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-notes exam.
• Write your answer in the blank space provided for each question.
• There are 18 pages, including some R output.
• For simplicity, ALL tests use the 5% significance level, and all VaR calculations use 1% tail probability.
• Round your answer to 3 significant digits.
• You may bring a PC or calculator to the exam.

Problem A: (42 pts) Answer briefly the following questions.

1. Questions 1 to 10. Consider the intraday 1-minute log returns, in percentages, of Caterpillar stock from January 4 to January 8, 2010. The summary statistics and some preliminary analysis of the returns are given in the attached output. Based on the results provided, is the mean of the log return zero? Why?

2. Is the distribution of the log returns skewed? Perform a statistical test to justify your conclusion.

3. Does the distribution of the log returns have heavy tails? Perform a statistical test to justify your conclusion.
4. Are there any serial correlations in the log return series? Why? State the null hypothesis you use to justify your answer.

5. Are there any ARCH-effects in the log returns? Why? State the null hypothesis you use to justify your answer.

6. An ARMA(0,0)+GARCH(1,1) model with Student-\(t\) innovations is entertained for the log return series. Is the model adequate? Write down the fitted model, including all the parameters.

7. Based on the fitted GARCH(1,1) model. Let \(v\) be the degrees of freedom of the Student-\(t\) innovation. Test \(H_0 : v = 5\) vs. \(H_a : v \neq 5\). What is the test statistic? Draw your conclusion.

8. An ARMA(0,0)+GARCH(1,1) model with skewed Student-\(t\) innovations is entertained for the data. Is the model adequate? Write down the fitted model, including all parameters.

9. Let \(\xi\) be the skew parameter of the fitted model. Test \(H_0 : \xi = 1\) vs \(H_a : \xi \neq 1\). What is the test statistic employed? Compute the \(p\) value of the test and draw your conclusion.

10. Compare the two ARMA(0,0)+GARCH(1,1) models. Which model do you select? Why?

11. Suppose that the price \(P_t\) of a stock follows the stochastic diffusion model

\[
\frac{dP_t}{P_t} = \mu dt + \sigma P_t dw_t,
\]
where \( \mu \) and \( \sigma \) are constant and \( w_t \) is the standard Brownian motion. What is the distribution of the log return of the stock from time \( t \) to \( T \)?

12. Let \( r_{1t} \) and \( r_{2t} \) be the monthly simple return of Coca Cola stock and the S&P 500 composite index from January 1960 to December 2009. Let \( r_t = (r_{1t}, r_{2t})' \). Is the bivariate return \( r_t \) serially correlated? Why? State the null hypothesis you use to justify your conclusion.


\[
\text{M1: } \quad x_t = 10.0 + 0.1t + a_t + 0.5a_{t-1} \\
\text{M2: } \quad x_t = x_{t-1} + a_t + 0.5a_{t-1}
\]

where \( \{a_t\} \) is a sequence of normal random variables with mean zero and variance 2. Assume that \( x_{100} = 10 \) and \( a_{100} = -2 \). For each model, compute a 95\% interval forecast of \( x_{101} \) at the forecast origin \( t = 100 \).

14. For each model, compute the variance of 2-step ahead forecast error at the forecast origin 100.

15. For each model, compute the 1000-step-ahead prediction of \( x_{1100} \) at the forecast origin \( t = 100 \).

16. State two weaknesses in using RiskMetrics to compute value at risk (VaR) of a financial position.

17. Besides the econometric modeling such as GARCH modeling, describe two additional methods that can be used to estimate stock volatility.
18. Consider a 3-2-1 feed-forward neural network with skip layer. Suppose that the output variable is binary. Write down the econometric model of this network.

19. Describe two difficulties one often faces in assessing credit risk of a loan.

20. Describe two financial applications of seasonal time series models.

21. Describe two effects of overlooking the serial correlations in a linear regression model.

**Problem B.** (18 points) This problem is concerned with forecasting the VIX index of Chicago Board Options Exchange (CBOE). The data span is from January 2, 2004, to December 31, 2009. Two approaches are considered. In the first approach, a pure time series model is used for the VIX index. In the second approach, we employ the lag-1 volatility of the S&P 500 index as an explanatory variable. The latter is estimated by a Gaussian ARMA(1,0)-GARCH(1,1) model using daily log returns, in percentages, of the S&P 500 index. Details are given in the attached output. [Note that the estimated volatility is not annualized. One can multiply the estimate by \( \sqrt{252} \), but this will not affect the analysis.]

1. Write down the fitted ARMA(1,0)-GARCH(1,1) model for the daily log returns of the S&P 500 index. Are all estimates statistical significant?

2. Write down the pure time series model for the VIX index. Based on the output provided, is the model adequate? Why?

3. Write down the model for VIX index when the lag-1 S&P 500 volatility is used as an explanatory variable. Is the model adequate? Why?
4. Based of the fitted model, does the lag-1 S&P 500 volatility contribute significantly in modeling the VIX index? Why?

5. Based on the in-sample fitting, which of the two models of the VIX index is preferred? Why?

6. Based on the backtesting procedure, which model is selected? Why?

**Problem C.** (10 pts) Consider the quarterly earnings per share of Abbott Laboratories from 1992 to the first quarter of 2010 for 73 observations. Log-transformation of the earnings is taken to stabilize the variability. Two time series models are entertained. The first model is a pure time series model, whereas the second contains a quarterly dummy variable.

1. Write down the fitted pure time series model for the log earning series, including residual variance.

2. Is the fitted model adequate? Is there any ARCH effects in the earnings? Why?

3. Write down the fitted model with the dummy variable for the first quarter.

4. Is the dummy variable significant at the 5% level? What is the implication of the dummy variable?
5. Select a model between the two and justify your choice of the model.

**Problem D.** (30 points) Consider the daily log returns of the stocks of Apple and J.P. Morgan Chase from January 3, 2001, to December 31, 2009. The tick symbols are AAPL and JPM, respectively. Suppose that Manager A holds a long position of $1 million on each of the two stocks. Use the attached output to answer the following questions.

1. Manager A decides to use RiskMetrics to calculate VaR of her financial position. To this end, the special Gaussian IGARCH(1,1) model is fitted to the two log-return series. For both stock returns, the $\alpha$ parameter of the IGARCH model is 0.94. Prediction of the conditional variance is given in the output. Calculate the VaR for each stock for the next trading day.

2. What are the corresponding expected shortfalls for each financial position?

3. The correlation between the two log returns is 0.327. What is the VaR of Manager A’s financial position for the next 10 trading days?

4. Manager A worries about the heavy tails of the returns so that she adopts an econometric approach with Student-$t$ innovations to calculate VaR for her position. Write down the fitted GARCH(1,1) model for AAPL.

5. What are the VaR of each financial position based on the econometric approach?
6. Manager A also tries the traditional extreme value theory with block size 21 on the Apple stock. What are the estimates of \((\xi, \sigma, \mu)\)? What is the VaR for her position on the Apple stock?

7. Finally, Manager A uses the peaks over threshold (POT) approach. She decides to use 4% and 3% as the threshold for the Apple and Chase stock, respectively. Write down the parameter estimates for both stocks?

8. What are the expected shortfall for each of the two positions Manager A has?

9. Manager B holds a short position of $1 million on the J.P. Morgan Chase stock and a long position of $1 million on the Apple stock. She also decides to use Gaussian GARCH models to estimate VaR. Compute the VaR and expected shortfall for each of the two stock positions for the next trading day.

10. What is the VaR and expected shortfall of the next trading day for Manager B?
Computer output.

*** Problem A ***

```r
> da=read.table("taq-cat-t-jan04t082010.txt",header=T)
> dim(da)
[1] 155240 6
> m1=hfrtn(da,1)
> rtn=m1$rtn * 100
> library(fBasics)
> basicStats(rtn)

rtn
nobs 1945.000000
Mean 0.002939
Median 0.000000
SE Mean 0.001298
LCL Mean 0.000393
UCL Mean 0.005486
Stdev 0.057260
Skewness -0.119386
Kurtosis 2.705273
```

```r
> Box.test(rtn,lag=10,type='Ljung')

Box-Ljung test
data: rtn
X-squared = 12.9595, df = 10, p-value = 0.2259

> r1=rtn-mean(rtn)
> Box.test(r1^2,lag=10,type='Ljung')

Box-Ljung test
data: r1^2
X-squared = 338.9631, df = 10, p-value < 2.2e-16

> library(fGarch)
> m2=garchFit(~arma(0,0)+garch(1,1),data=rtn,cond.dist=c("std"),trace=F)
> summary(m2)

Title: GARCH Modelling

Call:
garchFit(formula=~arma(0,0)+garch(1,1),data=rtn,cond.dist=c("std"),trace=F)

Mean and Variance Equation:
data ~ arma(0, 0) + garch(1, 1)
[data = rtn]
```
Conditional Distribution: std

Error Analysis:

| Parameter | Estimate | Std. Error | t value | Pr(>|t|) |
|-----------|----------|------------|---------|----------|
| mu        | 0.0017228| 0.0010634  | 1.620   | 0.10522  |
| omega     | 0.0001173| 0.0000433  | 2.709   | 0.00674 **|
| alpha1    | 0.0896036| 0.0199073  | 4.501   | 6.76e-06 ***|
| beta1     | 0.8752155| 0.0286844  | 30.512  | < 2e-16 ***|
| shape     | 6.4269766| 0.9513118  | 6.756   | 1.42e-11 ***|

---

Standardised Residuals Tests:

<table>
<thead>
<tr>
<th>Test</th>
<th>Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljung-Box Test R</td>
<td>7.891391</td>
<td>0.639445</td>
</tr>
<tr>
<td>Ljung-Box Test R^2</td>
<td>4.469669</td>
<td>0.9236828</td>
</tr>
<tr>
<td>Ljung-Box Test R^2</td>
<td>16.51443</td>
<td>0.6842411</td>
</tr>
</tbody>
</table>

Information Criterion Statistics:

<table>
<thead>
<tr>
<th>Statistic</th>
<th>AIC</th>
<th>BIC</th>
<th>SIC</th>
<th>HQIC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-3.059466</td>
<td>-3.045140</td>
<td>-3.059480</td>
<td>-3.054199</td>
</tr>
</tbody>
</table>

> m3=garchFit(~arma(0,0)+garch(1,1),data=rtn,cond.dist=c("sstd"),trace=F)
> summary(m3)

Title: GARCH Modelling

Call:
garchFit(formula="arma(0,0)+garch(1,1),data=rtn,cond.dist=c("sstd"),trace=F)

Mean and Variance Equation:

data ~ arma(0, 0) + garch(1, 1)
[data = rtn]

Conditional Distribution: sstd

Error Analysis:

| Parameter | Estimate | Std. Error | t value | Pr(>|t|) |
|-----------|----------|------------|---------|----------|
| mu        | 1.505e-03| 1.128e-03  | 1.334   | 0.18219  |
| omega     | 1.153e-04| 4.286e-05  | 2.690   | 0.00714 **|
| alpha1    | 8.919e-02| 1.986e-02  | 4.491   | 7.08e-06 ***|
| beta1     | 8.764e-01| 2.851e-02  | 30.741  | < 2e-16 ***|
| skew      | 9.829e-01| 2.949e-02  | 33.333  | < 2e-16 ***|
| shape     | 6.414e+00| 9.469e-01  | 6.774   | 1.25e-11 ***|

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</tr>
</thead>
<tbody>
<tr>
<td>Ljung-Box Test R Q(10)</td>
<td>7.859612</td>
<td>0.6425477</td>
</tr>
<tr>
<td>Ljung-Box Test R Q(20)</td>
<td>17.27405</td>
<td>0.6351137</td>
</tr>
<tr>
<td>Ljung-Box Test R^2 Q(10)</td>
<td>4.473388</td>
<td>0.9234758</td>
</tr>
<tr>
<td>Ljung-Box Test R^2 Q(20)</td>
<td>16.59355</td>
<td>0.6791862</td>
</tr>
</tbody>
</table>

Information Criterion Statistics:

<table>
<thead>
<tr>
<th></th>
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<th>HQIC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-3.058611</td>
<td>-3.041419</td>
<td>-3.058630</td>
<td>-3.052289</td>
</tr>
</tbody>
</table>

**

> da=read.table("m-kosp6009.txt",header=T)
> dim(da)
[1] 600 3
> head(da)
  date  ko    sp
1 19600129 -0.018333 -0.071464

> x=da[,2:3]
> source("mq.R")
> mq(x,10)
[1] "m, Q(m) and p-value:"
[1] 1.0000000 5.3734180 0.2510822

### Problem B ###

> da=read.table("vix0409.txt",header=T)
> da1=read.table("d-sp0409.txt",header=T)
> sp=log(da1[,9])
> sp=rev(sp)
> sp5=diff(sp)
> sp5=sp5*100
> m1=garchFit(~arma(1,0)+garch(1,1),data=sp5,trace=F)
> summary(m1)

Title: GARCH Modelling

Call:
garchFit(formula = ~arma(1, 0) + garch(1, 1), data = sp5, trace = F)

Mean and Variance Equation:
data ~ arma(1, 0) + garch(1, 1)
[data = sp5]
Conditional Distribution: norm

|            | Estimate | Std. Error | t value | Pr(>|t|) |
|------------|----------|------------|---------|----------|
| mu         | 0.001890 | 0.020753   | 0.091   | 0.92743  |
| ar1        | -0.080553| 0.027255   | -2.956  | 0.00312 **|
| omega      | 0.010641 | 0.003042   | 3.497   | 0.00047 ***|
| alpha1     | 0.071833 | 0.010461   | 6.867   | 6.56e-12 ***|
| beta1      | 0.918575 | 0.011104   | 82.728  | < 2e-16 ***|

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Standardised Residuals Tests:

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<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Ljung-Box Test R Q(10)</td>
<td>6.961551 0.7290697</td>
</tr>
<tr>
<td>Ljung-Box Test R^2 Q(10)</td>
<td>19.65038 0.0327384</td>
</tr>
</tbody>
</table>

Information Criterion Statistics:

<table>
<thead>
<tr>
<th>Statistics</th>
<th>AIC</th>
<th>BIC</th>
<th>SIC</th>
<th>HQIC</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2.789048</td>
<td>2.806654</td>
<td>2.789026</td>
<td>2.795605</td>
</tr>
</tbody>
</table>

> vsp5=volatility(m1)
> vix=da$Close

> m2=arima(vix,order=c(0,1,5))
> m2
Call: arima(x = vix, order = c(0, 1, 5))

Coefficients:

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Value</th>
<th>s.e.</th>
</tr>
</thead>
<tbody>
<tr>
<td>ma1</td>
<td>-0.1746</td>
<td>0.0256</td>
</tr>
<tr>
<td>ma2</td>
<td>-0.1420</td>
<td>0.0261</td>
</tr>
<tr>
<td>ma3</td>
<td>0.0231</td>
<td>0.0265</td>
</tr>
<tr>
<td>ma4</td>
<td>-0.1035</td>
<td>0.0249</td>
</tr>
<tr>
<td>ma5</td>
<td>0.0541</td>
<td>0.0246</td>
</tr>
</tbody>
</table>

sigma^2 estimated as 3.347: log likelihood = -3054.68, aic = 6121.35

> Box.test(m2$residuals,lag=5,type='Ljung')
Box-Ljung test

X-squared = 0.5616, df = 5, p-value = 0.9897

### Set up regression analysis ###

> y=vix[2:1511]
> x=vsp5[1:1510]
> m3=lm(y~x)
> summary(m3)
Call: lm(formula = y ~ x)
Coefficients:

| Estimate | Std. Error | t value | Pr(>|t|) |
|----------|------------|---------|----------|
| (Intercept) | 4.4314 | 0.1627 | 27.24 | <2e-16 *** |
| x | 14.2225 | 0.1187 | 119.85 | <2e-16 *** |

---

```r
m4 = arima(y, order = c(1, 0, 5), xreg = x)
m4
```

Call: arima(x = y, order = c(1, 0, 5), xreg = x)

Coefficients:

<table>
<thead>
<tr>
<th>ar1</th>
<th>ma1</th>
<th>ma2</th>
<th>ma3</th>
<th>ma4</th>
<th>ma5</th>
<th>intercept</th>
<th>x</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.9936</td>
<td>-0.1695</td>
<td>-0.1688</td>
<td>0.0158</td>
<td>-0.1131</td>
<td>0.0375</td>
<td>18.5480</td>
<td>1.8546</td>
</tr>
</tbody>
</table>

s.e. 0.0028 0.0258 0.0285 0.0272 0.0254 0.0260 4.1251 0.7057

sigma^2 estimated as 3.322: log likelihood = -3050.83, aic = 6119.66

```r
Box.test(m4$residuals, lag = 5, type = 'Ljung')
```

Box-Ljung test
data: m4$residuals
X-squared = 0.6534, df = 5, p-value = 0.9854

```r
source("backtest.R")
```

```r
backtest(m2, vix, 1400, 1)
```

[1] "RMSE of out-of-sample forecasts"
[1] 1.322074

[2] "Mean absolute error of out-of-sample forecasts"
[1] 0.95049

```r
backtest(m4, y, 1399, 1, xre = x)
```

[1] "RMSE of out-of-sample forecasts"
[1] 1.321974

[2] "Mean absolute error of out-of-sample forecasts"
[1] 0.9475994

### Problem C ###

```r
da = read.table("q-abt-earns.txt", header = T)
```

```r
abt = log(da$earns)
m1 = arima(abt, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1), period = 4))
m1
```

Call:

arima(x = abt, order = c(0, 1, 1), seasonal = list(order = c(0, 1, 1), period = 4))

Coefficients:

<table>
<thead>
<tr>
<th>ma1</th>
<th>sma1</th>
</tr>
</thead>
</table>

12
> Box.test(m1$residuals, lag=12, type='Ljung')

Box-Ljung test

data: m1$residuals
X-squared = 17.6555, df = 12, p-value = 0.1266

> Box.test(m1$residuals^2, lag=12, type='Ljung')

Box-Ljung test

data: m1$residuals^2
X-squared = 12.8455, df = 12, p-value = 0.3804

> Q1=c(rep(c(1,0,0,0),18),1)
> Q2=c(rep(c(0,1,0,0),18),0)
> Q3=c(rep(c(0,0,1,0),18),0)
> x=cbind(Q1,Q2,Q3)
> m3=arima(abt, order=c(0,1,1), seasonal=list(order=c(1,0,1), period=4), xreg=x)
> m3

Coefficients:
   ma1  sar1  sma1    Q1    Q2    Q3
-0.530 0.916 -0.288 0.201 0.019 0.080

s.e. 0.137 0.054 0.115 0.083 0.086

sigma^2 estimated as 0.003100: log likelihood = 99.37, aic = -192.74

> Box.test(m3$residuals, lag=12, type='Ljung')

Box-Ljung test

data: m3$residuals
X-squared = 17.9953, df = 12, p-value = 0.1158

> m3=arima(abt, order=c(0,1,1), seasonal=list(order=c(1,0,1), period=4), xreg=x)
> m3

Coefficients:
   ma1  sar1  sma1    Q1    Q2    Q3
-0.550 0.930 -0.296 0.174

s.e. 0.135 0.046 0.112 0.087

sigma^2 estimated as 0.003031: log likelihood = 103.58, aic = -197.17

> m3=arima(abt, order=c(0,1,1), seasonal=list(order=c(1,0,1), period=4), xreg=Q1)
> m3

Call:
arima(x=abt, order=c(0,1,1), seasonal=list(order=c(1,0,1), period=4), xreg=Q1)

Coefficients:
   ma1  sar1  sma1    Q1
-0.550 0.929 -0.296 0.173

s.e. 0.135 0.046 0.112 0.077

sigma^2 estimated as 0.003031: log likelihood = 103.58, aic = -197.17

> Box.test(m3$residuals, lag=12, type='Ljung')

Box-Ljung test

data: m3$residuals
X-squared = 17.9953, df = 12, p-value = 0.1158
> Box.test(m3$residuals^2,lag=12,type='Ljung')
  Box-Ljung test
  data: m3$residuals^2
  X-squared = 12.8751, df = 12, p-value = 0.3782

######## Problem D ########
> da=read.table("d-aapl0009.txt",header=T)
> aapl=log(da[,2]+1)
> da=read.table("d-jpm0009.txt",header=T)
> jpm=log(da$rtn+1)
> source("garchoxfit_R.txt")
> m1=garchOxFit(formula.mean=~arma(0,0),formula.var=~igarch(1,1),
    series=aapl,include.mean=F,include.var=F)
  ** SPECIFICATIONS **
  Dependent variable : X
  Mean Equation : ARMA (0, 0) model.
  Variance Equation : IGARCH (1, 1) model.
  The distribution is a Gauss distribution.

  Maximum Likelihood Estimation (Std.Errors based on Second derivatives)
<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std.Error</th>
<th>t-value</th>
<th>t-prob</th>
</tr>
</thead>
</table>
  ARCH(Alpha1) | 0.063110  | 0.0069393 | 9.095  | 0.0000 |
  GARCH(Beta1) | 0.937090  |

> v1=.94*m1$condvars[2515]+.06*aapl[2515]^2
> v1
  [1] 0.000242971
>
> m2=garchOxFit(formula.mean=~arma(0,0),formula.var=~igarch(1,1),
    series=jpm,include.mean=F,include.var=F)
  ** SPECIFICATIONS **
  Dependent variable : X
  Mean Equation : ARMA (0, 0) model.
  Variance Equation : IGARCH (1, 1) model.
  The distribution is a Gauss distribution.

  Maximum Likelihood Estimation (Std.Errors based on Second derivatives)
<table>
<thead>
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<th>t-value</th>
<th>t-prob</th>
</tr>
</thead>
</table>
  ARCH(Alpha1) | 0.062925  | 0.0064783 | 9.713  | 0.0000 |
  GARCH(Beta1) | 0.937275  |

> v2=.94*m2$condvars[2515]+.06*jpm[2515]^2
> v2
  [1] 0.0002425415
> cor(aapl,jpm)
[1] 0.3269751
>
> naapl=-aapl
> njpm=-jmp
> m3=garchOxFit(formula.mean=~arma(0,0),formula.var=~garch(1,1),
series=naapl,cond.dist="t")
** SPECIFICATIONS **
Dependent variable : X
Mean Equation : ARMA (0, 0) model.
Variance Equation : GARCH (1, 1) model.
The distribution is a Student distribution, with 5.65644 degrees of freedom.

Maximum Likelihood Estimation (Std.Errors based on Second derivatives)

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std.Error</th>
<th>t-value</th>
<th>t-prob</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cst(M)</td>
<td>-0.001750</td>
<td>0.00048958</td>
<td>-3.574</td>
</tr>
<tr>
<td>Cst(V)</td>
<td>0.070721</td>
<td>0.035931</td>
<td>1.968</td>
</tr>
<tr>
<td>ARCH(Alpha1)</td>
<td>0.035251</td>
<td>0.011375</td>
<td>3.099</td>
</tr>
<tr>
<td>GARCH(Beta1)</td>
<td>0.955929</td>
<td>0.013832</td>
<td>69.11</td>
</tr>
<tr>
<td>Student(DF)</td>
<td>5.656436</td>
<td>0.57868</td>
<td>9.775</td>
</tr>
</tbody>
</table>

Warning : To avoid numerical problems, the estimated parameter Cst(V), and its std.Error have been multiplied by 10^-4.

** FORECASTS **
Horizon  Mean  Variance
1  -0.00175  0.0003567

** TESTS **
Q-Statistics on Standardized Residuals
Q(  10)  =  13.2019  [0.2125992]
Q(  20)  =  20.7557  [0.4116331]

Q-Statistics on Squared Standardized Residuals
--> P-values adjusted by 2 degree(s) of freedom
Q(  10)  =  1.61024  [0.9907224]
Q(  20)  =  2.37685  [0.9999955]

> m4=garchOxFit(formula.mean=~arma(0,0),formula.var=~garch(1,1),
series=njpm,cond.dist="t")
** SPECIFICATIONS **
Dependent variable : X
Mean Equation : ARMA (0, 0) model.
Variance Equation: GARCH (1, 1) model. The distribution is a Student distribution, with 6.56734 degrees of freedom.

Maximum Likelihood Estimation (Std. Errors based on Second derivatives)

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Std.Error</th>
<th>t-value</th>
<th>t-prob</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cst(M)</td>
<td>-0.000384</td>
<td>0.000275</td>
<td>-1.393</td>
</tr>
<tr>
<td>Cst(V)</td>
<td>0.013672</td>
<td>0.005945</td>
<td>2.300</td>
</tr>
<tr>
<td>ARCH(Alpha1)</td>
<td>0.074476</td>
<td>0.013055</td>
<td>5.705</td>
</tr>
<tr>
<td>GARCH(Beta1)</td>
<td>0.926346</td>
<td>0.011697</td>
<td>79.20</td>
</tr>
<tr>
<td>Student(DF)</td>
<td>6.567341</td>
<td>0.82263</td>
<td>7.983</td>
</tr>
</tbody>
</table>

Warning: To avoid numerical problems, the estimated parameter Cst(V), and its std. Error have been multiplied by 10^-4.

** FORECASTS **

<table>
<thead>
<tr>
<th>Horizon</th>
<th>Mean</th>
<th>Variance</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>-0.0003835</td>
<td>0.0002057</td>
</tr>
</tbody>
</table>

** TESTS **

Q-Statistics on Standardized Residuals

\[ Q(10) = 4.53337 \quad [0.9200956] \]
\[ Q(20) = 7.54049 \quad [0.9944977] \]

Q-Statistics on Squared Standardized Residuals

--> P-values adjusted by 2 degree(s) of freedom

\[ Q(10) = 7.30922 \quad [0.5036675] \]
\[ Q(20) = 31.1431 \quad [0.0277094] \]

> m5=gev(naapl,21)
> m5
$n.all: 2515$
$n: 120$
$block: 21$

$par.est$

\[
\begin{array}{ccc}
  & xi & sigma & mu \\
 0.26260313 & 0.01908837 & 0.03810798 \\
\end{array}
\]

$par.ses$

\[
\begin{array}{ccc}
  & xi & sigma & mu \\
 0.061607967 & 0.001523823 & 0.001916449 \\
\end{array}
\]

> source("evtVaR.R")
> evtVaR(.263,.0191,.0381,21,.01)
[1] 0.07481174

> m6=gpd(naapl,.04)
> m6
$n: 2515
$threshold: 0.04
$p.less.thresh: 0.9232604
$n.exceed: 193

$par.est
   xi    beta
0.33483791 0.01381806

$par.ses
   xi    beta
0.088925869 0.001527254

> riskmeasures(m6,c(.99,.999))
   p    quantile  sfall
[1,] 0.990 0.08038102 0.1214825
[2,] 0.999 0.17524986 0.2641077

> m7=gpd(njpm,.03)
> m7
$n: 2515
$threshold: 0.03
$p.less.thresh: 0.9033797
$n.exceed: 243

$par.est
   xi    beta
0.23143662 0.01802384

$par.ses
   xi    beta
0.078624711 0.001795892

> riskmeasures(m7,c(.99,.999))
   p    quantile  sfall
[1,] 0.990 0.0837644 0.1234058
[2,] 0.999 0.1764237 0.2439674

> d1=garchFit(~arma(0,0)+garch(1,1),data=naapl,trace=F)
> summary(d1)
Title: GARCH Modelling

Call:
garchFit(formula=~arma(0,0)+garch(1,1),data=naapl,trace=F)

Mean and Variance Equation:
  data ~ arma(0, 0) + garch(1, 1)
  [data = naapl]

Conditional Distribution: norm

|            | Estimate  | Std. Error | t value | Pr(>|t|) |
|------------|-----------|------------|---------|----------|
| mu         | -2.497e-03 | 5.270e-04  | -4.737  | 2.17e-06 *** |
| omega      | 3.492e-05  | 1.047e-05  | 3.336   | 0.000851 *** |
| alpha1     | 1.403e-01  | 1.941e-02  | 7.226   | 4.97e-13 *** |
| beta1      | 8.420e-01  | 2.474e-02  | 34.040  | < 2e-16 *** |

---

> predict(d1,1)

  meanForecast  meanError  standardDeviation
  1  -0.002496616  0.02015748  0.02015748

> d2=garchFit(~arma(0,0)+garch(1,1),data=jpm,trace=F)
> summary(d2)
Title: GARCH Modelling

Call:
garchFit(formula=~arma(0,0)+ arch(1,1),data=jpm,trace=F)

Mean and Variance Equation:
  data ~ arma(0, 0) + garch(1, 1)
  [data = jpm]

Conditional Distribution: norm

|            | Estimate  | Std. Error | t value | Pr(>|t|) |
|------------|-----------|------------|---------|----------|
| mu         | 4.736e-04  | 2.881e-04  | -1.644  | 0.10028 |
| omega      | 1.289e-06  | 4.501e-07  | 2.864   | 0.00419 ** |
| alpha1     | 8.204e-02  | 1.062e-02  | 7.726   | 1.11e-14 *** |

---

> predict(d2,1)

  meanForecast  meanError  standardDeviation
  1  0.0004735529  0.01408376  0.01408376