case2

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# High-level Process and Notes

Introduction -> Background -> Load two (2) stocks data -> Log diff -> Stationary test -> ARIMA model fit -> ARIMA model analysis -> GARCH model fit -> SGARCH NORM, SGARCH SSTD, TGARCH, EGARCH, GJRGARCH -> GARCH Analysis and Comparison -> APARCH Model fit -> Conclusion Notes: 1. P-value analysis is done on each tests (if applicable). 2. Model is compared using AIC (less better) and Log likelihood (higher better). 3. Interpretation is provided as comments on last line for each code chunk. 4. Due to the nature of the stock (appears stationary) MAC log diff was not used and price is used instead for model. This is to provide further analysis since Log Returns model generates ARIMA(0,0,0). 5. For GARCH and APARCH models ICT stock was used and compared for better analysis.

# Introduction

Sector: Transportation Services Companies: MacroAsia Corporation (PSE:MAC) and International Container Terminal Services, Inc. (PSE:ICT)

# 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. NOTE: MAC stock has been in 3-5 PHP Range since 2007. Hence, SARIMA modeling (Stationary ARIMA) might be more suitable rather than ARIMA.

# ICT Background

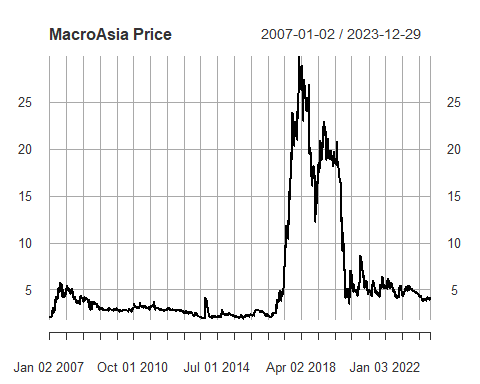
International Container Terminal Services, Inc. (ICT) was incorporated on December 24, 1987 to operate, manage and develop the Manila International Container Terminal (MICT), which handles international container cargo at the Port of Manila. ICT provide ancillary services such as storage, container stripping 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,tsm,remotes,fpp3, ggplot2, urca, plotly, ggfortify)  
remotes::install\_github("KevinKotze/tsm")

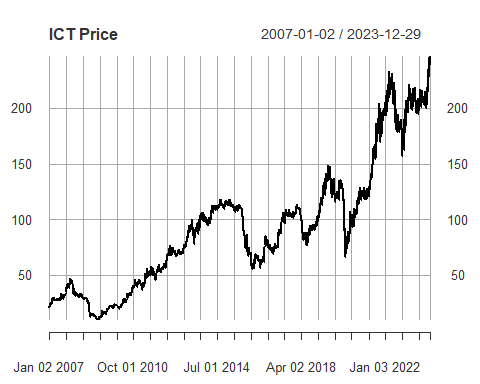
## Skipping install of 'tsm' from a github remote, the SHA1 (d5d5529e) has not changed since last install.  
## Use `force = TRUE` to force installation

# PART 1: Data Preparation

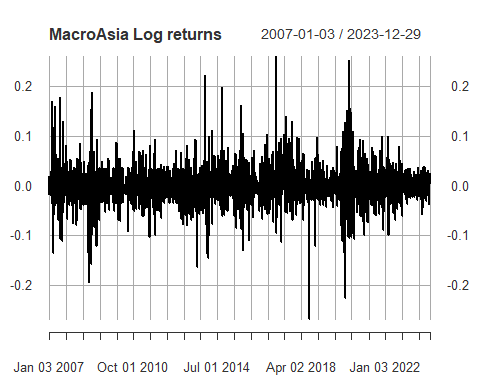
# Load MacroAsia   
mdata <- read\_excel('MAC.xlsx', sheet = 'Sheet 1')  
  
# XTS Conversion  
mdata <- data.frame(date = as.Date(mdata$date), value = mdata$close)  
mdata <- xts(mdata$value, order.by = mdata$date)  
mdata <- na.omit(mdata)  
plot(mdata, main = 'MacroAsia Price')



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')

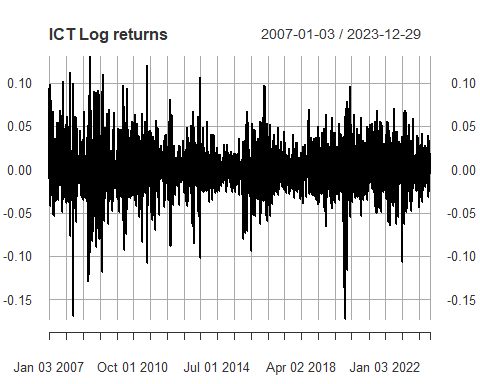


mdata\_ret <- na.omit(diff(log(mdata)))  
plot(mdata\_ret,main = 'MacroAsia Log returns')



# 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')



# volatility clustering around 2008 and 2020

# PART 2: ARIMA Model Identification

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

# 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

# Hypothesis testing = Reject Null hypothesis | Data is stationary

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

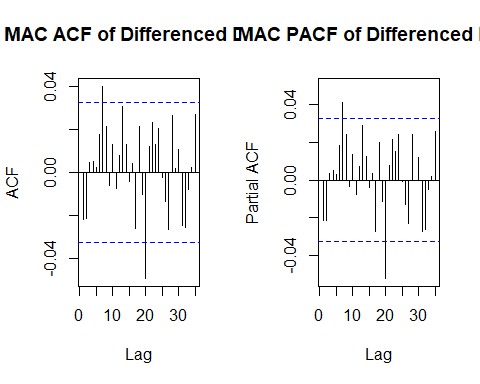
# Fail to REJECT NUll Hypothesis | Data is stationary  
  
kpss.test(idata\_ret, null = "Level") # TS is level stationary

## 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

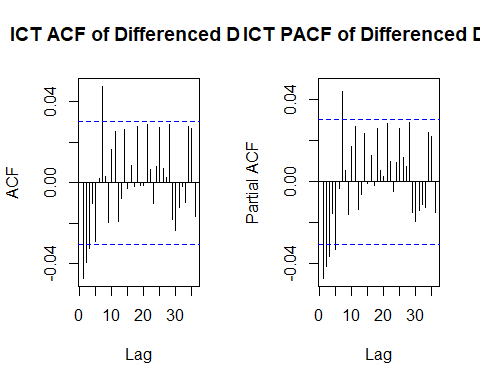
# Reject null hypothesis as data is not level stationary

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 use ARIMA to model

par(mfrow = c(1,2))  
Acf(idata\_ret, main = 'ICT ACF of Differenced Data')  
Pacf(idata\_ret, main = 'ICT PACF of Differenced Data')



# 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 use ARIMA to model

# PART 3: ARIMA Model

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)

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

# 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

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

summary(ict\_arima\_model)

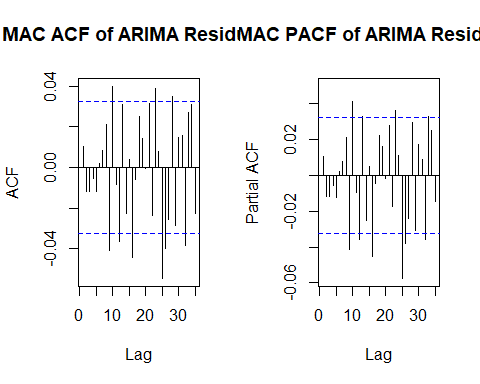
## Series: idata\_ret   
## ARIMA(2,0,1) with non-zero mean   
##   
## Coefficients:  
## ar1 ar2 ma1 mean  
## 0.5075 -0.0221 -0.5596 6e-04  
## s.e. 0.1256 0.0187 0.1250 3e-04  
##   
## sigma^2 = 0.000549: log likelihood = 9663.28  
## AIC=-19316.55 AICc=-19316.54 BIC=-19284.91  
##   
## Training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

# 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

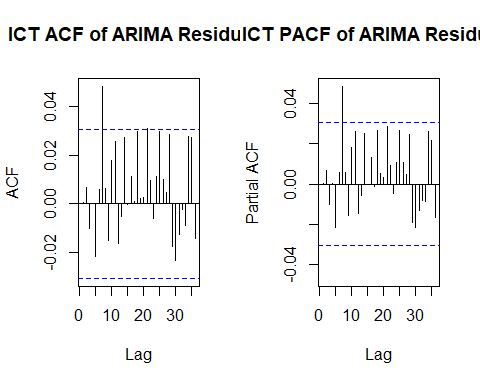
# PART 4: Residual Analysis

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")



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

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")



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

# 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

# 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

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

# 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

# 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

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

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

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

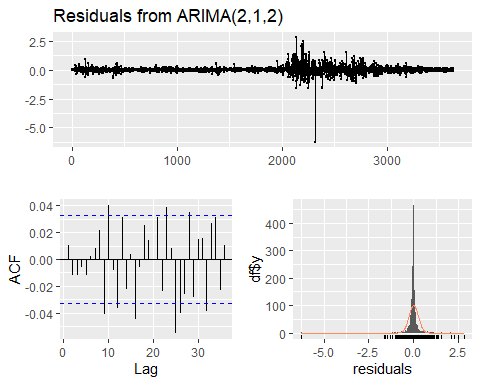
ict\_arima\_model2 <- Arima(idata, order = c(1,0,1)) # AR(1) and MA(1) components are significant  
summary(ict\_arima\_model2)

## 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

lmtest::coeftest(ict\_arima\_model2)

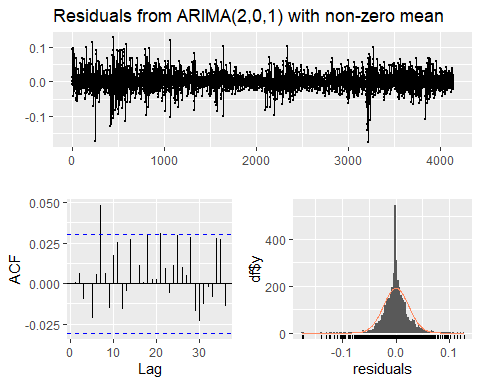
##   
## z test of coefficients:  
##   
## Estimate Std. Error z value Pr(>|z|)   
## ar1 0.99976404 0.00028459 3512.9676 <2e-16 \*\*\*  
## ma1 -0.15344287 0.01705814 -8.9953 <2e-16 \*\*\*  
## intercept 93.14184118 79.26104334 1.1751 0.2399   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01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

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

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

# Lower AIC = Better  
AIC(mac\_arima\_model) # Better Model per AIC

## [1] 550.1486

AIC(mac\_arima\_model2)

## [1] 572.9989

BIC(mac\_arima\_model)

## [1] 581.1377

BIC(mac\_arima\_model2)

## [1] 597.7912

# Lower AIC = Better  
AIC(ict\_arima\_model) # Better Model per AIC

## [1] -19316.55

AIC(ict\_arima\_model2)

## [1] 18564.18

BIC(ict\_arima\_model)

## [1] -19284.91

BIC(ict\_arima\_model2)

## [1] 18589.5

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

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

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

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

mac\_arima\_model # ARIMA(2,1,2) # Invalid model due to differencing factor

## 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

ict\_arima\_model2 # ARIMA(1,0,1) # Not used since higher AIC and BIC

## 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

ict\_arima\_model # ARIMA(2,0,1) Model used as Final model, AR2 component significant, MA component not significant

## 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

print('best model: ARIMA(2,0,1)')

## [1] "best model: ARIMA(2,0,1)"

======================================================

# PART 5 : GARCH Model

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

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 : 0.5510209

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

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

# 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 mixed and sensitive to changes  
# 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

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

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 : 0.3898969

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 stable  
# 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 : 0.866818

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 : 1.043684

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 : 0.4902868

#show(ict\_egarch\_model)  
# No material difference from previous sGARCH models

# Fit TGARCH model for comparison  
ict\_tgarch\_spec <- ugarchspec(variance.model = list(model = "fGARCH", submodel = "TGARCH", garchOrder = c(1, 1)),  
 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 : 0.53651

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

# 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 : 4.334118

# There is no material difference in AIC from the previous sGARCH,TGARCH,eGARCH Models. Log likehihood was accounted but not strictly measured for GARCH models

# PART 7: Conclusion

MAC is not a viable ARIMA model as the data is stationary (5PHP since 2007) and there is no clear trend. This was confirmed when auto.arima best model geenrates only ARIMA(0,0,0) simply after sometime the model will forecast 0. This was not viable for further analysis so for MAC the price was used to model rather than log returns. This generated in auto.arima a model with a differencing factor ARIMA(2,1,2). However this model was not used for modeling GARCH and APARCH. Mainly because of the (1) differencing fator in the model ARIMA(2,1,2) and that the stock is stationary and lacks volatility, assuming.

ICT was a viable and good model. ICT was used to model ARIMA(2,0,1) and modeled volatility using GARCH and compared several GARCH models such as different distributions (std and norm) and panel data modeling via APARCH and compared with the previous GARCH models.

The results for the other GARCH was not material and sGARCH can be used to model the volatility sufficiently. AIC (lower better) was used to compare the models.

# PART 8: Model Equation

ict\_arima\_model # Final ARIMA

## 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

# AR(1) coefficient: 0.5075  
# AR(2) coefficient: -0.0221  
# MA(1) coefficient: -0.5596  
# Mean term: 6×10^-4

Final ARIMA(2,0,1) model equation

Final GARCH Model equation

GARCH\_OBJECT <- ict\_garch\_model\_std  
# GARCH OPTIMAL PARAMETERS  
# mu(-0.000246)  
# ar1(0.699)  
# ar2(0.0123)  
# ma1(-0.742)  
  
# ict\_garch\_model\_std # FINAL SGARCH SSTD MODEL BASED ON AIC AND LOG LIKELIHOOD   
# Significant parameters (p < 0.001):  
# ar1: 0.699996 (p = 0.000015)  
# ma1: -0.742878 (p = 0.000004)  
  
# Non-significant parameters:  
# mu (mean): -0.000246 (p = 0.262133)  
# ar2: 0.012324 (p = 0.527241)

# PART 9 APPENDIX: MULTIVARIATE GARCH

library(zoo)  
residuals\_1 <- ict\_arima\_model$residuals  
residuals\_2 <- ict\_arima\_model2$residuals  
  
# Combine into a multivariate matrix  
residuals\_matrix <- cbind(residuals\_1, residuals\_2)  
  
residuals\_matrix <- apply(residuals\_matrix, 2, function(x) na.locf(x, na.rm = FALSE))  
residuals\_matrix <- na.omit(residuals\_matrix)  
dim(residuals\_matrix) # shape of matrix n>2

## [1] 4151 2

any(is.na(residuals\_matrix)) # FALSE

## [1] FALSE

library(rmgarch) # install.packages('rmgarch')

## Warning: package 'rmgarch' was built under R version 4.3.3

##   
## Attaching package: 'rmgarch'

## The following objects are masked from 'package:dplyr':  
##   
## first, last

## The following objects are masked from 'package:xts':  
##   
## first, last

data\_m <- residuals\_matrix  
spec <- ugarchspec(variance.model = list(model = "sGARCH"),   
 mean.model = list(armaOrder = c(0,0)))  
dcc.spec <- dccspec(uspec = multispec(replicate(2, spec)),   
 dccOrder = c(1,1), model = "DCC")  
dcc.fit <- dccfit(dcc.spec, data = data\_m)  
show(dcc.fit)

##   
## \*---------------------------------\*  
## \* DCC GARCH Fit \*  
## \*---------------------------------\*  
##   
## Distribution : mvnorm  
## Model : DCC(1,1)  
## No. Parameters : 11  
## [VAR GARCH DCC UncQ] : [0+8+2+1]  
## No. Series : 2  
## No. Obs. : 4151  
## Log-Likelihood : 2331.342  
## Av.Log-Likelihood : 0.56   
##   
## Optimal Parameters  
## -----------------------------------  
## Estimate Std. Error t value Pr(>|t|)  
## [residuals\_1].mu 0.000326 0.000288 1.131775 0.257729  
## [residuals\_1].omega 0.000017 0.000005 3.044803 0.002328  
## [residuals\_1].alpha1 0.138855 0.023997 5.786248 0.000000  
## [residuals\_1].beta1 0.840323 0.025223 33.315663 0.000000  
## [residuals\_2].mu 0.034628 0.017446 1.984814 0.047165  
## [residuals\_2].omega 0.012184 0.010220 1.192239 0.233167  
## [residuals\_2].alpha1 0.085256 0.029750 2.865778 0.004160  
## [residuals\_2].beta1 0.913744 0.032588 28.039110 0.000000  
## [Joint]dcca1 0.000000 0.000093 0.000095 0.999924  
## [Joint]dccb1 0.959981 0.319413 3.005450 0.002652  
##   
## Information Criteria  
## ---------------------  
##   
## Akaike -1.1180  
## Bayes -1.1012  
## Shibata -1.1180  
## Hannan-Quinn -1.1120  
##   
##   
## Elapsed time : 2.345125

bekk\_spec <- gogarchspec(mean.model = list(model = "constant"),   
 variance.model = list(model = "BEKK"))  
#bekk\_fit <- gogarchfit(bekk\_spec, data = data\_m)