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LAMPIRAN

Lampiran 1. Data Penelitian

Periode	LQ45	IHSG	ISSI	Inflasi	Nilai Tukar
Januari 2018	1.095,78	6.465,09	192,70	3,25	13447,36
Februari 2018	1.106,51	6.585,65	195,39	3,18	13657,95
Maret 2018	1.047,48	6.355,09	187,44	3,40	13827,29
April 2018	1.011,84	6.215,51	185,83	3,41	13872,05
Mei 2018	941,16	5.883,80	176,07	3,23	14130,00
Juni 2018	930,37	5.903,13	175,63	3,12	14106,36
Juli 2018	924,88	5.866,61	175,10	3,18	14486,64
Agustus 2018	945,12	5.984,44	177,41	3,20	14632,57
September 2018	925,70	5.870,37	174,07	2,88	14943,00
Oktober 2018	912,25	5.798,11	172,93	3,16	15254,74
November 2018	947,15	5.950,36	176,47	3,23	14770,38
Desember 2018	980,54	6.137,17	181,57	3,13	14569,47
Januari 2019	1.014,98	6.383,26	189,50	2,82	14233,91
Februari 2019	1.018,72	6.492,39	193,09	2,57	14105,37
Maret 2019	1.011,90	6.450,89	190,87	2,48	14282,10
April 2019	1.017,59	6.447,70	189,19	2,83	14213,32
Mei 2019	956,24	6.103,30	178,52	3,32	14464,76
Juni 2019	1.001,00	6.297,61	183,76	3,28	14297,73
Juli 2019	1.021,96	6.387,30	186,97	3,32	14114,26
Agustus 2019	982,87	6.262,87	187,19	3,49	14313,05
September 2019	982,35	6.259,74	191,21	3,39	14181,57
Oktober 2019	965,79	6.159,34	188,74	3,13	14188,21
November 2019	975,16	6.125,94	185,70	3,00	14139,06
Desember 2019	1.000,04	6.217,98	186,32	2,72	14087,54
Januari 2020	1.013,91	6.225,77	182,78	2,68	13800,89
Februari 2020	951,56	5.855,49	168,98	2,98	13845,03
Maret 2020	745,90	4.786,92	139,44	2,96	15270,55
April 2020	690,85	4.600,98	137,78	2,67	15946,77
Mei 2020	684,13	4.599,33	141,09	2,19	14980,72
Juni 2020	763,53	4.925,87	147,40	1,96	14266,93
Juli 2020	789,82	5.062,86	148,39	1,54	14655,32
Agustus 2020	823,13	5.226,65	151,51	1,32	14798,13
September 2020	785,23	5.063,16	147,23	1,42	14922,20

Periode	LQ45	IHSG	ISSI	Inflasi	Nilai Tukar
Oktober 2020	778,32	5.071,64	149,10	1,44	14822,88
November 2020	865,90	5.483,82	160,09	1,59	14308,00
Desember 2020	940,46	5.978,13	176,67	1,68	14243,95
Januari 2021	978,46	6.247,35	184,62	1,55	14132,21
Februari 2021	950,58	6.199,80	182,74	1,38	14112,31
Maret 2021	941,79	6.252,84	181,71	1,37	14489,48
April 2021	898,16	6.012,27	177,28	1,42	14630,98
Mei 2021	874,17	5.877,76	173,13	1,68	14464,76
Juni 2021	879,62	6.040,89	173,81	1,33	14409,92
Juli 2021	840,72	6.055,42	175,18	1,52	14583,75
Agustus 2021	850,32	6.111,32	174,87	1,59	14469,69
September 2021	866,17	6.114,24	175,38	1,60	14328,24
Oktober 2021	947,70	6.525,46	185,56	1,66	14269,45
November 2021	950,55	6.630,99	187,77	1,75	14334,82
Desember 2021	938,93	6.585,78	188,01	1,87	14400,56
Januari 2022	945,69	6.649,14	188,09	2,18	14406,92
Februari 2022	969,71	6.816,80	192,89	2,06	14422,81
Maret 2022	1.005,27	6.958,40	195,98	2,64	14420,38
April 2022	1.047,54	7.198,95	204,85	3,47	14440,58
Mei 2022	1.016,79	6.851,61	202,54	3,55	14681,04
Juni 2022	1.018,10	7.046,87	204,00	4,35	14762,02
Juli 2022	959,00	6.769,37	200,08	4,94	15059,30
Agustus 2022	1.012,21	7.115,57	208,45	4,69	14924,89
September 2022	1.025,06	7.188,82	209,73	5,95	15046,63
Oktober 2022	996,33	6.986,44	204,83	5,71	15494,56
November 2022	1.003,34	7.046,16	207,26	5,42	15737,02
Desember 2022	948,87	6.840,13	212,34	5,51	15693,07
Januari 2023	926,02	6768,61	214,06	5,28	15371,71
Februari 2023	950,62	6885,58	212,55	5,47	15201,63
Maret 2023	933,52	6748,64	207,95	4,97	15377,22
April 2023	947,23	6831,37	211,43	4,33	14941,05
Mei 2023	942,66	6735,19	204,56	4	14884,91
Juni 2023	949,31	6673,74	199,58	3,52	15006,66
Juli 2023	958,59	6826,16	205,97	3,08	15114,95
Agustus 2023	962,18	6899,06	209,99	3,27	15321,36
September 2023	960,75	6967,65	216,72	2,28	15430,97

Periode	LQ45	IHSG	ISSI	Inflasi	Nilai Tukar
Oktober 2023	925,96	6861,98	212,26	2,56	15819,93
November 2023	913,32	6909,09	207,15	2,86	15695,50
Desember 2023	953,25	7166,34	210,29	2,61	15590,94

Lampiran 2. Analisis Deskriptif

```
# Package
library(readxl)
library(ggplot2)
library(copula)
library(gcmr)

# Input Data
Data <- read_excel("D:/NAY/FD BIRU/gcmr/hasil/calondataupdate.xlsx"
,
                   col_types = c("text", "date", "numeric",
                                 "numeric", "numeric", "numeric", "
numeric"))
# Definisi Peubah
y1 <- Data$LQ45
y2 <- Data$IHSG
y3 <- Data$ISSI
x1 <- Data$Inflasi
x2 <- Data$`Nilai Tukar`

# Deskriptif & Plot #==========================================
Data_des = as.data.frame(Data[,3:7])
Des <- matrix(0,5,4)
colnames(Des) <- c("Minimal","Maksimal","Rata-rata","Varians")
rownames(Des) <- names(Data_des)
for (d in 1:5) {
  Des[d,1] = round(min(Data_des[,d]),3)
  Des[d,2] = round(max(Data_des[,d]),3)
  Des[d,3] = round(mean(Data_des[,d]),3)
  Des[d,4] = round(var(Data_des[,d]),3)
}
Des

##                Minimal  Maksimal Rata-rata    Varians
## LQ45           684.129  1106.512   940.814   6968.915
## IHSG          4599.331  7198.951  6276.112 397517.075
## ISSI           137.775   216.715   185.774    381.979
## Inflasi          1.320     5.950     2.952      1.417
## Nilai Tukar 13447.364 15946.769 14634.060 312612.237

Dy1 = cbind.data.frame(Periode = as.Date(Data$Tanggal), `Harga Saha
m LQ45`  = y1)
ggplot(Dy1, aes(x = Periode, y = `Harga Saham LQ45` )) +
  geom_line(colour="orange", size = 0.8) +
  scale_x_date(date_labels = "%m-%Y", date_breaks = "4 month") +
  theme(axis.text.x = element_text(angle = 90))

Dy2 = cbind.data.frame(Periode = as.Date(Data$Tanggal), `Harga Saha
m IHSG` = y2)
```

```
ggplot(Dy2, aes(x = Periode, y = `Harga Saham IHSG` )) +
  geom_line(colour="darkgreen", size = 0.8) +
  scale_x_date(date_labels = "%m-%Y", date_breaks = "4 month") +
  theme(axis.text.x = element_text(angle = 90))

 Dy3 = cbind.data.frame(Periode = as.Date(Data$Tanggal), `Harga Sah
am ISSI` = y3)
ggplot(Dy3, aes(x = Periode, y = `Harga Saham ISSI` )) +
  geom_line(colour="darkred", size = 0.8) +
  scale_x_date(date_labels = "%m-%Y", date_breaks = "4 month") +
  theme(axis.text.x = element_text(angle = 90))

Dx1 = cbind.data.frame(Periode = as.Date(Data$Tanggal), Inflasi = x
1)
ggplot(Dx1, aes(x = Periode, y = Inflasi )) +
  geom_line(colour="deepskyblue", size = 0.8) +
  scale_x_date(date_labels = "%m-%Y", date_breaks = "4 month") +
  theme(axis.text.x = element_text(angle = 90))

Dx2 = cbind.data.frame(Periode = as.Date(Data$Tanggal), `Nilai Tuka
r` = x2)
ggplot(Dx2, aes(x = Periode, y = `Nilai Tukar` )) +
  geom_line(colour="green", size = 0.8) +
  scale_x_date(date_labels = "%m-%Y", date_breaks = "4 month") +
  theme(axis.text.x = element_text(angle = 90))

#plot sebaran data
par(mfrow=c(1,2))
plot(x1, y1, xlab = "Inflasi (persen)", ylab = "LQ45 (rupiah)")
plot(x2, y1, xlab = "Nilai Tukar (rupiah)", ylab = "LQ45 (rupiah)")

plot(x1, y2, xlab = "Inflasi (persen)", ylab = "IHSG (rupiah)")
plot(x2, y2, xlab = "Nilai Tukar (rupiah)", ylab = "IHSG (rupiah)")

plot(x1, y3, xlab = "Inflasi (persen)", ylab = "ISSI (rupiah)")
plot(x2, y3, xlab = "Nilai Tukar (rupiah)", ylab = "ISSI (rupiah)")
```

Lampiran 3. Uji Korelasi Pearson

```
# Korelasi pearson #============================================
y = as.data.frame(Data[,3:5])
x = as.data.frame(Data[,6:7])
pe = matrix(0,2,3)
colnames(pe) = c("S","p-value","rho"); rownames(pe) = c("a","b")
Pears = list()
for (s1 in 1:3) {
  for (s2 in 1:2) {
    korsr = cor.test(y[,s1], x[,s2], method='pearson')
    rownames(pe)[s2] = paste(names(y[s1]), "and", names(x[s2]))
    pe[s2,1] = korsr$statistic
    pe[s2,2] = korsr$p.value
    pe[s2,3] = korsr$estimate
  }
  Pears[[s1]] = pe
}
Pearson = rbind(Pears[[1]],Pears[[2]],Pears[[3]]); Pearson

##                                S      p-value        rho
## LQ45 and Inflasi      3.934473 1.941061e-04  0.4255535
## LQ45 and Nilai Tukar -3.278450 1.627353e-03 -0.3648396
## IHSG and Inflasi      5.139433 2.386707e-06  0.5234144
## IHSG and Nilai Tukar  1.175441 2.438011e-01  0.1391257
## ISSI and Inflasi      6.351564 1.857236e-08  0.6046576
## ISSI and Nilai Tukar  1.933453 5.722522e-02  0.2251579
```

Lampiran 4 Contoh Perhitungan Manual Uji Korelasi Pearson

LQ45 (X)	Inflasi (Y)	X^2	Y^2	XY
1.095,78	3,25	1.200.744	10,56	3.561,30
1.106,51	3,18	1.224.368	10,11	3.518,71
1.047,48	3,40	1.097.212	11,56	3.561,43
1.011,84	3,41	1.023.823	11,63	3.450,38
941,16	3,23	885.788	10,43	3.039,96
930,37	3,12	865.580	9,73	2.902,74
924,88	3,18	855.402	10,11	2.941,12
945,12	3,20	893.261	10,24	3.024,40
925,70	2,88	856.926	8,29	2.666,03
912,25	3,16	832.203	9,99	2.882,72
947,15	3,23	897.100	10,43	3.059,31
980,54	3,13	961.460	9,80	3.069,09
1.014,98	2,82	1.030.183	7,95	2.862,24
1.018,72	2,57	1.037.785	6,60	2.618,10
1.011,90	2,48	1.023.931	6,15	2.509,50
1.017,59	2,83	1.035.499	8,01	2.879,79
956,24	3,32	914.388	11,02	3.174,70
1.001,00	3,28	1.001.993	10,76	3.283,27
1.021,96	3,32	1.044.412	11,02	3.392,92
982,87	3,49	966.033	12,18	3.430,21
982,35	3,39	965.017	11,49	3.330,18
965,79	3,13	932.752	9,80	3.022,93
975,16	3,00	950.943	9,00	2.925,49
1.000,04	2,72	1.000.084	7,40	2.720,11
1.013,91	2,68	1.028.010	7,18	2.717,27
951,56	2,98	905.459	8,88	2.835,64
745,90	2,96	556.363	8,76	2.207,86
690,85	2,67	477.267	7,13	1.844,56
684,13	2,19	468.032	4,80	1.498,24
763,53	1,96	582.977	3,84	1.496,52
789,82	1,54	623.812	2,37	1.216,32
823,13	1,32	677.538	1,74	1.086,53
785,23	1,42	616.589	2,02	1.115,03
778,32	1,44	605.784	2,07	1.120,78
865,90	1,59	749.775	2,53	1.376,77

940,46	1,68	884.456	2,82	1.579,96
978,46	1,55	957.388	2,40	1.516,62
950,58	1,38	903.610	1,90	1.311,81
941,79	1,37	886.971	1,88	1.290,25
898,16	1,42	806.697	2,02	1.275,39
874,17	1,68	764.173	2,82	1.468,61
879,62	1,33	773.725	1,77	1.169,89
840,72	1,52	706.811	2,31	1.277,90
850,32	1,59	723.052	2,53	1.352,02
866,17	1,60	750.245	2,56	1.385,87
947,70	1,66	898.140	2,76	1.573,19
950,55	1,75	903.548	3,06	1.663,46
938,93	1,87	881.590	3,50	1.755,80
945,69	2,18	894.330	4,75	2.061,60
969,71	2,06	940.336	4,24	1.997,60
1.005,27	2,64	1.010.572	6,97	2.653,92
1.047,54	3,47	1.097.349	12,04	3.634,98
1.016,79	3,55	1.033.861	12,60	3.609,60
1.018,10	4,35	1.036.526	18,92	4.428,73
959,00	4,94	919.686	24,40	4.737,47
1.012,21	4,69	1.024.560	22,00	4.747,24
1.025,06	5,95	1.050.755	35,40	6.099,13
996,33	5,71	992.665	32,60	5.689,02
1.003,34	5,42	1.006.686	29,38	5.438,09
948,87	5,51	900.362	30,36	5.228,30
926,02	5,28	857.507	27,88	4.889,37
950,62	5,47	903.685	29,92	5.199,91
933,52	4,97	871.459	24,70	4.639,59
947,23	4,33	897.247	18,75	4.101,51
942,66	4	888.613	16,00	3.770,65
949,31	3,52	901.186	12,39	3.341,56
958,59	3,08	918.893	9,49	2.952,45
962,18	3,27	925.784	10,69	3.146,32
960,75	2,28	923.036	5,20	2.190,50
925,96	2,56	857.404	6,55	2.370,46
913,32	2,86	834.154	8,18	2.612,10
953,25	2,61	908.681	6,81	2.487,98

ΣX	**ΣY**	**ΣX^2**	**ΣY^2**	**ΣXY**
67.738,61	212,57	64.224.235	728,17	202.990,98

n	72
r	0,4255535

Lampiran 5 Uji Normalitas

```
# Pengujian asumsi normalitas # =================================
library(nortest)
Data_des = as.data.frame(Data[,3:7])
ad = matrix(0,5,2)
colnames(ad) <- c("A_Hitung","P-value")
rownames(ad) <- names(Data_des)
for (k in 1:5) {
  ad[k,1] = ad.test(Data_des[,k])$statistic
  ad[k,2] = ad.test(Data_des[,k])$p.value
}
ad

##              A_Hitung      P-value
## LQ45        2.4658476 2.703369e-06
## IHSG        1.4271994 1.003884e-03
## ISSI        1.2049204 3.580554e-03
## Inflasi     1.6095807 3.541235e-04
## Nilai Tukar 0.9586404 1.468254e-02
```

Lampiran 6 Transformasi

```
# Transformasi peubah ke bentuk Uniform [0,1] # ==================
Data_des = as.data.frame(Data[,3:7])
Data_T = matrix(0, nrow=dim(Data_des)[1], ncol= 5)
colnames(Data_T) = names(Data_des)
for (t in 1:5) {
  Data_T[,t] <- as.matrix(rank(Data_des[,t], ties.method = "average
")/73)
 }
Data_Trans = as.data.frame(Data_T)

# Plot sebaran data hasil transformasi
plot(Data_Trans[,1], Data_Trans[,4], xlab = "Inflasi", ylab = "LQ45
")
plot(Data_Trans[,1], Data_Trans[,5], xlab = "Nilai Tukar", ylab = "
LQ45")

plot(Data_Trans[,2], Data_Trans[,4], xlab = "Inflasi, ylab = "IHSG
")
plot(Data_Trans[,2], Data_Trans[,5], xlab = "Nilai Tukar", ylab = "
IHSG")

plot(Data_Trans[,3], Data_Trans[,4], xlab = "Inflasi", ylab = "ISSI
")
plot(Data_Trans[,3], Data_Trans[,5], xlab = "Nilai Tukar", ylab = "
ISSI")
```

Lampiran 7 Cullen Frey Graph

```
# Identifikasi sebaran marginal peubah terikat # ================
library(fitdistrplus)

library(logspline)

descdist( data = y1 , discrete = FALSE)

## summary statistics
## ------
## min:  684.1288   max:  1106.512
## median:  950.5678
## mean:  940.8141
## estimated sd:  83.48003
## estimated skewness:  -1.116837
## estimated kurtosis:  4.596788

beta_y1 = fitdist(Data_Trans[,1], "beta")
plot(beta_y1)

summary(beta_y1)

## Fitting of the distribution ' beta ' by maximum likelihood
## Parameters :
##        estimate Std. Error
## shape1 1.088772  0.1684978
## shape2 1.088772  0.1684977
## Loglikelihood:  0.1775641   AIC:  3.644872   BIC:  8.198204
## Correlation matrix:
##           shape1    shape2
## shape1 1.0000000 0.6636677
## shape2 0.6636677 1.0000000

descdist( data = y2 , discrete = FALSE)

## summary statistics
## ------
## min:  4599.331   max:  7198.951
## median:  6280.24
## mean:  6276.112
## estimated sd:  630.4896
## estimated skewness:  -0.8980071
## estimated kurtosis:  3.516824

beta_y2 = fitdist(Data_Trans[,2], "beta")
plot(beta_y2)

summary(beta_y2)
```

```
## Fitting of the distribution ' beta ' by maximum likelihood
## Parameters :
##        estimate Std. Error
## shape1 1.088772  0.1684978
## shape2 1.088772  0.1684977
## Loglikelihood:  0.1775641   AIC:  3.644872   BIC:  8.198204
## Correlation matrix:
##           shape1    shape2
## shape1 1.0000000 0.6636677
## shape2 0.6636677 1.0000000
```

```
descdist( data = y3 , discrete = FALSE)
```

```
## summary statistics
## ------
## min:  137.7752   max:  216.715
## median:  187.082
## mean:  185.7738
## estimated sd:  19.54429
## estimated skewness:  -0.6500023
## estimated kurtosis:  3.065527
```

```
beta_y3 = fitdist(Data_Trans[,3], "beta")
plot(beta_y3)
```

```
summary(beta_y3)
```


```
## Fitting of the distribution ' beta ' by maximum likelihood
## Parameters :
##        estimate Std. Error
## shape1 1.088772  0.1684978
## shape2 1.088772  0.1684977
## Loglikelihood:  0.1775641   AIC:  3.644872   BIC:  8.198204
## Correlation matrix:
##           shape1    shape2
## shape1 1.0000000 0.6636677
## shape2 0.6636677 1.0000000
```

Lampiran 8 Fitting Copula

```
# Fitting copula #================================================
#y1 dan x1
nc_y1_x1=normalCopula(0.4255535)
fitCopula(nc_y1_x1,cbind(Data_Trans[,4],Data_Trans[,1]),method="ml"
)

## Call: fitCopula(nc_y1_x1, data = cbind(Data_Trans[, 4], Data_Tra
ns[,
##     1]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: normalCopula
##  rho.1
## 0.5182
## The maximized loglikelihood is 9.743
## Optimization converged

tc_y1_x1=tCopula(0.4255535)
fitCopula(tc_y1_x1,cbind(Data_Trans[,4],Data_Trans[,1]),method="ml"
)

## Call: fitCopula(tc_y1_x1, data = cbind(Data_Trans[, 4], Data_Tra
ns[,
##     1]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: tCopula
##     rho.1        df
## 5.180e-01 1.895e+05
## The maximized loglikelihood is 9.743
## Optimization converged

#y1 dan x2
nc_y1_x2=normalCopula(-0.3648396)
fitCopula(nc_y1_x2,cbind(Data_Trans[,5],Data_Trans[,1]),method="ml"
)

## Call: fitCopula(nc_y1_x2, data = cbind(Data_Trans[, 5], Data_Tra
ns[,
##     1]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: normalCopula
##   rho.1
## -0.4657
## The maximized loglikelihood is 7.529
## Optimization converged
```

```
tc_y1_x2=tCopula(-0.3648396)
fitCopula(tc_y1_x2,cbind(Data_Trans[,5],Data_Trans[,1]),method="ml"
)

## Call: fitCopula(tc_y1_x2, data = cbind(Data_Trans[, 5], Data_Tra
ns[,
##     1]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: tCopula
##      rho.1         df
##    -0.4657 22421.2393
## The maximized loglikelihood is 7.529
## Optimization converged

#y2 dan x1
nc_y2_x1=normalCopula(0.5234144)
fitCopula(nc_y2_x1,cbind(Data_Trans[,4],Data_Trans[,2]),method="ml"
)

## Call: fitCopula(nc_y2_x1, data = cbind(Data_Trans[, 4], Data_Tra
ns[,
##     2]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: normalCopula
## rho.1
## 0.564
## The maximized loglikelihood is 12.06
## Optimization converged

tc_y2_x1=tCopula(0.5234144)
fitCopula(tc_y2_x1,cbind(Data_Trans[,4],Data_Trans[,2]),method="ml"
)

## Call: fitCopula(tc_y2_x1, data = cbind(Data_Trans[, 4], Data_Tra
ns[,
##     2]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: tCopula
##     rho.1        df
##    0.5638 6532.9706
## The maximized loglikelihood is 12.06
## Optimization converged

#y2 dan x2
nc_y2_x2=normalCopula(0.1391257)
fitCopula(nc_y2_x2,cbind(Data_Trans[,5],Data_Trans[,2]),method="ml"
)
```

```
## Call: fitCopula(nc_y2_x2, data = cbind(Data_Trans[, 5], Data_Tra
ns[,
##     2]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: normalCopula
##  rho.1
## 0.2366
## The maximized loglikelihood is 1.696
## Optimization converged

tc_y2_x2=tCopula(0.1391257)
fitCopula(tc_y2_x2,cbind(Data_Trans[,5],Data_Trans[,2]),method="ml"
)

## Call: fitCopula(tc_y2_x2, data = cbind(Data_Trans[, 5], Data_Tra
ns[,
##     2]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: tCopula
## rho.1    df
## 0.290 6.045
## The maximized loglikelihood is 2.438
## Optimization converged

#y3 dan x1
nc_y3_x1=normalCopula(0.6046576)
fitCopula(nc_y3_x1,cbind(Data_Trans[,4],Data_Trans[,3]),method="ml"
)

## Call: fitCopula(nc_y3_x1, data = cbind(Data_Trans[, 4], Data_Tra
ns[,
##     3]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: normalCopula
## rho.1
## 0.611
## The maximized loglikelihood is 14.88
## Optimization converged

tc_y3_x1=tCopula(0.6046576)
fitCopula(tc_y3_x1,cbind(Data_Trans[,4],Data_Trans[,3]),method="ml"
)

## Warning in fitCopula.ml(copula, u = data, method = method, start
= start, :
## Hessian matrix not invertible: system is computationally singula
```

```
r: reciprocal
## condition number = 2.37268e-08

## Call: fitCopula(tc_y3_x1, data = cbind(Data_Trans[, 4], Data_Tra
ns[,
##     3]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: tCopula
##  rho.1     df
##  0.612 72.754
## The maximized loglikelihood is 14.88
## Optimization converged

#y3 dan x2
nc_y3_x2=normalCopula(0.2251579)
fitCopula(nc_y3_x2,cbind(Data_Trans[,5],Data_Trans[,3]),method="ml"
)

## Call: fitCopula(nc_y3_x2, data = cbind(Data_Trans[, 5], Data_Tra
ns[,
##     3]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: normalCopula
##  rho.1
## 0.2668
## The maximized loglikelihood is 2.185
## Optimization converged

tc_y3_x2=tCopula(0.2251579)
fitCopula(tc_y3_x2,cbind(Data_Trans[,5],Data_Trans[,3]),method="ml"
)

## Call: fitCopula(tc_y3_x2, data = cbind(Data_Trans[, 5], Data_Tra
ns[,
##     3]), ... = pairlist(method = "ml"))
## Fit based on "maximum likelihood" and 72 2-dimensional observati
ons.
## Copula: tCopula
##  rho.1     df
## 0.3232 3.3464
## The maximized loglikelihood is 4.699
## Optimization converged
```

Lampiran 9 Simulasi 1000 data

```
#scatterplot simulasi data y1
par(mfrow=c(1,2))
Simul_x1_y1 = normalCopula(0.5182)
Simulasi_Nino34All = rCopula(1000,Simul_x1_y1)
plot(Simulasi_Nino34All,xlab="Inflasi",ylab="LQ45",col="royalblue3"
)
Simul_x2_y1 = normalCopula(-0.4657)
Simulasi_Nino34Barat = rCopula(1000,Simul_x2_y1)
plot(Simulasi_Nino34Barat,xlab="Nilai Tukar",ylab="LQ45",col="orang
e")

#scatterplot simulasi data y2
par(mfrow=c(1,2))
Simul_x1_y2 = normalCopula(0.5640)
Simulasi_Nino34All = rCopula(1000,Simul_x1_y2)
plot(Simulasi_Nino34All,xlab="Inflasi",ylab="IHSG",col="royalblue3"
)
Simul_x2_y2 = tCopula(0.2900)
Simulasi_Nino34Barat = rCopula(1000,Simul_x2_y2)
plot(Simulasi_Nino34Barat,xlab="Nilai Tukar",ylab="IHSG",col="orang
e")

#scatterplot simulasi data y3
par(mfrow=c(1,2))
Simul_x1_y3 = normalCopula(0.6110)
Simulasi_Nino34All = rCopula(1000,Simul_x1_y3)
plot(Simulasi_Nino34All,xlab="Inflasi",ylab="ISSI",col="royalblue3"
)
Simul_x2_y3 = tCopula(0.3232)
Simulasi_Nino34Barat = rCopula(1000,Simul_x2_y3)
plot(Simulasi_Nino34Barat,xlab="Nilai Tukar",ylab="ISSI",col="orang
e")
```

Lampiran 10 GCMR

```
# Estimasi parameter copula dan model GCMR #====================
library(gcmr)
modely1x1 <- gcmr(Data_Trans[,1]~Data_Trans[,4], marginal = beta.ma
rg, cormat = ind.cormat)
summary(modely1x1)

##
## Call:
## gcmr(formula = Data_Trans[, 1] ~ Data_Trans[, 4], marginal = bet
a.marg,
##     cormat = ind.cormat)
##
##
## Coefficients marginal model:
##                        Estimate Std. Error z value Pr(>|z|)
## mean.(Intercept)        -0.9767     0.2419  -4.038 5.40e-05 ***
## mean.Data_Trans[, 4]    1.9750     0.4323   4.568 4.92e-06 ***
## dispersion              2.8809     0.4291   6.713 1.90e-11 ***
##
## No coefficients in the Gaussian copula
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## log likelihood = -9.871,  AIC = -13.742

modely1x2 <- gcmr(Data_Trans[,1]~Data_Trans[,5], marginal = beta.ma
rg, cormat = ind.cormat)
summary(modely1x2)

##
## Call:
## gcmr(formula = Data_Trans[, 1] ~ Data_Trans[, 5], marginal = bet
a.marg,
##     cormat = ind.cormat)
##
##
## Coefficients marginal model:
##                        Estimate Std. Error z value Pr(>|z|)
## mean.(Intercept)         0.7702     0.2421   3.181 0.001468 **
## mean.Data_Trans[, 5]   -1.5645     0.4322  -3.620 0.000295 ***
## dispersion               2.6042     0.3774   6.900 5.21e-12 ***
##
## No coefficients in the Gaussian copula
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## log likelihood = -6.4477,  AIC = -6.8953
```

```
modely2x1 <- gcmr(Data_Trans[,2]~Data_Trans[,4], marginal = beta.ma
rg, cormat = ind.cormat)
summary(modely2x1)

##
## Call:
## gcmr(formula = Data_Trans[, 2] ~ Data_Trans[, 4], marginal = bet
a.marg,
##     cormat = ind.cormat)
##
##
## Coefficients marginal model:
##                        Estimate Std. Error z value Pr(>|z|)
## mean.(Intercept)        -0.9906     0.2441  -4.059 4.93e-05 ***
## mean.Data_Trans[, 4]     1.9558     0.4173   4.687 2.78e-06 ***
## dispersion               2.8941     0.4276   6.768 1.31e-11 ***
##
## No coefficients in the Gaussian copula
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## log likelihood = -10.167,  AIC = -14.334

modely2x2 <- gcmr(Data_Trans[,2]~Data_Trans[,5], marginal = beta.ma
rg, cormat = ind.cormat)
summary(modely2x2)

##
## Call:
## gcmr(formula = Data_Trans[, 2] ~ Data_Trans[, 5], marginal = bet
a.marg,
##     cormat = ind.cormat)
##
##
## Coefficients marginal model:
##                        Estimate Std. Error z value Pr(>|z|)
## mean.(Intercept)        -0.4036     0.2559  -1.577   0.1147
## mean.Data_Trans[, 5]     0.8037     0.4415   1.821   0.0687 .
## dispersion               2.2812     0.3250   7.019 2.24e-12 ***
##
## No coefficients in the Gaussian copula
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## log likelihood = -1.8061,  AIC = 2.3879

modely3x1 <- gcmr(Data_Trans[,3]~Data_Trans[,4], marginal = beta.ma
rg, cormat = ind.cormat)
summary(modely3x1)
```

```
##
## Call:
## gcmr(formula = Data_Trans[, 3] ~ Data_Trans[, 4], marginal = bet
a.marg,
##     cormat = ind.cormat)
##
##
## Coefficients marginal model:
##                         Estimate Std. Error z value Pr(>|z|)
## mean.(Intercept)         -1.0844     0.2405  -4.509 6.51e-06 ***
## mean.Data_Trans[, 4]      2.1454     0.4121   5.207 1.92e-07 ***
## dispersion                3.0754     0.4594   6.694 2.18e-11 ***
##
## No coefficients in the Gaussian copula
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## log likelihood = -12.306,  AIC = -18.612
```

```
modely3x2 <- gcmr(Data_Trans[,3]~Data_Trans[,5], marginal = beta.ma
rg, cormat = ind.cormat)
summary(modely3x2)
```

```
##
## Call:
## gcmr(formula = Data_Trans[, 3] ~ Data_Trans[, 5], marginal = bet
a.marg,
##     cormat = ind.cormat)
##
##
## Coefficients marginal model:
##                         Estimate Std. Error z value Pr(>|z|)
## mean.(Intercept)         -0.4905     0.2579  -1.902   0.0571 .
## mean.Data_Trans[, 5]      0.9715     0.4432   2.192   0.0284 *
## dispersion                2.3304     0.3350   6.956 3.49e-12 ***
##
## No coefficients in the Gaussian copula
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## log likelihood = -2.5496,  AIC = 0.90088
```

Lampiran 11 Nilai Kritis Anderson Darling (A)

	Level of Significance (α= Type I Error)				
n	0.20	0.15	0.10	0.05	0.01
58	0.5041008	0.5561218	0.6305560	0.7591591	1.017233
59	0.4955597	0.5473194	0.6220034	0.7387219	0.9823399
60	0.5019493	0.5448074	0.6112021	0.7257367	1.023222
61	0.4970607	0.5500755	0.6146068	0.7381287	1.029202
62	0.5038795	0.5488949	0.6174755	0.7389317	0.9899883
63	0.5008945	0.5522652	0.6225338	0.7408447	0.9984367
64	0.5083809	0.5651475	0.6351047	0.7575722	1.035576
65	0.5034600	0.5512009	0.6210823	0.7369995	1.019421
66	0.5056152	0.5513268	0.6228599	0.7395401	0.9776191
67	0.4956703	0.5476418	0.6135138	0.7234917	1.002739
68	0.4987144	0.5423241	0.6143417	0.7315444	0.9953613
69	0.4891967	0.5374489	0.6148720	0.7375908	1.016052
70	0.5006447	0.5449486	0.6086006	0.7174299	0.9944189
71	0.5036469	0.5571595	0.6310691	0.7516361	0.9956664
72	0.5042152	0.5534744	0.6187972	0.7528877	1.098568
73	0.4993744	0.5456963	0.6249349	0.7475891	0.9832656
74	0.4938010	0.5401573	0.6125678	0.7294769	1.027989
75	0.5070686	0.5569229	0.6184120	0.7290077	1.064887

Lampiran 12 Estimasi Parameter Copula

Penjabaran fungsi Maximum Likelihood Copula

Misalkan

$$\begin{gathered} u_1 = F_1(x_1) \sim U[0,1] \\ u_2 = F_2(x_2) \sim U[0,1] \\ \vdots \\ u_p = F_p(x_p) \sim U[0,1] \end{gathered}$$

$$\mu = 0; \sigma_{ii} = \sigma_{jj} = 1; \boldsymbol{R} = \frac{\sigma_{ij}}{\sigma_i \sigma_j}$$

$$\Sigma_{(p+1)\times(p+1)} = \boldsymbol{R} = \begin{bmatrix} 1 & r_{12} & \dots & r_{p1} \\ r_{21} & 1 & \dots & r_{p2} \\ \vdots & \vdots & \ddots & \vdots \\ r_{p1} & r_{p2} & \dots & 1 \end{bmatrix} = \begin{bmatrix} \mathbf{R}_{p-1} & \mathbf{r} \\ \mathbf{r}^{\mathbf{T}} & 1 \end{bmatrix}$$

Sehingga

$$C(\boldsymbol{u}) = (2\pi)^{-p/2} |\boldsymbol{R}|^{-1/2} \exp[(\boldsymbol{u})' \boldsymbol{R}^{-1} (\boldsymbol{u})]$$

$$C(u_1, u_2, \dots u_p) = \frac{exp\left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[\left(u_p\right)\right]\right] \times (\boldsymbol{R}^{-1} - \boldsymbol{I}) \times \left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[\left(u_p\right)\right]\right]}{|\boldsymbol{R}|^{-1/2}}$$

di mana

$\boldsymbol{I}$: Matriks Identitas berdimensi $n \times n$

$\boldsymbol{R}$: Matriks hubungan berdimensi 2×2

$\mathbf{R}_{p-1}$: Matriks hubungan antar peubah $x_1, \dots x_p$ berdimensi $(p+1) \times (p+1)$

$\mathbf{r}$: Vektor hubungan antar peubah x_p dan $x_1, \dots, x_{p-1}$ berdimensi $(p+1) \times 1$

Fungsi Likelihood copula

$$L = f\left(x_1, \dots, x_{p-1}, x_p\right)$$

$$L = F_1(x_1) \times \dots \times F_p\left(x_p\right). C\left(F_1(x_1) \times \dots \times F_p\left(x_p\right)\right)$$

$$\ln L = \ln\left[F_1(x_1) \times \dots \times F_p\left(x_p\right). C\left(F_1(x_1) \times \dots \times F_p\left(x_p\right)\right)\right]$$

$$= \ln\left[F_1(x_1) \times \dots \times F_p\left(x_p\right). \frac{exp\left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[\left(u_p\right)\right]\right] \times (\boldsymbol{R}^{-1} - \boldsymbol{I}) \times \left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[\left(u_p\right)\right]\right]}{|\boldsymbol{R}|^{-1/2}}\right]$$

$$= \ln \prod_{i=1}^{p} F_p(x_p)$$
$$+ \ln \left[\frac{exp\left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[(u_p)\right]\right] \times (\boldsymbol{R}^{-1} - \boldsymbol{I}) \times \left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[(u_p)\right]\right]}{|\boldsymbol{R}|^{-1/2}} \right]$$

$$= \ln \prod_{i=1}^{p} F_p(x_p) + \frac{\left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[(u_p)\right]\right] \times (\boldsymbol{R}^{-1} - \boldsymbol{I}) \times \left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[(u_p)\right]\right]}{|\boldsymbol{R}|^{-1/2}}$$

$$\ln L = \frac{\left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[(u_p)\right]\right] \times (\boldsymbol{R}^{-1} - \boldsymbol{I}) \times \left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[(u_p)\right]\right]}{|\boldsymbol{R}|^{-1/2}}$$
$$+ \ln \prod_{i=1}^{p} F_p(x_p)$$

Diturunkan terhadap parameter Φ

$$\frac{\partial \ln L}{\partial \Phi} = \frac{\frac{\left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[(u_p)\right]\right] \times (\boldsymbol{R}^{-1} - \boldsymbol{I}) \times \left[\Phi^{-1}[(u_1)], \dots, \Phi^{-1}\left[(u_p)\right]\right]}{|\boldsymbol{R}|^{-1/2}} + \ln \prod_{i=1}^{p} F_p(x_p)}{\partial \Phi}$$

$$= \frac{\frac{\prod_{i=1}^{p} \Phi^{-1}(u_p)\,(\boldsymbol{R}^{-1} - \boldsymbol{I})\left[\prod_{i=1}^{p} \Phi^{-1}(u_p)\right]'}{|\boldsymbol{R}|^{-1/2}} + \ln \prod_{i=1}^{p} F_p(x_p)}{\partial \Phi}$$

$$\frac{\partial \ln L}{\partial \Phi} = -n\Phi^{-n-1} \prod_{i=1}^{p} \Phi^{-1}(u_p)\,(\boldsymbol{R}^{-1} - \boldsymbol{I}) + 0$$

disamakan dengan nol

$$-n\Phi^{-n-1} \prod_{i=1}^{p} \Phi^{-1}(u_p)\,(\boldsymbol{R}^{-1} - \boldsymbol{I}) + 0 = 0$$

$$-n\Phi^{-n-1} \prod_{i=1}^{p} \Phi^{-1}(u_p)\,(\boldsymbol{R}^{-1} - \boldsymbol{I}) = 0$$

$$\ln L = -n\Phi^{-n-1} \prod_{i=1}^{p} \Phi^{-1}(u_p)\,(\boldsymbol{R}^{-1} - \boldsymbol{I})$$

Turunan terhadap parameter berbentuk nonlinier maka parameter copula Φ diduga dengan metode iterasi.

Penjabaran copula normal

$$u_j = Uniform(0,1); j = 1,2,\dots,p$$

di mana $\boldsymbol{R}$ merupakan matriks korelasi dengan $\frac{p(p-1)}{2}$ parameter bersifat konstan positif semidefinite.

Normal copula ditulis sebagai

$$C_R(u_1,\dots,u_p) = \Phi_R \Phi^{-1}(u_1),\dots,\Phi^{-1}(u_p)$$

di mana $\Phi \sim N_m(0,\boldsymbol{R})$

Φ : fungsi sebaran peubah acak normal baku

Φ_R : *p*-ragam sebaran normal baju $\Phi_R \sim N_m(0,\boldsymbol{R})$

Misalkan: $\boldsymbol{U} = (u_1,u_2,\dots,u_p)$ merupakan hasil transformasi suatu peubah acak berasal dari suatu copula yang bersifat:

1. Vektor normal multivariat $\boldsymbol{Z} \sim \boldsymbol{N}(\boldsymbol{0},\boldsymbol{R})$, di mana $\boldsymbol{R}$ adalah p-dimensional korelasi matriks.
2. Transformasi vektor $\boldsymbol{Z}$ ke $\boldsymbol{U} = \left(\Phi(Z_1),\dots,\Phi(Z_p)\right)^{\boldsymbol{T}}$ di mana Φ adalah fungsi sebaran univariat normal baku.

Dekomposisi Cholerky matriks korelasi yakni $\boldsymbol{R} = \mathbf{LL^T}$ di mana $\mathbf{L}$ adalah batas bawah matriks segitiga dengan diagonal utama bernilai positif.

Jika $\boldsymbol{Z} \sim \boldsymbol{N}(\boldsymbol{0},\boldsymbol{1})$ maka $\boldsymbol{LZ} \sim \boldsymbol{N}(\boldsymbol{0},\boldsymbol{R})$

Penduga matriks ragam peragam ($\boldsymbol{R}$) dari contoh yakni

$\boldsymbol{u}_i{}^{\boldsymbol{T}} = (u_{i,1},\dots,u_{i,p})$ di mana $i = 1,2,\dots,n$

Maka fungsi log likelihood

$$\log L\left(\boldsymbol{R}; u_1,\dots,u_p\right) = \sum_{t=1}^{n} \log f_{\boldsymbol{R}}\left(\Phi^{-1}(u_{t,1}),\dots,\Phi^{-1}(u_{t,p})\right) - \sum_{t=1}^{n}\sum_{j=1}^{m} \log \phi\, \Phi^{-1}(u_{t,j})$$

di mana

$f_{\boldsymbol{R}}$: fungsi kepadatan peluang gabungan $N_m(\boldsymbol{0},\boldsymbol{\Phi_R})$

ϕ : fungsi kepadatan peluang univariat $N(0,\sigma^2)$

Kedudukan tidak terikat dari parameter dapat dihilangkan karena proses optimasi. Maka asumsi $\boldsymbol{R}$ dapat diduga

$$\widehat{\boldsymbol{R}} = \frac{1}{n}\sum_{t=1}^{n} \boldsymbol{\zeta_i \zeta_i'}$$

di mana

$$\boldsymbol{\zeta_i} = \left(\Phi^{-1}\left(u_{t,1}\right), \dots, \Phi^{-1}\left(u_{t,p}\right)\right)^{\boldsymbol{T}}$$

Sehingga normalisasi operator untuk aproximasi menggunakan MLE yakni

$$\Delta(\boldsymbol{R}) = diag\left(\sigma_{11}^{1/2}, \dots, \sigma_{pp}^{1/2}\right)$$

$$\wp(\boldsymbol{R}) = diag\left(\left(\Delta(\boldsymbol{R})\right)^{-1}\boldsymbol{R}\left(\Delta(\boldsymbol{R})\right)^{-1}\right)$$

Lampiran 13. Riwayat Hidup

A. Data Pribadi

1. Nama : Nalto Batty Mangiri
2. Tempat, Tgl Lahir : Luwuk, 12 Maret 1999
3. Alamat : Jl. Mamoa V Lorong 2 Nomor 7
4. Kewarganegaraan : Indonesia

B. Riwayat Pendidikan

1. Tamat SMA Tahun 2017 di SMA Negeri 3 Luwuk
2. Sarjana (S1) Tahun 2020 di Universitas Negeri Makassar
3. Magister (S2) Tahun 2024 di Universitas Hasanuddin