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Time Series and Forecasting Methods

Assignment: Time Series Analysis of JP Morgan US Fund

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In this assignment we will perform a time series analysis on JP Morgan US Fund.

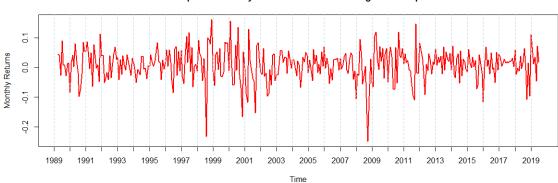
We will use the $OSGIX\ JPMorgan\ Mid\ Cap\ Growth\ A$ as a dependent variable and the below as the independent variables:

$$x_1 = Mkt - Rf, x_2 = SMB, x_3 = HML, x_4 = RMW, x_5 = CMA, x_6 = MOM$$

The starting date of dataset is August 1987 until July 2019. However, since we observe that there are null values from August 198 until April 1989 for this specific dependent variable we will start the analysis from April 1989 until July 2019.

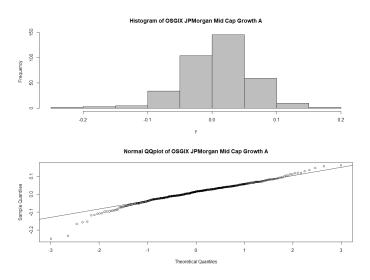
Data exploration

To start with, we will try to build time series models on some dependent variable OSGIX (AR, MA, ARMA). We will first test the hypothesis that the series of OSGIX is stationary over time using unit root testing along with other tests.



Time Series plot of Monthly Returns of OSGIX JPMorgan Mid Cap Growth A

From the above plot we can observe that the mean of the data is around zero, specifically between -0.1 and 0.1, and there is no trend. However, there are a few peaks during random time periods. We can assume from the above plot that the series seems to be stationary. Now, we will proceed with the histogram and the QQ-plot.



From the above histogram we can observe that there is a slight left skewness in the distribution of the data and the data appear to roughly follow a zero-mean normal distribution. In addition we observe that there is a slight left fat tail in the distribution.

In this case, we will proceed with the Shapiro-Wilk normality test.

```
Shapiro-Wilk normality test
```

```
data: y
W = 0.96645, p-value = 2.019e-07
```

Since p-value = 2.019e-07, for a=0.05 significance level, we reject the null hypothesis so we assume that the data is not normally distributed.

Now we can proceed with the augmented Dickey-Fuller test of unit root based on Random Walk with Drift, since we can do so as there was not any trend observed in the previous plots.

The value of the test statistic is: -17.2711 149.146

Test regression drift

```
Call:
lm(formula = z.diff ~ z.lag.1 + 1)
```

```
Min 1Q Median 3Q Max -0.243243 -0.030247 0.003265 0.033924 0.150493
```

Coefficients:

Residuals:

```
Estimate Std. Error t value Pr(>|t|)
(Intercept) 0.008380 0.002875 2.914 0.00379 **
z.lag.1 -0.904326 0.052361 -17.271 < 2e-16 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
Residual standard error: 0.05399 on 361 degrees of freedom Multiple R-squared: 0.4524, Adjusted R-squared: 0.4509 F-statistic: 298.3 on 1 and 361 DF, p-value: < 2.2e-16
```

Value of test-statistic is: -17.2711 149.146

```
Critical values for test statistics:

1pct 5pct 10pct
tau2 -3.44 -2.87 -2.57
phi1 6.47 4.61 3.79
```

Let assume that the initial model is $Y_t = \mu + \rho Y_{t-1} + \epsilon_t$ and by applying reparametrization we get $\Delta Y = \mu + \beta Y_{t-1} + \epsilon_t$. So,

$$H_0$$
: $\beta = 0$
 H_a : $\beta \neq 0$

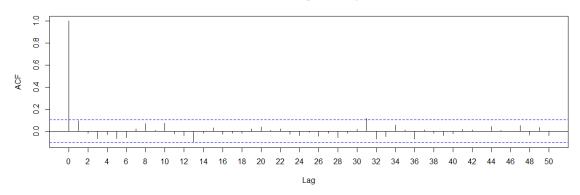
From the above results we observe that $\hat{\mu} = 0.008380$ and the $\hat{\beta} = -0.904326$. The value of test-statistic is: -17.2711 whereas the critical values are $\{-3.44, -2.87, -2.57\}$ for a $\{0.01, 0.05, 0.1\}$ significance levels respectively. This means that we reject the null hypothesis that the model has a unit root.

Now, we can proceed with the Box-Jenkins methodology.

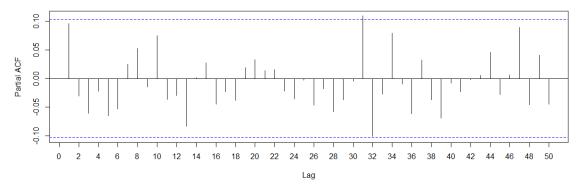
1.Identification step

To begin with, we will plot the ACF and the PACF of OSGIX.

ACF of OSGIX JPMorgan Mid Cap Growth A



PACF of OSGIX JPMorgan Mid Cap Growth A



It is known that the ACF and PACF plots should be considered together to define the process. For the AR process, we expect that the ACF plot will gradually decrease and simultaneously the PACF should have a sharp drop after p significant lags. To define a MA process, we expect the opposite from the ACF and PACF plots, meaning that: the ACF should show a sharp drop after a certain q number of lags while PACF should show a geometric or gradual decreasing trend.

On the above plots we observe that the fifty lag observations are located within the boundaries of significance, except for the lag 31 of PACF, where we observe that there is a slight violation. We have some indications of non-statistical significant autocorrelations regarding the values of the time series, however we will proceed with the Box-Pierce test for autocorrelations.

H₀:
$$\rho_1 = \rho_2 = ... = \rho_{50} = 0$$

H_a: $\rho_i \neq 0$ for at least one $i \leq 50$

Box-Pierce test

data: y X-squared = 36.767, df = 50, p-value = 0.9183

From the above, since p-value = 0.9183, we do not reject the null hypothesis for a=0.05 significance level which means that $\rho_1=\rho_2=...=\rho_{50}=0$. In fact, now we can clearly state that we do not have statistically significant autocorrelations for a=0.05 in any lag for OSGIX.

2. Estimation step

Since we do not have statistically significant autocorrelations for a=0.05 in any lag for OSGIX, we will proceed with the below model:

$$Y_t = \mu + \epsilon_t$$

Call:

arima(x = OSGIX, order = c(0, 0, 0))

Coefficients:

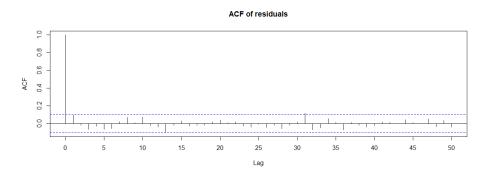
intercept

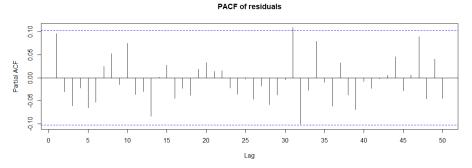
0.0056

s.e. 0.0023

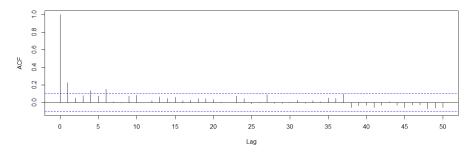
 $sigma^2$ estimated as 0.001412: log likelihood = 491.7, aic = -979.41

3. Diagnostic plots

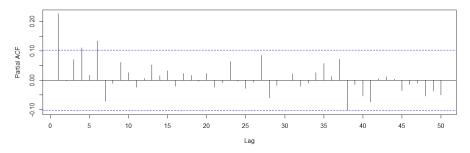








PACF of squared residuals



From the above plots can state that we should probably use a GARCH model. It is known that the ACF plot of squared residuals gives us information about the appropriate GARCH terms, whereas the PACF plot gives us information about the appropriate ARCH terms.

We can observe a slightly statistically significant autocorrelations for a=0.05 in lags 1, 4, 6 of squared residuals and a slightly statistically significant partial autocorrelations for a=0.05 in lags 1, 4 and 6.

This means that there is probably a violation of heteroscedasticity of the observed data.

Heteroscedasticity issue

Box-Ljung test

data: residuals^2
X-squared = 74.181, df = 50, p-value = 0.0148

We observe that the p-value = 0.0148, so this means that we reject the null hypothesis. In other words, there is a $\rho_i \neq 0$.

Developing appropriate model

Having said the above, we will built an ARCH(1) model and a GARCH(1,1) and we will check which one fits better based on the AIC criterion.

ARCH(1)

```
Title:
 GARCH Modelling
 garchFit(formula = \sim garch(1, 0), data = y, trace = F)
Mean and Variance Equation:
 data \sim garch(1, 0)
<environment: 0x000001fadc1d9e40>
 [data = y]
Conditional Distribution:
 norm
Coefficient(s):
               omega
                         alpha1
0.0129388 0.0021041 0.2890552
Std. Errors:
 based on Hessian
Error Analysis:
        Estimate Std. Error t value Pr(>|t|)
       0.0129388 0.0027155
                                4.765 1.89e-06 ***
                                9.438 < 2e-16 ***
omega 0.0021041
                   0.0002229
alpha1 0.2890552
                   0.0953026
                                3.033 0.00242 **
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Log Likelihood:
558.5041
            normalized: 1.534352
Description:
 Sun Nov 07 14:05:32 2021 by user: sofia
Standardised Residuals Tests:
                                Statistic p-Value
 Jarque-Bera Test
                         Chi^2 57.66983 2.999823e-13
 Shapiro-Wilk Test R
                                0.978392 2.853769e-05
                        W
 Ljung-Box Test
                         Q(10) 10.74748 0.3775276
                    R
 Ljung-Box Test
                    R
                         Q(15)
                               16.82526
                                         0.3294171
 Ljung-Box Test
                    R
                         Q(20)
                                18.14795
                                         0.5776627
                               20.91129
 Ljung-Box Test
                    R^2 Q(10)
                                         0.0217207
                    R^2 Q(15)
 Ljung-Box Test
                               26.41649
                                         0.03386634
 Ljung-Box Test
                    R^2 Q(20) 32.09888
                                         0.04225605
 LM Arch Test
                         TR^2
                                15.80833
                                         0.2001733
Information Criterion Statistics:
               BIC
                                   HQIC
                          SIC
```

-3.052220 -3.020101 -3.052354 -3.039454

So from the above we can conclude the below:

Proposed model: $Y_t = 0.0129388 + \epsilon_t$, $\sigma^2 = 0.0021041 + 0.2890552\epsilon_{t-1}^2$

Standardised Residuals Tests:

- Jarque-Bera Test for Residuals: We observe that the p-Value = 2.999823e-13. This means that we reject the null hypothesis at a=0.05 significance level. In other words, t there is a violation in the normality of the Residuals.
- Shapiro-Wilk Test for Residuals: We observe that the p-Value = 2.853769e-05. This means that we reject the null hypothesis at a = 0.05 significance level. In other words, there is a violation in the normality of the Residuals.
- Ljung-Box Test for Residuals: There are three Ljung-Box tests for the Residuals and we observe that all the three p-Values are greater than a = 0.05 significance level. This means that we do not reject the null hypothesis, so there is no statistically significant autocorrelations in lags 10, 15 and 20.
- Ljung-Box Test for squared Residuals: There are three Ljung-Box tests for the squared Residuals and we observe that all the three p-Values are less than a = 0.05 significance level. This means that we reject the null hypothesis in lags 10, 15 and 20.
- LM Arch Test for Residuals: The ARCH-LM test is the standard test to detect autore-gressive conditional heteroscedasticity. We observe that the p-Value = 0.2001733. This means that we do not reject the null hypothesis at a=0.05 significance level, therefore the residuals are heteroscedastic.

GARCH(1, 1)

```
Title:
 GARCH Modelling
Call:
 garchFit(formula = ~garch(1, 1), data = y, trace = F)
Mean and Variance Equation:
 data \sim qarch(1, 1)
<environment: 0x000001fadbe406d8>
 [data = y]
Conditional Distribution:
 norm
Coefficient(s):
                            alpha1
                                          beta1
        mu
                 omega
           0.00017365 0.15819631
                                     0.79174581
0.01056794
Std. Errors:
 based on Hessian
```

```
Error Analysis:
```

```
Estimate
                 Std. Error
                             t value Pr(>|t|)
       1.057e-02
                   2.484e-03
                                4.255 2.09e-05 ***
mu
omega 1.736e-04
                   8.811e-05
                                1.971 0.04874 *
alpha1 1.582e-01
                   5.114e-02
                                3.094
                                       0.00198 **
beta1 7.917e-01
                   6.164e-02
                               12.844 < 2e-16 ***
```

- - -

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

Log Likelihood:

569.3302 normalized: 1.564094

Description:

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Standardised Residuals Tests:

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	89.06871	0
Shapiro-Wilk Test	R	W	0.9688967	5.106265e-07
Ljung-Box Test	R	Q(10)	12.8709	0.2309797
Ljung-Box Test	R	Q(15)	17.54966	0.2870802
Ljung-Box Test	R	Q(20)	20.20024	0.4454684
Ljung-Box Test	R^2	Q(10)	2.593138	0.9894479
Ljung-Box Test	R^2	Q(15)	4.59588	0.9950302
Ljung-Box Test	R^2	Q(20)	6.279072	0.9984643
LM Arch Test	R	TR^2	3.066375	0.995057

Information Criterion Statistics:

```
AIC BIC SIC HQIC -3.106210 -3.063384 -3.106448 -3.089189
```

So from the above we can conclude the below:

Proposed model: $Y_t = 1.057e^{-02} + \epsilon_t$, $\sigma^2 = 1.736e^{-04} + 1.582e^{-01}\epsilon_{t-1}^2 + 7.917e^{-0}\sigma_{t-1}^2$

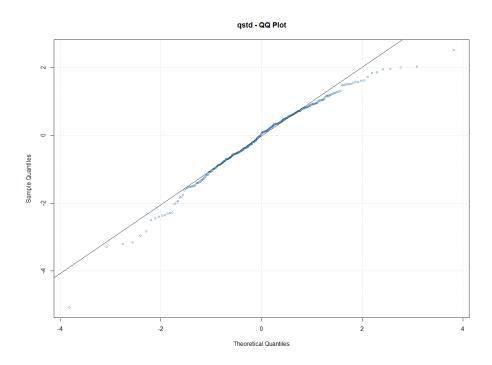
Standardised Residuals Tests:

- Jarque-Bera Test for Residuals: We observe that the p-Value = 0. This means that we reject the null hypothesis at a = 0.05 significance level. In other words, there is a violation in the normality of the Residuals.
- Shapiro-Wilk Test for Residuals: We observe that the p-Value = $5.106265e^{-07}$. This means that we reject the null hypothesis at a = 0.05 significance level. In other words, there is a violation in the normality of the Residuals.
- Ljung-Box Test for Residuals: There are three Ljung-Box tests for the Residuals and we observe that all the three p-Values are greater than a=0.05 significance level. This means that we do not reject the null hypothesis, so there is no statistically significant autocorrelations in lags 10, 15 and 20.
- Ljung-Box Test for squared Residuals: There are three Ljung-Box tests for the squared Residuals and we observe that all the three p-Values are greater than a = 0.05 significance level. This means that we do not reject the null hypothesis in lags 10, 15 and 20.

• LM Arch Test for Residuals: The ARCH-LM test is the standard test to detect autoregressive conditional heteroscedasticity. We observe that the p-Value = 0.995057. This means that we do not reject the null hypothesis at a=0.05 significance level, therefore the residuals are heteroscedastic.

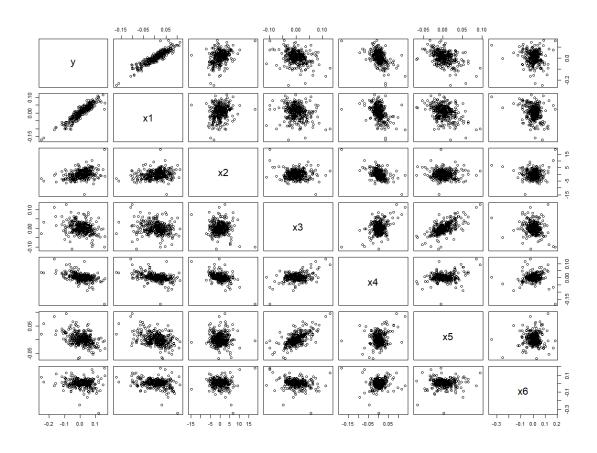
Taking into consideration the two models ARCH(1) and GARCH(1,1) we observe that the AIC is -3.052220 and -3.106210 respectively. Since the GARCH(1,1) has a lower AIC will we proceed with model.

In addition, running the Jarque-Bera and Shapiro-Wilk Test for Residual we have observed a slight violation the best scenario is to use a Student-t distribution.



Regression analysis

To begin with, we will start with a scatterplot of variables' correlation.



```
хЗ
                                   х5
                 x2
                             x4
                                          х6
У
    1.00
          0.92
                0.37 -0.29 -0.47 -0.43 -0.12
x1
    0.92
          1.00
                0.21 -0.17 -0.40 -0.38
                                       -0.25
   0.37
          0.21
                1.00 -0.10 -0.46 -0.06
                                        0.00
                                  0.65 -0.20
x3 -0.29 -0.17 -0.10
                      1.00
                            0.35
x4 -0.47 -0.40 -0.46
                      0.35
                            1.00
                                  0.22
                                        0.08
x5 -0.43 -0.38 -0.06
                      0.65
                                  1.00
                                        0.03
                            0.22
                                        1.00
x6 -0.12 -0.25 0.00 -0.20
                            0.08
                                  0.03
```

n= 364

```
Ρ
          x1
                  x2
                         х3
                                 x4
                                        x5
          0.0000\ 0.0000\ 0.0000\ 0.0000\ 0.0000\ 0.0235
                  0.0000 \ 0.0010 \ 0.0000 \ 0.0000 \ 0.0000
x1 0.0000
x2 0.0000 0.0000
                         0.0619 0.0000 0.2842 0.9286
x3 0.0000 0.0010 0.0619
                                0.0000 0.0000 0.0001
x4 0.0000 0.0000 0.0000 0.0000
                                        0.0000 0.1443
x5 0.0000 0.0000 0.2842 0.0000 0.0000
                                               0.5066
x6 0.0235 0.0000 0.9286 0.0001 0.1443 0.5066
```

From the previous page we observe that there is a statistically significant correlation among the variables Y and x1, x2, x3, x4, x5, x6 at a = 0.05 significance level. This means that the variables are independent.

Let's proceed with the regression model:

```
Call
```

```
lm(formula = y \sim x1 + x2 + x3 + x4 + x5 + x6)
```

Residuals:

```
Min 1Q Median 3Q Max -0.069669 -0.010662 0.000553 0.009312 0.077207
```

Coefficients:

```
Estimate Std. Error t value Pr(>|t|)
                       0.0009946
                                   1.480
(Intercept)
            0.0014722
                                            0.1397
                                  41.534
х1
            1.1074995
                       0.0266650
                                          < 2e-16 ***
х2
            0.0032032
                       0.0003498
                                   9.156
                                          < 2e-16 ***
x3
            -0.1167858
                       0.0470280
                                  -2.483
                                            0.0135 *
            -0.0123838
                       0.0469052
                                  -0.264
                                            0.7919
x4
            -0.1491719
                       0.0663786
                                  -2.247
                                            0.0252 *
x5
х6
            0.1013989
                       0.0215202
                                   4.712 3.52e-06 ***
Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

Residual standard error: 0.01774 on 357 degrees of freedom Multiple R-squared: 0.8943, Adjusted R-squared: 0.8926 F-statistic: 503.6 on 6 and 357 DF, p-value: < 2.2e-16

From the above we observe that the Adjusted R-squared = 0.8926, which is really good. We observe also that all coefficients of the x variables, except for x4, are statistically significant. We will use the stepwise elimination methods in order to insert or remove independent variables from our model according to BIC.

Stepwise elimination method

```
Step Df
             Deviance Resid. Df Resid. Dev
                                                 AIC
                            363 1.0631543 -2122.273
       NA
                   NA
2 + x1 - 10.892201831
                            362 0.1709525 -2785.523
                                0.1351673 -2869.016
3 + x2 - 10.035785200
                            361
4 + x3 - 10.014993442
                            360
                                 0.1201739 -2909.813
5 + x6 - 10.006253588
                                 0.1139203 -2927.265
                            359
6 + x5 -1 0.001569866
                            358 0.1123504 -2930.316
```

Call:

```
lm(formula = y \sim x1 + x2 + x3 + x6 + x5)
```

Coefficients:

(Intercept)	x1	x2	x3	x6	x5
0.001413	1.109789	0.003242	-0.121056	0.100834	-0.146394

The process starts with an empty model. In the first step it adds 1 because it offers the greater reduction of BIC in comparison to the other variables. Then it adds x^2 e.t.c.

Combining everything we have done so far, we will proceed with a multiple regression model, with external regressors and the proposed Garch(1,1).

```
*-----*

* GARCH Model Fit *

*-----*
```

Conditional Variance Dynamics

GARCH Model : sGARCH(1,1)
Mean Model : ARFIMA(0,0,0)

Distribution: norm

Optimal Parameters

	Estimate	Std. Error	t value	Pr(> t)
mu	0.001332	0.000796	1.6722	0.094476
mxreg1	1.042074	0.021211	49.1284	0.000000
mxreg2	0.003633	0.000307	11.8506	0.000000
mxreg3	-0.094460	0.042818	-2.2061	0.027380
mxreg4	-0.050626	0.044699	-1.1326	0.257384
mxreg5	-0.322848	0.057979	-5.5684	0.000000
mxreg6	0.115617	0.020500	5.6398	0.000000
omega	0.000029	0.000013	2.1983	0.027928
alpha1	0.242350	0.073371	3.3031	0.000956
beta1	0.661919	0.098581	6.7144	0.000000

Robust Standard Errors:

```
        mu
        0.001332
        0.000893
        1.49206
        0.135684

        mxreg1
        1.042074
        0.022669
        45.96893
        0.000000

        mxreg2
        0.003633
        0.000354
        10.25949
        0.000000

        mxreg3
        -0.094460
        0.056369
        -1.67575
        0.093787

        mxreg4
        -0.050626
        0.050731
        -0.99792
        0.318320

        mxreg5
        -0.322848
        0.067183
        -4.80549
        0.000002

        mxreg6
        0.115617
        0.026837
        4.30819
        0.000016

        omega
        0.000029
        0.000015
        2.02134
        0.043245

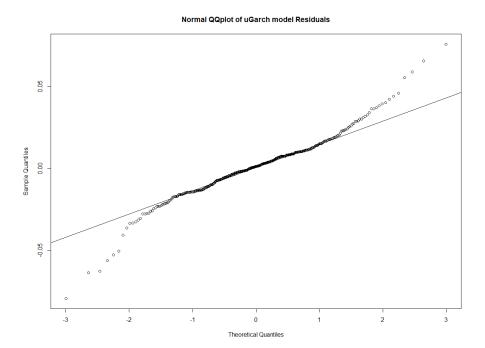
        alphal
        0.242350
        0.083708
        2.89519
        0.003789

        betal
        0.661919
        0.113562
        5.82868
        0.000000
```

LogLikelihood: 999.8167

Information Criteria

Akaike -5.4386 Bayes -5.3315 Shibata -5.4400 Hannan-Quinn -5.3960 From the above we also observe that x3, x4 are possibly statistically insignificant, since their corresponding p-values are greater than the a=0.5 significance level.



From the above plot we observe that there are fat tails so the normality have been violated. In addition, running the Jarque-Bera and Shapiro-Wilk Test for Residual we have observed a violation and as said also in the begging the best scenario is to use a Student-t distribution.

Jarque Bera Test

```
data: residuals(model_res)
X-squared = 140.49, df = 2, p-value < 2.2e-16</pre>
```

AIC and BIC information criteria

Excluding x3

In	fo	rr	na	t	i	01	า	(21	r:	Ĺ	te	9	r:	Ĺá	3															
		-	-		-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

Akaike -5.4285 Bayes -5.3214 Shibata -5.4299 Hannan-Quinn -5.3859

Excluding x4

Information Criteria

Akaike -5.4419 Bayes -5.3348 Shibata -5.4433 Hannan-Quinn -5.3993

Excluding x3 and x4

Information Criteria

Akaike -5.4276 Bayes -5.3312 Shibata -5.4288 Hannan-Quinn -5.3893

From the above we observe that the best AIC score is obtained when we removed only the x4 regressor. So, the proposed model is:

$$\begin{split} Y_t &= \gamma_0 + \gamma_1 Y_{1,t} + \gamma_2 Y_{2,t} + \gamma_3 Y_{3,t} + \gamma_5 Y_{5,t} + \gamma_6 Y_{6,t} \\ & \epsilon_t | \Phi t - 1 \sim N(0, \sigma_t^2) \\ & \sigma_t^2 = a_0 + a \epsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \end{split}$$