Review Session 3: Volatility Modeling

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Introduction to Volatility Modeling

Realized Volatility: Note that

$$\operatorname{Var}_{t}(r_{t+1}) = \mathbb{E}_{t}[(r_{t+1} - \mathbb{E}_{t}(r_{t+1}))^{2}] = \mathbb{E}_{t}[r_{t+1}^{2}] - (\mathbb{E}_{t}[r_{t+1}])^{2}$$

► One way to estimate is using residual: e_t = r_{t+1} - E_t[r_{t+1}], suppose that i = 1, · · · , n are daily residual, then an estimation for monthly volatility is

$$\hat{\sigma_t}^2 = \left(\sum_{i=1}^n e_i^2\right) \tag{1}$$

Introduction to Volatility Modeling

Implied Volatility: From option prices.

Recall Black-Scholes Formula:

$$C_0 = S_0 N(d_1) - K e^{-rT} N(d_2)$$
(2)

where

$$d_{1} = \frac{\ln \frac{S_{0}}{K} + (r + \frac{1}{2}\sigma^{2})}{\sigma\sqrt{T}}$$

$$d_{2} = d_{1} - \sigma\sqrt{T}$$
(3)

If we know S₀, K, r, T, then we can solve the σ. Volatility obtained from options prices are so-called implied volatilities.

ARCH Model

The return process

$$r_t = \mu + \phi r_{t-1} + u_t \tag{4}$$

- Conditional Mean: $\mathbb{E}_{t-1}[r_t] = \mu + \phi r_{t-1}$
- What is unconditional mean and unconditional variance?
- The innovation:

$$u_t = r_t - \mathbb{E}_{t-1}[r_t]$$

- Can we have time-varying second moments of u_t?
- Suppose that ut follows AR(p) process:

$$u_t^2 = \zeta + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_p u_{t-p}^2 + w_t \qquad (5)$$

- Although the unconditional mean is constant, conditional mean E_{t-1}[u_t²] is time-varying.
- Can you use OLS to estimate ARCH? Yes.

GARCH Model

- One can present ARCH(1) as $u_t = \sqrt{h_t}v_t$ where v_t is i.i.d with mean 0 and variance 1.
- If $h_t = \zeta + \alpha u_{t-1}^2$, then it is ARCH(1) model
- ► GARCH(1,1):

$$h_t = \zeta + \delta h_{t-1} + \alpha u_{t-1}^2 \tag{6}$$

- $\blacktriangleright \ \delta + \alpha \le 1$
- ► GARCH(p,q):

$$h_t = \zeta + \sum_{i=1}^q \alpha_i u_{t-i}^2 + \sum_{j=1}^p \beta_j h_{t-j}$$

- Can you use OLS to estimate GARCH? No.
- ▶ IGARCH(1,1) is GARCH(1,1) when $\delta + \alpha = 1$
- AsyGARCH: Negative surprises increase volatility more than positive surprises

(G)ARCH Question

Consider the following ARCH(1) model:

$$u_t^2 = \zeta + \alpha u_{t-1}^2 + w_t \tag{7}$$

where $\operatorname{Cov}(u_{t-1}^2, w_t) = 0$ and $\alpha < 1$. (a) Find $\mathbb{E}_{t-1}[u_t^2]$ and $\mathbb{E}[u_t^2]$

(G)ARCH Question

(b) Now suppose that $u_t = \sqrt{h_t} v_t$, where v_t is i.i.d with mean zero and variance 1. And $h_t = \zeta + \alpha u_{t-1}^2$. Find $\mathbb{E}_{t-1}[u_t^2]$ and $\mathbb{E}[u_t^2]$ in this case.

(G)ARCH Question

(c) Consider GARCH(1,1) model:

$$h_t = \zeta + \delta h_{t-1} + \alpha u_{t-1}^2$$

Find $\mathbb{E}_{t-1}[u_t^2]$ and $\mathbb{E}[u_t^2]$ in this case.

MLE for (G)ARCH Question

Suppose that we have residuals u_t from regression $Y_t = c + \phi Y_{t-1} + u_t$. Consider

$$u_t = \sqrt{h_t} v_t, \quad h_t = \zeta + \alpha u_{t-1}^2$$

where v_t is i.i.d N(0,1). Find the log-likelihood function for (ζ, α) .

Test of Homoskedasticity vs ARCH(p)

Consider

$$u_t^2 = \zeta + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \dots + \alpha_p u_{t-p}^2 + w_t \qquad (8)$$

Testing Nested GARCH(p,q) Models

Likelihood ratio test

- Estimating GARCH(1,1), get log-likelihood function $\Lambda(\theta_0)$
- Estimating GARCH(2,2), get log-likelihood function $\Lambda(\theta_1)$
- Note that GARCH(1,1) is a special case of GARCH(2,2) (take α₂ = δ₂ = 0)
- Hence $\Lambda(\theta_0) < \Lambda(\theta_1)$
- Likelihood ratio:

$$LR = 2(\Lambda(\theta_1) - \Lambda(\theta_0)) \sim \chi^2(2)$$
(9)

Estimating ARCH(1) Using Python

- Python package: arch
- Sample code:

```
model = arch_model(ret_data, mean='AR', lags=1, p=1,
    q=0)
am = model.fit()
```

Equivalently:

```
model = arch_model(ret_data, mean='AR', lags=1,
    vol='ARCH', p=1)
am = model.fit()
```

```
• GARCH(1,1): Set q = 1
```