Lecture 2: The ARCH Model

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Outline

Volatility is measured with the conditional variance

- Volatility here refers to the conditional variance of a time series.
- For a return series $\{r_t\}$, we are now interested in

$$\sigma_t^2 = \mathrm{Var}(r_t \mid F_{t-1})$$

where F_{t-1} is the information set at time $t-1$.

Characteristics of volatility (1)

1. There exist volatility clusters. That is, volatility may be high for certain time periods and low for other periods.

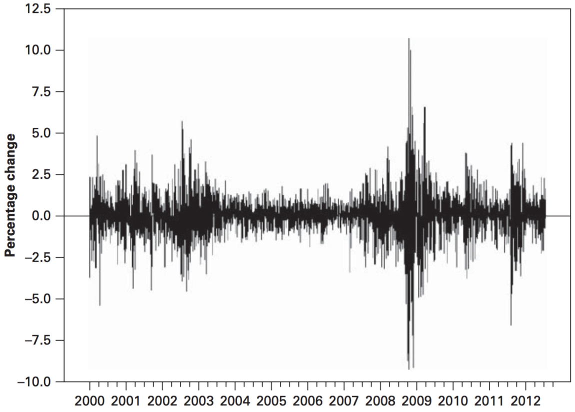

Figure: Percentage Change in the NYSE U.S.100 stock price index

Characteristics of volatility (2)

1. Volatility evolves over time in a continuous manner. That is, volatility jumps are rare.

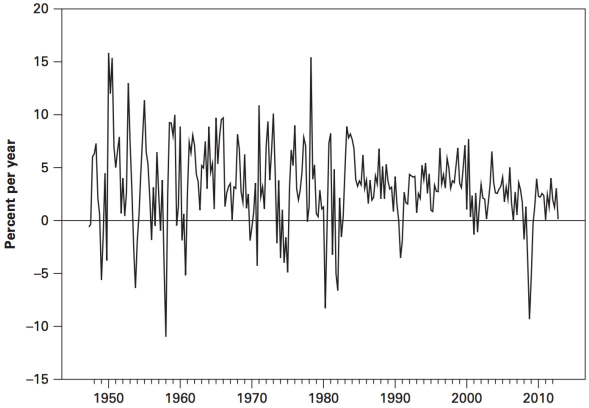

Figure: Annualized Growth Rate of Real GDP

Characteristics of volatility (3)

1. Volatility does not diverge to infinity. That is, volatility varies within some fixed range. Statistically speaking, this means that volatility is often stationary.

1. Volatility seems to react differently to a big price increase or a big price drop, referred to as the leverage effect.

The basic idea of building a volatility model

Consider the log return series $\{r_t\}$. The basic idea of a volatility model is

- $\{r_t\}$ may appear to be either serially uncorrelated or serially correlated with a minor order.
- However, $\{r_t\}$ is a dependent series and the dependence arises from its conditional variance.

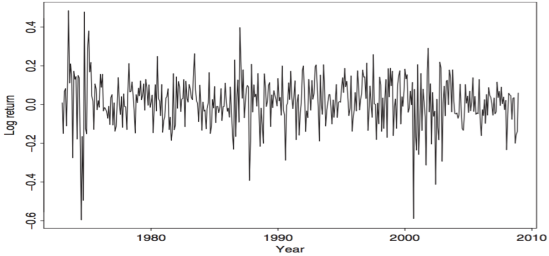

Figure: Time plot of monthly log returns of Intel stock from January 1973 to December 2008

The sample ACF of $\{r_t\}$ and $\{r_t^2\}$

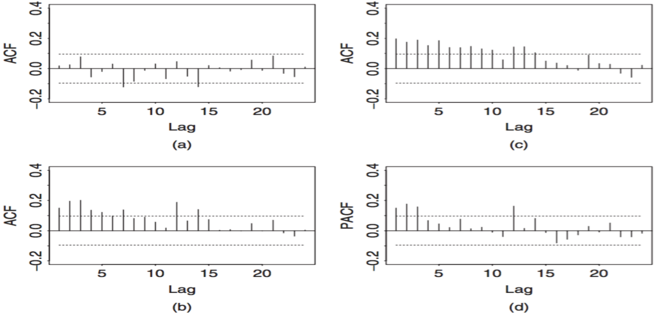

Figure: Sample ACF and PACF of various functions of monthly log stock returns of Intel Corporation from January 1973 to December 2008: (a) ACF of the log returns, (b) ACF of the squared log returns, (c) ACF of the absolute log returns, and (d) PACF of the squared log returns.

Decompose r_t into the mean and variance equations

To capture the dependence in a time series through its second moment but not the mean, we model the mean process and the variance process separately.

For a return series $\{r_t\}$, we can model it as

$$r_t = \mu_t + a_t \tag{1}$$

where μ_t represents the conditional mean and a_t is modeled to capture the conditional variance.

The mean equation

$$\mu_t = E(r_t \mid F_{t-1}) = \sum_{i=1}^{p} \phi_i y_{t-i} - \sum_{i=1}^{q} \theta_i a_{t-i} \tag{2}$$

$$y_t = r_t - \phi_0 - \sum_{i=1}^{k} \beta_i x_{it}$$

F_{t-1} is the information set at time $t-1$.

If you combine these two equations, and let $\mu_t = r_t - a_t$, you will find that it is just an ARMA(p, q) model with additional regressors x_{it}.

The variance equation

Denote the conditional variance of r_t with σ_t^2.

$$\begin{aligned}
\sigma_t^2 = \mathrm{Var}(r_t \mid F_{t-1}) &= E\left((r_t - E(r_t|F_{t-1}))^2|F_{t-1}\right) \\
&= E\left((r_t - \mu_t)^2 \mid F_{t-1}\right) \\
&= \mathrm{Var}(a_t \mid F_{t-1})
\end{aligned}$$

The variance equation (cont'd)

- If we assume that $E(a_t \mid F_{t-1}) = 0$, we can see that $\sigma_t^2 = E(a_t^2 \mid F_{t-1})$.
- We can use the lagged value of a_t^2 to represent the information set F_{t-1}
- The simplest model is a linear model, like the following

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2$$

The procedure of building a volatility model

Building a volatility model for an asset return series consists of four steps:

1. Specify a mean equation by testing for serial dependence in the data and, if necessary, building an econometric model (e.g., an ARMA model) for the return series to remove any linear dependence.
2. Use the squared residuals of the mean equation to test for ARCH effects.
3. Specify a volatility model if ARCH effects are statistically significant, and perform a joint estimation of the mean and volatility equations.
4. Check the fitted model carefully and refine it if necessary.

Testing for the presence of ARCH effect

The Ljung-Box test for the series of a_t^2

Upon obtaining the residuals from the estimation of an adequate mean equation, we can use the squared residuals $\{\hat{a}_t^2\}$ to test the existence of autocorrelation.

- The Ljung-Box test is used to test the null hypothesis $H_0 : \rho_1 = \cdots = \rho_m = 0$.
- The $Q(m)$ statistic is calculated and compared with the critical value from $\chi^2(m)$ distribution at the desired significance level.
- The rejection of the null hypothesis implies that there is autoregressive conditional heteroskedastic (ARCH) effect.

The LM test

An auxiliary regression

We estimate a AR(m) model regarding $\{\hat{a}_t^2\}$, that is,

$$\hat{a}_t^2 = \alpha_0 + \alpha_1 \hat{a}_{t-1}^2 + \cdots + \alpha_m \hat{a}_{t-m}^2 + e_t$$

The LM test

With this model, we test the joint hypothesis

$$H_0 : \alpha_1 = \cdots = \alpha_m = 0$$

- The LM statistic is NR^2 where N is the sample size of this regression and R^2 is the coefficient of the determination of this regression.
- Given the null hypothesis is true, this statistic follows a $\chi^2(m)$ distribution.

The LM test (cont'd)

Alternatively, we can use F statistic to test the joint hypothesis.

- Let $SSR_0 = \sum_{t=m+1}^{T}(\hat{a}_t^2 - \bar{\omega})^2$, where $\bar{\omega} = (1/T)\sum_{t=1}^{T}\hat{a}_t^2$.
- Let $SSR_1 = \sum_{t=m+1}^{T}\hat{e}_t^2$ where $\hat{e}_t$ is the residuals from the regression.
- The F statistic is

$$F = \frac{(SSR_0 - SSR_1)/m}{SSR_1/(T-2m-1)} \sim F(m, T-2m-1)$$

- Rejecting the null hypothesis motivates us to model the possible ARCH effect.

An example

Go back to Figure 4. Since the return series is already stationary, we directly test the squared return series to check the ARCH effect.

- In the LM test of the ARCH effect, $F = 53.62$ and the p value is close to zero.
- The Ljung–Box statistics of the a_t^2 series also shows strong ARCH effects with $Q(12) = 89.85$, the p value of which is close to zero.
- Therefore, we can confirm that the return series of Intel stock has an ARCH effect, and next we need to model such an effect.

The basic idea of an ARCH model

Consider a series of shocks $\{a_t\}$ in a return series $\{r_t\}$. The basic idea of an Autoregressive Conditional Heteroskedasticity (ARCH) model is

1. the shock a_t of the return series is serially uncorrelated but dependent;
2. the dependence of a_t can be modeled through an autoregressive process of a_t^2.

The ARCH(m) model

An ARCH(m) model takes the following form

$$a_t = \sigma_t \epsilon_t, \ \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 \tag{3}$$

where $\epsilon_t \sim i.i.d.(0,1)$, $\alpha_0 > 0$ and $\alpha_i \geq 0$ for $i = 1, \ldots, m$.

- The assumption of $\mathrm{Var}(\epsilon_t) = 1$ is to make the analysis regarding the properties of the ARCH(m) model easy;
- The assumption of $\alpha_0 > 0$ and $\alpha_i \geq 0$ is to ensure the conditional variance of a_t is positive.
- $\alpha_1, \ldots, \alpha_m$ should also satisfy some regularity conditions to ensure the unconditional variance of a_t is finite.

The Properties of an ARCH Model

- Let's take an ARCH(1) model as an example to discuss the properties of ARCH model.
- The goal is to see how such a model can capture the basic idea mentioned above and the stylized fact that highly volatile periods tend to be followed by high volatility periods.

Assume an ARCH(1) model as follows

$$a_t = \sigma_t \epsilon_t, \ \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2, \ \epsilon_t \sim i.i.d.(0,1) \tag{4}$$

where $a_0 > 0$ and $a_1 \geq 0$.

The unconditional mean and variance of a_t

The unconditional mean

$$E(a_t) = E(\sigma_t \epsilon_t) = E(\sigma_t)E(\epsilon_t) = 0$$

The second equality is ensured because σ_t and ϵ_t are independent, and the third equality comes from the assumption of $E(\epsilon_t) = 0$.

The unconditional variance

$$\begin{aligned} \mathrm{Var}(a_t) &= E(a_t^2) = E(\sigma_t^2 \epsilon_t^2) \\ &= E(\alpha_0 + \alpha_1 a_{t-1}^2) \cdot 1 = \alpha_0 + \alpha_1 \mathrm{Var}(a_{t-1}) \end{aligned}$$

Assuming the unconditional mean of a_t is a constant(why?), we can have

$$\mathrm{Var}(a_t) = \frac{\alpha_0}{1 - \alpha_1}$$

Since the variance should be positive and finite, we must have $0 \leq \alpha_1 < 1$.

The unconditional covariance of a_t

Since ϵ_t and ϵ_{t-i} for $i \neq 0$ are independent,

$$\begin{aligned}\mathrm{Cov}(a_t, a_{t-i}) &= E(a_t a_{t-i}) = E(\sigma_t \epsilon_t \sigma_{t-i} \epsilon_{t-i}) \\ &= E(\sigma_t \sigma_{t-i}) E(\epsilon_t \epsilon_{t-i}) = 0\end{aligned}$$

- What we get now?
  - a_t has constant unconditional mean and variance,
  - a_t is serially uncorrelated.

The kurtosis of a_t

- Assume that $\epsilon \sim N(0,1)$, implying that $E(\epsilon_t^4) = 3$. Thus, we have

$$\begin{aligned} E(a_t^4) &= E(\sigma_t^4 \epsilon_t^4) = E(\sigma_t^4)E(\epsilon_t^4) = 3E(\sigma_t^4) \\ &= 3\left(\alpha_0^2 + 2\alpha_0\alpha_1 E(a_{t-1}^2) + \alpha_1^2 E(a_{t-1}^4)\right) \end{aligned}$$

- Assume that a_t is fourth-order stationary so that we can define $m_4 = E(a_t^4) = E(a_{t-1}^4)$. Then, using the fact that $E(a_t^2) = \alpha_0/(1-\alpha_1)$, we can solve m_4 from the above equation.

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

The kurtosis of a_t (cont'd)

This result regarding m_4 has two important implications:

1. Since the fourth moment of a_t is positive, we see that α_1 must also satisfy the condition $1 - 3\alpha_1^2 > 0$, that is, $0 \leq \alpha_1^2 < \frac{1}{3}$.
2. The kurtosis of a_t is

$$\text{kurtosis} = \frac{E(a_t^4)}{E(a_t^2)^2} = \frac{3(1-\alpha_1^2)}{1-3\alpha_1^2} > 3$$

Thus, the the excess kurtosis of a_t is positive and the tail distribution of a_t is heavier than that of a normal distribution.

The conditional mean

- Let's write $E_{t-1}(a_t)$ to represent the conditional mean given the information set F_{t-1}, i.e., $E(E(a_t \mid F_{t-1}))$.
- Since ϵ_t is i.i.d, we have $E_{t-1}(\epsilon_t) = E(\epsilon_t) = 0$. Thus,

$$E_{t-1}(a_t) = E_{t-1}(\sigma_t \epsilon_t) = E_{t-1}\left((\alpha_0 + \alpha_1 a_{t-1}^2)^{1/2} \epsilon_t\right)$$
$$= (\alpha_0 + \alpha_1 a_{t-1}^2)^{1/2} E_{t-1}(\epsilon_t) = 0$$

The conditional variance

- The conditional variance of a_t is

$$\begin{aligned}
\mathrm{Var}_{t-1}(a_t) &= E_{t-1}(a_t^2) = E_{t-1}\left(\sigma_t^2 \epsilon_t^2\right) \\
&= E_{t-1}\left((\alpha_0 + \alpha_1 a_{t-1}^2)\epsilon_t^2\right) \\
&= E_{t-1}(\alpha_0 + \alpha_1 a_{t-1}^2) E_{t-1}(\epsilon_t^2) \\
&= (\alpha_0 + \alpha_1 a_{t-1}^2) E(\epsilon_t^2) \\
&= \alpha_0 + \alpha_1 a_{t-1}^2 = \sigma_t^2
\end{aligned}$$

- How does the conditional variance capture the stylized fact?

The definition of the likelihood function

The likelihood function is the joint density function $f(\mathbf{y}|\boldsymbol{\theta})$ when we consider it as a function of the parameters $\boldsymbol{\theta}$ given a set of data $\mathbf{y}$.

- $\mathbf{y} = (y_1, \ldots, y_T)$ represents the observations, which are assumed to be identically independently distributed.
- $\boldsymbol{\theta} = (\theta_1, \ldots, \theta_k)$ represents all parameters in the model (i.e., data generating process) that generates $\mathbf{y}$.
- For each observation y_t, its (marginal) PDF is $f(y_t|\boldsymbol{\theta})$.

The likelihood function when y_t is independent

The likelihood function

$$L(\boldsymbol{\theta}|\mathbf{y}) = \prod_{t=1}^{T} f(y_t|\boldsymbol{\theta}) \tag{5}$$

The log-likelihood function

$$\ell(\boldsymbol{\theta}|\mathbf{y}) = \sum_{t=1}^{T} \ell_t(\boldsymbol{\theta}|y_t) \tag{6}$$

where $\ell_t(\boldsymbol{\theta}|y_t) = \ln(f(y_t|\boldsymbol{\theta}))$ is the contribution to the loglikelihood function.

The joint density when y_t is dependent

If $y_1, y_2, \ldots, y_T$ are dependent, their joint density can be written as

$$f(y_1, y_2, \ldots, y_T) = f(y_1)f(y_2|y_1)\cdots f(y_T|y_1, \ldots, y_{T-1})$$

or conveniently denoted as

$$f(\mathbf{y}^T) = \prod_{t=1}^{T} f(y_t|\mathbf{y}^{t-1})$$

The likelihood and log-likelihood functions when y_t is dependent

When $\mathbf{y}$ is also dependent on $\boldsymbol{\theta}$, the likelihood function is then

$$L(\boldsymbol{\theta}|\mathbf{y}^T) = \prod_{t=1}^{T} f(y_t|\mathbf{y}^{t-1}, \boldsymbol{\theta}) \tag{7}$$

And the log-likelihood function is

$$\ell(\mathbf{y}^T|\boldsymbol{\theta}) = \sum_{t=1}^{T} \ell_t(\boldsymbol{\theta}|\mathbf{y}^t) \tag{8}$$

The maximum likelihood (ML) estimator

- The ML estimator maximizes the log-likelihood function over the parameter space in which $\boldsymbol{\theta}$ lies in.

$$\max_{\{\theta \in \Theta\}} \ell(\mathbf{y}^T|\boldsymbol{\theta}) = \sum_{t=1}^{T} \ell_t(\boldsymbol{\theta}|\mathbf{y}^t) \tag{9}$$

- The ML estimator is usually obtained by computational methods, like the Newton or quasi-Newton method.

The assumption of the distribution of ϵ_t

Consider an ARCH(m) model

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

- Assume that $\epsilon_t \sim N(0, 1)$ and ϵ_t is i.i.d.
- How can we get the likelihood function of an ARCH(m) model based on this assumption?

The distribution of a_t

The conditional distribution of a_t

$$\epsilon_t \sim N(0,1) \Rightarrow a_t \mid F_{t-1} \sim N(0, \sigma_t^2)$$

where σ_t^2 is given by the ARCH(m) model. The conditional PDF of each a_t for $t = 1, \dots, T$ is

The conditional PDF of a_t

$$f(a_t | F_{t-1}) = \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(-\frac{a_t^2}{2\sigma_t^2}\right)$$

where F_{t-1} is the information set represented by $(a_1, \dots, a_{t-1})$.

The joint density for $a_1, \ldots, a_T$ given the parameter vector α

- For convenience, we suppress $\boldsymbol{\alpha} = (\alpha_0, \alpha_1, \ldots, \alpha_m)$ in the conditional joint density $f(a_1, \ldots, a_T \mid \boldsymbol{\alpha})$.
- Since $a_1, \ldots, a_T$ are not independent, we have the joint density as

$$
\begin{aligned}
f(a_1, a_2, \ldots, a_T) &= f(a_T|F_{T-1})f(a_{T-1}|F_{T-2}) \cdots f(a_{m+1}|F_m)f(a_1, \ldots, a_m) \\
&= \prod_{t=m+1}^{T} \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(-\frac{a_t^2}{2\sigma_t^2}\right) \times f(a_1, \ldots, a_m) \qquad (10)
\end{aligned}
$$

The conditional likelihood function

Dropping $f(a_1, \ldots, a_m)$ because the exact form of it is often complicated, we get the conditional likelihood function

$$L(\boldsymbol{\alpha}|a_1, \ldots, a_T) = \prod_{t=m+1}^{T} \frac{1}{\sqrt{2\pi\sigma_t^2}} \exp\left(-\frac{a_t^2}{2\sigma_t^2}\right) \tag{11}$$

- $\boldsymbol{\alpha}$ enters the likelihood function through

$$\sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2$$

- Maximizing the likelihood function results in the maximum likelihood estimator under the normality assumption.

The conditional log-likelihood function

Taking logarithm of the likelihood function yields the log-likelihood function

$$\ell(\boldsymbol{\alpha}|a_1, \ldots, a_T) = \sum_{t=m+1}^{T} \left[-\frac{1}{2}\ln(2\pi) - \frac{1}{2}\ln(\sigma_t^2) - \frac{1}{2}\frac{a_t^2}{\sigma_t^2} \right] \tag{12}$$

The log-likelihood function can be simplified as

$$\ell(\boldsymbol{\alpha}|a_1, \ldots, a_T) = -\frac{1}{2}\sum_{t=m+1}^{T} \left[\ln(\sigma_t^2) + \frac{a_t^2}{\sigma_t^2} \right]$$

Order determination

- Before estimating an ARCH(m) model, we need to determine the order m.
- The basic idea is that we treat an ARCH(m) model as an AR process of $\{a_t^2\}$, and apply the partial autocorrelation function (PACF) to determine m.

Why using the PACF?

We justify the use of the PACF of $\{a_t^2\}$ to determine m through two perspectives.

1. We can consider a_t^2 as an unbiased estimator of σ_t^2 given the sample data because $E_{t-1}(a_t^2) = \sigma_t^2$. Therefore, we use a_t^2 as an approximate to σ_t^2.
2. We can define $\eta_t = a_t^2 - \sigma_t^2$. It can be shown that
   - $E(\eta_t) = 0$ and $E(\eta_t \eta_{t-s}) = 0$ for $s > 0$.
   - But η_t is not i.i.d. because a_t^2 is dependent.

   So an ARCH(m) model is essentially an AR(m) model, except that η_t is not i.i.d. That is,

$$a_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \cdots + \alpha_m a_{t-m}^2 + \eta_t$$

Alternative distribution assumptions of ϵ_t

- ϵ_t has a Student-t distribution: capture the heavy-tail of volatility.
- ϵ_t has a skew-Student-t distribution: capture the skewness of asset return.
- ϵ_t has a general error distribution: enclose the normal distribution and heavy-tail distributions.

Model checking

The standardized residuals

Compute the standardized residuals

$$\tilde{a}_t = \frac{\hat{a}_t}{\hat{\sigma}_t}$$

which should mimic the behavior of ϵ_t.

Check the mean equation

- Use the Ljung-Box statistic for $\{\tilde{a}_t\}$.

Check the volatility equation

- Use the Ljung-Box statistic for $\{\tilde{a}_t^2\}$.
- Use the QQ plot or the Shapiro-Wilk test for normality assumption.

Forecasting

1-step-ahead forecast

$$\sigma_h^2(1) = \alpha_0 + \alpha_1 a_h^2 + \cdots + \alpha_m a_{h+1-m}^2$$

2-step-ahead forecast

$$\sigma_h^2(2) = \alpha_0 + \alpha_1 \sigma_h^2(1) + \alpha_2 a_h^2 + \cdots + \alpha_m a_{h+2-m}^2$$

ℓ-step-ahead forecast

$$\sigma_h^2(\ell) = \alpha_0 + \sum_{i=1}^{m} \alpha_i \sigma_h^2(\ell - i)$$

An ARCH model for the monthly log returns of Intel stock

The proposed model

$$r_t = \mu + \alpha_t, a_t = \sigma_t \epsilon_t, \sigma_t^2 = \alpha_0 + \alpha_1 a_{t-1}^2 + \alpha_2 a_{t-2}^2 + \alpha_3 a_{t-3}^2$$

The estimated model

$$r_t = \underset{(0.0057)}{0.0122} + a_t, \sigma_t^2 = \underset{(0.0010)}{0.0106} + \underset{(0.0757)}{0.2131} a_{t-1}^2 + \underset{(0.0480)}{0.0770} a_{t-2}^2 + \underset{(0.0688)}{0.0599} a_{t-3}^2$$

Since α_2 and α_3 are statistically insignificant, we drop the last two terms and re-estimate the model.

$$r_t = \underset{(0.0053)}{0.0126} + a_t, \sigma_t^2 = \underset{(0.0010)}{0.0111} + \underset{(0.0761)}{0.3560} a_{t-1}^2$$

Model checking

The Ljung-Box test

- $Q(10)$ for $\{\tilde{a}_t\}$ is 12.64, p-value = 0.24 $\Rightarrow$ no autocorrelation.
- $Q(10)$ for $\{\tilde{a}_t^2\}$ is 14.75, p-value = 0.14 $\Rightarrow$ no autocorrelation.

The sample ACF

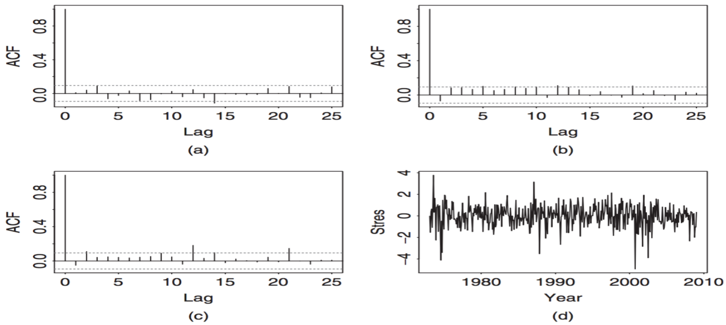

Figure 3.5 Model checking statistics of Gaussian ARCH(1) model in Eq. (3.12) for monthly log returns of Intel stock from January 1973 to December 2008: Parts (a), (b), and (c) show sample ACF of standardized residuals, their squared series, and absolute series, respectively; part (d) is time plot of standardized residuals.