

**The University of Chicago, Booth School of Business**  
Business 41202, Spring Quarter 2016, 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 18 pages, including some R output.
- For simplicity, 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. Also, unless specified, all tests use 5% type-I error.
- 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. Give two advantages of using the sub-sampling method over the method of optimal sampling interval in computing (daily) realized volatility of a stock.
  
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  $G(x_t) = \exp(x_t/2)$ . Derive the stochastic diffusion equation for  $G(x_t)$ .

3. Give two methods that can be used to specify the order of an autoregressive time series.
  
4. Describe two methods discussed in class that can be used to predict the direction of a price movement (up or down).
  
5. Describe two methods that can be used to obtain time-varying correlations between two asset returns.
  
6. Give two reasons that the observed log returns of an asset follow an MA(1) model.
  
7. Consider the time series model  $x_t = 0.1x_{t-1} + 0.72x_{t-2} + a_t$ , where  $a_t$  are iid  $N(0, \sigma^2)$ . Is the model mean-reverting? If yes, what is the half-life?
  
8. Give two special features of an ARCH(1) model that fare well with empirical features of asset returns.
  
9. Correlations play an important role in statistical analysis and applications. Provide two weakness of the usual Pearson correlation in measuring relationship between variables.
  
10. Suppose that we are interested in the log returns of an asset for the next five (5) trading days, i.e.  $r_t^{(5)} = r_{t+1} + r_{t+2} + \cdots + r_{t+5}$ . State two conditions under which  $\text{Var}[r_t^{(5)}|F_{t-1}] = 5\text{Var}[r_{t+1}|F_{t-1}]$ , where  $F_{t-1}$  denotes the information available at time  $t - 1$ .

11. **(For Questions 11-15):** Consider the adjusted daily stock prices of BHP and VALE used in Lecture Note 10. A linear model is used to find the linear relationship between the prices. Based on the fitted model, we define  $w_t = \text{bhp}_t - 2.718\text{vale}_t$ . An AR(4) model is selected. Write down the fitted model, including residual variance.
12. The Box-Ljung statistics give  $Q(10) = 6.00$  for the residuals of the fitted AR(4) model. Based on the test statistic, are there residual serial correlations in the first 10 lags? Why?
13. Based on the ADF unit-root test and using the 1% type-I error, is there any opportunity for pairs-trading using the two stocks? Why?
14. Consider a bi-variate time series of the two stock prices, namely  $\mathbf{x}_t = (\text{bhp}_t, \text{vale}_t)'$ . If vector autoregressive models are entertained, what order is selected for the series? Why?
15. A VAR(2) model is entertained for  $\mathbf{x}_t$  series. Write down the fitted AR(1) coefficient matrix. Interpret the meaning of the (1,2)-th element  $\phi_{12}$  of the AR(1) coefficient.
16. The Ljung-Box statistics are widely used in analyzing financial time series. Describe two specific applications of the statistics.
17. Give two characteristics of price changes in tick-by-tick transaction data.

18.  $R^2$  is commonly used in linear regression analysis. Why is it not useful in time series analysis? State a condition under which  $R^2$  can still be used in analyzing financial time series.
19. Describe two cases under which nonlinear models can be useful in analyzing financial data.
20. Give one advantage and one disadvantage of imposing price limits on stock trading.

**Problem B.** (16 points) Consider the daily log returns of Costco stock (COST) and the yield-to-maturity of U.S. 10-year treasury notes (TNX) for a period with sample size 2367. Suppose that the portfolio of interest consists of 10K of long position on each of the asset. Based on the attached output, answer the following questions. The variables used in R are “cost” and “tnx”, respectively.

1. Are the daily log returns of COST serially correlated? Write down the null hypothesis and draw your conclusion.
2. (3 points) A Gaussian ARMA-GARCH(1,1) model is entertained, but the estimated AR coefficients are relatively small and the normality test rejects the normality assumption. A GARCH(1,1) model with standardized Student- $t$  distribution is fitted. Write down the fitted model, including innovations.
3. Predictions of the fitted GARCH(1,1) model are provided. Based on the predictions, compute VaR and Expected shortfall (ES) of holding the COST stock.

4. Compute the VaR and ES of the COST stock for the next 10 trading days.
5. If RiskMetrics is used, what are the VaR and ES for holding the COST stock?
6. (3 points) The sample correlations between the two log returns is 0.197. Compute the VaR of the portfolio.
7. If the long position of the treasury notes is changed to a short position, compute the VaR of the new portfolio.

**Problem C.** (19 points) Consider the daily log returns of Amazon (AMZN) stock and the ETF (exchange-traded fund) of VIX index (VXX) starting from January 30, 2009 for 1846 observations. In the R output, the variables of the daily log returns are “amzn” and “vxx”, respectively.

$$yd_t = \begin{cases} 1 & \text{if } amzn_t \geq 0, \\ 0 & \text{if } amzn_t < 0. \end{cases}$$

Similarly, we define  $y1d_t$  and  $y2d_t$  using  $amzn_{t-1}$  and  $amzn_{t-2}$ , respectively. Let the lag-2 value of  $amzn_t$  as “y2” in the R output.

1. A simple logistic regression is used to model  $yd_t$  using  $y1d_t$  as the predictor. Write down the fitted model. What is the meaning of the fitted coefficient  $-0.172$  of  $y1d_t$ .

2. Another logistic regression is fitted to  $y_{d_t}$  using  $y_{t-2}$  and  $y1d_t$  as regressors. Based on the AIC criterion, does  $y_{t-2}$  contribute significantly to modeling  $y_{d_t}$ ? Why?
  
3. Suppose  $y_{t-2} = 0.01$  and  $y1d_t = 0$ . Use the fitted logistic model to compute the probability  $P(y_{d_t} = 1)$ .
  
4. (5 points) Using  $y_{t-2}$  and  $y1d_t$  as input, a 2-4-1 neural network is fitted to  $y_{d_t}$ . Write down the fitted model.
  
5. Based on the fitted neural network model, compute  $P(y_{d_t} = 1)$  given  $y_{t-2} = 0.01$  and  $y1d_t = 0$ .
  
6. Define the directions of lag-1 and lag-2 VXX log returns in a similar way as those of  $y1d_t$  and  $y2d_t$  and denote the variables by  $v1d_t$  and  $v2d_t$ . A logistic regression is entertained with regressors  $y_{t-1}, y_{t-2}, y1d_t, y2d_t, v1d_t$  and  $v2d_t$ . Based on the fitted model, does lagged values of VXX log return contribute significantly in predicting the direction of AMZN price movement? Why?
  
7. Finally, let  $\mathbf{r}_t = (\text{amzn}_t, \text{vxx}_t)'$  be a bi-variate log return series. A dynamic conditional correlation model is fitted. Write down the fitted coefficients  $\hat{\theta}_1$  and  $\hat{\theta}_2$ ? Are these estimates statistically significant at the 5% level? Why?

8. Based on the output, what is the time-varying correlation between the two asset returns at  $t = 1843$ ?

**Problem D.** (25 points) Consider the daily log returns of Costco stock (COST) for a recent period with 2368 observations. For risk assessment, we assume a long position of \$1 million on the stock. Based on the attached R output, answer the following questions.

1. Is the expected value of the log return zero? Why?
2. Is the distribution of the log returns skewed? Why? Perform a statistical test to support your answer.
3. Based on the fitted GARCH(1,1) model, does the stock have a leverage effect? Why?
4. Compute VaR and ES of the financial position using the fitted GARCH(1,1) model (denoted by **h1** in the output).
5. Compute the VaR and ES of the position for the next 5 trading days using the fitted GARCH(1,1) model.
6. Compared with Question 3 of Problem B, does the leverage effect affect the VaR calculation? Why?

7. If the extreme value theory with block maximum (size 21) is used, what is the VaR for the next trading day? What is the VaR for the next 10-trading days?
8. If the theory of Peaks over Threshold with threshold 0.02 is used, write down the parameter estimates. Are these estimates significantly different from zero? Why?
9. If the theory of Peaks over Threshold with threshold 0.02 is employed, what are the VaR for the next trading day and the next 10 trading days?
10. If the theory of Peaks over Threshold with threshold 0.025 is used, what are the VaR and ES?
11. (1 point) Is VaR sensitive to the choice of thresholds in this particular case? Why?
12. The log returns of VIX index might be helpful in computing VaR for the financial position. To this end, a quantile regression ( $\tau = 0.95$ ) is used with four input variables (lag-1 and lag-2 of COST stock returns and lag-1 and lag-2 of VIX returns). Based on the fitted model, do the past values of VIX returns contribute significantly to model? Why?
13. Based on the quantile regression, what is the  $\text{VaR}_{0.95}$  if the input variables assume the value (0.08, 0.01, 0.03, 0.01)?



## R output

```
### Problem A ###
> da <- read.table("d-bhp0206.txt",header=T)
> da1 <- read.table("d-vale0206.txt",header=T)
> bhp <- as.numeric(da$adjclose)
> vale <- da1$adjclose
> m1 <- lm(bhp~vale)
> summary(m1)
Call:lm(formula = bhp ~ vale)
Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.34624    0.07571   70.61  <2e-16 ***
vale         2.71827    0.01297  209.65  <2e-16 ***
---
> wt <- bhp - 2.718*vale
> m2 <- arima(wt,order=c(4,0,0))
> m2
Call:arima(x = wt, order = c(4, 0, 0))
Coefficients:
          ar1      ar2      ar3      ar4  intercept
      0.8378  0.0544  0.0096  0.0687         5.3018
s.e.  0.0324  0.0424  0.0424  0.0325         0.3501

sigma^2 estimated as 0.1099:  log likelihood = -299.31,  aic = 610.62
> require(fUnitRoots)
> adfTest(wt,lags=3,type="c")
Title: Augmented Dickey-Fuller Test
Test Results:
PARAMETER:
  Lag Order: 3
STATISTIC:
  Dickey-Fuller: -3.4238
P VALUE:
  0.01078
> xt <- cbind(bhp,vale)
> require(MTS)
> VARorder(xt)
selected order: aic = 2
selected order: bic = 1
selected order: hq = 2
Summary table:
      p      AIC      BIC      HQ      M(p) p-value
[1,]  0  2.5285  2.5285  2.5285    0.0000  0.0000
[2,]  1 -6.4209 -6.4004 -6.4131  8326.3509  0.0000
[3,]  2 -6.4366 -6.3956 -6.4210   22.4069  0.0002
[4,]  3 -6.4358 -6.3743 -6.4123    7.0487  0.1333
```

```

[5,] 4 -6.4326 -6.3505 -6.4013 4.8623 0.3017
[6,] 5 -6.4310 -6.3285 -6.3919 6.3411 0.1751
[7,] 6 -6.4350 -6.3119 -6.3881 11.4146 0.0223
....
[14,] 13 -6.4122 -6.1455 -6.3106 5.5917 0.2318
> n1 <- VAR(xt,2)
Constant term:
Estimates: 0.09377638 -0.03698037
Std.Error: 0.05918219 0.02151984
AR coefficient matrix
AR( 1 )-matrix
      [,1] [,2]
[1,] 0.9092 0.42
[2,] 0.0305 1.02
standard error
      [,1] [,2]
[1,] 0.0399 0.11
[2,] 0.0145 0.04
AR( 2 )-matrix
      [,1] [,2]
[1,] 0.0756 -0.3751
[2,] -0.0226 -0.0451
standard error
      [,1] [,2]
[1,] 0.0400 0.11
[2,] 0.0145 0.04
Residuals cov-mtx:
      [,1] [,2]
[1,] 0.13450932 0.02856833
[2,] 0.02856833 0.01778478

### Problem B ###
> getSymbols("COST",from=XXXX,to=XXXX)
> getSymbols("^TNX",from=XXXX,to=XXXX)
> X1 <- COST[-951,] #Adjusing for difference in trading days.
> cost <- diff(log(as.numeric(X1[,6])))
> tn timer <- diff(log(as.numeric(TNX[,6])))
> Box.test(cost,lag=10,type='Ljung')
Box-Ljung test
data: cost
X-squared = 36.87, df = 10, p-value = 5.96e-05
> m1 <- arima(cost,order=c(4,0,0))
> require(fGarch)
> ncost <- -cost ### Long position
> m2 <- garchFit(~arma(4,0)+garch(1,1),data=ncost,trace=F)
> summary(m2)

```

Title: GARCH Modelling  
Std. Errors: based on Hessian

Error Analysis:

	Estimate	Std. Error	t value	Pr(> t )
mu	-9.252e-04	2.389e-04	3.872	0.000108 ***
ar1	-3.302e-02	2.198e-02	-1.502	0.133046
ar2	-2.526e-02	2.174e-02	-1.162	0.245196
ar3	-2.620e-02	2.187e-02	-1.198	0.230887
ar4	-4.929e-02	2.186e-02	-2.255	0.024130 *
omega	2.386e-06	6.924e-07	3.446	0.000569 ***
alpha1	5.731e-02	9.474e-03	6.049	1.45e-09 ***
beta1	9.314e-01	1.112e-02	83.746	< 2e-16 ***

---

```
> m3 <- garchFit(~garch(1,1),data=ncost,trace=F,cond.dist="std")
> summary(m3)
```

Title: GARCH Modelling

Call:

```
garchFit(formula=ncost~garch(1,1),data=ncost,cond.dist="std",trace=F)
```

Error Analysis:

	Estimate	Std. Error	t value	Pr(> t )
mu	-5.714e-04	2.172e-04	2.631	0.00851 **
omega	1.122e-06	4.877e-07	2.300	0.02145 *
alpha1	3.555e-02	7.377e-03	4.820	1.44e-06 ***
beta1	9.586e-01	8.501e-03	112.764	< 2e-16 ***
shape	5.293e+00	5.487e-01	9.645	< 2e-16 ***

---

Standardised Residuals Tests:

			Statistic	p-Value
Jarque-Bera Test	R	Chi^2	1520.714	0
Shapiro-Wilk Test	R	W	0.9657504	0
Ljung-Box Test	R	Q(10)	17.18641	0.07033959
Ljung-Box Test	R	Q(20)	22.22114	0.3286326
Ljung-Box Test	R^2	Q(10)	13.37984	0.2032031
Ljung-Box Test	R^2	Q(20)	18.78798	0.5356434

```
> pm3 <- predict(m3,5)
```

```
> pm3
```

	meanForecast	meanError	standardDeviation
1	-0.0005713715	0.01310475	0.01310475
2	-0.0005713715	0.01310953	0.01310953
3	-0.0005713715	0.01311428	0.01311428
4	-0.0005713715	0.01311900	0.01311900
5	-0.0005713715	0.01312369	0.01312369

```
> sqrt(sum(pm3$standardDeviation^2))
```

```
[1] 0.02932435
```

---

```

> source("RMfit.R")
> RMfit(cost)
Coefficient(s):
      Estimate Std. Error t value Pr(>|t|)
beta 0.96219179 0.00523815 183.689 < 2.22e-16 ***
---
Volatility prediction:
      Orig      Vpred
[1,] 2367 0.01289863

Risk measure based on RiskMetrics:
      prob      VaR      ES
[1,] 0.950 0.02121635 0.02660616
[2,] 0.990 0.03000669 0.03437760
[3,] 0.999 0.03985975 0.04343083
> RMfit(tnx)
Coefficient(s):
      Estimate Std. Error t value Pr(>|t|)
beta 0.94653947 0.00541354 174.847 < 2.22e-16 ***
---
Volatility prediction:
      Orig      Vpred
[1,] 2367 0.0217353

Risk measure based on RiskMetrics:
      prob      VaR      ES
[1,] 0.950 0.03575139 0.04483369
[2,] 0.990 0.05056388 0.05792924
[3,] 0.999 0.06716714 0.07318473
> cor(cost,tnx)
[1] 0.196606

### Problem C ###
> getSymbols("VXX",from=XXXX,to=XXXX)
[1] "VXX"
> getSymbols("AMZN",from=XXXX,to=XXXX)
[1] "AMZN"
> vxx <- diff(log(as.numeric(VXX[,6])))
> amzn <- diff(log(as.numeric(AMZN[,6])))
> cor(vxx,amzn)
[1] -0.4458341
> y <- amzn[3:1845]; y1 <- amzn[2:1844]; y2 <- amzn[1:1843]
> v1 <- vxx[2:1844]; v2 <- vxx[1:1843]
> yd <- ifelse(y >= 0, 1,0) ## create indicator for y >= 0.
> y1d <- ifelse(y1 >= 0,1,0)
> y2d <- ifelse(y2 >= 0,1,0)

```

```

> v1d <- ifelse(v1 >= 0,1,0)
> v2d <- ifelse(v2 >= 0,1,0)
> k2 <- glm(yd ~ y1d,family=binomial)
> summary(k2)
Call:glm(formula = yd ~ y1d, family = binomial)
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.15276    0.06716   2.275   0.0229 *
y1d          -0.17169    0.09336  -1.839   0.0659 .
---
AIC: 2553.7

> k5 <- glm(yd~y2+y1d,family=binomial)
> summary(k5)
Call:glm(formula = yd ~ y2 + y1d, family = binomial)
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)  0.15997    0.06735   2.375   0.0175 *
y2          -3.72009    2.13469  -1.743   0.0814 .
y1d          -0.17575    0.09348  -1.880   0.0601 .
---
AIC: 2552.6

> require(nnet)
> XX <- cbind(y2,y1d)
> colnames(XX) <- c("y2","y1d")
> n3 <- nnet(XX,yd,size=4,linout=F,skip=T)
# weights:  19
initial value 618.865386
iter  10 value 454.523935
final value 454.503412
converged
> summary(n3)
a 2-4-1 network with 19 weights
options were - skip-layer connections
b->h1 i1->h1 i2->h1
  1.13   0.15  -0.43
b->h2 i1->h2 i2->h2
  0.66   0.50  -0.06
b->h3 i1->h3 i2->h3
  1.06   0.44  -0.95
b->h4 i1->h4 i2->h4
  1.03   0.42  -0.73
b->o h1->o h2->o h3->o h4->o i1->o i2->o
-0.52  0.08  0.59  0.46 -0.01 -0.29  0.05
> new <- matrix(c(0.01,-0.01,0,1),2,2)

```

```

> colnames(new) <- colnames(XX)
> predict(n3,new)
      [,1]
[1,] 0.564652
[2,] 0.551463

> k3 <- glm(yd~y1+y2+y1d+y2d+v1d+v2d,family=binomial)
> summary(k3)
Call:
glm(formula = yd~ y1+y2+y1d+y2d+v1d+v2d, family=binomial)
Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.1945     0.1303   1.492   0.1356
y1             0.8038     2.9460   0.273   0.7850
y2            -6.6722     3.0716  -2.172   0.0298 *
y1d           -0.2064     0.1323  -1.560   0.1187
y2d            0.1132     0.1340   0.845   0.3981
v1d           -0.0239     0.1022  -0.234   0.8152
v2d           -0.1534     0.1024  -1.498   0.1343
---
AIC: 2556.8
> require(MTS)
> rt <- cbind(amzn,vxx)
> m1=dccPre(rt)
Sample mean of the returns:  0.0005850894 -0.003360788
Component:  1
Estimates:  3e-06 0.129885 0.843406
se.coef   :  1e-06 0.016406 0.017044
t-value    :  4.893239 7.917109 49.48264
Component:  2
Estimates:  0.000116 0.151948 0.774099
se.coef   :  2.3e-05 0.020891 0.027977
t-value    :  5.022571 7.273467 27.66958
> names(m1)
[1] "marVol" "sresi" "est" "se.coef"
> sresi <- m1$sresi
> m2 <- dccFit(sresi)
Estimates:  0.87732 0.01339715 7.768572
st.errors:  0.07609449 0.00736214 0.8419459
t-values:   11.52935 1.819736 9.226925
> names(m2)
[1] "estimates" "Hessian" "rho.t"
> dim(rt)
[1] 1843 2
> m2$rho.t[1843,]
[1] 1.000000 -0.869967 -0.869967 1.000000

```

```
### Problem D ###
```

```
> basicStats(cost)
```

```

              cost
nobs      2368.000000
Minimum   -0.126729
Maximum    0.102118
Mean       0.000526
Median     0.000251
SE Mean    0.000297
LCL Mean   -0.000056
UCL Mean    0.001108
Variance    0.000209
Stdev       0.014442
Skewness    -0.061145
Kurtosis     8.075124

```

```
> ncost <- -cost ## logb position
```

```
> h1 <- garchFit(~garch(1,1),data=ncost,leverage=T,trace=F,cond.dist="std")
```

```
> summary(h1)
```

```
Title: GARCH Modelling
```

```
Call: garchFit(formula = ~garch(1, 1), data = ncost, cond.dist = "std",
  leverage = T, trace = F)
```

```
Conditional Distribution: std
```

```
Error Analysis:
```

	Estimate	Std. Error	t value	Pr(> t )
mu	-4.563e-04	2.159e-04	-2.114	0.034525 *
omega	1.877e-06	6.824e-07	2.750	0.005954 **
alpha1	3.419e-02	9.475e-03	3.608	0.000308 ***
gamma1	-4.993e-01	1.537e-01	-3.248	0.001161 **
beta1	9.490e-01	1.149e-02	82.623	< 2e-16 ***
shape	5.577e+00	6.047e-01	9.224	< 2e-16 ***

```
---
```

```
Standardised Residuals Tests:
```

			Statistic	p-Value
Ljung-Box Test	R	Q(10)	14.76373	0.1409164
Ljung-Box Test	R	Q(20)	19.77384	0.4721548
Ljung-Box Test	R <sup>2</sup>	Q(10)	7.22006	0.7045194
Ljung-Box Test	R <sup>2</sup>	Q(20)	14.02298	0.8293291
LM Arch Test	R	TR <sup>2</sup>	9.447568	0.6643011

```
> ph1 <- predict(h1,5)
```

```
> ph1
```

	meanForecast	meanError	standardDeviation
1	-0.0004563202	0.01312495	0.01312495
2	-0.0004563202	0.01308631	0.01308631

```

3 -0.0004563202 0.01304820      0.01304820
4 -0.0004563202 0.01301063      0.01301063
5 -0.0004563202 0.01297358      0.01297358
> sqrt(sum(ph1$standardDeviation^2))
[1] 0.0291781
> h2 <- gev(ncost,block=21)
> h2
$n.all
[1] 2367
$n
[1] 113
$data
[1] 0.023584785 0.035464721 0.033704948 0.016477272 0.012010509 0.010082928
....
[109] 0.025570888 0.033117406 0.030701923 0.024521016 0.016449090
$block
[1] 21
$par.ests
      xi      sigma      mu
0.293758810 0.008000867 0.016330655
$par.ses
      xi      sigma      mu
0.0837917491 0.0006299979 0.0008514014
$converged
[1] 0

> h3 <- gpd(ncost,thres=0.02)
> h3
$n
[1] 2367
$data
[1] 0.02358479 0.03546472 0.03370495 0.02094755 0.02668065 0.02351547
....
[127] 0.02358891 0.03311741 0.03070192 0.02209922 0.02452102
$threshold
[1] 0.02
$p.less.thresh
[1] 0.9446557
$n.exceed
[1] 131
$par.ests
      xi      beta
0.208974758 0.009144701
$par.ses
      xi      beta
0.099859198 0.001165717

```



```

$converged
[1] 0
> riskmeasures(h3,c(0.95,0.99,0.999))
      p   quantile   sfall
[1,] 0.950 0.02093858 0.03274710
[2,] 0.990 0.03880916 0.05533877
[3,] 0.999 0.07747592 0.10422060
> h4 <- gpd(ncost,threshold=0.03)
> h4
$data
[1] 0.03546472 0.03370495 0.03873395 0.03382808 0.04328677 0.03633464
....
[49] 0.03311741 0.03070192
$threshold
[1] 0.03
$p.less.thresh
[1] 0.9788762
$n.exceed
[1] 50
$par.ests
      xi      beta
0.393991088 0.008764191
$par.ses
      xi      beta
0.21968994 0.00217236
> riskmeasures(h4,c(0.95,0.99,0.999))
      p   quantile   sfall
[1,] 0.950 0.02359680 0.03389596
[2,] 0.990 0.03762174 0.05703909
[3,] 0.999 0.08174547 0.12984946
> getSymbols("^VIX",from=XXXX,to=XXXX)
[1] "VIX"
> vix <- diff(log(as.numeric(VIX[,6])))
> ncost <- -cost
> y <- ncost[3:2368]
> y1 <- ncost[2:2367]
> y2 <- ncost[1:2366]
> vix1 <- vix[2:2367]
> vix2 <- vix[1:2366]
> require(quantreg)
> XX <- cbind(y1,y2,vix1,vix2)
> colnames(XX) <- c("ym1","ym2","vixm1","vixm2")
> mm <- rq(y~.,data=data.frame(XX),tau=0.95)
> summary(mm)
Call: rq(formula = y ~ ., tau = 0.95, data = data.frame(XX))
tau: [1] 0.95

```

Coefficients:

	Value	Std. Error	t value	Pr(> t )
(Intercept)	0.02121	0.00097	21.80417	0.00000
ym1	0.07188	0.06557	1.09619	0.27311
ym2	0.00879	0.07377	0.11911	0.90520
vixm1	-0.03493	0.01322	-2.64118	0.00832
vixm2	0.00807	0.01353	0.59651	0.55089

> names(mm)

[1]	"coefficients"	"x"	"y"	"residuals"
[5]	"dual"	"fitted.values"	"formula"	"terms"
[9]	"xlevels"	"call"	"tau"	"rho"
[13]	"method"	"model"		

> new <- matrix(c(0.08,0.01,0.03,0.01),1,4)

> colnames(new) <- colnames(XX)

> predict(mm,data.frame(new))

1

0.02608507