

The University of Chicago, Booth School of Business
Business 41202, Spring Quarter 2015, Mr. Ruey S. Tsay

Final Exam

Booth Honor Code:

I pledge my honor that I have not violated the Honor Code during this examination.

Signature:

Name:

ID:

Notes:

- This is a 3-hour, open-book, and open-note exam.
- Write your answer in the blank space provided for each question.
- The exam has 19 pages, including some R output.
- For simplicity, **All** tests use the 5% significance level, and, if not specified, **risk-measure** calculations use 1% tail probability. Furthermore, unless specified, all value at risk (VaR) and expected shortfall (ES) are for the next trading day.
- Round your answer to 3 significant digits.
- You may bring a PC or calculator to the exam, but **no Internet or email or any communication is allowed during the exam!**

Problem A: (40 points) Answer briefly the following questions.

1. Describe two econometric methods discussed in the lectures that can be used to aid in making decision of a loan application.

2. Assume that x_t follows the stochastic diffusion equation $dx_t = \mu dt + \sigma dw_t$, where w_t is the Wiener process. Let $G(x_t) = x_t^2$. Derive the stochastic diffusion equation for $G(x_t)$.

3. Consider a call option contingent on Stock A, which pays no dividend. Suppose that we have $c_t = \$1.12$, $P_t = 30$, $K = 29$, $r = 3\%$ per annum, and the time to expiration is $T - t = 0.25$. Is there any arbitrage opportunity? Why?
4. Give two applications of seasonal time series models in finance.
5. What are the two critical assumptions used by RiskMetrics to justify the square root of time rule?
6. Describe two approaches to VaR calculation that use the extreme value theory in statistics.
7. Describe two methods that can be used to mitigate the impact of market micro-structure noises in computing realized volatility of a stock.
8. State two financial applications that require use of high-frequency transactions data.
9. The univariate GARCH(1,1) model is commonly used in volatility modeling, but it has its shares of weakness. Describe two weaknesses of model.

10. **(For Questions 10-16):** Consider the daily log return of Netflix (NFLX) stock, starting from January 3, 2007. A GARCH(1,1) model with skew Student- t innovations was entertained. Write down the fitted model.
11. Based on the fitted model, perform the hypothesis $H_0 : v = 5$ vs $H_a : v \neq 5$, where v denotes the degrees of freedom of the Student- t innovations. Draw your conclusion.
12. Based on the fitted model, is the distribution of the returns indeed skew? Perform test to justify your answer.
13. To check the risk premium of investing in the stock, a GARCH-M model is entertained. Write down the fitted model.
14. Based on the fitted model, is the risk premium statistically significant? Perform test to justify your answer.
15. The volatility obtained from model in Question 10 and the VIX index are used to better estimate the risk of shorting the stock. Specifically, we employ quantile regression with explanatory variables (a) the lag-1 return r_{t-1} (rtm1), (b) the lag-1 VIX index (vixm1), and (c) the lag-1 volatility (volm1). Write down the parameter estimates when the 95% quantiles are used. Are these estimates significantly different from zero? Why?
16. Given $(\text{rtm1}, \text{vixm1}, \text{volm1}) = (-0.00185, 0.1213, 0.03204)$, what is the VaR of the position with tail probability 0.05?

17. Let p_{1t} and p_{2t} be the daily log prices of two stocks. Assume that both p_{it} series are unit-root nonstationary. Let $w_t = p_{1t} - \gamma p_{2t}$ be a linear combination of the two log price series, where γ is a constant. It is also known that w_t follows the model

$$w_t = 0.787w_{t-1} + 0.213w_{t-2} + a_t, \quad a_t \sim_{iid} N(0, 2.4 \times 10^{-4}).$$

Can the two stocks be used in pairs trading? Why?

18. Describe two models that can be used to model price changes in intraday stock trading.
19. Give two applications of the regression model with time series errors in finance.
20. Why is expected shortfall a preferred risk measure over value at risk in finance? Under what condition are the two risk measures coherent?

Problem B. (12 points) Consider the monthly returns r_t of the Proctor & Gamble stock. Let

$$M_t = \begin{cases} 1 & \text{if } r_t > 0, \\ 0 & \text{if } r_t \leq 0. \end{cases}$$

Similarly, we define the directions of the S&P composite return and the value-weighted CRSP index return as follows:

$$S_t = \begin{cases} 1 & \text{if } sp_t > 0, \\ 0 & \text{if } sp_t \leq 0. \end{cases} \quad \text{and} \quad VW_t = \begin{cases} 1 & \text{if } vw_t > 0, \\ 0 & \text{if } vw_t \leq 0. \end{cases}$$

We model M_t using lagged values of M_t, S_t and VW_t as explanatory variables.

1. A logistic linear regression is employed using S_{t-1} as the explanatory variable. Write down the fitted model. Explain the meaning of the estimated coefficient of S_{t-1} .
2. Based on the fitted model, compute $P(M_t = 1 | S_{t-1} = 1)$ and $P(M_t = 1 | S_{t-1} = 0)$.
3. Another logistic linear regression is employed using VW_{t-1} as the explanatory variable. Compared with the model in part (1), which model do you prefer? Why?
4. A third logistic linear regression using M_{t-1}, S_{t-1} and M_{t-2} as explanatory variables is employed. Write down the fitted model. Is the model helpful in predicting $P(M_t = 1)$ given the past information? Why?
5. A 3-3-1 neural network with skip layer is entertained for M_t using the input variables M_{t-1}, S_{t-1} and M_{t-2} . White down the models for the two hidden nodes h_1 and h_3 .
6. Write down the model for the output node.

Problem C. (30 points) Consider a portfolio holding long two stocks: (a) Exxon-Mobil (XOM) and (b) Qualcomm (QCOM) each with \$1 million. To estimate the risk of the portfolio, we use daily log returns of the stocks, starting from January 3, 2003.

1. (2 points) Focus on the XOM stock. Is the expected return different from zero? Why?
2. (2 points) A Gaussian AR(1)+GARCH(1,1) model is entertained for the XOM stock. Write down the fitted model.
3. (2 points) Based on the fitted model in part (2). What are the VaR and ES for the XOM position?
4. (4 points) Focus on the QCOM stock. If the GARCH(1,1) model with Gaussian innovations is used, what are the VaR and Expected shortfall? Also, what are the VaR and ES for the next 10-trading days?
5. (3 points) Focus again on the QCOM stock. If the GARCH(1,1) model with Student- t innovations and leverage effect is used, what are the VaR and ES for the position? Is the leverage effect significant? Why?
6. (4 points) Using the RiskMetrics method, what are the VaR for the portfolio for the next trading day and for the next ten (10) trading days? You may use the sample correlation 0.45.

7. (4 points) Focus on the QCOM stock and apply the generalized extreme value theory with block size 42. Write down the parameter estimates. What is the corresponding VaR?
8. (5 points) Focus on the QCOM stock and apply the generalized Pareto distribution with threshold 1%. Write down the parameter estimates? Are the estimates statistically significant at the 5% level? What are the VaR and ES implied by the model? What is the VaR for the next 10 trading days?
9. (2 points) For the QCOM stock, we also considered threshold 0.02 and 0.03 in applying generalized Pareto distribution. Are the VaR and ES sensitive to the choice of the threshold when generalized Pareto distribution is used? Why?
10. (2 points) Revisit the RiskMetrics method, but consider a new portfolio that holds a short position on XOM with \$1 million and a long position on QCOM with \$2 million. What is the VaR for the portfolio if the sample correlation is used?

Problem D. (18 points) Consider the daily log returns of Exxon-Mobil (XOM) and Qualcomm (QCOM) stocks used before. For numerical stability, we use percentage log returns. That is, $\mathbf{x}_t = 100(\text{XOM}_t, \text{QCOM}_t)$. Some analysis of this bivariate series is given in the attached R output. Answer the following questions.

1. (2 points) Are there serial correlations in the \mathbf{x}_t series? Answer the question using the multivariate $Q(m)$ statistics with $m = 5$.
2. (4 points) A VAR(2) model is selected via the BIC and HQ criteria. In addition, we refined the fitted model by removing any estimate with t -ratio less than 1.5. What are the AR(1) and AR(2) coefficient matrices of the refined model?
3. (2 points) Does the refined model imply any Granger causality between the two daily log return series? Why?
4. (2 points) Are there any ARCH effects in the residuals of the fitted VAR(2) model? Why?
5. (2 points) The exponentially weighted moving average method is used to estimate the volatility matrices of \mathbf{a}_t , the residual series of the VAR(2) model. Write down the fitted model.

6. (2 points) Write down the range and mean of the resulting time-varying correlations.

7. (2 points) A DCC model with bivariate Student- t innovations is applied to the residual series \mathbf{a}_t . Write down the estimates of θ_1 , θ_2 and degrees of freedom of Student- t innovations of the DCC model.

8. (2 points) Write down the range and mean of the time-varying correlations based on the fitted DCC model.

```

### Problem A ###
> getSymbols("NFLX")
[1] "NFLX"
> dim(NFLX)
[1] 2113      6
> nflx=diff(log(as.numeric(NFLX[,6])))
> m1=garchFit(~garch(1,1),data=nflx,trace=F,cond.dist="sstd")
> summary(m1)
Title: GARCH Modelling
Call: garchFit(formula = ~garch(1, 1), data = nflx,
cond.dist = "sstd", trace = F)

```

Mean and Variance Equation:
data ~ garch(1, 1) [data = nflx]

Conditional Distribution: sstd

Std. Errors:
based on Hessian

Error Analysis:

	Estimate	Std. Error	t value	Pr(> t)
mu	1.816e-03	6.862e-04	2.647	0.00812 **
omega	1.205e-05	5.302e-06	2.272	0.02307 *
alpha1	1.947e-02	4.874e-03	3.994	6.49e-05 ***
beta1	9.740e-01	6.364e-03	153.058	< 2e-16 ***
skew	1.062e+00	3.101e-02	34.250	< 2e-16 ***
shape	2.921e+00	1.981e-01	14.744	< 2e-16 ***

Standardised Residuals Tests:

			Statistic	p-Value
Ljung-Box Test	R	Q(10)	9.915903	0.4479021
Ljung-Box Test	R	Q(20)	15.48999	0.7477177
Ljung-Box Test	R ²	Q(10)	2.265223	0.9938736
Ljung-Box Test	R ²	Q(20)	4.242158	0.9999249
LM Arch Test	R	TR ²	2.368085	0.9985969

```

> source("garchM.R")
> m2=garchM(nflx*100)
Maximized log-likelihood: -5690.617

```

Coefficient(s):

	Estimate	Std. Error	t value	Pr(> t)
mu	0.00313687	0.32035049	0.00979	0.99218725
gamma	0.01391811	0.02433044	0.57205	0.56729130
omega	0.14817126	0.04405056	3.36366	0.00076915 ***
alpha	0.01180186	0.00248391	4.75133	2.0208e-06 ***

```

beta  0.97735441  0.00487557 200.45956 < 2.22e-16 ***
---
> getSymbols("^VIX")
[1] "VIX"
> vix=as.numeric(VIX[,6])/100
> v1=volatility(m1)
> vix=vix[-1]
> X=cbind(nflx[-2112],vix[-2112],v1[-2112])
> colnames(X) <- c("rtm1","vixm1","volm1")
> X=data.frame(X)
> require(quantreg)
> mm=rq(nflx[-1]~rtm1+vixm1+volm1,data=X,tau=0.95)
> summary(mm)
Call: rq(formula=nflx[-1]~rtm1+vixm1+volm1,tau=0.95,data = X)
tau: [1] 0.95
Coefficients:
              Value   Std. Error t value Pr(>|t|)
(Intercept) 0.00849  0.01160     0.73164 0.46447
rtm1         0.08877  0.04481     1.98100 0.04772
vixm1        0.06788  0.02354     2.88391 0.00397
volm1        0.75807  0.32535     2.33001 0.01990

```

Problem B

```

> da=read.table("m-pg3dx-6015.txt",header=T)
> pg=da$RET; sp=da$sprtrn; vw=da$vwretcd
> Mt=rep(0,663)
> idx=seq(Mt)[pg > 0]
> Mt[idx]=1
> St=rep(0,663)
> idx=seq(St)[sp > 0]
> St[idx]=1
> VWt=rep(0,663)
> idx=seq(VWt)[vw > 0]
> VWt[idx]=1
> y=Mt[3:663]
> X=cbind(Mt[2:662],St[2:662],VWt[2:662],Mt[1:661],St[1:661],VWt[1:661])
> colnames(X) <- c("Mtm1","Stm1","VWtm1","Mtm2","Stm2","VWtm2")
> X=data.frame(X)
> g4=glm(y~Stm1,data=X,family=binomial)
> summary(g4)
Call: glm(formula=y~Stm1,family=binomial,data=X)
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4148      0.1246   3.329  0.00087 ***
Stm1          -0.3126      0.1605  -1.948  0.05138 .

```

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---
Null deviance: 907.81 on 660 degrees of freedom
Residual deviance: 903.99 on 659 degrees of freedom
AIC: 907.99
>
> g5=glm(y~VWtm1,data=X,family=binomial)
> summary(g5)
Call:glm(formula=y~VWtm1,family=binomial,data=X)
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4055      0.1278   3.172  0.00151 **
VWtm1        -0.2871      0.1619  -1.773  0.07626 .
---
Null deviance: 907.81 on 660 degrees of freedom
Residual deviance: 904.65 on 659 degrees of freedom
AIC: 908.65

> g1=glm(y~Mtm1+Stm1+Mtm2,data=X,family=binomial)
> summary(g1)
Call:
glm(formula=y~Mtm1+Stm1+Mtm2,family=binomial,data=X)
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.4441      0.1629   2.727  0.00639 **
Mtm1          0.2379      0.1673   1.423  0.15487
Stm1         -0.3814      0.1698  -2.246  0.02470 *
Mtm2         -0.2157      0.1589  -1.358  0.17451
---
Null deviance: 907.81 on 660 degrees of freedom
Residual deviance: 900.18 on 657 degrees of freedom
AIC: 908.18
> pg.X=X[,c(1,2,4)]
> require(nnet)
> g3=nnet(pg.X,y,size=3,linout=F,skip=T,maxit=10000)
# weights: 19
initial value 185.030949
.....
final value 159.713206
converged
> summary(g3)
a 3-3-1 network with 19 weights
options were - skip-layer connections
b->h1 i1->h1 i2->h1 i3->h1
-1.07 -6.46 -7.70 -1.04
b->h2 i1->h2 i2->h2 i3->h2
-0.80 -0.20 1.34 -0.99

```

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b->h3 i1->h3 i2->h3 i3->h3
-1.79 -5.52 -0.07 -4.73
b->o h1->o h2->o h3->o i1->o i2->o i3->o
1.46 -4.81 -1.46 2.87 0.00 -0.40 -0.56

##### Problem C #####
> getSymbols("XOM",from="2003-01-02",to='XXXX')
> getSymbols("QCOM",from="2003-01-02", to='XXXX')
> xom=diff(log(as.numeric(XOM[,6])))
> qcom=diff(log(as.numeric(QCOM[,6])))
> require(fBasics)
> basicStats(xom)

              xom
nobs          3119.000000
Minimum        -0.150271
Maximum         0.158631
Mean            0.000376
Median          0.000522
SE Mean         0.000270
LCL Mean        -0.000153
UCL Mean         0.000905
Variance        0.000227
Stdev           0.015069
Kurtosis        14.568729
> m1=garchFit(~arma(1,0)+garch(1,1),data=xom,trace=F)
> summary(m1)
Title: GARCH Modelling
Call:
garchFit(formula=~arma(1,0)+garch(1,1),data=xom,trace=F)
Mean and Variance Equation:
data ~ arma(1, 0) + garch(1, 1) [data = xom]

Conditional Distribution: norm
Error Analysis:
      Estimate Std. Error t value Pr(>|t|)
mu      5.860e-04  2.037e-04   2.877  0.00402 **
ar1     -6.146e-02  1.888e-02  -3.255  0.00113 **
omega    3.066e-06  7.227e-07   4.242 2.22e-05 ***
alpha1   6.832e-02  8.201e-03   8.331 < 2e-16 ***
beta1    9.143e-01  1.031e-02  88.645 < 2e-16 ***
---
> predict(m1,1)
      meanForecast meanError standardDeviation
1      0.00142278 0.009559212      0.009559212

```

```

> n1=garchFit(~garch(1,1),trace=F,data=qcom)
> summary(n1)
Title: GARCH Modelling
Call:
garchFit(formula=~garch(1,1),data=qcom,trace=F)

Mean and Variance Equation:
data ~ garch(1, 1) [data = qcom]

Conditional Distribution: norm
Error Analysis:
      Estimate Std. Error t value Pr(>|t|)
mu      8.308e-04  3.108e-04   2.674  0.0075 **
omega   9.910e-06  2.511e-06   3.947  7.92e-05 ***
alpha1  6.013e-02  1.281e-02   4.692  2.70e-06 ***
beta1   9.150e-01  1.711e-02  53.473  < 2e-16 ***
---
> pn1=predict(n1,10)
> pn1[,1]
      meanForecast meanError standardDeviation
1    0.00083083 0.01349758          0.01349758
> sum(pn1[,1])
[1] 0.0083083
> sqrt(sum(pn1[,3]^2))
[1] 0.04526265
>
> n2=garchFit(~garch(1,1),data=qcom,trace=F,cond.dist="std",leverage=T)
> summary(n2)
Title: GARCH Modelling
Call:
garchFit(formula = ~garch(1, 1), data = qcom, cond.dist = "std",
      leverage = T, trace = F)
Mean and Variance Equation:
data ~ garch(1, 1) [data = qcom]

Conditional Distribution: std
Error Analysis:
      Estimate Std. Error t value Pr(>|t|)
mu      4.959e-04  2.622e-04   1.891 0.058631 .
omega   4.879e-06  2.335e-06   2.090 0.036653 *
alpha1  6.564e-02  1.628e-02   4.032 5.54e-05 ***
gamma1  2.775e-01  8.124e-02   3.416 0.000635 ***
beta1   9.208e-01  2.086e-02  44.144  < 2e-16 ***
shape   5.008e+00  4.241e-01  11.808  < 2e-16 ***
---
> predict(n2,1)

```

```

    meanForecast  meanError standardDeviation
1 0.0004958917 0.01198818          0.01198818

> source("RMfit.R")
> RMfit(xom)
Coefficient(s):
      Estimate Std. Error t value Pr(>|t|)
beta 0.94485460 0.00511854 184.595 < 2.22e-16 ***
---
Volatility prediction:
      Orig      Vpred
[1,] 3119 0.008787326

Risk measure based on RiskMetrics:
      prob      VaR      ES
[1,] 0.950 0.01445386 0.01812573
[2,] 0.990 0.02044238 0.02342011
[3,] 0.999 0.02715488 0.02958772
> RMfit(qcom)
Coefficient(s):
      Estimate Std. Error t value Pr(>|t|)
beta 0.98526559 0.00187034 526.783 < 2.22e-16 ***
---
Volatility prediction:
      Orig      Vpred
[1,] 3119 0.01454408

Risk measure based on RiskMetrics:
      prob      VaR      ES
[1,] 0.950 0.02392288 0.03000025
[2,] 0.990 0.03383458 0.03876308
[3,] 0.999 0.04494457 0.04897122
>
> n3=gev(nqcom,block=42)
> n3
$n.all
[1] 3119
$n
[1] 75
$block
[1] 42
$par.ests
      xi      sigma      mu
0.16983957 0.01589501 0.03211348
$par.ses
      xi      sigma      mu

```

```

0.088992073 0.001565788 0.002065816
> source("evtVaR.R")
> evtVaR(.16983957,.01589501,.03211348,prob=0.01,n=42)
[1] 0.04687756

> n5=gpd(nqcom,thres=0.01)
> n5
$threshold
[1] 0.01
$p.less.thresh
[1] 0.7540878
$n.exceed
[1] 767
$par.ests
      xi      beta
0.13870970 0.01079914
$par.ses
      xi      beta
0.039680541 0.000563794

> riskmeasures(n5,c(0.95,0.99,0.999))
      p  quantile  sfall
[1,] 0.950 0.02925108 0.04488976
[2,] 0.990 0.05353968 0.07309001
[3,] 0.999 0.09921889 0.12612580

> n6=gpd(nqcom,thres=0.02)
> n6
$threshold
[1] 0.02
$p.less.thresh
[1] 0.8941969
$n.exceed
[1] 330
$par.ests
      xi      beta
0.15806404 0.01158948
$par.ses
      xi      beta
0.0584313714 0.0009071199
> riskmeasures(n6,c(0.95,0.99,0.999))
      p  quantile  sfall
[1,] 0.950 0.02922253 0.04471923
[2,] 0.990 0.05313387 0.07311966
[3,] 0.999 0.09986889 0.12862865
>

```



```

> n7=gpd(nqcom,thres=0.03)
> n7
$threshold
[1] 0.03
> riskmeasures(n7,c(.95,.99,.999))
      p   quantile   sfall
[1,] 0.950 0.02800613 0.04424018
[2,] 0.990 0.05263707 0.07513457
[3,] 0.999 0.10526986 0.14115148

##### Problem D #####
> xt=cbind(xom,qcom)*100
> mq(xt,lag=5)
Ljung-Box Statistics:
      m      Q(m)      df      p-value
[1,]  1.0      70.4      4.0          0
....
[4,]  4.0     121.4     16.0          0
[5,]  5.0     126.1     20.0          0
> VARorder(xt)
selected order: aic =  8
selected order: bic =  2
selected order: hq  =  2
Summary table:
      p    AIC    BIC    HQ    M(p) p-value
[1,]  0 1.9630 1.9630 1.9630  0.0000 0.0000
[2,]  1 1.9427 1.9504 1.9455 70.8544 0.0000
[3,]  2 1.9311 1.9467 1.9367 43.7166 0.0000
.....
[14,] 13 1.9318 2.0326 1.9680  5.3204 0.2560
> m1=VAR(xt,2)
> m1a=refVAR(m1,thres=1.5)
Constant term:
Estimates:  0.04716122 0.05697088
Std.Error:  0.02657513 0.03523412
AR coefficient matrix
AR( 1 )-matrix
      [,1] [,2]
[1,] -0.158  0
[2,] -0.151  0
standard error
      [,1] [,2]
[1,] 0.0178  0
[2,] 0.0236  0
AR( 2 )-matrix

```

```

      [,1]      [,2]
[1,] -0.1125  0.0000
[2,] -0.0462 -0.0382
standard error
      [,1]      [,2]
[1,] 0.0178 0.0000
[2,] 0.0263 0.0198

```

```

Residuals cov-mtx:
      [,1]      [,2]
[1,] 2.195934 1.261879
[2,] 1.261879 3.858024

```

```

AIC = 1.931771
BIC = 1.941462
HQ  = 1.93525
> at=m1a$residuals
> mq(at,lag=5)

```

```

Ljung-Box Statistics:
      m      Q(m)      df      p-value
[1,] 1.000    0.167    4.000        1.00
[2,] 2.000    2.773    8.000        0.95
[3,] 3.000   11.265   12.000        0.51
[4,] 4.000   17.394   16.000        0.36
[5,] 5.000   23.022   20.000        0.29

```

```

> MarchTest(at)
Q(m) of squared series(LM test):
Test statistic: 2049.431 p-value: 0
Rank-based Test:
Test statistic: 1099.14 p-value: 0
Q_k(m) of squared series:
Test statistic: 3373.666 p-value: 0
Robust Test(5%) : 518.9318 p-value: 0

```

```

> m5=EWMVol(at,lambda=-0.1)
Coefficient(s):
      Estimate Std. Error t value Pr(>|t|)
lambda 0.977078  0.001979  493.8   <2e-16 ***
---

```

```

> names(m5)
[1] "Sigma.t" "return" "lambda"
> Sigma.t=m5$Sigma.t
> rho.t=Sigma.t[,2]/sqrt(Sigma.t[,1]*Sigma.t[,4])
> basicStats(rho.t)

```

```

      rho.t
nobs      3117.000000

```

Minimum	-0.061344
Maximum	0.835189
Mean	0.377374
Median	0.367299
Stdev	0.176220
Skewness	0.114776
Kurtosis	-0.254821

```

> m2=dccPre(at,cond.dist="std")
Sample mean of the returns:  1.925554e-16 -8.452547e-17
Component:  1
Estimates:  0.025603 0.065358 0.920882 7.850586
se.coef   :  0.007783 0.01012 0.012033 1.0004
t-value   :  3.289602 6.458201 76.53113 7.847447
Component:  2
Estimates:  0.01598 0.04138 0.955651 4.837419
se.coef   :  0.009244 0.008684 0.009411 0.397061
t-value   :  1.728665 4.764824 101.551 12.18307
> sresi=m2$sresi
> m3=dccFit(sresi,ub=c(0.975,0.0249999))
Estimates:  0.9652854 0.01994169 5.648781
st.errors:  0.01233129 0.00591203 0.2925495
t-values:   78.27938 3.37307 19.30881
> names(m3)
[1] "estimates" "Hessian"  "rho.t"
> rho.t=m3$rho.t
> basicStats(rho.t[,2])
      X..rho.t..2
nobs      3117.000000
Minimum    0.063533
Maximum    0.593887
Mean       0.326043
Median     0.321755
Stdev      0.096598
Skewness   0.173898
Kurtosis   -0.354182

```