case2

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Introduction

Sector: Transportation Services Companies: MacroAsia Corporation (PSE:MAC) and International Container Terminal Services, Inc. (PSE:ICT) Interpretation: Interpretation is commented on last line(s) of each code chunk Note: For MacroAsia (MAC) price was used to model. This is to provide further analysis since Log Returns model generates ARIMA(0,0,0). Stationary data may have caused it.

MAC Background

MacroAsia Corporation (MAC), through its subsidiaries and associates, is engaged in aviation-support businesses at the Ninoy Aquino International Airport (NAIA), Manila Domestic Airport, Mactan-Cebu International Airport, Kalibo International Airport, Davao International Airport, and the General Aviation Areas. The group provides aircraft maintenance, repairs and overhaul services, in-flight catering services, airport ground handling services, charter flight services, and operates a special economic zone at the NAIA.

ICT Background

International Container Terminal Services, Inc. (ICT) was incorporated on December 24, 1987 to operate, manage and develop the Manila International Container Terminal (MICT), which handles international container cargo at the Port of Manila. ICT provide ancillary services such as storage, container stripping and stuffing, inspection, weighing and services for refrigerated containers or reefers, as well as roll-on/roll-off and anchorage services to non-containerized cargoes or general cargoes on a limited basis.

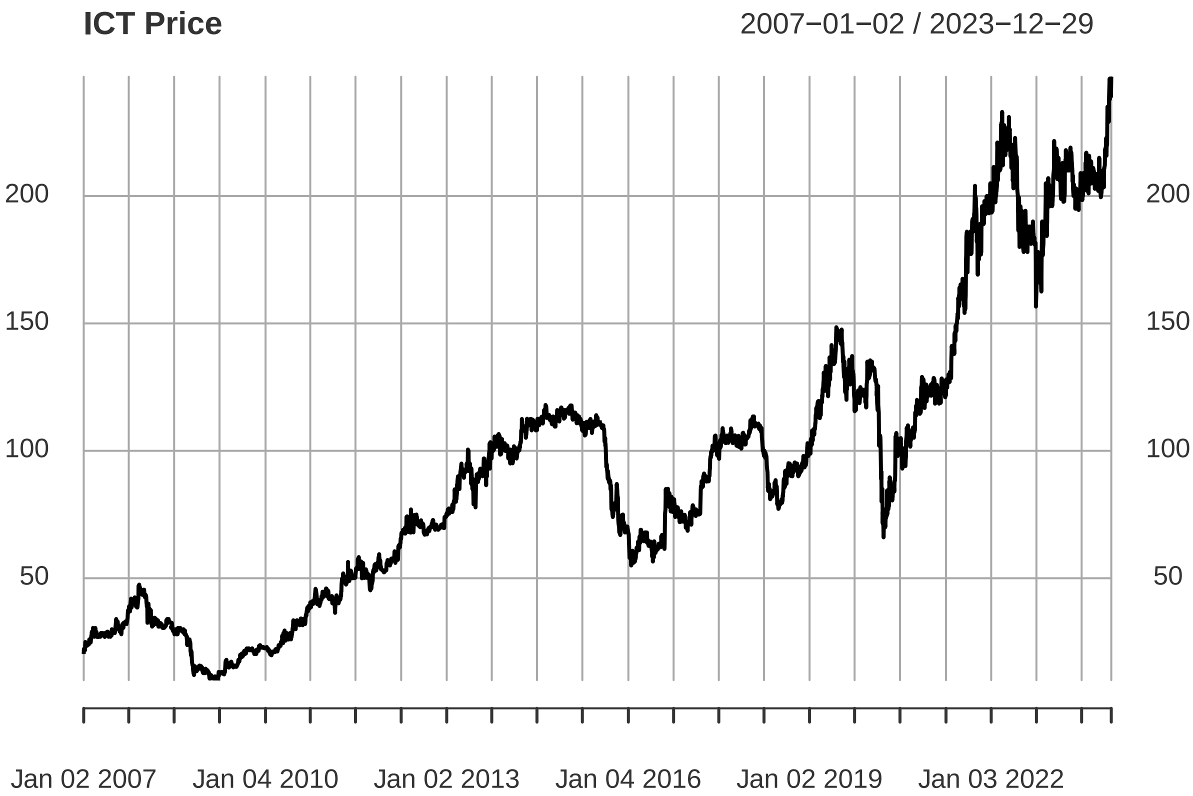
```
pacman::p_load(tseries,quantmod,forecast,timeSeries,FinTS,rugarch,dplyr,PerformanceAnalytics,readxl,xts
remotes::install_github("KevinKotze/tsm")
```

```
## Skipping install of 'tsm' from a github remote, the SHA1 (d5d5529e) has not changed since last insta
##   Use `force = TRUE` to force installation
```

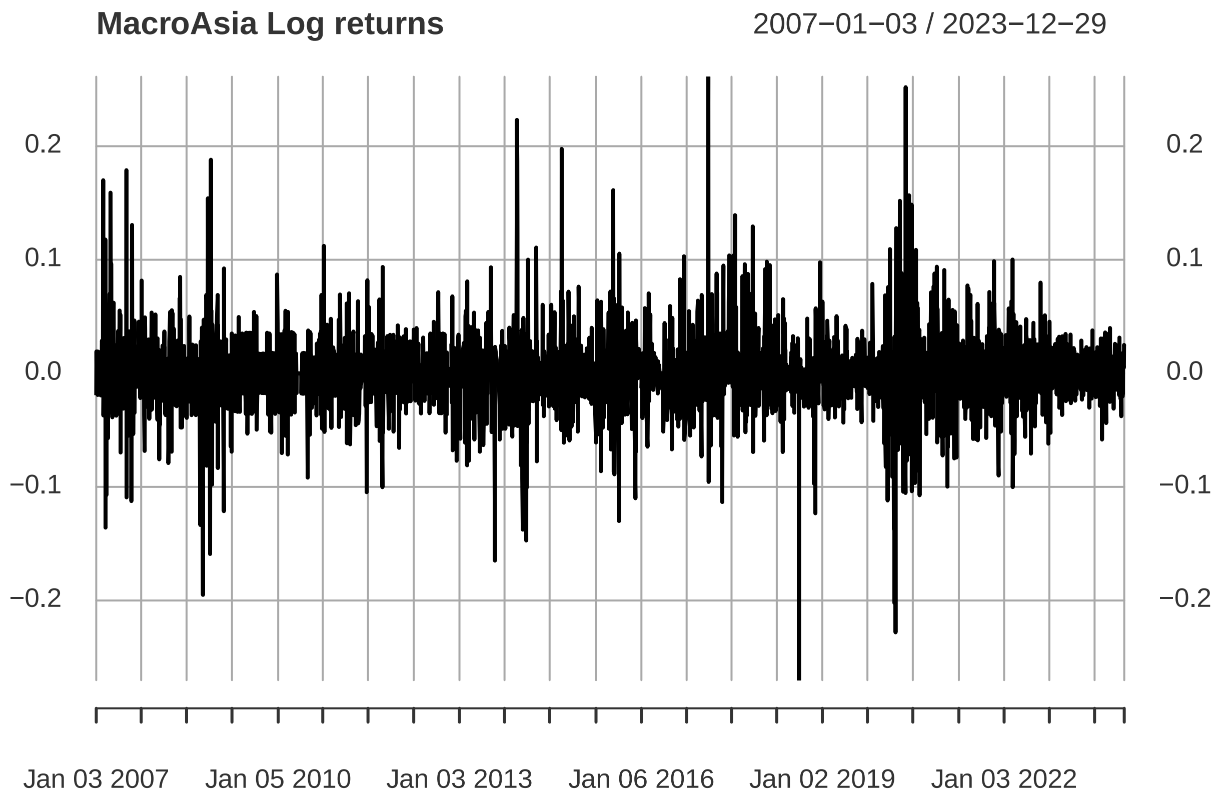
PART 1: Data Preparation

```
# Load MacroAsia
mdata <- read_excel('MAC.xlsx', sheet = 'Sheet 1')

# XTS Conversion
mdata <- data.frame(date = as.Date(mdata$date), value = mdata$close)
mdata <- xts(mdata$value, order.by = mdata$date)
mdata <- na.omit(mdata)
plot(mdata, main = 'MacroAsia Price')
```


```r
idata <- read_excel('ICT.xlsx', sheet = 'Sheet 1')

# XTS Conversion
idata <- data.frame(date = as.Date(idata$date), value = idata$close)
idata <- xts(idata$value, order.by = idata$date)
plot(idata, main = 'ICT Price')
```

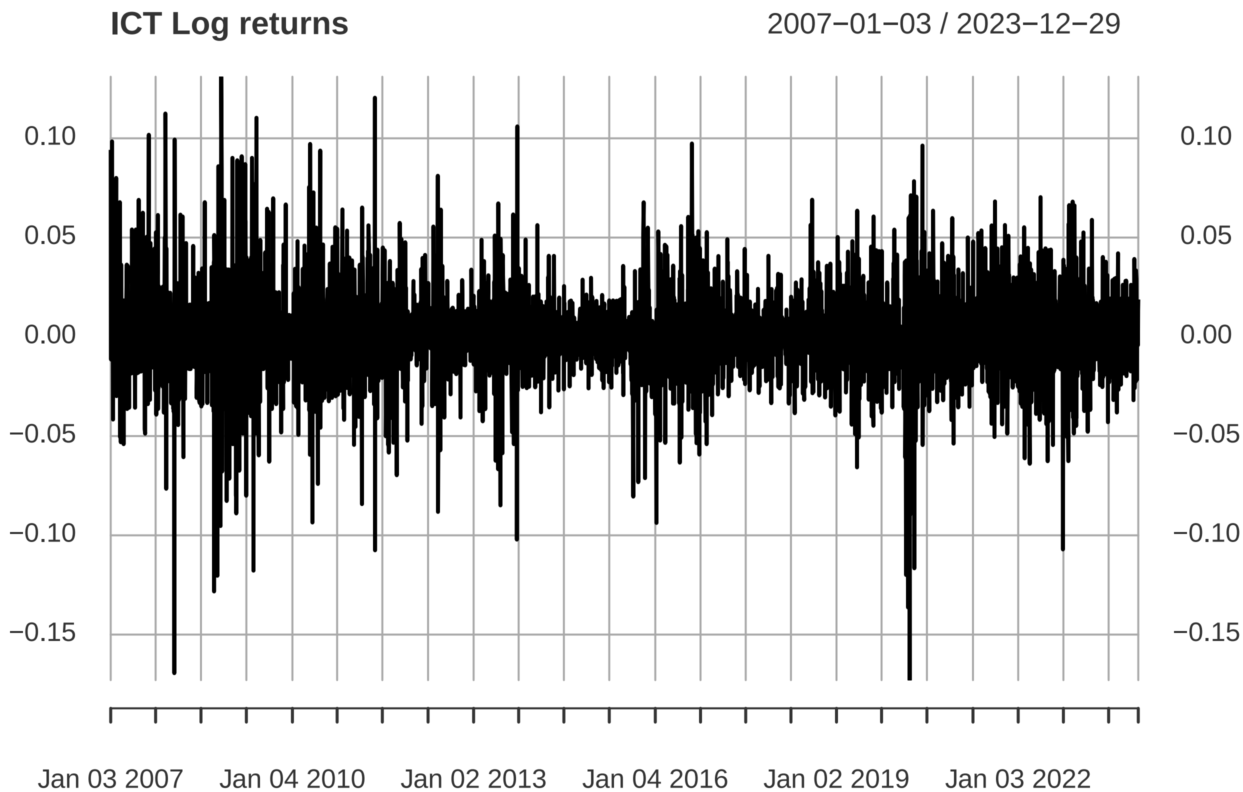



```
mdata_ret <- na.omit(diff(log(mdata)))
plot(mdata_ret,main = 'MacroAsia Log returns')
```




```
# volatility clustering around 2017 and 2020 hence ARIMA not sufficient model
```

```
idata_ret <- na.omit(diff(log(idata)))
plot(idata_ret, main = 'ICT Log returns')
```




```r
# volatility clustering around 2008 and 2020
```

PART 2: ARIMA Model Identification

```r
adf.test(mdata_ret) # H0: TS is not stationary
```

```
## Warning in adf.test(mdata_ret): p-value smaller than printed p-value
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  mdata_ret
## Dickey-Fuller = -13.877, Lag order = 15, p-value = 0.01
## alternative hypothesis: stationary
```

```r
# Hypothesis testing = Fail to Reject Null hypothesis | Data is not stationary

kpss.test(mdata_ret, null = "Level") # H0: TS is level stationary
```

```
## Warning in kpss.test(mdata_ret, null = "Level"): p-value greater than printed
## p-value
```

```
##
##  KPSS Test for Level Stationarity
##
## data:  mdata_ret
## KPSS Level = 0.17008, Truncation lag parameter = 9, p-value = 0.1
```

```r
# Hypothesis testing = Reject Null hypothesis | Data is stationary
```

```r
adf.test(idata_ret) # H0: TS is not stationary
```

```
## Warning in adf.test(idata_ret): p-value smaller than printed p-value
```

```
##
##  Augmented Dickey-Fuller Test
##
## data:  idata_ret
## Dickey-Fuller = -15.132, Lag order = 16, p-value = 0.01
## alternative hypothesis: stationary
```

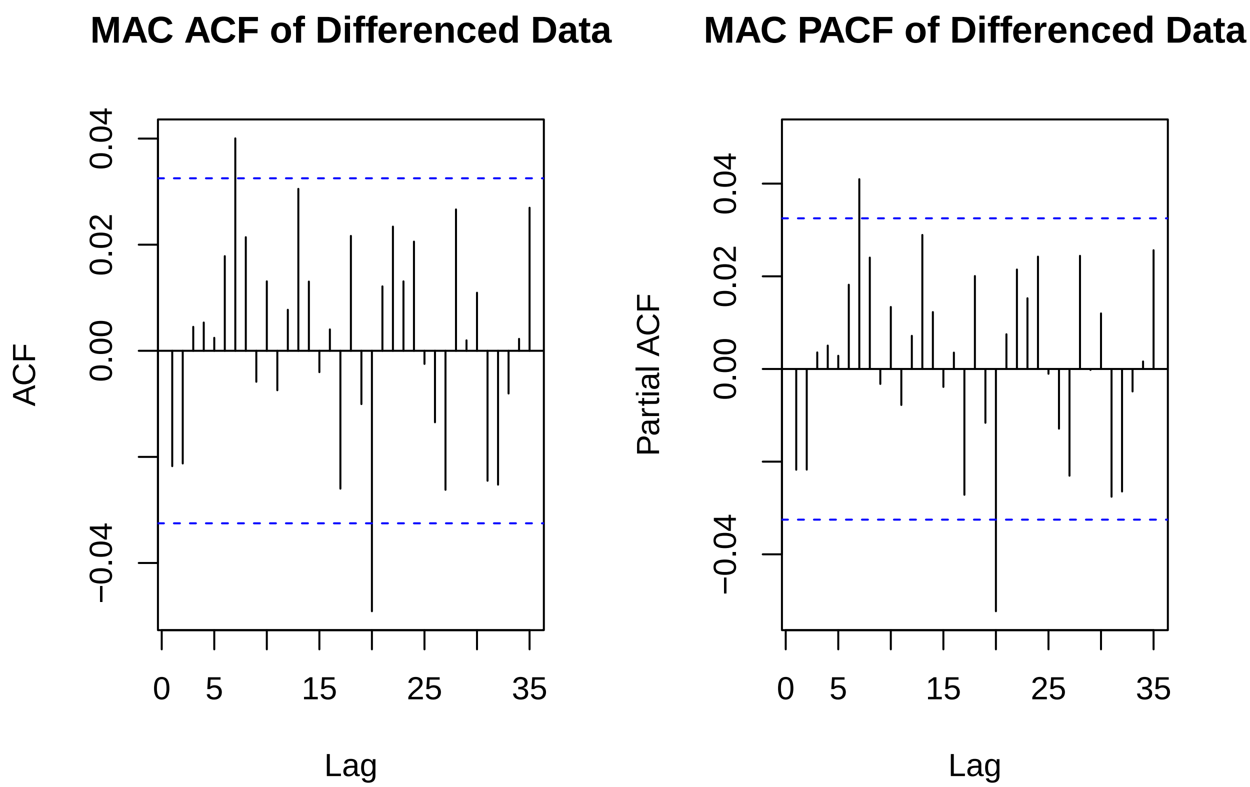
```r
# Fail to REJECT NUll Hypothesis | Data is stationary

kpss.test(idata_ret, null = "Level") # TS is level stationary
```

```
## Warning in kpss.test(idata_ret, null = "Level"): p-value greater than printed
## p-value
```

```
##
##  KPSS Test for Level Stationarity
##
## data:  idata_ret
## KPSS Level = 0.062549, Truncation lag parameter = 10, p-value = 0.1
```

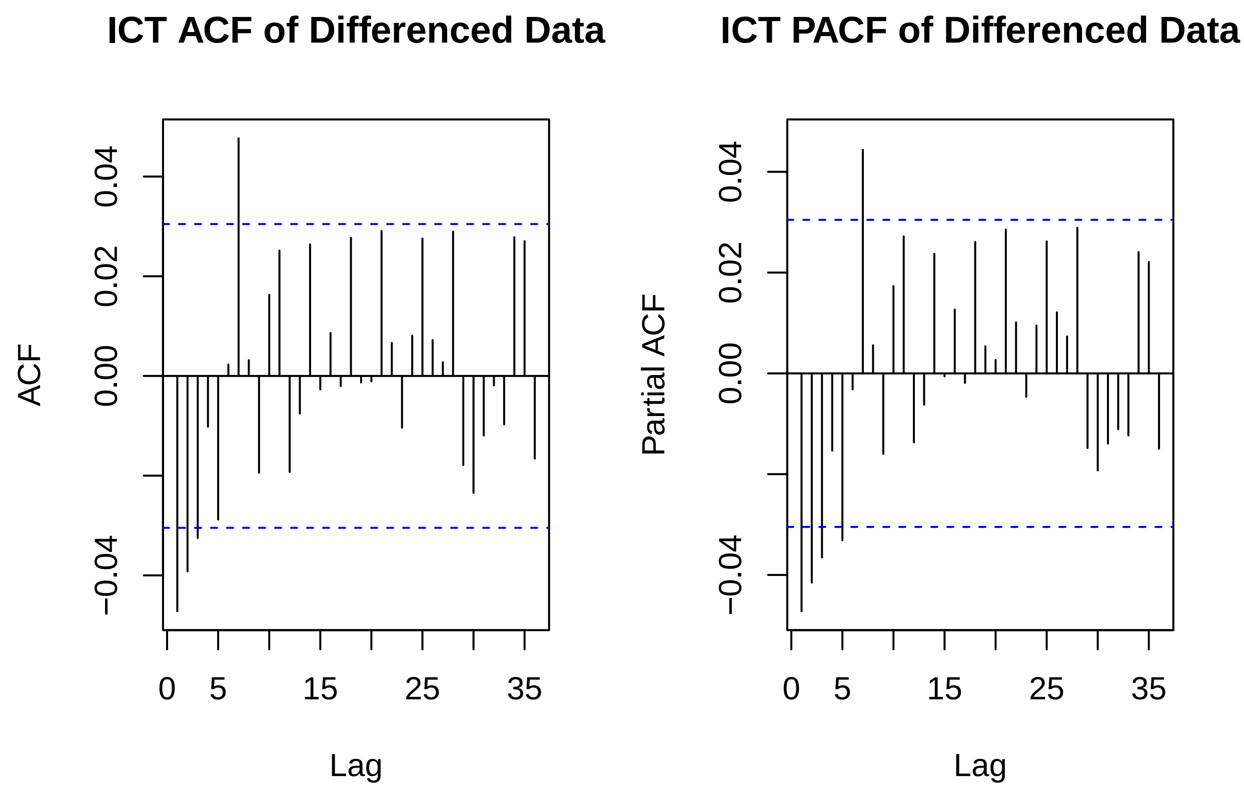
```r
# Reject null hypothesis as data is not level stationary
```

```r
par(mfrow = c(1,2))
Acf(mdata_ret, main = "MAC ACF of Differenced Data")
Pacf(mdata_ret, main = "MAC PACF of Differenced Data")
```




```
# There is significant spikes at different lags exceeding the bands and slight decay
# Significant spikes indicates it is not white noise. Meaning it will become ARIMA(0,0,0) and we cannot
```

```
par(mfrow = c(1,2))
Acf(idata_ret, main = 'ICT ACF of Differenced Data')
Pacf(idata_ret, main = 'ICT PACF of Differenced Data')
```




```r
# Significant spikes to the bands are observed around 0 to 5 Lag
# Significant spikes indicates it is not white noise. Meaning it will become ARIMA(0,0,0) and we cannot
```

PART 3: ARIMA Model

```r
mac_arima_model<- auto.arima(mdata, trace = T)
```

```
##
##  Fitting models using approximations to speed things up...
##
##  ARIMA(2,1,2) with drift         : 556.9214
##  ARIMA(0,1,0) with drift         : 579.1541
##  ARIMA(1,1,0) with drift         : 571.1387
##  ARIMA(0,1,1) with drift         : 569.5624
##  ARIMA(0,1,0)                    : 577.1688
##  ARIMA(1,1,2) with drift         : 566.12
##  ARIMA(2,1,1) with drift         : 567.2066
##  ARIMA(3,1,2) with drift         : 558.874
##  ARIMA(2,1,3) with drift         : Inf
##  ARIMA(1,1,1) with drift         : 566.2463
##  ARIMA(1,1,3) with drift         : 567.974
##  ARIMA(3,1,1) with drift         : 569.6654
```

```
##  ARIMA(3,1,3) with drift         : Inf
##  ARIMA(2,1,2)                    : 554.9014
##  ARIMA(1,1,2)                    : 564.1247
##  ARIMA(2,1,1)                    : 565.2241
##  ARIMA(3,1,2)                    : 556.8604
##  ARIMA(2,1,3)                    : Inf
##  ARIMA(1,1,1)                    : 564.2577
##  ARIMA(1,1,3)                    : 567.8766
##  ARIMA(3,1,1)                    : 569.8623
##  ARIMA(3,1,3)                    : Inf
##
##  Now re-fitting the best model(s) without approximations...
##
##  ARIMA(2,1,2)                    : 550.1652
##
##  Best model: ARIMA(2,1,2)
```

```r
summary(mac_arima_model)
```

```
## Series: mdata
## ARIMA(2,1,2)
##
## Coefficients:
##          ar1     ar2      ma1      ma2
##       0.1291  0.8467  -0.0850  -0.8709
## s.e.  0.0825  0.0810   0.0738   0.0712
##
## sigma^2 = 0.06801:  log likelihood = -270.07
## AIC=550.15   AICc=550.17   BIC=581.14
##
## Training set error measures:
##                        ME      RMSE       MAE         MPE     MAPE     MASE
## Training set 0.0003101588 0.2606044 0.1270813 -0.01221521 2.085351 1.010852
##                    ACF1
## Training set 0.01038884
```

```r
# Price is used for ARIMA model for this case, since Log Returns gets ARIMA (0,0,0) model
# ARIMA Model(2,1,2) = AR(2), Differencing = 1, MA(2)
mac_arima_model
```

```
## Series: mdata
## ARIMA(2,1,2)
##
## Coefficients:
##          ar1     ar2      ma1      ma2
##       0.1291  0.8467  -0.0850  -0.8709
## s.e.  0.0825  0.0810   0.0738   0.0712
##
## sigma^2 = 0.06801:  log likelihood = -270.07
## AIC=550.15   AICc=550.17   BIC=581.14
```

```r
ict_arima_model<- auto.arima(idata_ret, trace = T)
```

```
##
##  Fitting models using approximations to speed things up...
##
##  ARIMA(2,0,2) with non-zero mean : -19328.36
##  ARIMA(0,0,0) with non-zero mean : -19299.2
##  ARIMA(1,0,0) with non-zero mean : -19321.38
##  ARIMA(0,0,1) with non-zero mean : -19307.28
##  ARIMA(0,0,0) with zero mean     : -19298.58
##  ARIMA(1,0,2) with non-zero mean : -19326.84
##  ARIMA(2,0,1) with non-zero mean : -19330.4
##  ARIMA(1,0,1) with non-zero mean : -19324.05
##  ARIMA(2,0,0) with non-zero mean : -19325.64
##  ARIMA(3,0,1) with non-zero mean : -19328.15
##  ARIMA(3,0,0) with non-zero mean : -19328.32
##  ARIMA(3,0,2) with non-zero mean : -19326.28
##  ARIMA(2,0,1) with zero mean     : -19329.02
##
##  Now re-fitting the best model(s) without approximations...
##
##  ARIMA(2,0,1) with non-zero mean : -19316.54
##
##  Best model: ARIMA(2,0,1) with non-zero mean
```

```r
summary(ict_arima_model)
```

```
## Series: idata_ret
## ARIMA(2,0,1) with non-zero mean
##
## Coefficients:
##          ar1      ar2      ma1   mean
##       0.5075  -0.0221  -0.5596  6e-04
## s.e.  0.1256   0.0187   0.1250  3e-04
##
## sigma^2 = 0.000549:  log likelihood = 9663.28
## AIC=-19316.55   AICc=-19316.54   BIC=-19284.91
##
## Training set error measures:
##                        ME       RMSE        MAE MPE MAPE     MASE         ACF1
## Training set 1.883416e-05 0.02341935 0.01587055 NaN  Inf 0.667891 0.0004592458
```

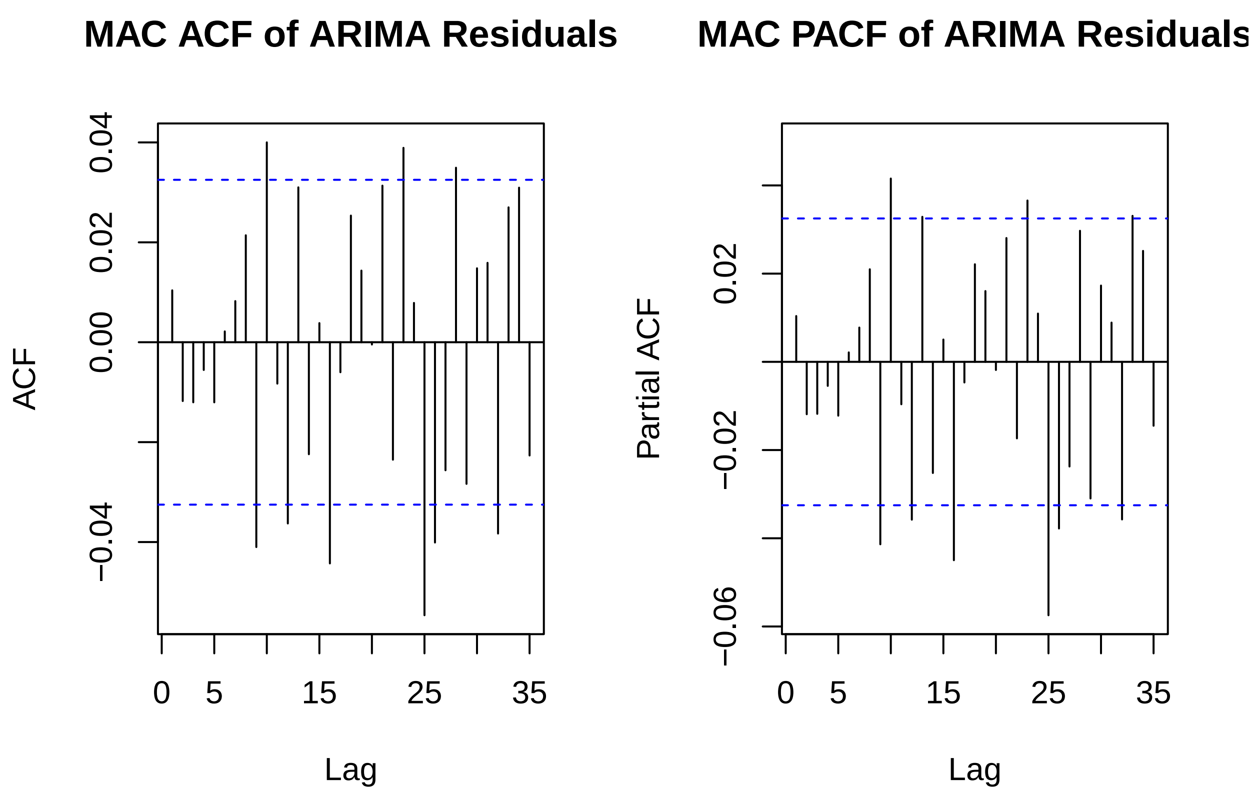
```r
# ARIMA(2,0,1) with non-zero mean  = AR(2), Differencing = 0, MA(1)
ict_arima_model
```

```
## Series: idata_ret
## ARIMA(2,0,1) with non-zero mean
##
## Coefficients:
##          ar1      ar2      ma1   mean
##       0.5075  -0.0221  -0.5596  6e-04
## s.e.  0.1256   0.0187   0.1250  3e-04
```

```
##
## sigma^2 = 0.000549:  log likelihood = 9663.28
## AIC=-19316.55   AICc=-19316.54   BIC=-19284.91
```

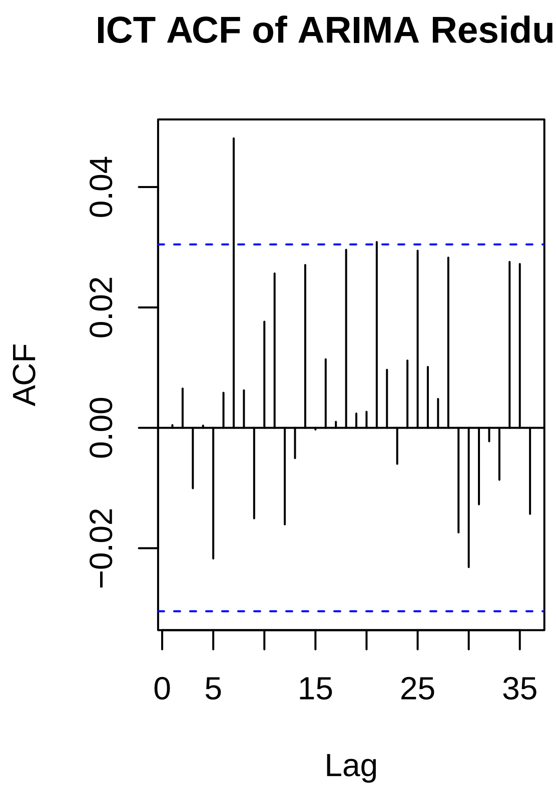
PART 4: Residual Analysis

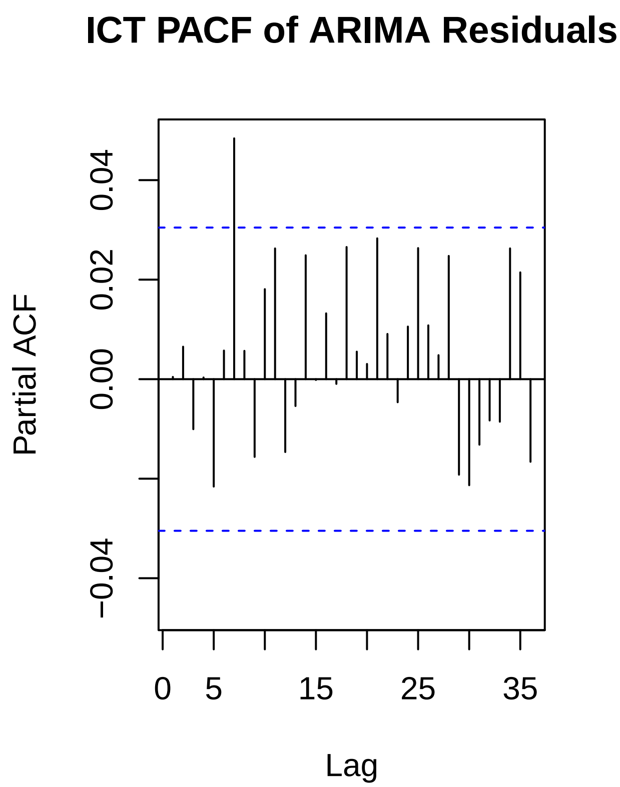
```r
par(mfrow = c(1,2))
Acf(mac_arima_model$residuals, main = "MAC ACF of ARIMA Residuals")
Pacf(mac_arima_model$residuals, main = "MAC PACF of ARIMA Residuals")
```




```r
# Significant spikes indicates it is not white noise. Meaning it will become ARIMA(0,0,0) and we cannot
```

```r
par(mfrow = c(1,2))
Acf(ict_arima_model$residuals, main = "ICT ACF of ARIMA Residuals")
Pacf(ict_arima_model$residuals, main = "ICT PACF of ARIMA Residuals")
```






```r
# Significant spikes indicates it is not white noise. Meaning it will become ARIMA(0,0,0) and we cannot
```

```r
# MAC Box Test
Box.test(mac_arima_model$residuals, type = "Ljung-Box") # H0 : No autocorrelation in the residuals
```

```
##
##  Box-Ljung test
##
## data:  mac_arima_model$residuals
## X-squared = 0.39253, df = 1, p-value = 0.531
```

```r
# Reject Null Hypothesis : There is no autocorrelation in the residuals

# MAC Coeftest
lmtest::coeftest(mac_arima_model)
```

```
##
## z test of coefficients:
##
##      Estimate Std. Error  z value Pr(>|z|)
## ar1  0.129126   0.082465   1.5658   0.1174
## ar2  0.846745   0.080970  10.4575   <2e-16 ***
## ma1 -0.085005   0.073798  -1.1519   0.2494
## ma2 -0.870897   0.071176 -12.2359   <2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# AR2 and MA2 are significant in our ARIMA(2,1,2) Model
```

```r
# ICT Box Test
Box.test(ict_arima_model$residuals, type = "Ljung-Box") # H0 : No autocorrelation in the residuals
```

```
##
##  Box-Ljung test
##
## data:  ict_arima_model$residuals
## X-squared = 0.00087336, df = 1, p-value = 0.9764
```

```r
# Reject Null Hypothesis : There is no autocorrelation in the residuals

# ICT Coeftest
lmtest::coeftest(ict_arima_model)
```

```
##
## z test of coefficients:
##
##              Estimate  Std. Error z value  Pr(>|z|)
## ar1        0.50746289  0.12558946  4.0406 5.330e-05 ***
## ar2       -0.02206060  0.01868779 -1.1805   0.23781
## ma1       -0.55959092  0.12495161 -4.4785 7.518e-06 ***
## intercept  0.00057419  0.00031199  1.8404   0.06571 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
# AR2 and MA2 are significant in our ARIMA(2,0,1) Model
```

```r
mac_arima_model2 <- Arima(mdata, order = c(
  1,0,1 #2,1,2
  )) # AR(1) and MA(1) components are significant
summary(mac_arima_model2)
```

```
## Series: mdata
## ARIMA(1,0,1) with non-zero mean
##
## Coefficients:
##          ar1     ma1    mean
##       0.9989  0.0585  6.4450
## s.e.  0.0007  0.0170  3.5253
##
## sigma^2 = 0.06834:  log likelihood = -282.5
## AIC=573   AICc=573.01   BIC=597.79
##
## Training set error measures:
##                        ME      RMSE       MAE        MPE     MAPE     MASE
## Training set 0.0004925188 0.2613065 0.1268104 -0.1037246 2.085238 1.008697
##                      ACF1
## Training set -0.001322572
```

```r
lmtest::coeftest(mac_arima_model2)
```

```
##
## z test of coefficients:
##
##             Estimate Std. Error   z value  Pr(>|z|)
## ar1       0.99892050 0.00066076 1511.7861 < 2.2e-16 ***
## ma1       0.05850434 0.01704050    3.4333 0.0005964 ***
## intercept 6.44498647 3.52528691    1.8282 0.0675171 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

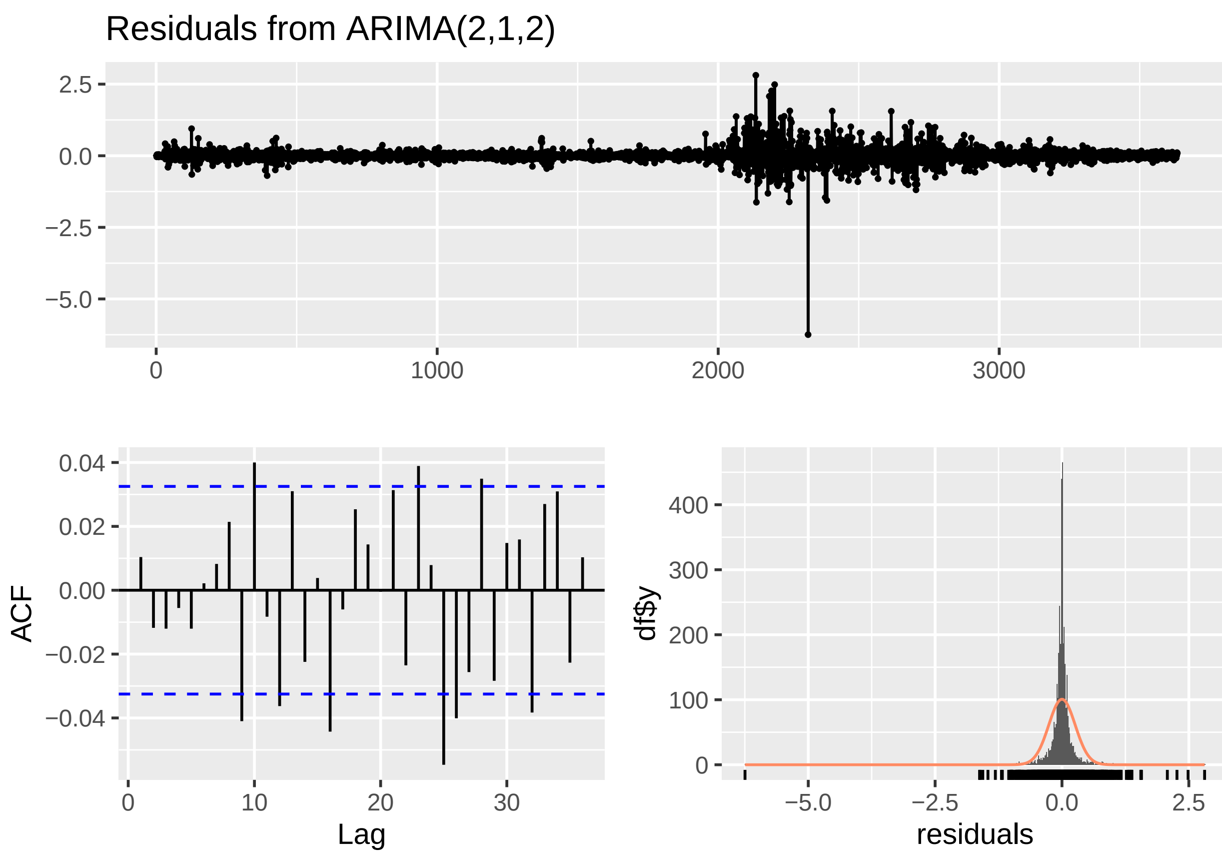
```r
ict_arima_model2 <- Arima(idata, order = c(1,0,1)) # AR(1) and MA(1) components are significant
summary(ict_arima_model2)
```

```
## Series: idata
## ARIMA(1,0,1) with non-zero mean
##
## Coefficients:
##          ar1      ma1     mean
##       0.9998  -0.1534  93.1418
## s.e.  0.0003   0.0171  79.2610
##
## sigma^2 = 5.14:  log likelihood = -9278.09
## AIC=18564.18   AICc=18564.19   BIC=18589.5
##
## Training set error measures:
##                      ME    RMSE      MAE        MPE     MAPE      MASE
## Training set 0.06368516 2.26632 1.392388 0.01761059 1.601683 0.9982589
##                    ACF1
## Training set 0.01257685
```

```r
lmtest::coeftest(ict_arima_model2)
```

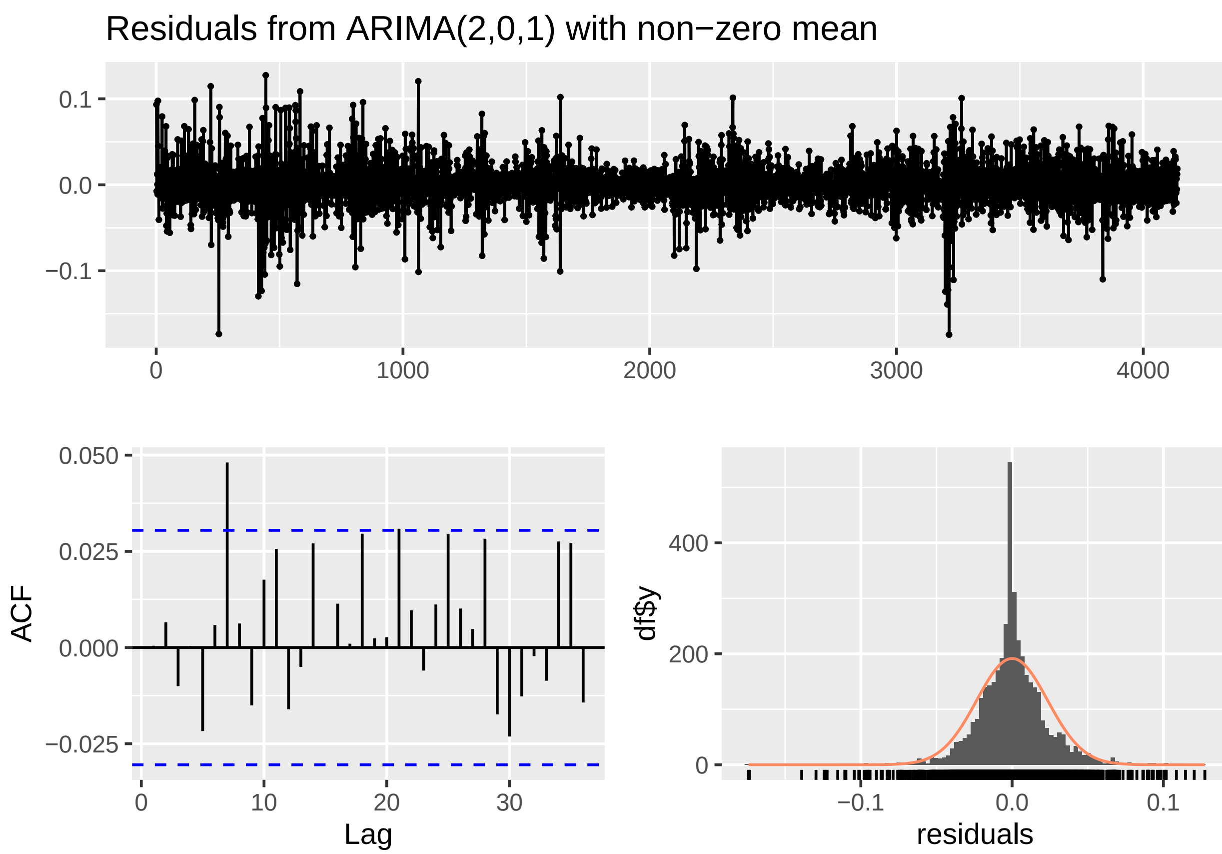
```
##
## z test of coefficients:
##
##              Estimate  Std. Error   z value Pr(>|z|)
## ar1        0.99976404  0.00028459 3512.9676   <2e-16 ***
## ma1       -0.15344287  0.01705814   -8.9953   <2e-16 ***
## intercept 93.14184118 79.26104334    1.1751   0.2399
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
forecast::checkresiduals(mac_arima_model)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(2,1,2)
## Q* = 15.962, df = 6, p-value = 0.01396
##
## Model df: 4.   Total lags used: 10
```

```
forecast::checkresiduals(ict_arima_model)
```




```
##
##  Ljung-Box test
##
## data:  Residuals from ARIMA(2,0,1) with non-zero mean
## Q* = 14.671, df = 7, p-value = 0.04046
##
## Model df: 3.   Total lags used: 10
```

```r
# Lower AIC = Better
AIC(mac_arima_model) # Better Model per AIC
```

```
## [1] 550.1486
```

```r
AIC(mac_arima_model2)
```

```
## [1] 572.9989
```

```r
BIC(mac_arima_model)
```

```
## [1] 581.1377
```

```r
BIC(mac_arima_model2)
```

```
## [1] 597.7912
```

```r
# Lower AIC = Better
AIC(ict_arima_model) # Better Model per AIC
```

```
## [1] -19316.55
```

```r
AIC(ict_arima_model2)
```

```
## [1] 18564.18
```

```r
BIC(ict_arima_model)
```

```
## [1] -19284.91
```

```r
BIC(ict_arima_model2)
```

```
## [1] 18589.5
```

```r
mac_arima_model_test <- FinTS::ArchTest(residuals(mac_arima_model), lags = 12) # H0: No ARCH effects
mac_arima_model_test
```

```
##
##  ARCH LM-test; Null hypothesis: no ARCH effects
##
## data:  residuals(mac_arima_model)
## Chi-squared = 28.938, df = 12, p-value = 0.004024
```

```r
# Fail to Reject Null Hypothesis | There is Arch effects hence MAC ARIMA Model is insufficient
# At Lag 36 we Reject Null
```

```r
ict_arima_model_test <- FinTS::ArchTest(residuals(ict_arima_model), lags = 12) # H0: No ARCH effects
ict_arima_model_test
```

```
##
##  ARCH LM-test; Null hypothesis: no ARCH effects
##
## data:  residuals(ict_arima_model)
## Chi-squared = 355.2, df = 12, p-value < 2.2e-16
```

```r
# Reject Null Hypothesis | There is Arch effects hence ICT ARIMA Model is insufficient
# All Lags have ARCH effects
```

```r
#mac_arima_model # ARIMA(2,1,2)
ict_arima_model # ARIMA(2,0,1)
```

```
## Series: idata_ret
## ARIMA(2,0,1) with non-zero mean
##
## Coefficients:
##          ar1      ar2      ma1   mean
##       0.5075  -0.0221  -0.5596  6e-04
## s.e.  0.1256   0.0187   0.1250  3e-04
##
## sigma^2 = 0.000549:  log likelihood = 9663.28
## AIC=-19316.55   AICc=-19316.54   BIC=-19284.91
```

```r
# The ARIMA Models are not sufficient as they have ARCH effects however the model is significant
```

===

PART 5 : GARCH Model

```r
ict_garch_spec_nd <- ugarchspec(
  mean.model = list(
     armaOrder = c(2,1)                        # 2 AR terms, 1 MA term | Adjusted for ARMA(2,0,1)
    ,include.mean = TRUE                       # explicitly include mean (mu)
    ,fixed.pars = list(ma2 = 0, ma3 = 0))     # Fix ma2 and ma3 to 0
  ,variance.model = list(
     model = "sGARCH"                          # GARCH model for volatility
    ,garchOrder = c(1, 1))                     # GARCH(1,1) model for conditional variance
  ,distribution.model = "norm"                 # sGARCH Normal Distribution
)
```

```
## Warning: unidentified option(s) in mean.model:
##  fixed.pars
```

```r
ict_garch_model_nd <- ugarchfit(spec = ict_garch_spec_nd
                              ,data = ict_arima_model$residuals
                              )
ict_garch_model_nd
```

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model   : sGARCH(1,1)
## Mean Model    : ARFIMA(2,0,1)
## Distribution : norm
```

```
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu      0.000265    0.000249   1.0646  0.28706
## ar1     0.742801    0.132227   5.6176  0.00000
## ar2     0.013925    0.024087   0.5781  0.56319
## ma1    -0.786374    0.134118  -5.8633  0.00000
## omega   0.000017    0.000003   6.2655  0.00000
## alpha1  0.138422    0.012892  10.7372  0.00000
## beta1   0.840615    0.013579  61.9063  0.00000
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu      0.000265    0.000258  1.02756 0.304156
## ar1     0.742801    0.110886  6.69876 0.000000
## ar2     0.013925    0.029893  0.46582 0.641346
## ma1    -0.786374    0.117819 -6.67441 0.000000
## omega   0.000017    0.000005  3.50028 0.000465
## alpha1  0.138422    0.023649  5.85326 0.000000
## beta1   0.840615    0.025817 32.56077 0.000000
##
## LogLikelihood : 10101.73
##
## Information Criteria
## ------------------------------------
##
## Akaike       -4.8790
## Bayes        -4.8683
## Shibata      -4.8790
## Hannan-Quinn -4.8753
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                          statistic   p-value
## Lag[1]                       3.653 5.597e-02
## Lag[2*(p+q)+(p+q)-1][8]      8.547 5.210e-08
## Lag[4*(p+q)+(p+q)-1][14]    12.873 1.317e-02
## d.o.f=3
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                      3.447 0.06338
## Lag[2*(p+q)+(p+q)-1][5]     4.399 0.20829
## Lag[4*(p+q)+(p+q)-1][9]     5.828 0.31844
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]    0.6629 0.500 2.000  0.4155
## ARCH Lag[5]    2.1035 1.440 1.667  0.4488
```

```
## ARCH Lag[7]    2.4859 2.315 1.543  0.6153
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  4.3183
## Individual Statistics:
## mu     0.2066
## ar1    0.3637
## ar2    0.1572
## ma1    0.3272
## omega  1.3934
## alpha1 0.5506
## beta1  0.7857
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.69 1.9 2.35
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value    prob sig
## Sign Bias           1.9565 0.05047   *
## Negative Sign Bias  1.9054 0.05680   *
## Positive Sign Bias  0.2073 0.83576
## Joint Effect        5.6143 0.13196
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     453.3    3.323e-84
## 2    30     474.0    6.266e-82
## 3    40     515.9    1.515e-84
## 4    50     519.8    6.521e-80
##
##
## Elapsed time : 0.591078
```

```r
show(ict_garch_spec_nd)
```

```
##
## *---------------------------------*
## *       GARCH Model Spec          *
## *---------------------------------*
##
## Conditional Variance Dynamics
## ------------------------------------
## GARCH Model      : sGARCH(1,1)
## Variance Targeting   : FALSE
##
## Conditional Mean Dynamics
## ------------------------------------
## Mean Model       : ARFIMA(2,0,1)
## Include Mean     : TRUE
```

```
## GARCH-in-Mean        : FALSE
##
## Conditional Distribution
## ------------------------------------
## Distribution :  norm
## Includes Skew     :  FALSE
## Includes Shape    :  FALSE
## Includes Lambda   :  FALSE
```

```r
coef(ict_garch_model_nd)
```

```
##            mu           ar1           ar2           ma1         omega
##  2.646058e-04  7.428007e-01  1.392484e-02 -7.863742e-01  1.663491e-05
##        alpha1         beta1
##  1.384220e-01  8.406151e-01
```

```r
# Ljung-Box Test indicates model is not fit and there is autocorrelation
# Squared residuals shows no autocorrelation
# There is no ARCH effects on residuals
# Joint statistic infers that our parameters are jointly unstable and individually the results are mixe
# Pearson Goodness-of-Fit infers model is not fit
# Sign bias shows the model is not able to capture positive and negative shocks
# Negative shocks vs positive shocks | Model appears to have a slight bias towards positive
```

```r
mac_garch_spec_nd <- ugarchspec(
  mean.model = list(
     armaOrder = c(2,2)                       # 2 AR terms, 2 MA term | Adjusted for ARMA(2,1,2)
    ,include.mean = TRUE                      # explicitly include mean (mu)
    ,fixed.pars = list(ma2 = 0, ma3 = 0))     # Fix ma2 and ma3 to 0
  ,variance.model = list(
     model = "sGARCH"                         # GARCH model for volatility
    ,garchOrder = c(1, 1))                    # GARCH(1,1) model for conditional variance
  ,distribution.model = "norm"                # sGARCH Normal Distribution
)
```

```
## Warning: unidentified option(s) in mean.model:
##  fixed.pars
```

```r
mac_garch_model_nd <- ugarchfit(spec = mac_garch_spec_nd
                             ,data = mac_arima_model$residuals
                             )
mac_garch_model_nd
```

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
```

```
## Mean Model   : ARFIMA(2,0,2)
## Distribution : norm
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error    t value Pr(>|t|)
## mu     -0.000054    0.001346  -0.039805 0.968249
## ar1    -0.246304    0.163682  -1.504768 0.132384
## ar2     0.527465    0.116240   4.537733 0.000006
## ma1     0.149564    0.159727   0.936375 0.349080
## ma2    -0.557906    0.105951  -5.265707 0.000000
## omega   0.000083    0.000021   3.927660 0.000086
## alpha1  0.054832    0.007081   7.743534 0.000000
## beta1   0.944168    0.007074 133.479064 0.000000
##
## Robust Standard Errors:
##         Estimate  Std. Error   t value Pr(>|t|)
## mu     -0.000054    0.001082 -0.049525 0.960501
## ar1    -0.246304    0.183321 -1.343568 0.179088
## ar2     0.527465    0.136165  3.873724 0.000107
## ma1     0.149564    0.177568  0.842290 0.399626
## ma2    -0.557906    0.118464 -4.709490 0.000002
## omega   0.000083    0.000118  0.699850 0.484021
## alpha1  0.054832    0.035685  1.536562 0.124401
## beta1   0.944168    0.041069 22.989978 0.000000
##
## LogLikelihood : 1868.312
##
## Information Criteria
## ------------------------------------
##
## Akaike       -1.0238
## Bayes        -1.0102
## Shibata      -1.0238
## Hannan-Quinn -1.0190
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                          statistic p-value
## Lag[1]                       2.545  0.1106
## Lag[2*(p+q)+(p+q)-1][11]     5.391  0.8442
## Lag[4*(p+q)+(p+q)-1][19]     7.534  0.8538
## d.o.f=4
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                      1.096  0.2952
## Lag[2*(p+q)+(p+q)-1][5]     1.145  0.8261
## Lag[4*(p+q)+(p+q)-1][9]     1.331  0.9682
## d.o.f=2
##
## Weighted ARCH LM Tests
```

```
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]   0.05689 0.500 2.000  0.8115
## ARCH Lag[5]   0.09559 1.440 1.667  0.9876
## ARCH Lag[7]   0.29495 2.315 1.543  0.9930
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  2.8628
## Individual Statistics:
## mu     0.02403
## ar1    0.73356
## ar2    0.35997
## ma1    0.87234
## ma2    0.42829
## omega  0.07654
## alpha1 0.30778
## beta1  0.23039
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.89 2.11 2.59
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           0.7846 0.4328
## Negative Sign Bias  0.3446 0.7304
## Positive Sign Bias  1.0533 0.2923
## Joint Effect        2.6540 0.4481
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     946.1   1.679e-188
## 2    30    1164.6   1.242e-226
## 3    40    1306.7   7.863e-249
## 4    50    1323.6   6.211e-245
##
##
## Elapsed time : 0.4053018
```

```r
show(mac_garch_spec_nd)
```

```
##
## *---------------------------------*
## *       GARCH Model Spec          *
## *---------------------------------*
##
## Conditional Variance Dynamics
## ------------------------------------
## GARCH Model      : sGARCH(1,1)
## Variance Targeting   : FALSE
```

```
##
## Conditional Mean Dynamics
## -----------------------------------
## Mean Model       : ARFIMA(2,0,2)
## Include Mean     : TRUE
## GARCH-in-Mean        : FALSE
##
## Conditional Distribution
## -----------------------------------
## Distribution :  norm
## Includes Skew    :  FALSE
## Includes Shape   :  FALSE
## Includes Lambda  :  FALSE
```

```
coef(mac_garch_model_nd)
```

```
##            mu           ar1           ar2           ma1           ma2
## -5.357957e-05 -2.463036e-01  5.274647e-01  1.495638e-01 -5.579059e-01
##         omega        alpha1         beta1
##  8.262031e-05  5.483189e-02  9.441681e-01
```

```
# Ljung-Box Test indicates model is  fit and there is no autocorrelation
# Squared residuals shows no autocorrelation
# There is no ARCH effects on residuals
# Joint statistic infers that our parameters are jointly stable and individually the results are mostly
# Pearson Goodness-of-Fit infers model is not fit
# There is no sign bias
```

```
ict_garch_spec_std <- ugarchspec(
  mean.model = list(
     armaOrder = c(2,1)                       # 2 AR terms, 1 MA term | Adjusted for ARMA(2,0,1)
    ,include.mean = TRUE                      # explicitly include mean (mu)
    ,fixed.pars = list(ma2 = 0, ma3 = 0))    # Fix ma2 and ma3 to 0
  ,variance.model = list(
     model = "sGARCH"                         # GARCH model for volatility
    ,garchOrder = c(1, 1))                    # GARCH(1,1) model for conditional variance
  ,distribution.model = "std"                # sGARCH Student's T Distribution
)
```

```
## Warning: unidentified option(s) in mean.model:
##  fixed.pars
```

```
ict_garch_model_std <- ugarchfit(spec = ict_garch_spec_std
                             ,data = ict_arima_model$residuals
                             )
ict_garch_model_std
```

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

```
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : sGARCH(1,1)
## Mean Model   : ARFIMA(2,0,1)
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     -0.000246    0.000220 -1.12136 0.262133
## ar1     0.699996    0.161692  4.32920 0.000015
## ar2     0.012324    0.019493  0.63222 0.527241
## ma1    -0.742878    0.160827 -4.61911 0.000004
## omega   0.000017    0.000003  5.27988 0.000000
## alpha1  0.159567    0.020401  7.82140 0.000000
## beta1   0.837860    0.018053 46.41121 0.000000
## shape   3.799825    0.262369 14.48277 0.000000
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     -0.000246    0.000213 -1.15889 0.246502
## ar1     0.699996    0.115400  6.06584 0.000000
## ar2     0.012324    0.018212  0.67668 0.498609
## ma1    -0.742878    0.113453 -6.54790 0.000000
## omega   0.000017    0.000004  4.83843 0.000001
## alpha1  0.159567    0.023538  6.77911 0.000000
## beta1   0.837860    0.022287 37.59353 0.000000
## shape   3.799825    0.284561 13.35328 0.000000
##
## LogLikelihood : 10326.84
##
## Information Criteria
## ------------------------------------
##
## Akaike       -4.9874
## Bayes        -4.9751
## Shibata      -4.9874
## Hannan-Quinn -4.9830
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                          statistic   p-value
## Lag[1]                        3.374 6.623e-02
## Lag[2*(p+q)+(p+q)-1][8]       7.795 3.614e-06
## Lag[4*(p+q)+(p+q)-1][14]     11.727 3.404e-02
## d.o.f=3
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                      2.972 0.08474
## Lag[2*(p+q)+(p+q)-1][5]     4.234 0.22625
```

```
## Lag[4*(p+q)+(p+q)-1][9]     5.869 0.31352
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]    0.8799 0.500 2.000  0.3482
## ARCH Lag[5]    2.5906 1.440 1.667  0.3549
## ARCH Lag[7]    2.9308 2.315 1.543  0.5267
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  6.0703
## Individual Statistics:
## mu     0.07271
## ar1    0.73974
## ar2    0.14921
## ma1    0.69345
## omega  0.45668
## alpha1 0.33706
## beta1  0.49995
## shape  0.79928
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.89 2.11 2.59
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias          1.27772 0.2014
## Negative Sign Bias 1.51658 0.1295
## Positive Sign Bias 0.08744 0.9303
## Joint Effect       2.87359 0.4115
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     173.2    6.611e-27
## 2    30     205.4    1.804e-28
## 3    40     221.8    2.006e-27
## 4    50     247.8    2.343e-28
##
##
## Elapsed time : 0.8846631
```

```
show(ict_garch_spec_std)
```

```
##
## *---------------------------------*
## *       GARCH Model Spec          *
## *---------------------------------*
##
```

```
## Conditional Variance Dynamics
## ------------------------------------
## GARCH Model      : sGARCH(1,1)
## Variance Targeting   : FALSE
##
## Conditional Mean Dynamics
## ------------------------------------
## Mean Model       : ARFIMA(2,0,1)
## Include Mean     : TRUE
## GARCH-in-Mean        : FALSE
##
## Conditional Distribution
## ------------------------------------
## Distribution :  std
## Includes Skew    :  FALSE
## Includes Shape   :  TRUE
## Includes Lambda  :  FALSE
```

```
coef(ict_garch_model_std)
```

```
##            mu           ar1           ar2           ma1         omega
## -2.464600e-04  6.999962e-01  1.232396e-02 -7.428783e-01  1.700688e-05
##        alpha1         beta1         shape
##  1.595675e-01  8.378604e-01  3.799825e+00
```

```
# Higher Log likelihood = Better
# Lower AIC = Better
# Both models (norm vs std) show preferable results
```

```
ict_gjrgarch_spec_std <- ugarchspec(
  mean.model = list(
     armaOrder = c(2,1)                       # 2 AR terms, 1 MA term | Adjusted for ARMA(2,0,1)
    ,include.mean = TRUE
    ,fixed.pars = list(ma2 = 0, ma3 = 0))
  ,variance.model = list(
     model = "gjrGARCH"                       # GJR GARCH model
    ,garchOrder = c(1, 1))
  ,distribution.model = "std"
)
```

```
## Warning: unidentified option(s) in mean.model:
##  fixed.pars
```

```
ict_gjrgarch_model_std <- ugarchfit(spec = ict_gjrgarch_spec_std
                              ,data = ict_arima_model$residuals
)
ict_gjrgarch_model_std
```

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

```
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : gjrGARCH(1,1)
## Mean Model   : ARFIMA(2,0,1)
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     -0.000334    0.000221 -1.50741 0.131707
## ar1     0.702098    0.154820  4.53493 0.000006
## ar2     0.010040    0.019284  0.52064 0.602620
## ma1    -0.744172    0.153803 -4.83847 0.000001
## omega   0.000017    0.000003  5.23711 0.000000
## alpha1  0.128719    0.020479  6.28548 0.000000
## beta1   0.836255    0.018360 45.54729 0.000000
## gamma1  0.068051    0.025930  2.62439 0.008680
## shape   3.816510    0.261909 14.57189 0.000000
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     -0.000334    0.000221 -1.50784 0.131596
## ar1     0.702098    0.116548  6.02411 0.000000
## ar2     0.010040    0.018281  0.54919 0.582873
## ma1    -0.744172    0.114323 -6.50938 0.000000
## omega   0.000017    0.000004  4.83493 0.000001
## alpha1  0.128719    0.024092  5.34289 0.000000
## beta1   0.836255    0.022271 37.54900 0.000000
## gamma1  0.068051    0.026559  2.56227 0.010399
## shape   3.816510    0.278531 13.70226 0.000000
##
## LogLikelihood : 10330.59
##
## Information Criteria
## ------------------------------------
##
## Akaike       -4.9887
## Bayes        -4.9749
## Shibata      -4.9887
## Hannan-Quinn -4.9838
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                          statistic   p-value
## Lag[1]                       3.526 6.042e-02
## Lag[2*(p+q)+(p+q)-1][8]      8.347 1.673e-07
## Lag[4*(p+q)+(p+q)-1][14]    12.360 2.035e-02
## d.o.f=3
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
```

```
##                          statistic p-value
## Lag[1]                        3.880 0.04885
## Lag[2*(p+q)+(p+q)-1][5]      5.510 0.11706
## Lag[4*(p+q)+(p+q)-1][9]      7.463 0.16341
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]     1.199 0.500 2.000  0.2736
## ARCH Lag[5]     3.148 1.440 1.667  0.2690
## ARCH Lag[7]     3.495 2.315 1.543  0.4252
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  6.2723
## Individual Statistics:
## mu     0.07249
## ar1    0.69479
## ar2    0.14679
## ma1    0.64935
## omega  0.47065
## alpha1 0.31785
## beta1  0.51430
## gamma1 0.45458
## shape  0.84418
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          2.1 2.32 2.82
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           1.4551 0.1457
## Negative Sign Bias  0.9278 0.3535
## Positive Sign Bias  0.4313 0.6662
## Joint Effect        3.9763 0.2640
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     170.6    2.146e-26
## 2    30     203.0    5.167e-28
## 3    40     232.8    1.972e-29
## 4    50     232.8    1.004e-25
##
##
## Elapsed time : 1.091907
```

```
show(ict_gjrgarch_spec_std)
```

```
##
```

```
## *---------------------------------*
## *       GARCH Model Spec          *
## *---------------------------------*
##
## Conditional Variance Dynamics
## ------------------------------------
## GARCH Model      : gjrGARCH(1,1)
## Variance Targeting   : FALSE
##
## Conditional Mean Dynamics
## ------------------------------------
## Mean Model       : ARFIMA(2,0,1)
## Include Mean     : TRUE
## GARCH-in-Mean        : FALSE
##
## Conditional Distribution
## ------------------------------------
## Distribution :  std
## Includes Skew     :  FALSE
## Includes Shape    :  TRUE
## Includes Lambda   :  FALSE
```

```
coef(ict_gjrgarch_model_std)
```

```
##            mu           ar1           ar2           ma1         omega
## -0.0003335813  0.7020984675  0.0100399299 -0.7441722559  0.0000173238
##        alpha1         beta1        gamma1         shape
##  0.1287194462  0.8362547163  0.0680505445  3.8165097446
```

```
# Higher Log likelihood and AIC shows little change from sGARCH model
```

```
# Exponential GARCH
ict_egarch_spec <- ugarchspec(variance.model = list(model = "eGARCH", garchOrder = c(1, 1)),
                          mean.model = list(armaOrder = c(0, 0), include.mean = TRUE),
                          distribution.model = "std")
ict_egarch_model <- ugarchfit(spec = ict_egarch_spec, data = ict_arima_model$residuals)
ict_egarch_model
```

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : eGARCH(1,1)
## Mean Model   : ARFIMA(0,0,0)
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
```

```
## mu     -0.000487    0.000261  -1.8682 0.061728
## omega  -0.324118    0.066467  -4.8764 0.000001
## alpha1 -0.038389    0.015678  -2.4486 0.014342
## beta1   0.956754    0.008738 109.4887 0.000000
## gamma1  0.297424    0.034329   8.6640 0.000000
## shape   3.785973    0.260233  14.5484 0.000000
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     -0.000487    0.000265  -1.8374 0.066154
## omega  -0.324118    0.076163  -4.2556 0.000021
## alpha1 -0.038389    0.017089  -2.2464 0.024676
## beta1   0.956754    0.010092  94.8046 0.000000
## gamma1  0.297424    0.043589   6.8234 0.000000
## shape   3.785973    0.264283  14.3254 0.000000
##
## LogLikelihood : 10326.06
##
## Information Criteria
## ------------------------------------
##
## Akaike       -4.9879
## Bayes        -4.9788
## Shibata      -4.9880
## Hannan-Quinn -4.9847
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.0604  0.8059
## Lag[2*(p+q)+(p+q)-1][2]    0.5007  0.6933
## Lag[4*(p+q)+(p+q)-1][5]    0.8994  0.8820
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                      7.553 0.00599
## Lag[2*(p+q)+(p+q)-1][5]     8.246 0.02560
## Lag[4*(p+q)+(p+q)-1][9]     9.954 0.05133
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]    0.4284 0.500 2.000  0.5128
## ARCH Lag[5]    1.6543 1.440 1.667  0.5527
## ARCH Lag[7]    2.4820 2.315 1.543  0.6161
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  2.3405
## Individual Statistics:
```

```
## mu     0.06503
## omega  0.56108
## alpha1 0.16817
## beta1  0.55109
## gamma1 0.13371
## shape  0.69704
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.49 1.68 2.12
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           1.1650 0.2441
## Negative Sign Bias  0.9789 0.3277
## Positive Sign Bias  0.6920 0.4890
## Joint Effect        3.5533 0.3139
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     346.5    5.387e-62
## 2    30     352.9    2.345e-57
## 3    40     394.8    2.177e-60
## 4    50     392.3    4.394e-55
##
##
## Elapsed time : 0.4575629
```

```r
#show(ict_egarch_model)
# No material difference from previous sGARCH models
```

```r
# Fit TGARCH model for comparison
ict_tgarch_spec <- ugarchspec(variance.model = list(model = "fGARCH", submodel = "TGARCH", garchOrder =
                          mean.model = list(armaOrder = c(0, 0), include.mean = TRUE),
                          distribution.model = "norm")
ict_tgarch_model <- ugarchfit(spec = ict_tgarch_spec, data = ict_arima_model$residuals)
ict_tgarch_model
```

```
##
## *---------------------------------*
## *          GARCH Model Fit        *
## *---------------------------------*
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : fGARCH(1,1)
## fGARCH Sub-Model : TGARCH
## Mean Model   : ARFIMA(0,0,0)
## Distribution : norm
##
```

```
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     -0.000105    0.000252 -0.41604 0.677380
## omega   0.001061    0.000177  5.98552 0.000000
## alpha1  0.145924    0.013123 11.11952 0.000000
## beta1   0.848351    0.015536 54.60410 0.000000
## eta11   0.139463    0.041164  3.38799 0.000704
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     -0.000105    0.000278 -0.37758 0.705739
## omega   0.001061    0.000354  2.99276 0.002765
## alpha1  0.145924    0.025695  5.67915 0.000000
## beta1   0.848351    0.031964 26.54111 0.000000
## eta11   0.139463    0.075426  1.84901 0.064457
##
## LogLikelihood : 10083.89
##
## Information Criteria
## ------------------------------------
##
## Akaike       -4.8714
## Bayes        -4.8637
## Shibata      -4.8714
## Hannan-Quinn -4.8687
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic p-value
## Lag[1]                     0.1107  0.7393
## Lag[2*(p+q)+(p+q)-1][2]    0.4529  0.7161
## Lag[4*(p+q)+(p+q)-1][5]    0.8175  0.8994
## d.o.f=0
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
## ------------------------------------
##                         statistic  p-value
## Lag[1]                      10.64 0.001108
## Lag[2*(p+q)+(p+q)-1][5]     11.15 0.004649
## Lag[4*(p+q)+(p+q)-1][9]     12.25 0.015902
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]   0.08583 0.500 2.000  0.7695
## ARCH Lag[5]   0.77694 1.440 1.667  0.8001
## ARCH Lag[7]   1.42958 2.315 1.543  0.8354
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  2.2151
```

```
## Individual Statistics:
## mu     0.6349
## omega  1.1561
## alpha1 1.1269
## beta1  1.2663
## eta11  0.2191
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          1.28 1.47 1.88
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           1.4595 0.1445
## Negative Sign Bias  1.4988 0.1340
## Positive Sign Bias  0.9567 0.3388
## Joint Effect        6.3756 0.0947   *
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     684.2   7.898e-133
## 2    30     697.6   3.208e-128
## 3    40     764.7   1.969e-135
## 4    50     772.7   8.610e-131
##
##
## Elapsed time : 0.5274279
```

```
# Log likelihood went down and AIC as well. Therefore, not much significant improvement from previous s
```

PART 6 : APARCH

```
ict_aparch_spec <- ugarchspec(
  variance.model = list(model = "apARCH",  # APARCH model
                        garchOrder = c(1, 1)),  # GARCH(1,1)
  mean.model = list(armaOrder = c(2, 1),
                    include.mean = TRUE),
  fixed.pars = list(ma2 = 0, ma3 = 0),  # MA(0,4) with only ma1 and ma4
  distribution.model = "std"  # Standardized t-distribution
)

ict_aparch_model <- ugarchfit(spec = ict_aparch_spec, data = ict_arima_model$residuals)
ict_aparch_model
```

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

```
##
## Conditional Variance Dynamics
## -----------------------------------
## GARCH Model  : apARCH(1,1)
## Mean Model   : ARFIMA(2,0,1)
## Distribution : std
##
## Optimal Parameters
## ------------------------------------
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     -0.000372    0.000219 -1.69919 0.089283
## ar1     0.702454    0.317074  2.21543 0.026731
## ar2     0.008875    0.016062  0.55253 0.580582
## ma1    -0.744600    0.314290 -2.36915 0.017829
## omega   0.000137    0.000114  1.19555 0.231871
## alpha1  0.171773    0.024297  7.06976 0.000000
## beta1   0.841681    0.022764 36.97450 0.000000
## gamma1  0.116068    0.044975  2.58073 0.009859
## delta   1.486464    0.195937  7.58645 0.000000
## shape   3.783711    0.259274 14.59350 0.000000
##
## Robust Standard Errors:
##         Estimate  Std. Error  t value Pr(>|t|)
## mu     -0.000372    0.000228 -1.63327 0.102413
## ar1     0.702454    0.521379  1.34730 0.177883
## ar2     0.008875    0.041109  0.21588 0.829079
## ma1    -0.744600    0.518500 -1.43607 0.150983
## omega   0.000137    0.000120  1.13954 0.254480
## alpha1  0.171773    0.032373  5.30603 0.000000
## beta1   0.841681    0.031870 26.41005 0.000000
## gamma1  0.116068    0.048632  2.38664 0.017003
## delta   1.486464    0.192551  7.71986 0.000000
## shape   3.783711    0.265739 14.23847 0.000000
##
## LogLikelihood : 10333.21
##
## Information Criteria
## ------------------------------------
##
## Akaike       -4.9895
## Bayes        -4.9742
## Shibata      -4.9895
## Hannan-Quinn -4.9841
##
## Weighted Ljung-Box Test on Standardized Residuals
## ------------------------------------
##                         statistic   p-value
## Lag[1]                      3.760 5.250e-02
## Lag[2*(p+q)+(p+q)-1][8]     9.082 2.003e-09
## Lag[4*(p+q)+(p+q)-1][14]   13.366 8.546e-03
## d.o.f=3
## H0 : No serial correlation
##
## Weighted Ljung-Box Test on Standardized Squared Residuals
```

```
## ------------------------------------
##                          statistic p-value
## Lag[1]                       5.655 0.01741
## Lag[2*(p+q)+(p+q)-1][5]      6.790 0.05828
## Lag[4*(p+q)+(p+q)-1][9]      8.639 0.09626
## d.o.f=2
##
## Weighted ARCH LM Tests
## ------------------------------------
##             Statistic Shape Scale P-Value
## ARCH Lag[3]    0.7988 0.500 2.000  0.3715
## ARCH Lag[5]    2.3539 1.440 1.667  0.3982
## ARCH Lag[7]    3.0403 2.315 1.543  0.5060
##
## Nyblom stability test
## ------------------------------------
## Joint Statistic:  3.7554
## Individual Statistics:
## mu     0.07406
## ar1    0.68700
## ar2    0.14578
## ma1    0.64153
## omega  0.55365
## alpha1 0.37020
## beta1  0.49843
## gamma1 0.18655
## delta  0.52807
## shape  0.63356
##
## Asymptotic Critical Values (10% 5% 1%)
## Joint Statistic:          2.29 2.54 3.05
## Individual Statistic:     0.35 0.47 0.75
##
## Sign Bias Test
## ------------------------------------
##                    t-value   prob sig
## Sign Bias           1.2885 0.1976
## Negative Sign Bias  0.9081 0.3639
## Positive Sign Bias  0.5473 0.5842
## Joint Effect        3.5844 0.3100
##
##
## Adjusted Pearson Goodness-of-Fit Test:
## ------------------------------------
##   group statistic p-value(g-1)
## 1    20     164.8    3.008e-25
## 2    30     191.9    6.214e-26
## 3    40     209.0    4.065e-25
## 4    50     226.8    1.096e-24
##
##
## Elapsed time : 4.293964
```

```
# There is no material difference in Log likelihood and AIC from the previous sGARCH,TGARCH,eGARCH Mode
```

Conclusion

MAC is not a viable ARIMA model as the data is stationary and there is no clear trend. Hence it returns ARIMA(0,0,0) however we have used price instead to get a viable analysis but this introduced a differencing factor ARIMA(2,1,2).

ICT was a viable and good model. We modeled ARIMA(2,0,1) and modeled volatility using GARCH. The results for the other GARCH was not material and sGARCH can be used to model the volatility sufficiently.