] -14.627

$BIC
[1] -14.60505
```



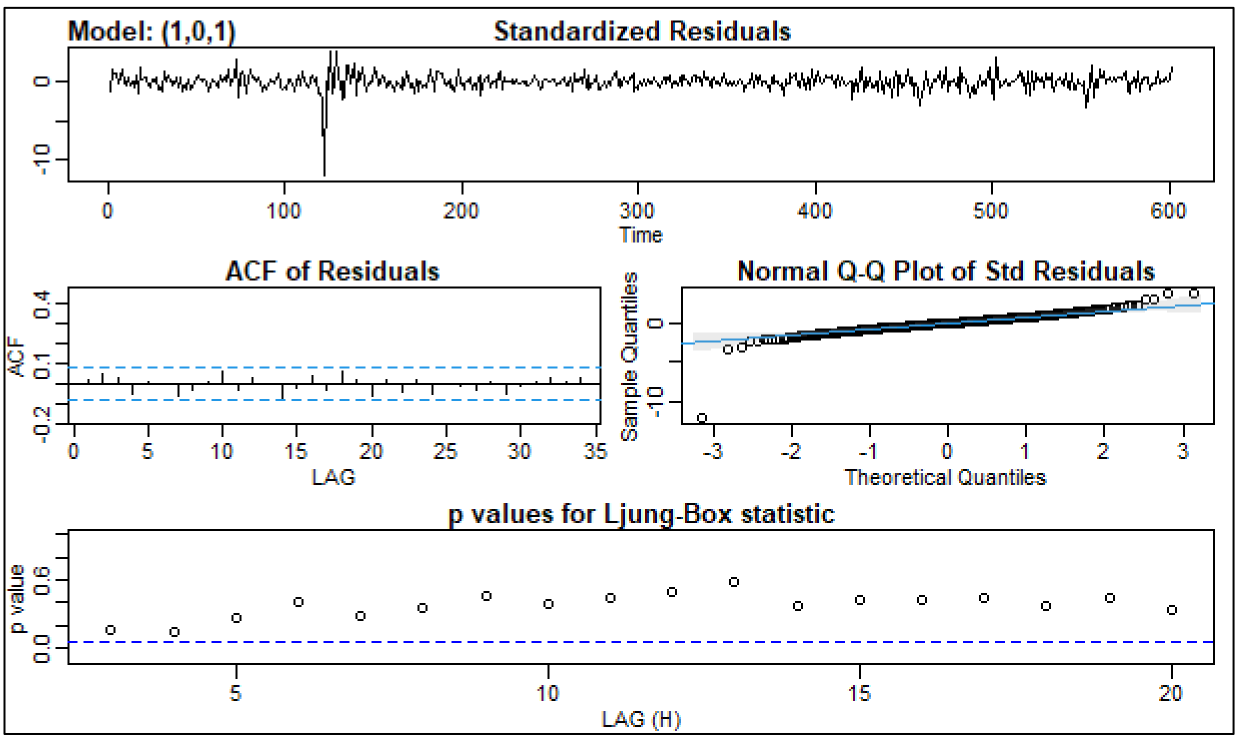
MA(1) Model:

```
Call:
stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
    Q), period = S), xreg = xmean, include.mean = FALSE, transform.pars = trans,
    fixed = fixed, optim.control = list(trace = trc, REPORT = 1, reltol = tol))

Coefficients:
         ma1  xmean
      0.0763      0
s.e.  0.0405      0

sigma^2 estimated as 2.575e-08:  log likelihood = 4391.06,  aic = -8776.11

$degrees_of_freedom
[1] 598

$ttable
      Estimate     SE t.value p.value
ma1     0.0763 0.0405  1.8861  0.0598
xmean   0.0000 0.0000 -0.2541  0.7995

$AIC
[1] -14.62685

$AICc
[1] -14.62682

$BIC
[1] -14.60487
```



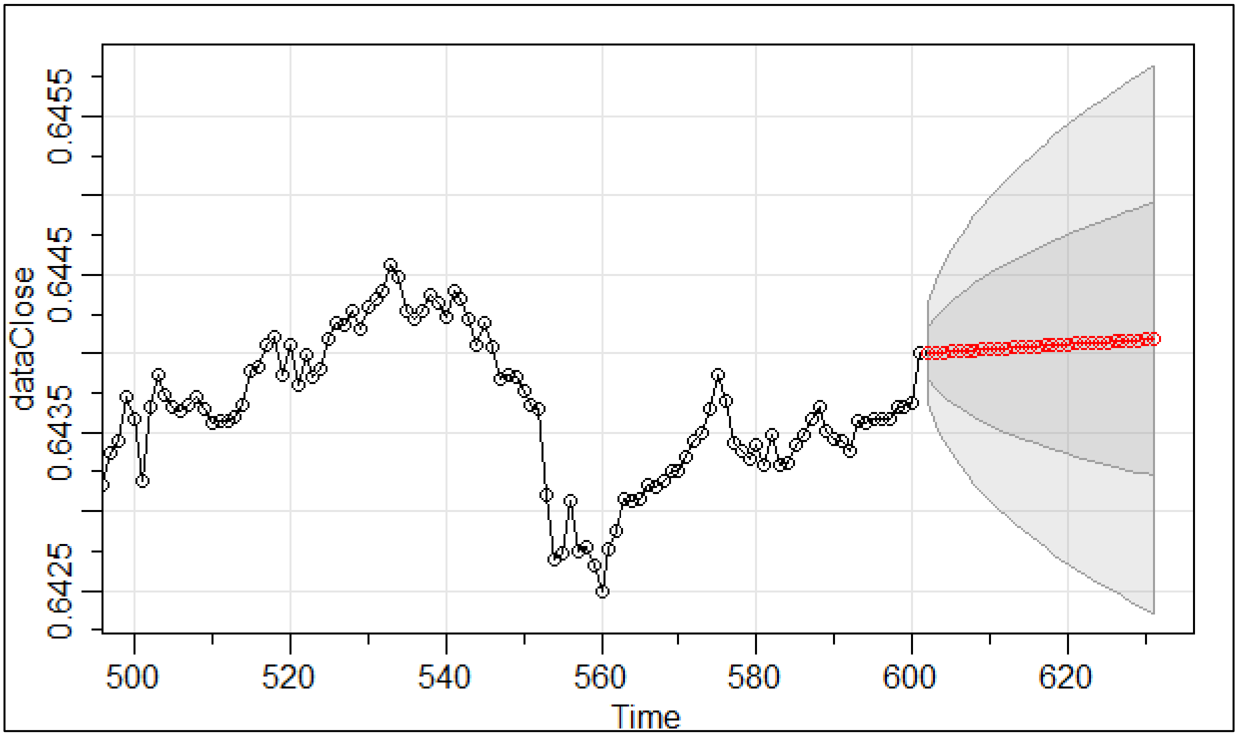
ARMA(1,1) Model:

```
Call:
stats::arima(x = xdata, order = c(p, d, q), seasonal = list(order = c(P, D,
    Q), period = S), xreg = xmean, include.mean = FALSE, transform.pars = trans,
    fixed = fixed, optim.control = list(trace = trc, REPORT = 1, reltol = tol))

Coefficients:
          ar1     ma1  xmean
      -0.5155  0.5822      0
s.e.   0.5011  0.4812      0

sigma^2 estimated as 2.574e-08:  log likelihood = 4391.14,  aic = -8774.29

$degrees_of_freedom
[1] 597

$ttable
      Estimate     SE t.value p.value
ar1    -0.5155 0.5011 -1.0288  0.3040
ma1     0.5822 0.4812  1.2098  0.2269
xmean   0.0000 0.0000 -0.2480  0.8042

$AIC
[1] -14.62382

$AICc
[1] -14.62375

$BIC
[1] -14.5945
```



Based on the result above, the most smaller error terms is AR(1) model. Since the Akaike Information Criterion(AIC), Akaike Information Criterion Correction (AICc) & Basing Information Criterion (BIC) are small compare to other 2 models. The Ljung-Box Statistics is used to validate p-value to keep the NULL. So, the P-value must be greater than blue dashed line. The mean of error term in AR(1) model is zero.

From previous discussion, the model that’s need to be considered is AR(1) Model. To forecast the next 30 miniutes:




```
$pred
Time Series:
Start = 602
End = 631
Frequency = 1
 [1] 0.6440031 0.6440062 0.6440093 0.6440123 0.6440154 0.6440185 0.6440216 0.6440246
 [9] 0.6440277 0.6440307 0.6440338 0.6440368 0.6440398 0.6440429 0.6440459 0.6440489
[17] 0.6440520 0.6440550 0.6440580 0.6440610 0.6440640 0.6440670 0.6440700 0.6440730
[25] 0.6440759 0.6440789 0.6440819 0.6440849 0.6440878 0.6440908

$se
Time Series:
Start = 602
End = 631
Frequency = 1
 [1] 0.0001612608 0.0002278854 0.0002788914 0.0003217938 0.0003595058 0.0003935229
 [7] 0.0004247340 0.0004537188 0.0004808803 0.0005065121 0.0005308361 0.0005540247
[13] 0.0005762153 0.0005975193 0.0006180284 0.0006378197 0.0006569581 0.0006754992
[19] 0.0006934913 0.0007109760 0.0007279902 0.0007445662 0.0007607328 0.0007765157
[25] 0.0007919380 0.0008070206 0.0008217822 0.0008362400 0.0008504096 0.0008643053
```

Now, in order to determine the model for volatility the test of ACF and PACF must be done.

The ARCH(1) Model with the mean model of ARFIMA(0,0,0):

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,0)
Mean Model      : ARFIMA(0,0,0)
Distribution    : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
mu       0.64656    0.000142 4568.28876 0.000000
omega    0.00000    0.000000    0.02369 0.981100
alpha1   0.97748    0.049433   19.77393 0.000000
shape   35.40940    7.834405    4.51973 0.000006

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu       0.64656  8.2610e-03 78.270973  0.00000
omega    0.00000  4.8000e-05  0.000174  0.99986
alpha1   0.97748  3.9192e+00  0.249408  0.80305
shape   35.40940  1.5675e+03  0.022590  0.98198

LogLikelihood : 3190.84

Information Criteria
------------------------------------

Akaike       -10.605
Bayes        -10.576
Shibata      -10.605
Hannan-Quinn -10.594

Weighted Ljung-Box Test on Standardized Residuals
------------------------------------
```

The ARCH(1) Model with the mean-model of ARFIMA(1,0,1):

```
*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,0)
Mean Model      : ARFIMA(1,0,1)
Distribution    : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.650217    0.001095 593.61859  0.00000
ar1     0.997152    0.001452 686.85906  0.00000
ma1     0.040595    0.040716   0.99703  0.31875
omega   0.000000    0.000000   0.46309  0.64330
alpha1  0.055576    0.008841   6.28639  0.00000
shape   5.511287    0.597198   9.22857  0.00000

Robust Standard Errors:
        Estimate  Std. Error   t value Pr(>|t|)
mu      0.650217    0.007943 81.855448  0.00000
ar1     0.997152    0.005633 177.031632  0.00000
ma1     0.040595    0.058987  0.688202  0.49133
omega   0.000000    0.000001  0.011181  0.99108
alpha1  0.055576    1.167409  0.047606  0.96203
shape   5.511287   12.445181  0.442845  0.65788

LogLikelihood : 4480.949

Information Criteria
------------------------------------

Akaike       -14.892
Bayes        -14.848
Shibata      -14.892
Hannan-Quinn -14.875
```

The ARCH(1) Model with the mean model of ARFIMA(2,0,2):

```
Console   Terminal ×   Jobs ×
~/
Conditional Variance Dynamics
-----------------------------------
GARCH Model     : sGARCH(1,0)
Mean Model      : ARFIMA(2,0,2)
Distribution    : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.650261    0.000915 710.98469 0.000000
ar1     0.512989    0.104191   4.92356 0.000001
ar2     0.488052    0.104433   4.67334 0.000003
ma1     0.544744    0.102271   5.32646 0.000000
ma2     0.037902    0.038022   0.99686 0.318833
omega   0.000000    0.000000   1.02749 0.304189
alpha1  0.053165    0.029052   1.83002 0.067247
shape   4.515512    0.414743  10.88750 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.650261     0.01482 43.877506 0.000000
ar1     0.512989     3.18764  0.160931 0.872148
ar2     0.488052     3.19681  0.152669 0.878660
ma1     0.544744     3.25175  0.167523 0.866958
ma2     0.037902     0.15161  0.249998 0.802589
omega   0.000000     0.00000  0.057386 0.954238
alpha1  0.053165     0.29989  0.177281 0.859287
shape   4.515512     1.24615  3.623585 0.000291

LogLikelihood : 4486.345

Information Criteria
------------------------------------

Akaike       -14.903
Bayes        -14.844
Shibata      -14.903
Hannan-Quinn -14.880

Weighted Ljung-Box Test on Standardized Residuals
```

The GARCH(1,1) Model with the mean model of ARFIMA(0,0,0):

```
Console    Terminal    Jobs
~/
> dataGarch1

*---------------------------------*
*          GARCH Model Fit        *
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model      : sGARCH(1,1)
Mean Model       : ARFIMA(0,0,0)
Distribution     : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
mu       0.64646    0.000148 4.3770e+03 0.000000
omega    0.00000    0.000000 1.7368e-02 0.986143
alpha1   0.86678    0.041233 2.1022e+01 0.000000
beta1    0.12663    0.075642 1.6741e+00 0.094113
shape   70.00138   24.299173 2.8808e+00 0.003967

Robust Standard Errors:
        Estimate  Std. Error    t value Pr(>|t|)
mu       0.64646    0.005150 125.524968  0.00000
omega    0.00000    0.000041   0.000136  0.99989
alpha1   0.86678   16.604045   0.052203  0.95837
beta1    0.12663   17.004475   0.007447  0.99406
shape   70.00138  143.223097   0.488758  0.62501

LogLikelihood : 3195.203

Information Criteria
------------------------------------

Akaike       -10.616
Bayes        -10.580
Shibata      -10.616
Hannan-Quinn -10.602

Weighted Ljung-Box Test on Standardized Residuals
```

The GARCH(1,1) Model with the mean model of ARFIMA(1,0,0):

```
Conditional Variance Dynamics
-----------------------------------
GARCH Model      : sGARCH(1,1)
Mean Model       : ARFIMA(1,0,0)
Distribution     : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
mu       0.65030    0.000638 1.0187e+03 0.000000
ar1      0.99644    0.001301 7.6616e+02 0.000000
omega    0.00000    0.000000 4.9470e-03 0.996053
alpha1   0.05082    0.019022 2.6717e+00 0.007547
beta1    0.89788    0.019788 4.5376e+01 0.000000
shape    3.95564    0.455896 8.6766e+00 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu       0.65030    0.067994 9.564023  0.00000
ar1      0.99644    0.109015 9.140380  0.00000
omega    0.00000    0.000433 0.000003  1.00000
alpha1   0.05082    1.159789 0.043819  0.96505
beta1    0.89788    6.476487 0.138637  0.88974
shape    3.95564   19.911986 0.198656  0.84253

LogLikelihood : 4495.937

Information Criteria
------------------------------------

Akaike       -14.942
Bayes        -14.898
Shibata      -14.942
Hannan-Quinn -14.924
```

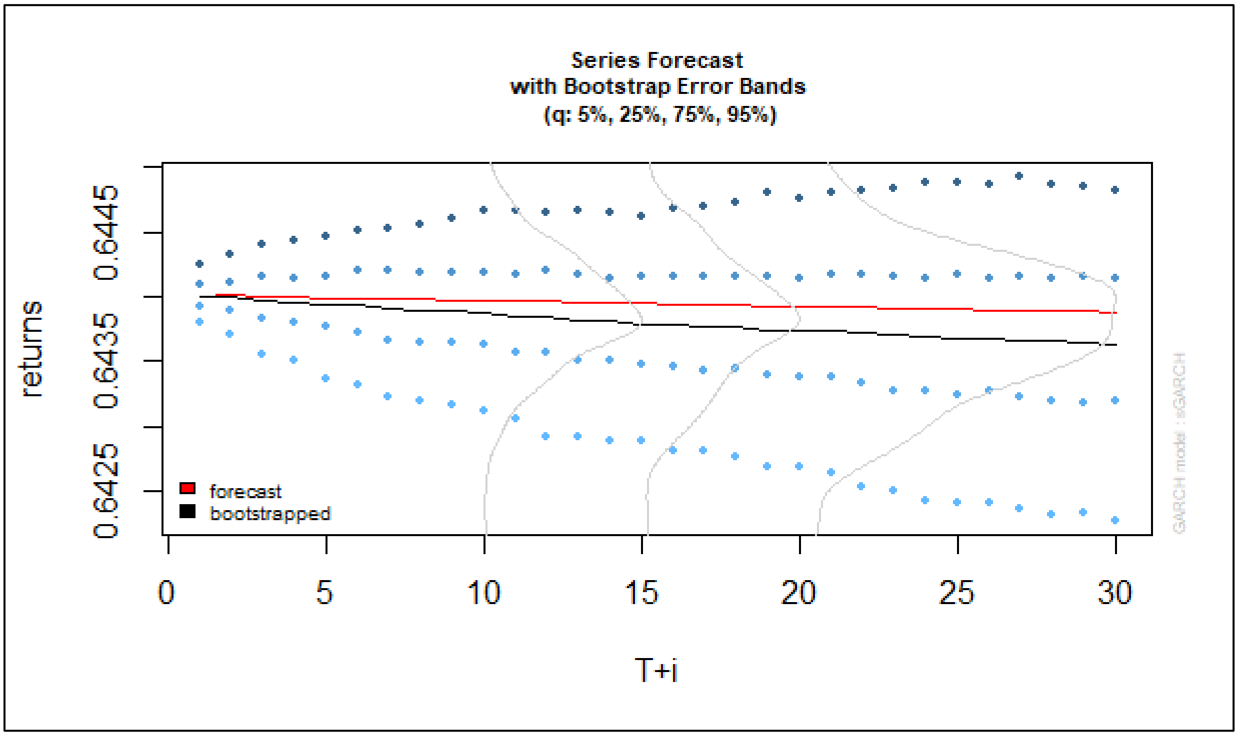
The GARCH(1,1) Model with the mean model of ARFIMA(1,0,1):

```
*---------------------------------*

Conditional Variance Dynamics
-----------------------------------
GARCH Model        : sGARCH(1,1)
Mean Model         : ARFIMA(1,0,1)
Distribution       : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
mu       0.65031    0.000644 1009.72101 0.000000
ar1      0.99611    0.001459  682.56759 0.000000
ma1      0.07610    0.042506    1.79035 0.073398
omega    0.00000    0.000000    0.00487 0.996114
alpha1   0.05086    0.019156    2.65499 0.007931
beta1    0.89780    0.020189   44.47042 0.000000
shape    3.95320    0.450124    8.78247 0.000000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu       0.65031    0.074682 8.707697  0.00000
ar1      0.99611    0.132939 7.492959  0.00000
ma1      0.07610    0.176676 0.430735  0.66666
omega    0.00000    0.000445 0.000003  1.00000
alpha1   0.05086    1.693325 0.030035  0.97604
beta1    0.89780    7.184365 0.124965  0.90055
shape    3.95320   17.031045 0.232117  0.81645

LogLikelihood : 4496.306

Information Criteria
------------------------------------

Akaike       -14.939
Bayes        -14.888
Shibata      -14.940
Hannan-Quinn -14.920

Weighted Ljung-Box Test on Standardized Residuals
```

The GARCH(1,1) Model with the mean model of ARFIMA(2,0,2):

```
Conditional Variance Dynamics
-----------------------------------
GARCH Model      : sGARCH(1,1)
Mean Model       : ARFIMA(2,0,2)
Distribution     : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
mu      0.650189    0.000372 1.7493e+03  0.00000
ar1     0.379532    0.028823 1.3168e+01  0.00000
ar2     0.621630    0.028724 2.1641e+01  0.00000
ma1     0.652989    0.030514 2.1400e+01  0.00000
ma2     0.047190    0.040253 1.1723e+00  0.24106
omega   0.000000    0.000000 4.9680e-03  0.99604
alpha1  0.050839    0.019558 2.5994e+00  0.00934
beta1   0.897800    0.019820 4.5297e+01  0.00000
shape   3.952846    0.484022 8.1667e+00  0.00000

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu      0.650189    0.066646 9.755806 0.000000
ar1     0.379532    0.158916 2.388260 0.016928
ar2     0.621630    0.185892 3.344033 0.000826
ma1     0.652989    0.344871 1.893431 0.058301
ma2     0.047190    0.414364 0.113885 0.909329
omega   0.000000    0.000445 0.000003 0.999998
alpha1  0.050839    0.777842 0.065358 0.947889
beta1   0.897800    6.140694 0.146205 0.883760
shape   3.952846   27.502821 0.143725 0.885718

LogLikelihood : 4503.334

Information Criteria
------------------------------------

Akaike       -14.956
Bayes        -14.890
Shibata      -14.957
Hannan-Quinn -14.931
```

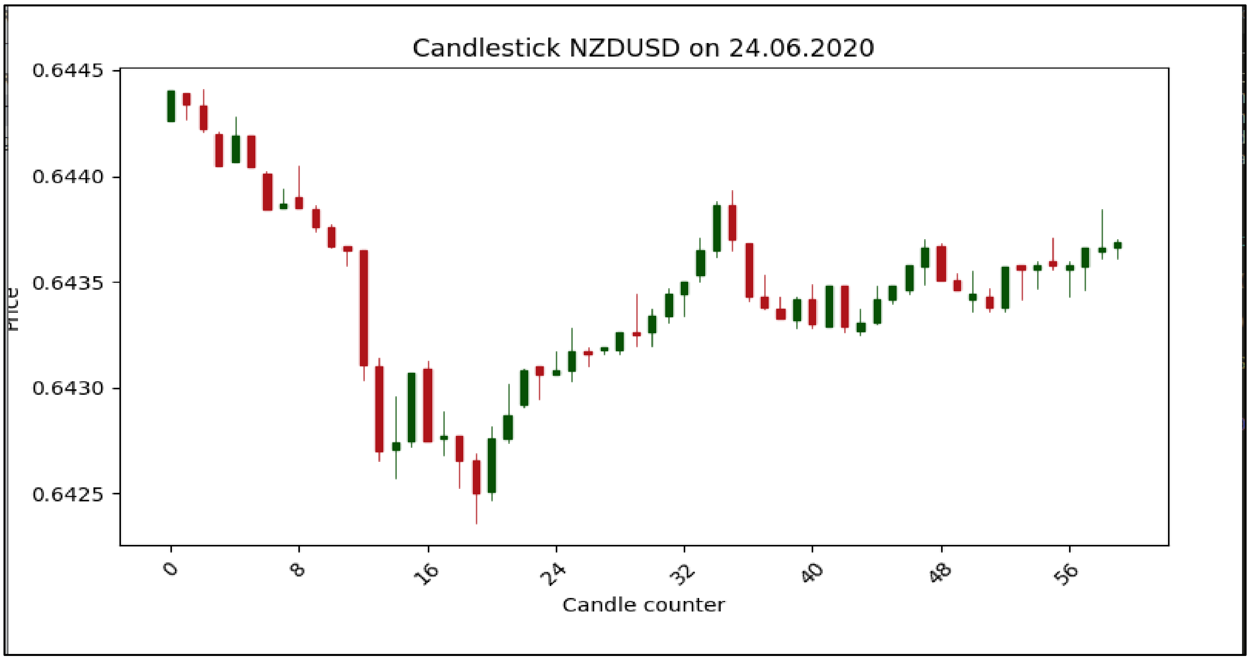
From all these models, the better model for forecast purpose is GARCH(1,1) with ARMA(2,2) Model because it has the lowest error terms.

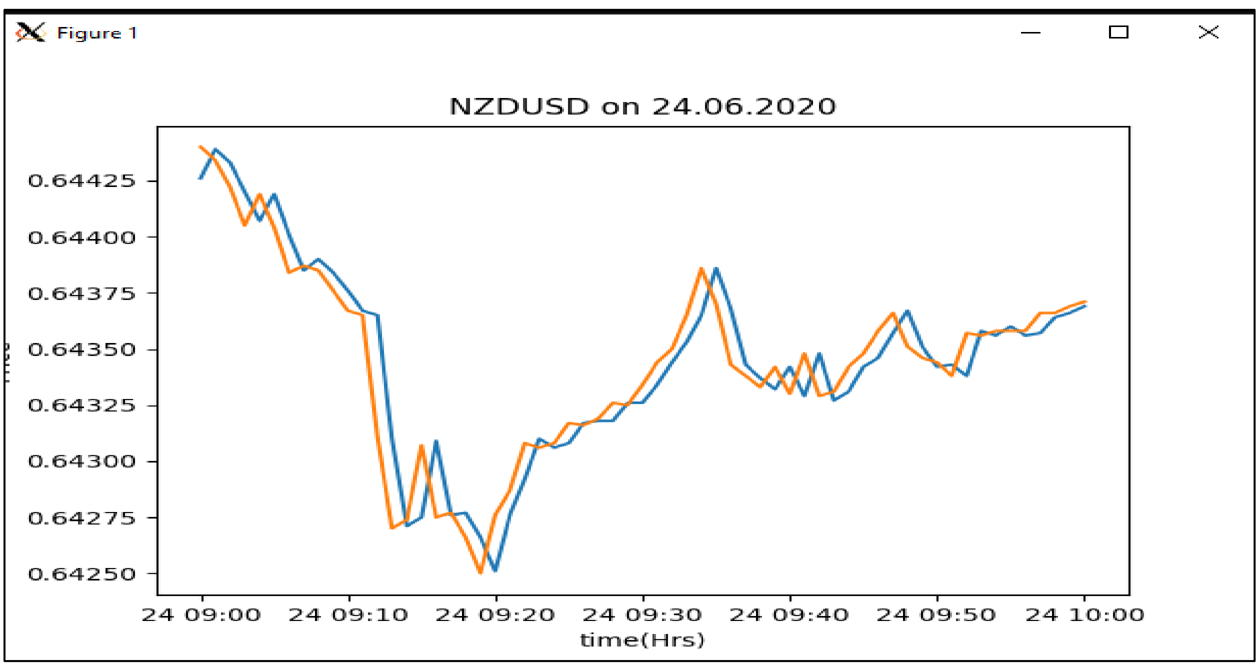



```
*------------------------------------*
*      GARCH Bootstrap Forecast      *
*------------------------------------*
Model : sGARCH
n.ahead : 30
Bootstrap method:  partial
Date (T[0]): 0601-01-01

Series (summary):
         min    q.25    mean    q.75     max forecast[analytic]
t+1  0.64227 0.64392 0.64400 0.64409 0.64432            0.64401
t+2  0.64215 0.64389 0.64400 0.64412 0.64453            0.64401
t+3  0.64211 0.64384 0.64398 0.64415 0.64471            0.64400
t+4  0.64167 0.64380 0.64396 0.64414 0.64482            0.64400
t+5  0.64102 0.64377 0.64394 0.64416 0.64495            0.64399
t+6  0.64118 0.64372 0.64394 0.64420 0.64503            0.64399
t+7  0.64081 0.64367 0.64392 0.64420 0.64511            0.64399
t+8  0.64093 0.64364 0.64390 0.64418 0.64555            0.64398
t+9  0.64134 0.64365 0.64389 0.64419 0.64558            0.64398
t+10 0.64108 0.64363 0.64388 0.64419 0.64578            0.64397
.....................

Sigma (summary):
          min    q0.25     mean    q0.75      max forecast[analytic]
t+1  0.000145 0.000145 0.000145 0.000145 0.000145           0.000145
t+2  0.000142 0.000142 0.000146 0.000146 0.000416           0.000145
t+3  0.000139 0.000140 0.000146 0.000147 0.000414           0.000146
t+4  0.000136 0.000139 0.000146 0.000148 0.000401           0.000146
t+5  0.000134 0.000138 0.000146 0.000147 0.000426           0.000147
t+6  0.000132 0.000137 0.000146 0.000148 0.000411           0.000147
t+7  0.000130 0.000137 0.000146 0.000148 0.000395           0.000148
t+8  0.000129 0.000137 0.000147 0.000149 0.000498           0.000148
t+9  0.000127 0.000136 0.000148 0.000149 0.000476           0.000149
t+10 0.000127 0.000136 0.000148 0.000149 0.000462           0.000149
.....................
```

PART B (Answer)

Forecast from time (1H) (9am-10am)

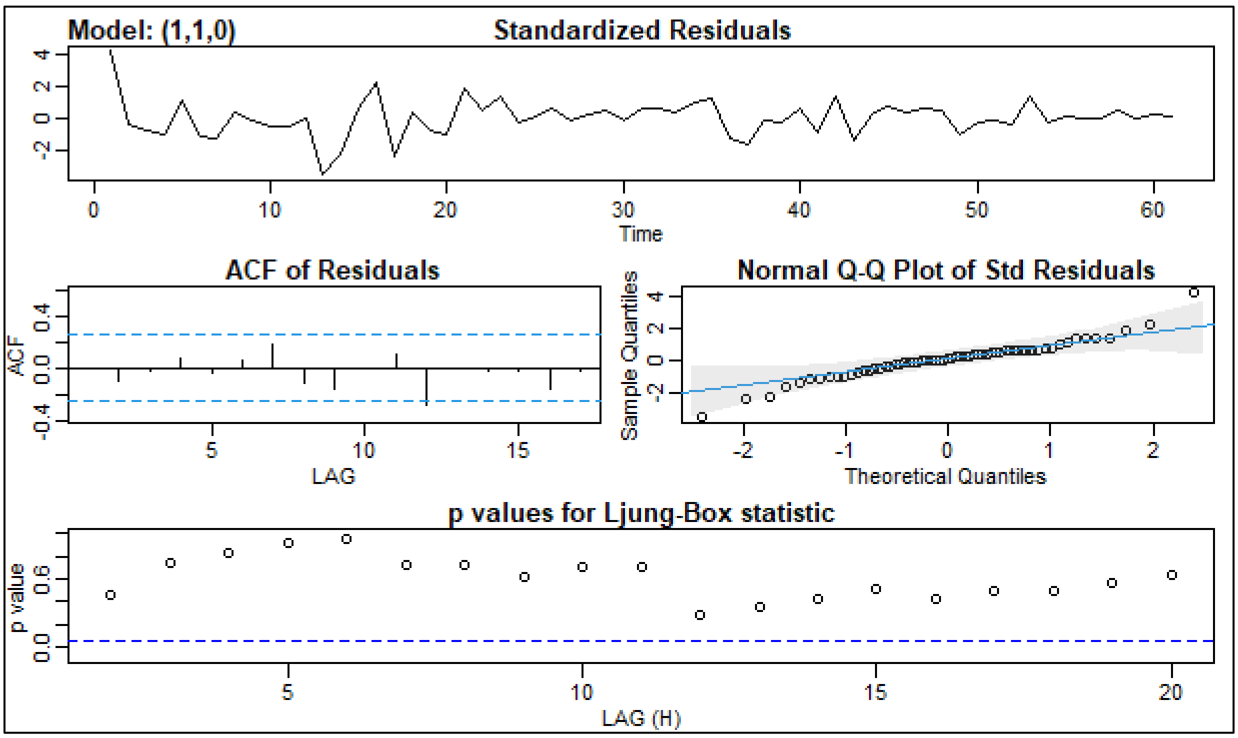




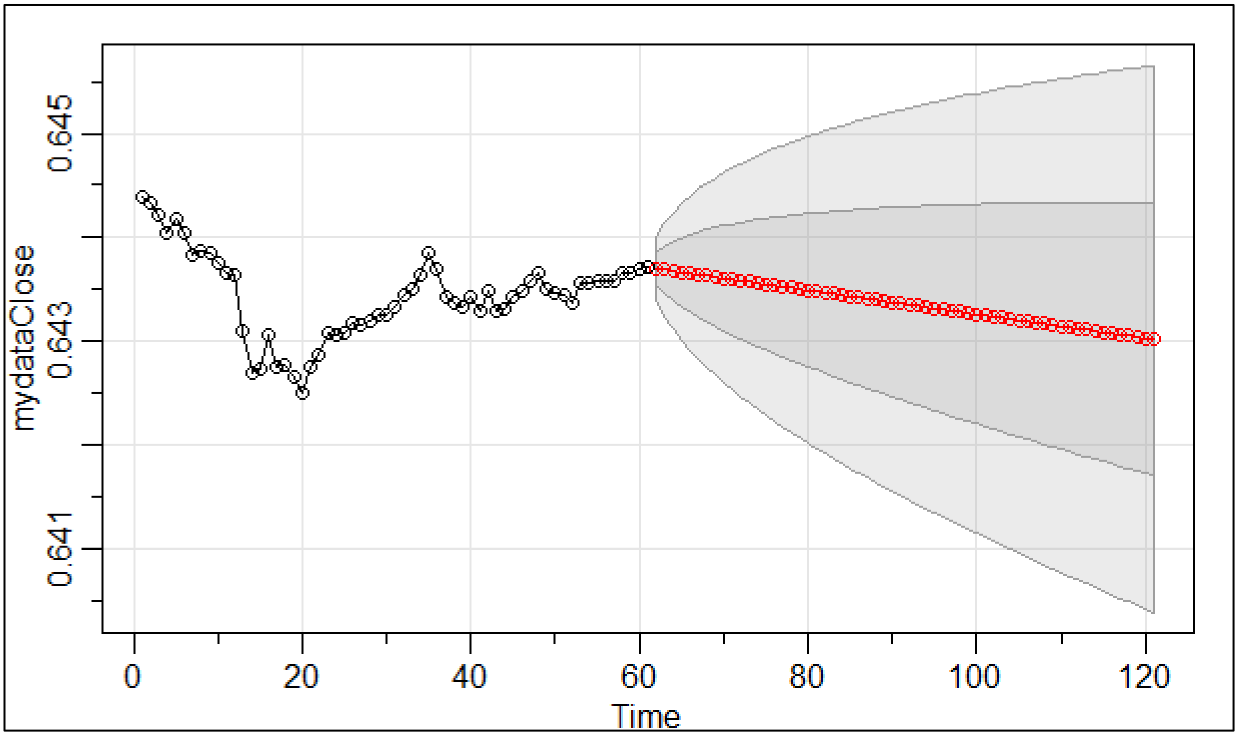
These 2 figures shows the actual data from 9am-10am on 24.6.2020

After the test, the model is ARIMA(1,1,0):

```
Coefficients:
         ar1  constant
      0.1168     0e+00
s.e.  0.1272     1e-04

sigma^2 estimated as 2.263e-08:  log likelihood = 442.98,  aic = -879.96

$degrees_of_freedom
[1] 58

$ttable
         Estimate     SE t.value p.value
ar1        0.1168 0.1272  0.9176  0.3626
constant   0.0000 0.0001 -0.0881  0.9301

$AIC
[1] -14.66602

$AICc
[1] -14.66251

$BIC
[1] -14.5613
```



Forecast another 1 hours:

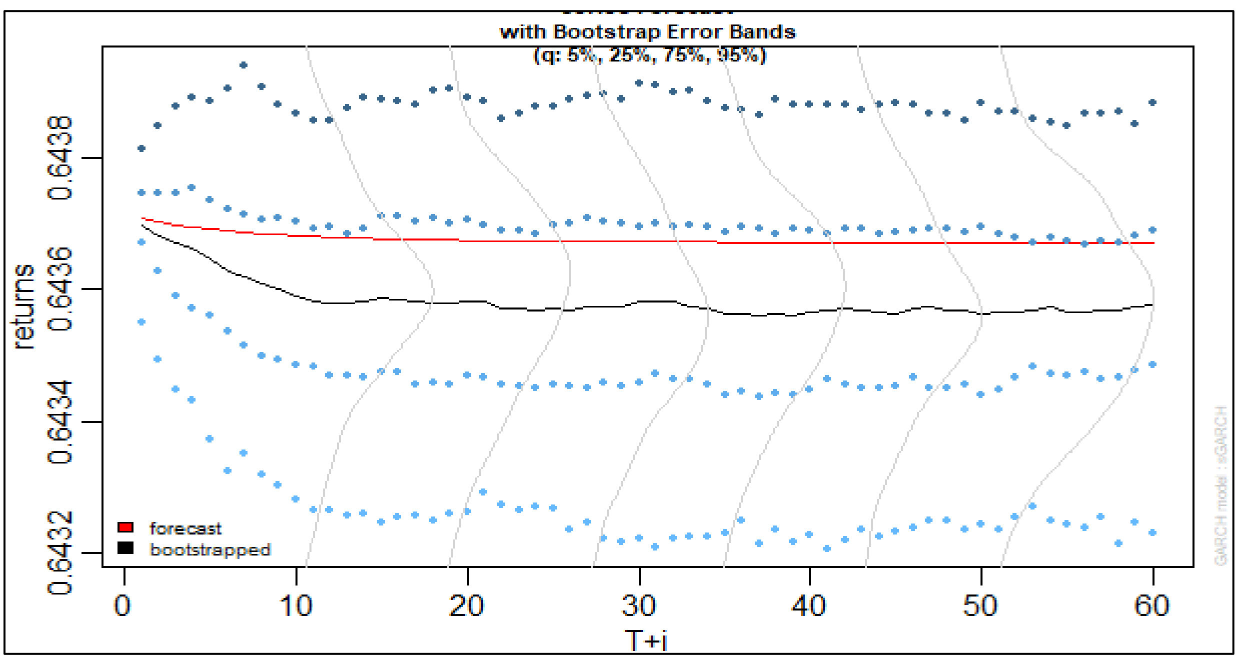



```
> sarima.for(mydataClose,60,1,1,0)
$pred
Time Series:
Start = 62
End = 121
Frequency = 1
 [1] 0.6437021 0.6436910 0.6436795 0.6436680 0.6436565 0.6436449 0.6436334 0.6436219
 [9] 0.6436103 0.6435988 0.6435872 0.6435757 0.6435642 0.6435526 0.6435411 0.6435295
[17] 0.6435180 0.6435065 0.6434949 0.6434834 0.6434719 0.6434603 0.6434488 0.6434372
[25] 0.6434257 0.6434142 0.6434026 0.6433911 0.6433795 0.6433680 0.6433565 0.6433449
[33] 0.6433334 0.6433218 0.6433103 0.6432988 0.6432872 0.6432757 0.6432642 0.6432526
[41] 0.6432411 0.6432295 0.6432180 0.6432065 0.6431949 0.6431834 0.6431718 0.6431603
[49] 0.6431488 0.6431372 0.6431257 0.6431141 0.6431026 0.6430911 0.6430795 0.6430680
[57] 0.6430564 0.6430449 0.6430334 0.6430218

$se
Time Series:
Start = 62
End = 121
Frequency = 1
 [1] 0.0001504224 0.0002254907 0.0002824153 0.0003297760 0.0003711544 0.0004083626
 [7] 0.0004424529 0.0004740983 0.0005037597 0.0005317691 0.0005583753 0.0005837702
[13] 0.0006081054 0.0006315036 0.0006540653 0.0006758743 0.0006970012 0.0007175062
[19] 0.0007374414 0.0007568516 0.0007757764 0.0007942504 0.0008123043 0.0008299656
[25] 0.0008472588 0.0008642060 0.0008808272 0.0008971406 0.0009131625 0.0009289082
[31] 0.0009443914 0.0009596247 0.0009746201 0.0009893881 0.0010039390 0.0010182819
[37] 0.0010324256 0.0010463782 0.0010601471 0.0010737395 0.0010871619 0.0011004207
[43] 0.0011135216 0.0011264701 0.0011392715 0.0011519306 0.0011644521 0.0011768404
[49] 0.0011890996 0.0012012337 0.0012132465 0.0012251415 0.0012369221 0.0012485916
[55] 0.0012601530 0.0012716093 0.0012829632 0.0012942176 0.0013053750 0.0013164378
```

For volatility prediction the model is GARCH(1,1):

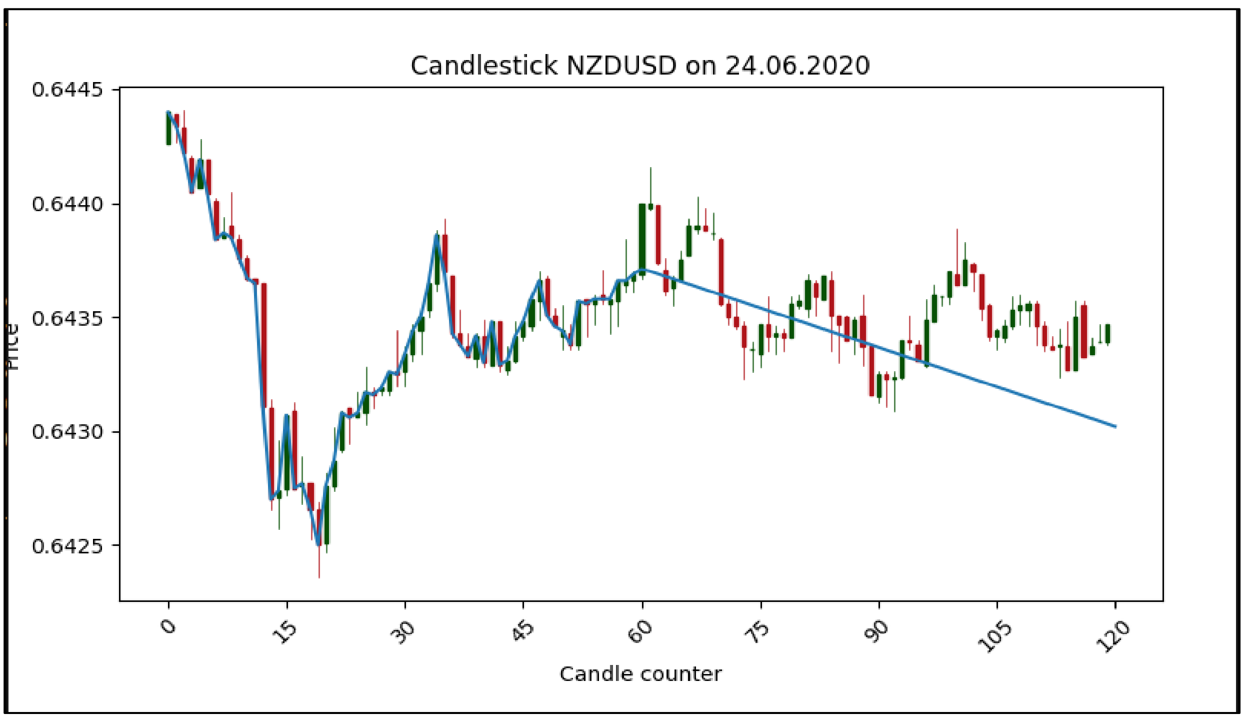
```
Conditional Variance Dynamics
-----------------------------------
GARCH Model      : sGARCH(1,1)
Mean Model       : ARFIMA(1,0,1)
Distribution     : std

Optimal Parameters
------------------------------------
        Estimate  Std. Error    t value Pr(>|t|)
mu       0.64367    0.000472 1.3631e+03  0.00000
ar1      0.87269    0.050481 1.7288e+01  0.00000
ma1      0.16260    0.113608 1.4313e+00  0.15235
omega    0.00000    0.000001 1.4600e-04  0.99988
alpha1   0.05000    0.086055 5.8103e-01  0.56122
beta1    0.90000    0.118696 7.5824e+00  0.00000
shape    4.00000    1.507541 2.6533e+00  0.00797

Robust Standard Errors:
        Estimate  Std. Error  t value Pr(>|t|)
mu       0.64367     0.40099 1.605210  0.10845
ar1      0.87269     4.93310 0.176904  0.85958
ma1      0.16260    17.99837 0.009034  0.99279
omega    0.00000     0.00234 0.000000  1.00000
alpha1   0.05000   123.59158 0.000405  0.99968
beta1    0.90000   168.94482 0.005327  0.99575
shape    4.00000   809.41671 0.004942  0.99606

LogLikelihood : 453.7463

Information Criteria
------------------------------------

Akaike       -14.647
Bayes        -14.405
Shibata      -14.670
Hannan-Quinn -14.552

Weighted Ljung-Box Test on Standardized Residuals
```

Forecast next 1 hour:



```
*------------------------------------*
*      GARCH Bootstrap Forecast      *
*------------------------------------*
Model : sGARCH
n.ahead : 60
Bootstrap method:  partial
Date (T[0]): 0061-01-01

Series (summary):
         min    q.25    mean    q.75     max forecast[analytic]
t+1  0.64344 0.64367 0.64370 0.64375 0.64401            0.64371
t+2  0.64325 0.64363 0.64368 0.64375 0.64406            0.64370
t+3  0.64320 0.64359 0.64367 0.64375 0.64411            0.64370
t+4  0.64289 0.64357 0.64366 0.64376 0.64414            0.64370
t+5  0.64296 0.64356 0.64365 0.64374 0.64413            0.64369
t+6  0.64300 0.64354 0.64363 0.64372 0.64421            0.64369
t+7  0.64282 0.64352 0.64362 0.64372 0.64432            0.64369
t+8  0.64287 0.64350 0.64361 0.64371 0.64431            0.64369
t+9  0.64295 0.64349 0.64360 0.64371 0.64429            0.64368
t+10 0.64299 0.64348 0.64359 0.64370 0.64441            0.64368
.....................

Sigma (summary):
         min   q0.25    mean   q0.75      max forecast[analytic]
t+1  7.2e-05 7.2e-05 7.2e-05 7.2e-05 0.000072            7.2e-05
t+2  6.9e-05 6.9e-05 7.2e-05 7.2e-05 0.000096            7.1e-05
t+3  6.7e-05 6.8e-05 7.1e-05 7.2e-05 0.000099            7.0e-05
t+4  6.5e-05 6.6e-05 7.1e-05 7.3e-05 0.000120            7.0e-05
t+5  6.3e-05 6.5e-05 7.1e-05 7.3e-05 0.000137            6.9e-05
t+6  6.1e-05 6.4e-05 7.1e-05 7.3e-05 0.000136            6.9e-05
t+7  6.0e-05 6.3e-05 7.1e-05 7.4e-05 0.000131            6.8e-05
t+8  5.8e-05 6.3e-05 7.1e-05 7.6e-05 0.000125            6.8e-05
t+9  5.7e-05 6.3e-05 7.1e-05 7.5e-05 0.000148            6.7e-05
t+10 5.6e-05 6.2e-05 7.1e-05 7.6e-05 0.000141            6.7e-05
.....................
```

Comparing with actual result(9am-11am):



(Blue line is the forecast price value)

As you can see, after 60 minutes (10am) the actual result follow the forecast predicted using GARCH(1,1) with ARMA(1,1) model. The economic event that occur on 24.6.2020 was cash rates. Cash rate is an interest rates that been performing by the banks to clients. Usually when the actual rate are greater than forecast rate it is good for currency. Short term interest rates are the paramount factor in currency valuation usually traders look at most other indicators merely to predict how rates will change in the future. The actual value 0.25% which is equal to the forecast value. From chart above, the decreasing trend of the actual result is identical to the trend of the forecast. But due to economic cash rates the trend is volatile and fluctuates. This is an opportunity for the traders to trade in the market. The rate decision is usually priced into the market so it may influence the market equity. To enhance the volatility prediction the model must have smaller errors term and lower AIC,AICc and BIC value. These factors may influence the forecasting values and volatility prediction. The order or dependencies of the models must be taken into consideration to choose the best performance models.

Others Example:

Date	2:24pm	Currency	Impact		Detail	Actual	Forecast	Previous
Sun Jun 21								
Mon Jun 22	7:00am	AUD		RBA Gov Lowe Speaks				
	11:00pm	CAD		BOC Gov Macklem Speaks				
Tue Jun 23	3:15pm	EUR		French Flash Services PMI		50.3	44.9	31.1
		EUR		French Flash Manufacturing PMI		52.1	46.1	40.6
	3:30pm	EUR		German Flash Manufacturing PMI		44.6	41.5	36.6
		EUR		German Flash Services PMI		45.8	41.7	32.6
	4:00pm	EUR		Flash Manufacturing PMI		46.9	43.8	39.4
		EUR		Flash Services PMI		47.3	40.5	30.5
	4:30pm	GBP		Flash Manufacturing PMI		50.1	45.2	40.7
		GBP		Flash Services PMI		47.0	39.1	29.0
	4:45pm	GBP		BOE Gov Bailey Speaks				
	9:45pm	USD		Flash Manufacturing PMI		49.6	50.0	39.8

The red and orange flags indicates on how the economic events may fluence market equity. When the actual value is greater than forecasted value it tell us about that our forecast model is valid and high accuracy, and when the actual value is less than forecasted value, it will indicates that our prediction models is less accurate. All these values can be used to analysis for future references.

Example of scripts used in R language.

arma.R

```r
library("astsa")
mydata <- read.csv("R/GBPJPY-2020_05_01-2020_06_01.csv")

head(mydata)
# show contents
time<-order(mydata$time)


mydataClose<-ts(mydata$close,start=min(time),end=max(time))
# transform a data frame into a time series

plot(mydataClose)
# Check if a longitudinal trend exists

acf2 (mydataClose)
# use ACF and PACF to identify potential models

sarima (mydataClose, 1, 0, 0)
# Build an AR(1) model. First parameter is the time series data. Second parameter is the order of AR. Third parameter is the number of differencing. Last parame

sarima.for(mydataClose, 5, 1, 0, 0)
# Forcast of sales revenues for the next 5 days based on the AR(1) model.

sarima (mydataClose, 0, 0, 1)
# Build an MA(1) model. Just for demo purpose. MA(1) is not the best model for this case.

sarima (mydataClose, 1, 0, 1)
# Build an over-parameterized ARMA(1,1) model. Just for demo purpose. ARMA(1,1) is not the best model for this case.

sarima (mydataClose, 1, 1, 1)
# Build an over-parameterized ARIMA model. Just for demo purpose. ARIMA(1,1,1) is not the best model for this case.
```

skrip.R

```r
library("quantmod")
library("rugarch")

data <- read.csv("R/GBPJPY-2020_05_01-2020_06_01.csv")
dataClose<-data["close"]

data1<-ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(1,1)),mean.model=list(armaOrder=c(1,1)),distribution.model="std")

dataGarch1<-ugarchfit(spec=data1,data=dataClose)

data2<-ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(1,1)),mean.model=list(armaOrder=c(0,0)),distribution.model="std")
dataGarch2<-ugarchfit(spec=data2,data=dataClose)

data3<-ugarchspec(variance.model=list(model="sGARCH",garchOrder=c(1,1)),mean.model=list(armaOrder=c(2,2)),distribution.model="std")
dataGarch3<-ugarchfit(spec=data3,data=dataClose)
```