Financial Econometrics
Review Session Notes 7

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Contents

1 Simulating GARCH models

In the session, we will be working with the daily return series for the S&P 500. Begin by loading the **sp500daily.xls** file into EViews. Estimate a T-GARCH(1,1,1) model for the data. To do this, use the following code:

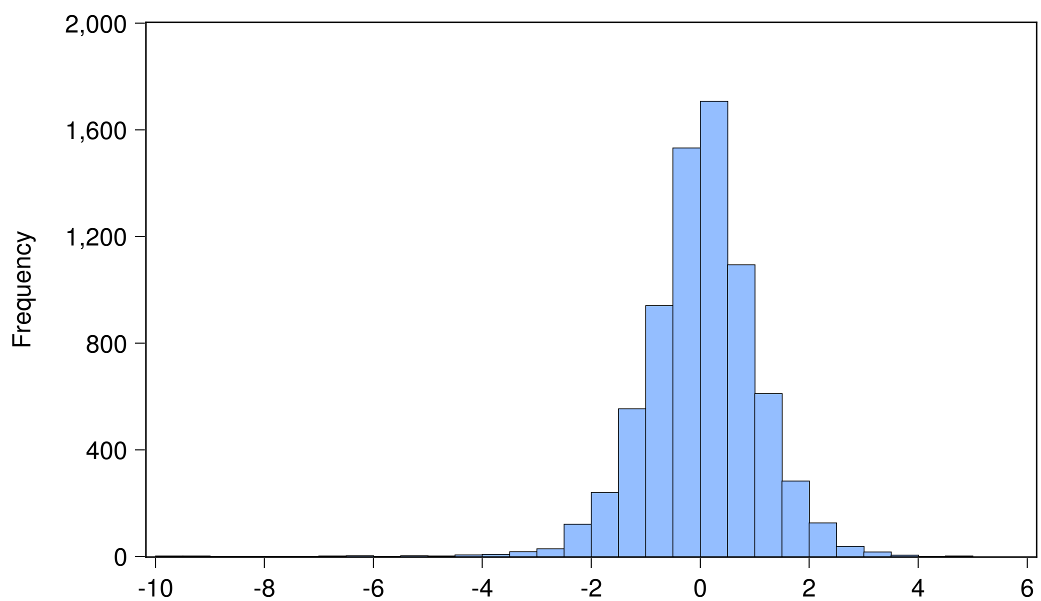
```
equation tgarch11.arch(1,1,thrsh=1) return
```

To save the conditional variances, use:

```
tgarch11.makegarch tgarch11var 'save the conditional GARCH variance
series tgarch11vol=@sqrt(tgarch11var) 'compute the corresponding vol
series tgarch11err=return/tgarch11vol 'compute the standardized residuals
'graph errhist.distplot tgarch11err
```

The histogram of the standardized residuals is presented in Fig. 1. Consider now simulating the model for k periods into the future, using normally distributed errors. To do this, we will follow the procedure described in the homework. Let the last observation in your sample be at time T. The first draw (r_{T+1}) will be obtained by randomly drawing a value from a Normal(0,1) distribution and multiplying it by $\sqrt{h_{T+1}}$ (which is the last conditional variance estimated in your model). You now have a simulated draw of r_{T+1} that can be used to update and get h_{T+2}. Again, take another random draw from a

Figure 1: Standardized residuals



Normal(0,1) and multiply it by $\sqrt{h_{T+2}}$ to get a simulated value for r_{T+2}. Continue this out through r_{T+30} and sum them up to get the cumulative return over the 30- day period. This is one realization (possible outcome) of the 30-day return obtained by simulating the model. We repeat this 2000 times and plot the histogram in Fig. 2. The code for this is below.

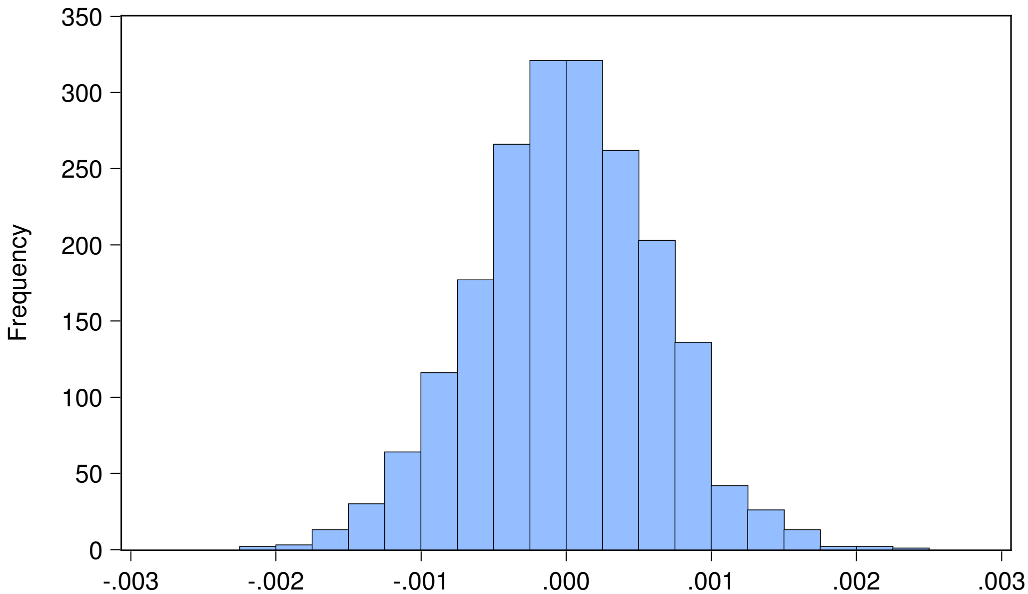
```
scalar omega=c(1)
scalar alpha=c(2)
scalar beta=c(3)
scalar gamma=c(4)

scalar T=7329 'last date in the sample
scalar nperiods=30
scalar nsim=2000
matrix(nperiods+1, nsim) ht_norm_for=tgarch11var(T) 'pre-create a matrix for ht
matrix(nperiods, nsim) rt_norm_for 'pre-create a matrix for the simulations of rt
matrix eps=@mnrnd(nperiods, nsim) 'pre-simulate the matrix of random errors
vector(nsim) ret_cum_norm=0 'pre-create the vector of cumulative returns

for !j=1 to nsim
for !i=1 to nperiods
rt_norm_for(!i, !j)=eps(!i, !j)*ht_norm_for(!i, !j)
ht_norm_for(!i+1, !j)=omega+alpha*rt_norm_for(!i,!j)^2+beta*ht_norm_for(!i, !j)
+gamma*rt_norm_for(!i,!j)*(rt_norm_for(!i,!j)-@abs(rt_norm_for(!i,!j)))/2
ret_cum_norm(!j)=ret_cum_norm(!j)+rt_norm_for(!i,!j)
next
next
```

Once we have the distribution of 30-day returns, we can use the quantile function to compute the cut-off levels for different probabilities. For example, to compute the 1% VaR, we would use

```
scalar VaR_norm=@quantile(ret_cum_norm,0.01)
```

Consider now repeating the above exercise but using the bootstrapped errors. The first draw (r_{T+1}) will be obtained by randomly selecting a single value of the z_ts obtained from your fitted model above and multiplying it by $\sqrt{h_{T+1}}$. You now have a simulated draw of r_{T+1} that can be used to update and get h_{T+2}. Again, take another random draw from the z_ts and multiply it by $\sqrt{h_{T+2}}$ to get a simulated value for r_{T+2}. Continue this out through r_{T+30} and sum them up to get the cumulative return over the 30- day period. This is one realization (possible outcome) of the 30-day return obtained by simulating the model. We repeat this 2000 times and plot the histogram in Fig. 3. The code for this is below.

Figure 2: 30-day cumulated return, Normal errors

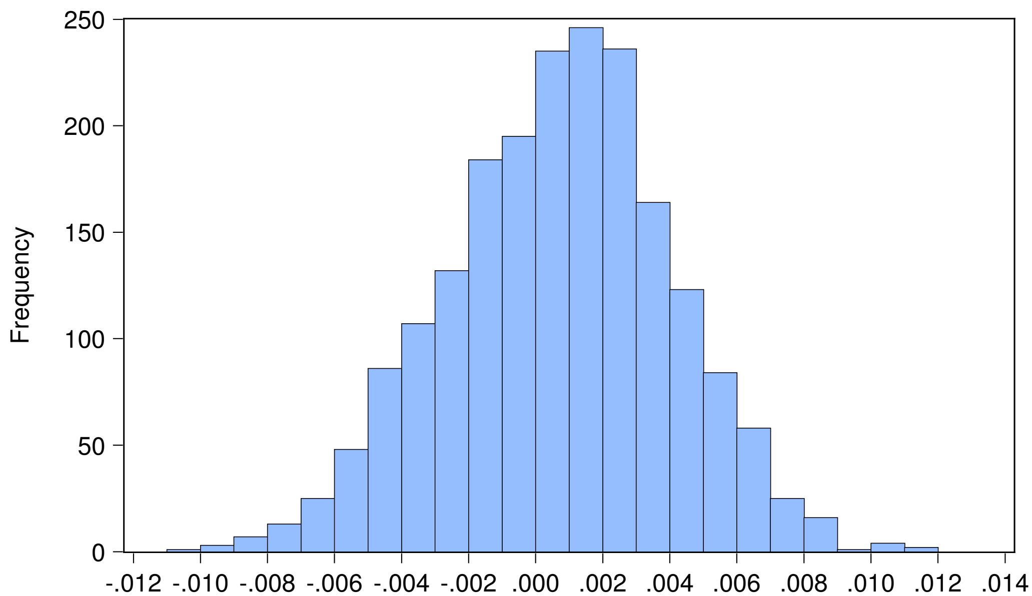



```
matrix u=@round((T-1)*@mrnd(nperiods, nsim))+1
matrix(nperiods+1, nsim) ht_boot_for=tgarch11var(T) 'pre-create a matrix for ht
matrix(nperiods, nsim) rt_boot_for 'pre-create a matrix for the simulations of rt
vector(nsim) ret_cum_boot=0 'pre-create the vector of cumulative returns

for !j=1 to nsim
for !i=1 to nperiods
rt_boot_for(!i, !j)=tgarch11err(u(!i, !j))*ht_boot_for(!i, !j)
ht_norm_for(!i+1, !j)=omega+alpha*rt_boot_for(!i,!j)^2+beta*ht_boot_for(!i, !j)
+gamma*rt_boot_for(!i,!j)*(rt_boot_for(!i,!j)-@abs(rt_boot_for(!i,!j)))/2
ret_cum_boot(!j)=ret_cum_boot(!j)+rt_boot_for(!i,!j)
next
next
```

2 Estimating Vector Autoregressions

For this part of the session, we will be working the T-bills data, contained in Tbill.xls. For simplicity, rename the series **yield3m**, **yield6m**, **yield1y**, **yield5y**. To estimate a VAR, use:

Figure 3: 30-day cumulated return, Empirical errors




```
varest 1 2 yield3m yield6m yield1y yield5y
```

This creates a var object in your EViews workfile. Most of the diagnostics concerning the model can be done directly from the object. For example, to examine the impulse response functions for the time series, we select the **Impulse** tab and select the appropriate options for the output. For the graph in Fig. 4, I selected the **Combined Graphs** option. Notice that, by default, EViews calculates the non-cumulated impulse response function. To get the cumulated impulse response function, select **Accumulated Responses** (Fig. 5).

Figure 4: Impulse response functions

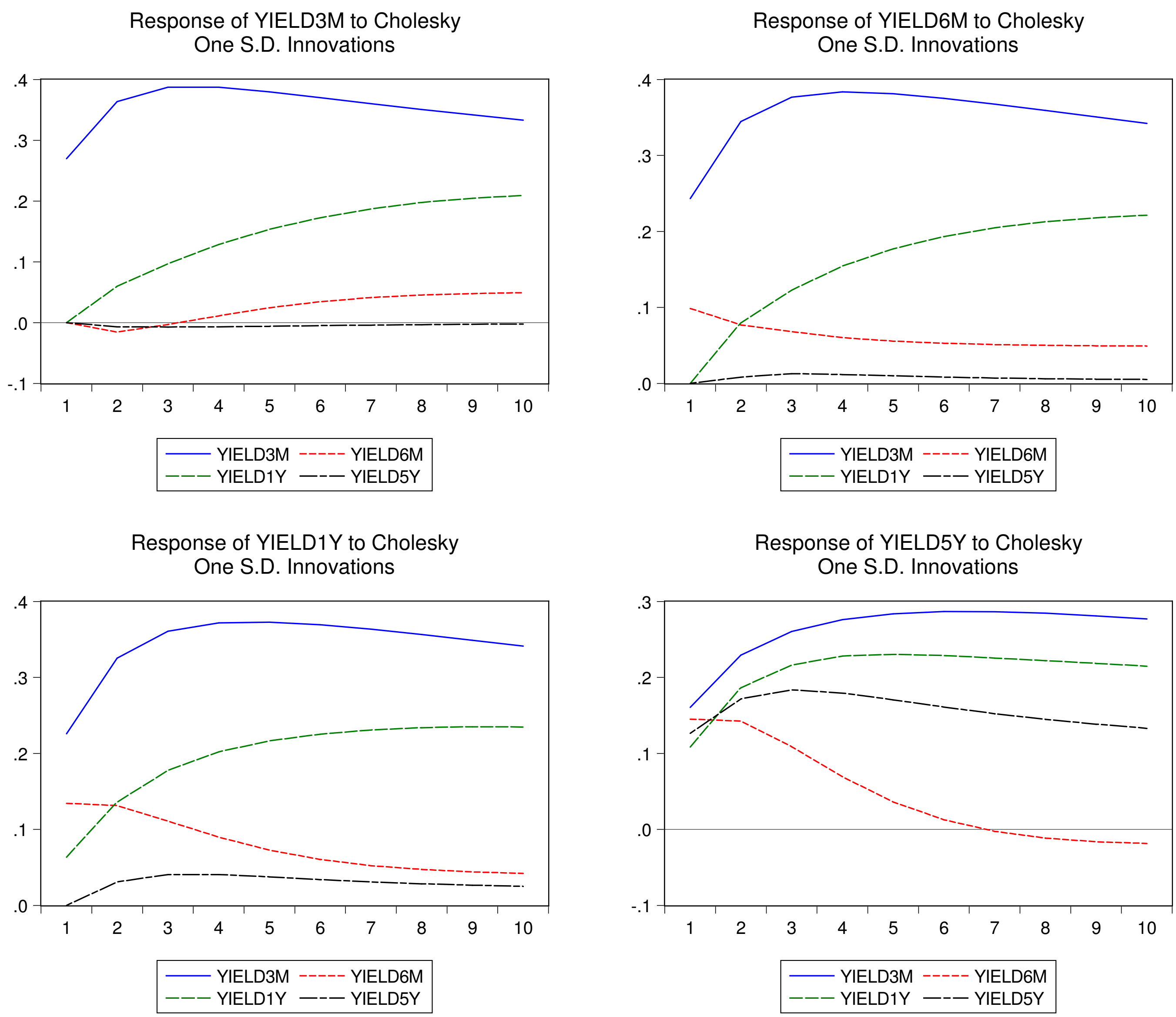


Figure 5: Cumulated impulse response functions