What is asset volatility?
Answer: conditional standard deviation of the asset returns

Why is volatility important?
Has many important applications

- Option (derivative) pricing, e.g., Black-Scholes formula
- Risk management, e.g. value at risk (VaR)
- Asset allocation, e.g., minimum-variance portfolio; see pages 184-185 of Campbell, Lo and MacKinlay (1997).
- Interval forecasts

A key characteristic: Not directly observable!!

How to calculate volatility?
There are several definitions of volatility. Our use of conditional standard deviation is just one of them.

1. Use high-frequency data: French, Schwert & Stambaugh (1987); see Section 3.15.
   - Realized volatility of daily returns in recent literature: use intraday log returns.
   - Use daily high, low, and closing (log) prices, e.g. range = daily high - daily low.
2. Implied volatility of options data, e.g., VIX of CBOE. Figure 1.

3. Econometric modeling: use daily or monthly returns

We focus on the econometric modeling first. Use of high frequency data will be discussed later.

**Note:** In most applications, volatility is annualized. This can easily be done by considering the data frequency. For instance, if we use daily returns in econometric modeling, then the annualized volatility (in the U.S.) is

\[ \sigma_t^* = \sqrt{252} \sigma_t, \]

where \( \sigma_t \) is the estimated volatility from the employed model. If we use monthly returns, then the annualized volatility is

\[ \sigma_t^* = \sqrt{12} \sigma_t, \]
where $\sigma_t$ is the estimated volatility from the employed model for the monthly returns. Our discussion, however, continues to use $\sigma_t$ for simplicity.

**Basic idea** of econometric modeling

Shocks of asset returns are NOT serially correlated, but dependent. That is, the serial dependence is nonlinear.

As shown by the ACF of returns and absolute returns of some assets we discussed so far.

**Basic structure**

$$r_t = \mu_t + a_t, \quad \mu_t = \phi_0 + \sum_{i=1}^{p} \phi_i r_{t-i} - \sum_{i=1}^{q} \theta_i a_{t-i},$$

Volatility models are concerned with time-evolution of

$$\sigma_t^2 = \text{Var}(r_t|F_{t-1}) = \text{Var}(a_t|F_{t-1}).$$

the conditional variance of a return.

Revisit the daily closing index of the S&P500 index from 1950 to 2010. The log returns follow approximately an MA(2) model

$$r_t = 0.00028 + a_t + 0.039a_{t-1} - 0.051a_{t-2}.$$ 

How about the volatility?
Is volatility constant over time?
NO! See the ACF of squared residuals!
How to model the evolving volatility?

**Two general categories**

- "Fixed function" and
- Stochastic function
of the available information.

**Univariate volatility models discussed:**

1. Autoregressive conditional heteroscedastic (ARCH) model of Engle (1982),
2. Generalized ARCH (GARCH) model of Bollerslev (1986),
3. GARCH-M models,
4. IGARCH models (used by RiskMetrics),
5. Exponential GARCH (EGARCH) model of Nelson (1991),
6. Threshold GARCH model of Zakoian (1994) or GJR model of Glosten, Jagannathan, and Runkle (1993),
7. Asymmetric parametric ARCH (APARCH) models of Ding, Granger and Engle (1994), [TGARCH and GJR models are special cases of APARCH models.]
8. Stochastic volatility (SV) models of Melino and Turnbull (1990), Harvey, Ruiz and Shephard (1994), and Jacquier, Polson and Rossi (1994).

**ARCH model**

\[ a_t = \sigma_t \epsilon_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2, \]

where \( \{\epsilon_t\} \) is a sequence of iid r.v. with mean 0 and variance 1, \( \alpha_0 > 0 \) and \( \alpha_i \geq 0 \) for \( i > 0 \).

Distribution of \( \epsilon_t \): Standard normal, standardized Student-t, generalized error dist (ged), or their skewed counterparts.

**Properties of ARCH models**
Consider an ARCH(1) model

\[ a_t = \sigma_t \epsilon_t, \quad \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2, \]

where \( \alpha_0 > 0 \) and \( \alpha_1 \geq 0 \).

1. \( \mathbb{E}(a_t) = 0 \)
2. \( \text{Var}(a_t) = \frac{\alpha_0}{1 - \alpha_1} \) if \( 0 < \alpha_1 < 1 \)
3. Under normality,

\[ m_4 = \frac{3\alpha_0^2(1 + \alpha_1)}{(1 - \alpha_1)(1 - 3\alpha_1^2)}, \]

provided \( 0 < \alpha_1^2 < 1/3 \).

The 3rd property implies heavy tails.

**Advantages**

- Simplicity
- Generates volatility clustering
- Heavy tails (high kurtosis)

**Weaknesses**

- Symmetric btw positive & negative prior returns
- Restrictive
- Provides no explanation
- Not sufficiently adaptive in prediction

**Building an ARCH Model**
1. Modeling the mean effect and testing for ARCH effects
   \( H_0: \) no ARCH effects versus \( H_a: \) ARCH effects

   Use Q-statistics of squared residuals; McLeod and Li (1983) & Engle (1982)

2. Order determination

   Use PACF of the squared residuals

3. Estimation: Conditional MLE


   R provides many plots for model checking and for presenting the results.

5. Software: Many packages available, e.g., Eviews, Matlab, and R. We use R package fGarch.

   **Estimation:** Conditional MLE or Quasi MLE

   **Special Note:** In this course, we estimate volatility models using the R package fGarch with garchFit command. The program is easy to use and allows for several types of innovational distributions: The default is Gaussian (**norm**), standardized Student-\( t \) distribution (**std**), generalized error distribution (**ged**), skew normal distribution (**snorm**), skew Student-\( t \) (**sstd**), skew generalized error distribution (**sged**), and standardized inverse normal distribution (**snig**). Except for the inverse normal distribution, other distribution functions are discussed in the textbook. Readers should check the book for details about the density functions and their parameters.

   **Example:** Monthly log returns of Intel stock

```r
> library(fGarch)
> da=read.table("m-intc7303.txt",header=T)
> head(da)
   date   rtn
1 19730131 0.01005
   .....  
6 19730629 0.13333
> intc=log(da$rtn+1)  # log returns
> acf(intc)
> acf(intc^2)
> pacf(intc^2)
> Box.test(intc^2,lag=10,type='Ljung')
  Box-Ljung test

data:  intc^2
X-squared = 59.7216, df = 10, p-value = 4.091e-09

> m1=garchFit(~garch(3,0),data=intc,trace=F)  # trace=F reduces the amount of output.
> summary(m1)
Title: GARCH Modelling
Call: garchFit(formula = ~garch(3, 0), data = intc, trace = F)

Mean and Variance Equation:
   data ~ garch(3, 0)
   [data = intc]

Conditional Distribution: norm

Coefficient(s):   
   mu    omega    alpha1   alpha2   alpha3
0.016572  0.012043  0.208649  0.071837  0.049045

Std. Errors:
   based on Hessian

Error Analysis:

Standardised Residuals Tests:            Statistic   p-Value
```
Jarque-Bera Test R Chi^2 169.7731 0
Shapiro-Wilk Test R W 0.9606957 1.970413e-08
Ljung-Box Test R Q(10) 10.97025 0.3598405
Ljung-Box Test R Q(15) 19.59024 0.1882211
Ljung-Box Test R Q(20) 20.82192 0.40768
Ljung-Box Test R^2 Q(10) 5.376602 0.864644
Ljung-Box Test R^2 Q(15) 22.73460 0.08993976
Ljung-Box Test R^2 Q(20) 23.70577 0.255481
LM Arch Test R TR^2 20.48506 0.05844884

Information Criterion Statistics:
AIC BIC SIC HQIC
-1.228111 -1.175437 -1.228466 -1.207193

> m1=garchFit(~garch(1,0),data=intc,trace=F)
> summary(m1)
Title: GARCH Modelling
Call: garchFit(formula = ~garch(1, 0), data = intc, trace = F)

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

Conditional Distribution: norm

Coefficient(s):
mu omega alpha1
0.016570 0.012490 0.363447

Std. Errors:
based on Hessian

Error Analysis:
Estimate Std. Error t value Pr(>|t|)
mu 0.016570 0.006161 2.689 0.00716 **
omega 0.012490 0.001549 8.061 6.66e-16 ***
alpha1 0.363447 0.131598 2.762 0.00575 **
---
Log Likelihood:
230.2423 normalized: 0.6189309

Standardised Residuals Tests:

<table>
<thead>
<tr>
<th>Test</th>
<th>Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jarque-Bera Test R</td>
<td>Chi^2 169.7731</td>
<td>0</td>
</tr>
<tr>
<td>Shapiro-Wilk Test R</td>
<td>W 0.9606957</td>
<td>1.970413e-08</td>
</tr>
<tr>
<td>Test</td>
<td>Type</td>
<td>Lags</td>
</tr>
<tr>
<td>--------------------------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>Ljung-Box Test R</td>
<td>Q(10)</td>
<td>13.72604</td>
</tr>
<tr>
<td>Ljung-Box Test R</td>
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<td>Ljung-Box Test R</td>
<td>Q(20)</td>
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<td>Ljung-Box Test $R^2$</td>
<td>Q(10)</td>
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<td>Ljung-Box Test $R^2$</td>
<td>Q(15)</td>
<td>30.11276</td>
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<tr>
<td>Ljung-Box Test $R^2$</td>
<td>Q(20)</td>
<td>31.46404</td>
</tr>
<tr>
<td>LM Arch Test R $TR^2$</td>
<td></td>
<td>22.036</td>
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Information Criterion Statistics:

<table>
<thead>
<tr>
<th>Criterion</th>
<th>Value</th>
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<tbody>
<tr>
<td>AIC</td>
<td>-1.221733</td>
</tr>
<tr>
<td>BIC</td>
<td>-1.190129</td>
</tr>
<tr>
<td>SIC</td>
<td>-1.221861</td>
</tr>
<tr>
<td>HQIC</td>
<td>-1.209182</td>
</tr>
</tbody>
</table>

> plot(m1)

Make a plot selection (or 0 to exit):

1: Time Series
2: Conditional SD
3: Series with 2 Conditional SD Superimposed
4: ACF of Observations
5: ACF of Squared Observations
6: Cross Correlation
7: Residuals
8: Conditional SDs
9: Standardized Residuals
10: ACF of Standardized Residuals
11: ACF of Squared Standardized Residuals
12: Cross Correlation between $r^2$ and $r$
13: QQ-Plot of Standardized Residuals

Selection: 13
Selection: 0

The fitted ARCH(1) model is

$$r_t = 0.0176 + a_t, \quad a_t = \sigma_t \epsilon_t, \quad \epsilon_t \sim N(0, 1)$$

$$\sigma^2_t = 0.0125 + 0.363 \sigma^2_{t-1}.$$ 

Model checking statistics indicate that there are some higher order dependence in the volatility, e.g., see $Q(15)$ for the squared standardized residuals. It turns out that a GARCH(1,1) model fares better for the data.

Next, consider Student-t innovations.

**R demonstration**

```r
> m2=garchFit(~garch(1,0),data=intc,cond.dist="std",trace=F)
> summary(m2)
```
Title: GARCH Modelling

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

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

Conditional Distribution: std ===== Standardized Student-t.

Coefficient(s):
-----------------
mu  omega  alpha1  shape
0.021571 0.013424 0.259867 5.985979

Error Analysis:
-----------------
Estimate  Std. Error  t value  Pr(>|t|)
mu 0.021571 0.006054 3.563 0.000366 ***
omega 0.013424 0.001968 6.820 9.09e-12 ***
alpha1 0.259867 0.119901 2.167 0.030209 *
shape 5.985979 1.660030 3.606 0.000311 *** <= Estimate of degrees of freedom

---

Log Likelihood:
-----------------
242.9678 normalized: 0.6531391

Standardised Residuals Tests:
-----------------
\begin{tabular}{lllll}
Jarque-Bera Test & R & Chi\(^2\) & 130.8931 & 0 \\
Shapiro-Wilk Test & R & W & 0.9637529 & 5.744026e-08 \\
Ljung-Box Test & R & Q(10) & 14.31288 & 0.1591926 \\
 & R & Q(15) & 23.34043 & 0.07717449 \\
 & R & Q(20) & 24.87286 & 0.2063387 \\
Ljung-Box Test & R\(^2\) & Q(10) & 15.35917 & 0.1195054 \\
 & R\(^2\) & Q(15) & 33.96318 & 0.003446127 \\
 & R\(^2\) & Q(20) & 35.46828 & 0.01774746 \\
LM Arch Test & R & TR\(^2\) & 24.11517 & 0.01961957 \\
\end{tabular}

Information Criterion Statistics:
-----------------
\begin{tabular}{lllll}
AIC & BIC & SIC & HQIC \\
-1.284773 & -1.242634 & -1.285001 & -1.268039 \\
\end{tabular}

> plot(m2)
Make a plot selection (or 0 to exit):
-----------------
1:  Time Series
2:  Conditional SD
The fitted model with Student-t innovations is

\[ r_t = 0.0216 + a_t, \quad a_t = \sigma_t \epsilon_t, \quad \epsilon \sim t_{5.99} \]
\[ \sigma_t^2 = 0.0134 + 0.260 a_{t-1}^2. \]

We use \( t_{5.99} \) to denote the standardized Student-t distribution with 5.99 d.f.

Comparison with normal innovations:

- Using a heavy-tailed dist for \( \epsilon_t \) reduces the ARCH effect.
- The difference between the models is small for this particular instance.

You may try other distributions for \( \epsilon_t \).

**GARCH Model**

\[ a_t = \sigma_t \epsilon_t, \]
\[ \sigma_t^2 = \alpha_0 + \sum_{i=1}^{m} \alpha_i a_{t-i}^2 + \sum_{j=1}^{s} \beta_j \sigma_{t-j}^2 \]

where \( \{\epsilon_t\} \) is defined as before, \( \alpha_0 > 0, \alpha_i \geq 0, \beta_j \geq 0 \), and \( \sum_{i=1}^{\max(m,s)} (\alpha_i + \beta_i) < 1 \).

Re-parameterization:
Let \( \eta_t = a_t^2 - \sigma_t^2 \). \( \{\eta_t\} \) un-correlated series.

The GARCH model becomes
\[ a_t^2 = \alpha_0 + \sum_{i=1}^{\max(m,s)} (\alpha_i + \beta_i) a_{t-i}^2 + \eta_t - \sum_{j=1}^{s} \beta_j \eta_{t-j}. \]

This is an ARMA form for the squared series \( a_t^2 \).
Use it to understand properties of GARCH models, e.g. moment equations, forecasting, etc.
Focus on a GARCH(1,1) model
\[ \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \beta_1 \sigma_{t-1}^2, \]

- Weak stationarity: \( 0 \leq \alpha_1, \beta_1 \leq 1, (\alpha_1 + \beta_1) < 1 \).
- Volatility clusters
- Heavy tails: if \( 1 - 2\alpha_1^2 - (\alpha_1 + \beta_1)^2 > 0 \), then
\[
\frac{E(a_t^4)}{[E(a_t^2)]^2} = \frac{3[1-(\alpha_1+\beta_1)^2]}{1-(\alpha_1+\beta_1)^2-2\alpha_1^2} > 3.
\]
- For 1-step ahead forecast,
\[ \sigma_h^2(1) = \alpha_0 + \alpha_1 a_h^2 + \beta_1 \sigma_h^2. \]

For multi-step ahead forecasts, use \( a_t^2 = \sigma_t^2 \epsilon_t^2 \) and rewrite the model as
\[ \sigma_{t+1}^2 = \alpha_0 + (\alpha_1 + \beta_1) \sigma_t^2 + \alpha_1 \sigma_t^2 (\epsilon_t^2 - 1). \]
2-step ahead volatility forecast

\[ \sigma_h^2(2) = \alpha_0 + (\alpha_1 + \beta_1)\sigma_h^2(1). \]

In general, we have

\[ \sigma_h^2(\ell) = \alpha_0 + (\alpha_1 + \beta_1)\sigma_h^2(\ell - 1), \quad \ell > 1. \]

This result is exactly the same as that of an ARMA(1,1) model with AR polynomial \( 1 - (\alpha_1 + \beta_1)B. \)

**Example**: Monthly excess returns of S&P 500 index starting from 1926 for 792 observations.

The fitted of a Gaussian AR(3) model

\[
\begin{align*}
\tilde{r}_t &= r_t - 0.0062 \\
\tilde{r}_t &= 0.089\tilde{r}_{t-1} - 0.024\tilde{r}_{t-2} - 0.123\tilde{r}_{t-3} + 0.007 + a_t,
\end{align*}
\]

\[ \hat{\sigma}_a^2 = 0.00333. \]

For the GARCH effects, use a GARCH(1,1) model, we have

A joint estimation:

\[
\begin{align*}
r_t &= 0.032r_{t-1} - 0.030r_{t-2} - 0.011r_{t-3} + 0.0077 + a_t \\
\sigma_t^2 &= 7.98 \times 10^{-5} + 0.853\sigma_{t-1}^2 + 0.124a_{t-1}^2.
\end{align*}
\]

Implied unconditional variance of \( a_t \) is

\[
\frac{0.0000798}{1 - 0.853 - 0.1243} = 0.00352
\]

close to the expected value. All AR coefficients are statistically insignificant.

A simplified model:

\[
r_t = 0.00745 + a_t, \quad \sigma_t^2 = 8.06 \times 10^{-5} + 0.854\sigma_{t-1}^2 + 0.122a_{t-1}^2.
\]
Model checking:
For $\tilde{a}_t$: $Q(10) = 11.22(0.34)$ and $Q(20) = 24.30(0.23)$.
For $\tilde{a}_t^2$: $Q(10) = 9.92(0.45)$ and $Q(20) = 16.75(0.67)$.
Forecast: 1-step ahead forecast:

$$\sigma_h^2(1) = 0.00008 + 0.854\sigma_h^2 + 0.122a_h^2$$

<table>
<thead>
<tr>
<th>Horizon</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>$\infty$</th>
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<td>.0074</td>
<td>.0074</td>
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<tr>
<td>Volatility</td>
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<td>.054</td>
<td>.054</td>
<td>.054</td>
<td>.054</td>
<td>.059</td>
</tr>
</tbody>
</table>

**R demonstration:**

```r
> sp5=scan("sp500.txt")
Read 792 items
> pacf(sp5)
> m1=arima(sp5,order=c(3,0,0))
> m1
Call: arima(x = sp5, order = c(3, 0, 0))

Coefficients:
  ar1     ar2     ar3     intercept
    0.0890  -0.0238  -0.1229     0.0062
s.e.  0.0353  0.0355  0.0353     0.0019

sigma^2 estimated as 0.00333:  log likelihood = 1135.25, aic=-2260.5
> m2=garchFit(~arma(3,0)+garch(1,1),data=sp5,trace=F)
> summary(m2)

Title:  GARCH Modelling
Call:
  garchFit(formula = ~arma(3,0)+garch(1, 1), data = sp5, trace = F)

Mean and Variance Equation:
  data ~ arma(3, 0) + garch(1, 1)
  [data = sp5]

Conditional Distribution: norm

Error Analysis:

| Estimate   | Std. Error | t value | Pr(>|t|) |
|------------|------------|---------|----------|
| mu         | 7.708e-03  | 1.607e-03 | 4.798    | 1.61e-06 *** |
| ar1        | 3.197e-02  | 3.837e-02 | 0.833    | 0.40473      |
| ar2        | -3.026e-02 | 3.841e-02 | -0.788   | 0.43076      |
```
ar3  -1.065e-02  3.756e-02  -0.284  0.77677
omega  7.975e-05  2.810e-05  2.838  0.00454  **
alpha1  1.242e-01  2.247e-02  5.529  3.22e-08  ***
beta1  8.530e-01  2.183e-02  39.075  < 2e-16  ***
---
Log Likelihood:
1272.179  normalized:  1.606287

Standardised Residuals Tests:

<table>
<thead>
<tr>
<th>Statistic</th>
<th>p-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Jarque-Bera Test</td>
<td>R Chi^2 73.04842 1.110223e-16</td>
</tr>
<tr>
<td>Shapiro-Wilk Test</td>
<td>R W 0.985797  5.961994e-07</td>
</tr>
<tr>
<td>Ljung-Box Test</td>
<td>R Q(10) 11.56744  0.315048</td>
</tr>
<tr>
<td>Ljung-Box Test</td>
<td>R Q(15) 17.78747  0.2740039</td>
</tr>
<tr>
<td>Ljung-Box Test</td>
<td>R Q(20) 24.11916  0.2372256</td>
</tr>
<tr>
<td>Ljung-Box Test</td>
<td>R^2 Q(10) 10.31614  0.4132089</td>
</tr>
<tr>
<td>Ljung-Box Test</td>
<td>R^2 Q(15) 14.22819  0.5082978</td>
</tr>
<tr>
<td>Ljung-Box Test</td>
<td>R^2 Q(20) 16.79404  0.6663038</td>
</tr>
<tr>
<td>LM Arch Test</td>
<td>R TR^2 13.34305  0.3446075</td>
</tr>
</tbody>
</table>

Information Criterion Statistics:

<table>
<thead>
<tr>
<th>AIC</th>
<th>BIC</th>
<th>SIC</th>
<th>HQIC</th>
</tr>
</thead>
<tbody>
<tr>
<td>-3.194897</td>
<td>-3.153581</td>
<td>-3.195051</td>
<td>-3.179018</td>
</tr>
</tbody>
</table>

> m2=garchFit(~garch(1,1),data=sp5,trace=F)
> summary(m2)
Title: GARCH Modelling
Call: garchFit(formula = ~garch(1, 1), data = sp5, trace = F)

Mean and Variance Equation:
data ~ garch(1, 1)
[data = sp5]

Conditional Distribution: norm

Error Analysis:

| Estimate  | Std. Error | t value | Pr(>|t|) |
|-----------|------------|---------|---------|
| mu 7.450e-03 | 1.538e-03 | 4.845 1.27e-06  *** |
| omega 8.061e-05 | 2.833e-05 | 2.845 0.00444  ** |
| alpha1 1.220e-01 | 2.202e-02 | 5.540 3.02e-08  *** |
| beta1 8.544e-01 | 2.175e-02 | 39.276 < 2e-16  *** |
---
Log Likelihood:
1269.455  normalized:  1.602848

Standardised Residuals Tests:
Statistic p-Value

Jarque-Bera Test R Chi^2 80.32111 0
Shapiro-Wilk Test R W 0.9850517 3.141228e-07
Ljung-Box Test R Q(10) 11.22050 0.340599
Ljung-Box Test R Q(15) 17.99703 0.262822
Ljung-Box Test R Q(20) 24.29896 0.2295768
Ljung-Box Test R^2 Q(10) 9.920157 0.4475259
Ljung-Box Test R^2 Q(15) 14.21124 0.509572
Ljung-Box Test R^2 Q(20) 16.75081 0.6690903
LM Arch Test R TR^2 13.04872 0.3655092

Information Criterion Statistics:

<table>
<thead>
<tr>
<th></th>
<th>AIC</th>
<th>BIC</th>
<th>SIC</th>
<th>HQIC</th>
</tr>
</thead>
</table>

> plot(m2)

Make a plot selection (or 0 to exit):

1: Time Series
2: Conditional SD
3: Series with 2 Conditional SD Superimposed
4: ACF of Observations
5: ACF of Squared Observations
6: Cross Correlation
7: Residuals
8: Conditional SDs
9: Standardized Residuals
10: ACF of Standardized Residuals
11: ACF of Squared Standardized Residuals
12: Cross Correlation between r^2 and r
13: QQ-Plot of Standardized Residuals

Selection: 3

> predict(m2,6)

<table>
<thead>
<tr>
<th></th>
<th>meanForecast</th>
<th>meanError</th>
<th>standardDeviation</th>
</tr>
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<tbody>
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<tr>
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<td>6</td>
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<td>0.05431038</td>
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</tr>
</tbody>
</table>

Turn to Student-t innovation. (R output omitted.)
Figure 3: Monthly S&P 500 excess returns and fitted volatility

**Estimation of degrees of freedom:**

\[
\begin{align*}
    r_t &= 0.0085 + a_t, \quad a_t = \sigma_t \epsilon_t, \quad \epsilon_t \sim t_7 \\
    \sigma_t^2 &= .000125 + .113 a_{t-1}^2 + .842 \sigma_{t-1}^2,
\end{align*}
\]

where the estimated degrees of freedom is 7.00.

**Forecasting evaluation**

Not easy to do; see Andersen and Bollerslev (1998).

**IGARCH model**

An IGARCH(1,1) model:

\[
a_t = \sigma_t \epsilon_t, \quad \sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + (1 - \beta_1) a_{t-1}^2.
\]

For the monthly excess returns of the S&P 500 index, we have

\[
r_t = .007 + a_t, \quad \sigma_t^2 = .0001 + .806 \sigma_{t-1}^2 + .194 a_{t-1}^2
\]
For an IGARCH(1,1) model,
\[ \sigma^2_h(\ell) = \sigma^2_h(1) + (\ell - 1)\alpha_0, \quad \ell \geq 1, \]
where \( h \) is the forecast origin.
Effect of \( \sigma^2_h(1) \) on future volatilities is persistent, and the volatility forecasts form a straight line with slope \( \alpha_0 \). See Nelson (1990) for more info.
Special case: \( \alpha_0 = 0 \).
used in RiskMetrics to VaR calculation.
**Example:** An IGARCH(1,1) model for the monthly excess returns of S&P500 index from 1926 to 1991 is given below via R.
\[
\begin{align*}
    r_t &= 0.0074 + a_t, \quad a_t = \sigma_t \epsilon_t \\
    \sigma^2_t &= 5.11 \times 10^{-5} + 0.143a^2_{t-1} + 0.857\sigma^2_{t-1}.
\end{align*}
\]
**R demonstration:** Using R script `Igarch.R`.

```r
> source("Igarch.R")
> m4=Igarch(sp5)
Maximized log-likelihood: -1268.205

Coefﬁcient(s):

|                  | Estimate | Std. Error | t value | Pr(>|t|) |
|------------------|----------|------------|---------|----------|
| mu               | 7.41587e-03 | 1.52545e-03 | 4.86144 | 1.1653e-06 *** |
| omega            | 5.10855e-05 | 1.74923e-05 | 2.92046 | 0.0034952 ** |
| beta             | 8.57124e-01 | 2.14420e-02 | 39.97404 | < 2.22e-16 *** |
```