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University of New South Wales
School of Economics
Financial Econometrics
Tutorial 6

1. (ARCH model characteristics)

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(a) The specification $\varepsilon_t|\Omega_{t-1} \sim N(0, \sigma_t^2)$ implies that the conditional mean of ε_t is 0. The conditional mean of y_t is $c + \phi_1 y_{t-1}$. The unconditional mean of ε_t is 0, by iterated expectations. The unconditional mean of y_t is also obtained by Rule 5: $E(y_t) = c + \phi_1 E(y_{t-1})$ and stationarity $E(y_t) = E(y_{t-1}) = c/(1 - \phi_1)$.

(b) The specification $\varepsilon_t|\Omega_{t-1} \sim N(0, \sigma_t^2)$ implies that the conditional variance of ε_t is σ_t^2. The conditional variance of y_t is the same as that of ε_t, σ_t^2, because the conditional mean $c + \phi_1 y_{t-1}$ of y_t is fixed for given information set Ω_{t-1}. As the conditional mean of ε_t is zero, the unconditional variance of ε_t is obtained by $E(\varepsilon_t^2) = E\{E(\varepsilon_t^2|\Omega_{t-1})\} = E(\sigma_t^2) = \alpha_0 + \alpha_1 E(\varepsilon_{t-1}^2) + \alpha_2 E(\varepsilon_{t-2}^2)$ and stantionarity $E(\sigma_t^2) = E(\varepsilon_{t-1}^2) = E(\varepsilon_{t-2}^2) = \alpha_0/(1 - \alpha_1 - \alpha_2)$.

For the unconditional variance of y_t, we find $\mathrm{Var}(y_t) = \phi_1^2 \mathrm{Var}(y_{t-1}) + \mathrm{Var}(\varepsilon_t)$ because ε_t is uncorrelated with y_{t-1}. Then, by stationarity, $\mathrm{Var}(y_t) = \mathrm{Var}(y_{t-1}) = \mathrm{Var}(\varepsilon_t)/(1 - \phi_1^2)$. Finally, $\mathrm{Var}(\varepsilon_t) = E(\sigma_t^2) = \alpha_0 + \alpha_1 E(\varepsilon_{t-1}^2) + \alpha_2 E(\varepsilon_{t-2}^2) = \alpha_0/(1 - \alpha_1 - \alpha_2)$ as stationarity implies $\mathrm{Var}(\varepsilon_t) = E(\varepsilon_{t-1}^2) = E(\varepsilon_{t-2}^2)$.

(c) Yes, ε_t is a WN process because its variance is finite, mean is zero (verified in Part (a) and (b)) and autocovariances are zero for any $j > 0$: (iterated expectations)

$$\gamma_j = \mathrm{Cov}(\varepsilon_t, \varepsilon_{t-j}) = E(\varepsilon_t \varepsilon_{t-j}) = E\{E(\varepsilon_t \varepsilon_{t-j}|\Omega_{t-1})\} = E\{E(\varepsilon_t|\Omega_{t-1})\varepsilon_{t-j}\} = E\{0\} = 0.$$

However, ε_t is NOT an independent WN process because the conditional variance of ε_t is a function of ε_{t-1} and ε_{t-2}, by definition.

(d) The ARCH model differ from the standard homoscedastic model in that the conditional variance of the shock (or error term) is a function of lagged shocks whereas the conditional variance of the shock in any standard ARMA model is a constant. The variance equation in the ARCH model is designed to capture "clustering" or the dependence structure in squared shocks.

(e) It is easily seen from the variance equation: $\partial\sigma_t^2/\partial\varepsilon_{t-1}^2 = \alpha_1$.

(f) Now the variance equation is simplified to $\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2$. First, we find $E(\varepsilon_t^4) = E\{E(\varepsilon_t^4 | \Omega_{t-1})\} = E\{3\sigma_t^4\} = 3E\{\alpha_0^2 + 2\alpha_0\alpha_1\varepsilon_{t-1}^2 + \alpha_1^2\varepsilon_{t-1}^4\}$. Because $E(\varepsilon_{t-1}^2) = \alpha_0/(1-\alpha_1)$ by part (b) and $E(\varepsilon_t^4) = E(\varepsilon_{t-1}^4)$ by stationarity, it then follows that

$$E(\varepsilon_t^4) = 3\{\alpha_0^2 + 2\alpha_0\alpha_1[\alpha_0/(1-\alpha_1)]\}/(1-3\alpha_1^2) = 3\alpha_0^2(1+\alpha_1)/[(1-\alpha_1)(1-3\alpha_1^2)].$$

Finally, we find the unconditional kurtosis,

$$\text{Kurtosis} = \frac{E([\varepsilon_t - E(\varepsilon_t)]^4)}{(\text{Var}(\varepsilon_t))^2} = \frac{E(\varepsilon_t^4)}{[E(\varepsilon_t^2)]^2} = 3\,\frac{1-\alpha_1^2}{1-3\alpha_1^2} > 3,$$

and conclude that the unconditional distribution of ε_t is non-normal with heavy tails (kurtosis > 3), noting that its conditional distribution is normal.

2. (GARCH model characteristics)

(a-b) From $\varepsilon_t | \Omega_{t-1} \sim N(0, \sigma_t^2)$, it is clear that $E(\varepsilon_t | \Omega_{t-1}) = 0$ and $\text{Var}(\varepsilon_t | \Omega_{t-1}) = \sigma_t^2$. It follows that $E(y_t | \Omega_{t-1}) = c + \phi_1 y_{t-1}$ and $\text{Var}(y_t | \Omega_{t-1}) = \sigma_t^2$. The unconditional means are obtained by iterated expectations:

$$E(\varepsilon_t) = E\{E(\varepsilon_t | \Omega_{t-1})\} = E\{0\} = 0,$$

$$E(y_t) = E\{E(y_t | \Omega_{t-1})\} = c + \phi_1 E(y_{t-1}) \text{ and}$$

$$E(y_t) = E(y_{t-1}) = c/(1-\phi_1).$$

Because the (conditional) mean of ε_t is zero, we find

$$\text{Var}(\varepsilon_t) = E\{\text{Var}(\varepsilon_t | \Omega_{t-1})\} = E\{\sigma_t^2\} = \alpha_0 + \alpha_1 E(\varepsilon_{t-1}^2) + \beta_1 E(\sigma_{t-1}^2)$$

and, by stationarity,

$$\text{Var}(\varepsilon_t) = E\{\sigma_t^2\} = E(\varepsilon_{t-1}^2) = E(\sigma_{t-1}^2) = \alpha_0/(1-\alpha_1-\beta_1).$$

Further $\text{Var}(y_t) = \phi_1^2 \text{Var}(y_{t-1}) + \text{Var}(\varepsilon_t)$ because ε_t is uncorrelated with y_{t-1}. Again, by stationarity, we find $\text{Var}(y_t) = \text{Var}(y_{t-1}) = \text{Var}(\varepsilon_t)/(1-\phi_1^2)$.

(c) Yes, ε_t is a WN process because its variance is finite, mean is zero (verified in Part (a) and (b)) and autocovariances are zero for any $j > 0$:

$$\gamma_j = \text{Cov}(\varepsilon_t, \varepsilon_{t-j}) = E(\varepsilon_t \varepsilon_{t-j}) = E\{E(\varepsilon_t \varepsilon_{t-j} | \Omega_{t-1})\} = E\{E(\varepsilon_t | \Omega_{t-1})\varepsilon_{t-j}\} = E\{0\} = 0.$$

However, ε_t is NOT an independent WN process because the conditional variance of ε_t is a function of ε_{t-1}, by definition.

(d) It is easily seen from the variance equation: $\partial\sigma_t^2/\partial\varepsilon_{t-1}^2 = \alpha_1$. Note that σ_{t-1}^2 in the variance equation is a function of Ω_{t-2}.

(e-i) We show that $w_t = \varepsilon_t^2 - \sigma_t^2$ has a zero mean and zero autocorrelations. First, because $E(\varepsilon_t|\Omega_{t-1}) = 0$, $E(w_t|\Omega_{t-1}) = E(\varepsilon_t^2|\Omega_{t-1}) - \sigma_t^2 = \sigma_t^2 - \sigma_t^2 = 0$, implying $E(w_t) = 0$. Second, $\mathrm{Cov}(w_t, w_{t-j}) = E(w_t w_{t-j}) = E\{E(w_t|\Omega_{t-1})w_{t-j}\} = E\{0\} = 0$, for all $j \geq 1$.

(e-ii) It only involves some substitutions:

$$\begin{aligned}\varepsilon_t^2 &= \sigma_t^2 + w_t = \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 + w_t \\ &= \alpha_0 + \alpha_1\varepsilon_{t-1}^2 + \beta_1(\varepsilon_{t-1}^2 - w_{t-1}) + w_t \\ &= \alpha_0 + (\alpha_1 + \beta_1)\varepsilon_{t-1}^2 + w_t - \beta_1 w_{t-1},\end{aligned}$$

i.e., an ARMA(1,1) for ε_t^2.

(f) When $\alpha_1 + \beta_1 = 1$, the variance equation

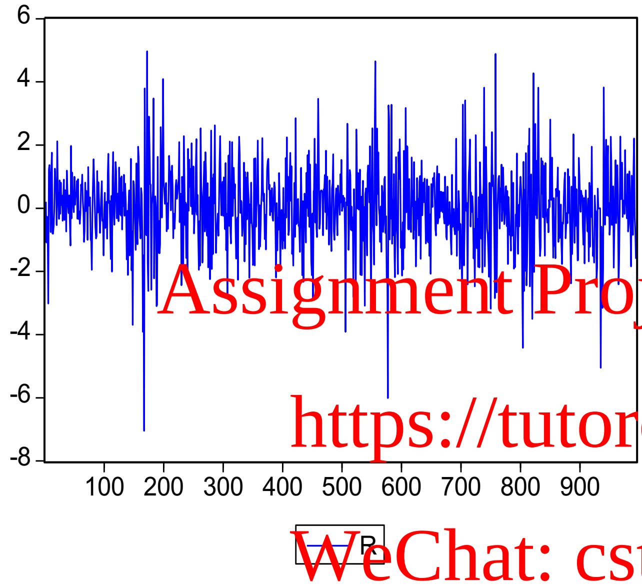
$$\sigma_t^2 = \omega(1 - \alpha_1 - \beta_1) + \alpha_1\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2 = (1 - \beta_1)\varepsilon_{t-1}^2 + \beta_1\sigma_{t-1}^2$$

becomes an EWMA of ε_t^2.

COMPUTING EXERCISES

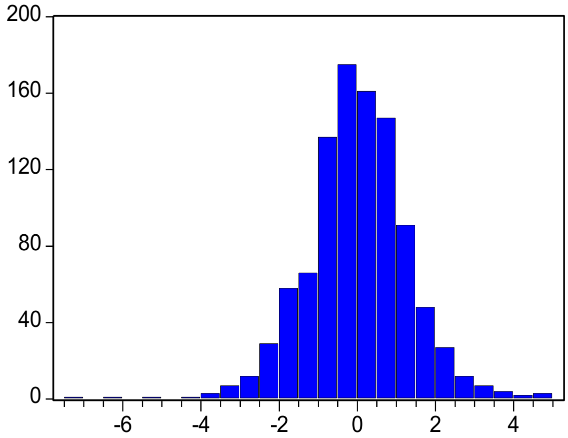
3. (Estimation of ARCH)

(a) The time series plot, histogram and correlogram of the return series are given below. The correlogram shows little autocorrelation in the return (large p-values for Ljung-Box Q-statistics). The data distribution in the histogram is roughly "bell shaped" but has a negative skewness (-0.147) and large kurtosis (5.016). The normality is rejected (JB = 171.74 with a tiny p-value).



Sample: 1 994
Included observations: 993

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0021	0.964
		2	-0.044	-0.044	1.9170	0.383
		3	-0.040	-0.040	3.5306	0.317
		4	0.036	0.034	4.8316	0.305
		5	-0.067	-0.071	9.2784	0.098
		6	-0.019	-0.017	9.6264	0.141
		7	-0.003	-0.006	9.6378	0.210
		8	0.023	-0.031	10.146	0.255
		9	0.018	-0.015	10.477	0.313
		10	0.017	0.011	10.774	0.375
		11	-0.056	-0.063	13.903	0.238
		12	0.077	0.079	19.814	0.071
		13	0.058	0.052	23.255	0.039
		14	-0.009	-0.012	23.336	0.055
		15	0.039	0.058	24.848	0.052
		16	-0.041	-0.053	26.553	0.047



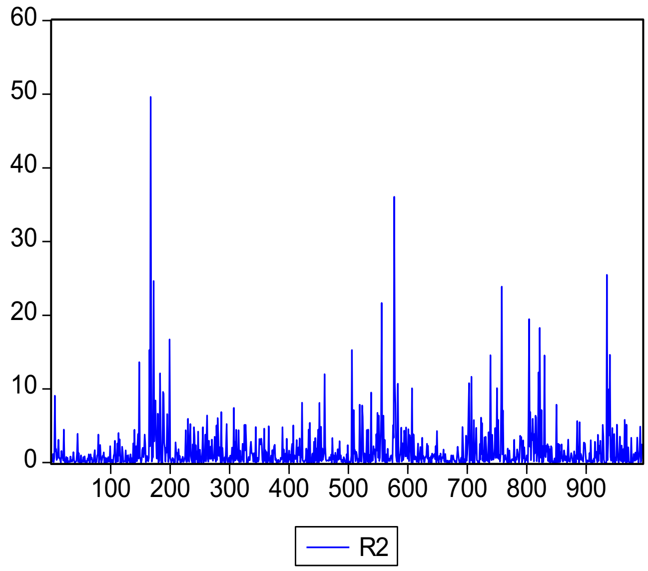
Series: R
Sample 1 994
Observations 993

Mean	0.015735
Median	0.007796
Maximum	4.964596
Minimum	-7.043759
Std. Dev.	1.301875
Skewness	-0.146823
Kurtosis	5.016094
Jarque-Bera	171.7420
Probability	0.000000

(b) For the squared return series, the clustering is prominent in the time series plot and the correlogram reveals strong autocorrelations (tiny p-values for the Q-statistics).

Sample: 1 994
Included observations: 993

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.116	0.116	13.515	0.000
		2	0.138	0.126	32.447	0.000
		3	0.045	0.016	34.436	0.000
		4	0.043	0.020	36.296	0.000
		5	0.162	0.153	62.675	0.000
		6	0.056	0.017	65.776	0.000
		7	0.089	0.043	73.631	0.000
		8	0.072	0.047	78.819	0.000
		9	0.026	-0.008	79.521	0.000
		10	0.050	0.010	82.082	0.000
		11	0.064	0.047	86.265	0.000
		12	0.042	0.004	88.038	0.000
		13	-0.014	-0.055	88.249	0.000
		14	0.010	0.002	88.358	0.000
		15	0.001	-0.009	88.358	0.000
		16	0.093	0.077	97.092	0.000



(c) The LM test for ARCH effect rejects the null hypothesis of no ARCH effect (tiny p-values). We note that the auxiliary equation in the test have large coefficients at lag 1,2 and 5. We conclude that the ARCH effect should be accounted for in the model for the return series.

ARCH Test:

F-statistic	11.13600	Probability	0.000000
Obs*R-squared	53.01425	Probability	0.000000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares

Sample (adjusted): 7 994
Included observations: 988 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.058869	0.144610	7.322252	0.0000
RESID^2(-1)	0.096896	0.031449	3.081046	0.0021
RESID^2(-2)	0.122086	0.031600	3.863463	0.0001
RESID^2(-3)	-0.004176	0.031837	-0.131154	0.8957
RESID^2(-4)	0.004833	0.031617	0.152863	0.8785
RESID^2(-5)	0.152973	0.031463	4.861981	0.0000

R-squared	0.053658	Mean dependent var	1.690413
Adjusted R-squared	0.048840	S.D. dependent var	3.394152
S.E. of regression	3.310230	Akaike info criterion	5.237967
Sum squared resid	10760.38	Schwarz criterion	5.267698
Log likelihood	-2581.556	F-statistic	11.13600
Durbin-Watson stat	2.004102	Prob(F-statistic)	0.000000

Dependent Variable: R
Method: Least Squares

Sample (adjusted): 2 994
Included observations: 993 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.015735	0.041314	0.380854	0.7034

R-squared	0.000000	Mean dependent var	0.015735
Adjusted R-squared	0.000000	S.D. dependent var	1.301875
S.E. of regression	1.301875	Akaike info criterion	3.366494
Sum squared resid	1681.319	Schwarz criterion	3.371430
Log likelihood	-1670.464	Durbin-Watson stat	1.994052

(d) From the ARCH(5) estimation results, $\hat{\alpha}_0$ (1.029) is significantly positive. The point estimates of $(\alpha_1, \ldots, \alpha_5)$ are all non-negative. The point estimate of $\alpha_1 + \cdots + \alpha_5$ is positive and less than one. Hence the restrictions on the ARCH parameters are satisfied. We plot the return over the plot of σ_t^2 (called GARCH01 in EViews). It is visually clear that the conditional variance follows the variations in the return and the clustering closely. The LM test for ARCH effect cannot reject the null of no ARCH effect in the standardised residual series (large p-value).

Dependent Variable: R
Method: ML - ARCH (Marquardt) - Normal distribution

Sample (adjusted): 2 994
Included observations: 993 after adjustments
Convergence achieved after 12 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*RESID(-2)^2 + C(5)*RESID(-3)^2 + C(6)*RESID(-4)^2 + C(7)*RESID(-5)^2

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.049577	0.037379	1.326328	0.1847
Variance Equation				
C	1.029249	0.154755	6.650848	0.0000
RESID(-1)^2	0.067458	0.049048	1.375381	0.1690
RESID(-2)^2	0.141911	0.072688	1.952344	0.0509
RESID(-3)^2	0.027673	0.041101	0.673291	0.5008
RESID(-4)^2	0.049543	0.038767	1.277979	0.2013
RESID(-5)^2	0.104078	0.041422	2.512608	0.0120

R-squared	-0.000676	Mean dependent var	0.015735
Adjusted R-squared	-0.006766	S.D. dependent var	1.301875
S.E. of regression	1.306271	Akaike info criterion	3.316074
Sum squared resid	1682.456	Schwarz criterion	3.350621
Log likelihood	-1639.431	Durbin-Watson stat	1.992704

ARCH Test:

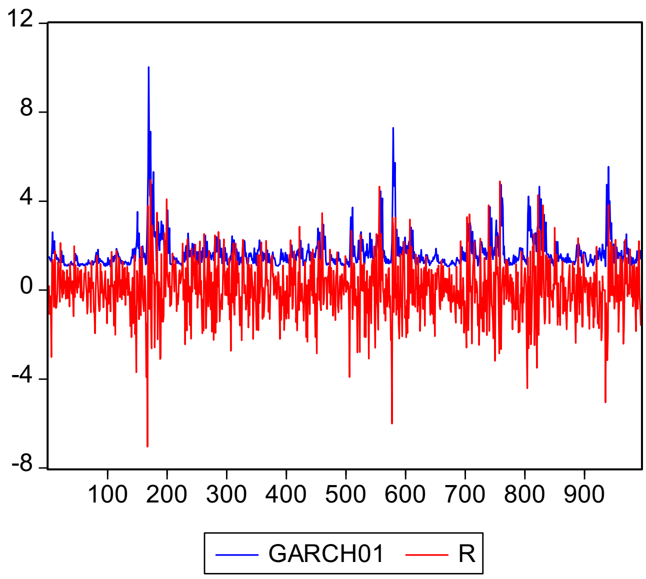
F-statistic	0.366277	Probability	0.871806
Obs*R-squared	1.839143	Probability	0.870925

Test Equation:
Dependent Variable: STD_RESID^2
Method: Least Squares

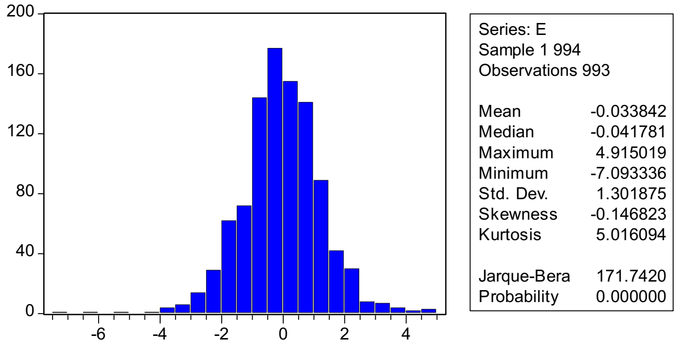
Sample (adjusted): 7 994
Included observations: 988 after adjustments
White Heteroskedasticity-Consistent Standard Errors & Covariance

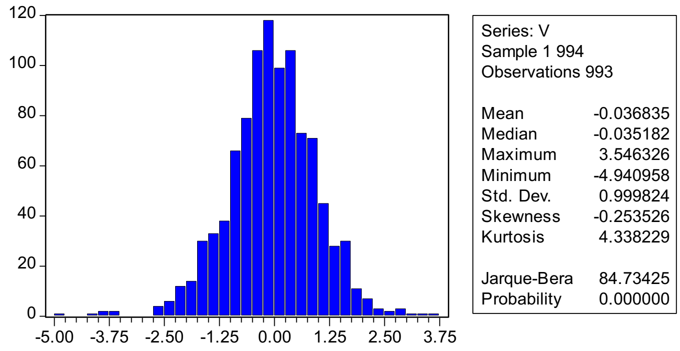
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.998874	0.097108	10.28624	0.0000
STD_RESID^2(-1)	0.001226	0.029508	0.041550	0.9669
STD_RESID^2(-2)	0.027790	0.054465	0.510229	0.6100
STD_RESID^2(-3)	0.010317	0.036485	0.282764	0.7774
STD_RESID^2(-4)	-0.028865	0.021436	-1.346571	0.1784
STD_RESID^2(-5)	-0.013435	0.024427	-0.550002	0.5824

R-squared	0.001861	Mean dependent var	0.995998
Adjusted R-squared	-0.003221	S.D. dependent var	1.829877
S.E. of regression	1.832821	Akaike info criterion	4.055644
Sum squared resid	3298.768	Schwarz criterion	4.085375
Log likelihood	-1997.488	F-statistic	0.366277
Durbin-Watson stat	1.998431	Prob(F-statistic)	0.871806



(e) The histograms indicate that the distributions of both the residuals (E) and the standardised residuals (V) are non-normal (large JB statistics and tiny p-values). The correlograms show that the squared residuals (E2) have strong autocorrelations but the squared standardised residuals (V2) have little. This is consistent with the LM test results in parts (c) and (d). The ARCH(5) model does a good job in accounting for the autocorrelations in the squared residuals.





Correlogram of E2

Sample: 1 994
Included observations: 993

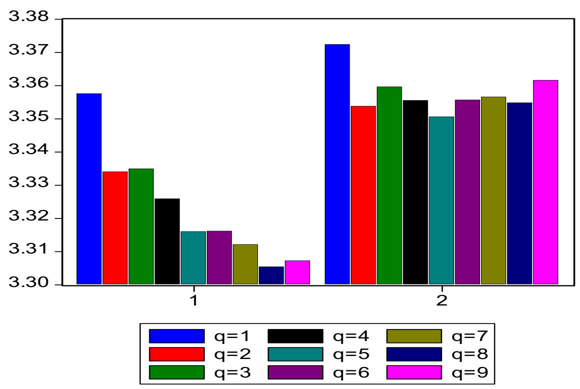
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.118	0.118	13.835	0.000
		2	0.145	0.133	34.707	0.000
		3	0.046	0.016	36.792	0.000
		4	0.041	0.016	38.472	0.000
		5	0.160	0.151	64.105	0.000
		6	0.056	0.018	67.219	0.000
		7	0.091	0.044	75.470	0.000
		8	0.070	0.045	80.414	0.000
		9	0.025	-0.010	81.029	0.000
		10	0.049	0.010	83.482	0.000
		11	0.065	0.048	87.707	0.000
		12	0.044	0.005	89.624	0.000
		13	-0.014	-0.055	89.809	0.000
		14	0.012	0.004	89.964	0.000
		15	-0.001	-0.010	89.965	0.000
		16	0.091	0.075	98.377	0.000

Correlogram of V2

Sample: 1 994
Included observations: 993

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.001	0.001	0.0013	0.971
		2	0.026	0.026	0.6766	0.713
		3	0.009	0.009	0.7628	0.858
		4	-0.030	-0.031	1.6740	0.795
		5	-0.014	-0.015	1.8733	0.866
		6	0.012	0.014	2.0208	0.918
		7	0.032	0.033	3.0480	0.881
		8	0.045	0.043	5.0580	0.751
		9	-0.004	-0.007	5.0740	0.828
		10	0.028	0.026	5.8789	0.825
		11	0.045	0.047	7.8949	0.723
		12	0.012	0.014	8.0361	0.782
		13	-0.006	-0.008	8.0668	0.839
		14	-0.005	-0.007	8.0873	0.885
		15	-0.016	-0.015	8.3426	0.909
		16	0.040	0.041	9.9532	0.869

(f) We may use AIC or SIC to choose the number of lags in ARCH models. For ARCH(q), the AIC and SIC for q = 1,2,…,9 are displayed in the bar chart below, where AICs are in group 1 on the left and SICs are in group 2 on the right. Clearly, AIC selects q = 8 but SIC selects q = 5.

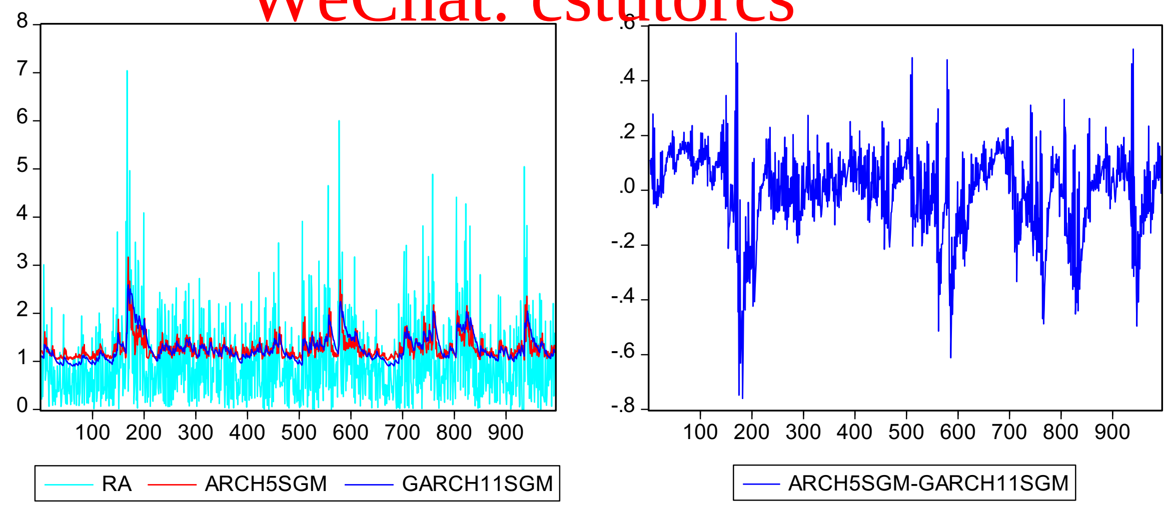


Based on SIC and the principle of parsimony, the ARCH(5) model stays for the variance equation. For the mean equation, as the returns have little autocorrelation, a more sophisticated ARMA specification is unlikely to improve the model's fit.

4. (Estimation of GARCH)

(a) The estimation results at Part (e) below indicate that all restriction on the parameters are satisfied: $\alpha_0 > 0$, $\alpha_1 \geq 0$, $\beta_1 \geq 0$ and $\alpha_1 + \beta_1 < 1$. We also note that the β_1 estimate is about 0.9, the α_1 estimate is about 0.1 and the $\alpha_1 + \beta_1$ estimate is very close to 1.

(b) The plot below contain the absolute return series (RA) and σ_t series from ARCH(5) and GARCH(1,1) respectively. Both σ_t series match the variations in the return. However the two σ_t series differ markedly in a number of places. The GARCH σ_t appears smoother than the ARCH σ_t.



(c) The LM test for ARCH effect (see below) cannot reject that the null hypothesis that there is no ARCH effect in the standardised residuals, as the p-value is quite large (0.17). The correlogram of the squared standardised residuals also indicate that there are no autocorrelations. Hence the GARCH variance equation has adequately captured the clustering in the error term ε_t.

ARCH Test:

F-statistic	1.553443	Probability	0.170654
Obs*R-squared	7.753346	Probability	0.170363

Test Equation:
Dependent Variable: STD_RESID^2
Method: Least Squares

Sample (adjusted): 7 994
Included observations: 988 after adjustments
White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.968768	0.094300	10.27322	0.0000
STD_RESID^2(-1)	-0.010058	0.027461	-0.366253	0.7143
STD_RESID^2(-2)	0.073431	0.065495	1.121177	0.2625
STD_RESID^2(-3)	-0.020112	0.030708	-0.654941	0.5127
STD_RESID^2(-4)	-0.040896	0.022349	-1.829879	0.0676
STD_RESID^2(-5)	0.025099	0.032189	0.779727	0.4357

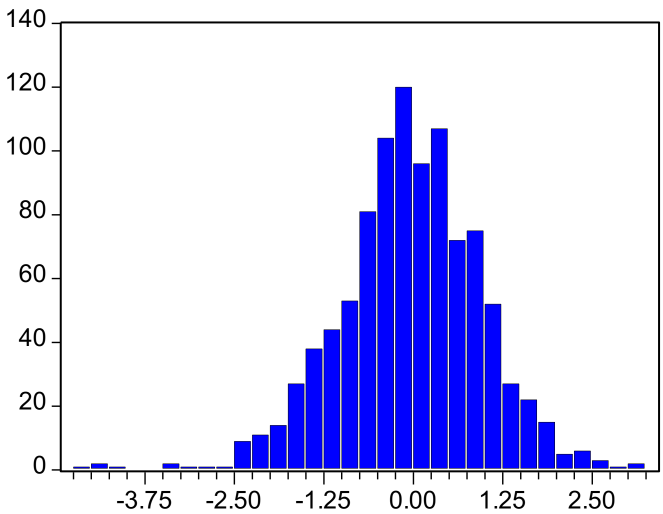
R-squared	0.007848	Mean dependent var	0.996322
Adjusted R-squared	0.002796	S.D. dependent var	1.834917
S.E. of regression	1.832350	Akaike info criterion	4.055130
Sum squared resid	3297.071	Schwarz criterion	4.084861
Log likelihood	-1997.234	F-statistic	1.553443
Durbin-Watson stat	1.998554	Prob(F-statistic)	0.170654

Correlogram of Standardized Residuals Squared

Sample: 2 994
Included observations: 993

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.013	-0.013	0.1692	0.681
		2	0.069	0.069	4.9755	0.083
		3	-0.020	-0.018	5.3764	0.146
		4	-0.038	-0.043	6.8073	0.146
		5	0.021	0.023	7.2599	0.202
		6	-0.016	-0.011	7.5290	0.275
		7	0.021	0.016	7.9864	0.334
		8	0.005	0.007	8.0145	0.432
		9	-0.020	-0.022	8.4264	0.492
		10	-0.011	-0.013	8.5389	0.576
		11	0.007	0.013	8.5950	0.659
		12	-0.026	-0.026	9.2913	0.678
		13	-0.008	-0.012	9.3559	0.746
		14	-0.020	-0.016	9.7581	0.780
		15	-0.023	-0.023	10.306	0.800
		16	0.002	0.001	10.309	0.850

(d) The histogram of the standardised residual show that the null hypothesis of normality is strongly rejected (virtually zero p-value). Nonetheless, the kurtosis is much smaller than the kurtosis in the return series, which confirms that the variance equation can partially explain the excess kurtosis in the return series.



Series: Standardized Residuals
Sample 2 994
Observations 993

Mean	-0.037499
Median	-0.029158
Maximum	3.045820
Minimum	-4.590708
Std. Dev.	1.000489
Skewness	-0.367698
Kurtosis	4.339797
Jarque-Bera	96.64633
Probability	0.000000

(e) The estimation results with or without the quasi ML robust standard errors are given below. They are different and may lead to different conclusions. Generally, the robust standard errors in the variance equation are larger.

Dependent Variable: R
Method: ML - ARCH (Marquardt) - Normal distribution

Sample (adjusted): 2 994
Included observations: 993 after adjustments
Convergence achieved after 11 iterations
Bollerslev-Wooldrige robust standard errors & covariance
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.042397	0.036383	1.165292	0.2439
		Variance Equation		
C	0.073836	0.032445	2.275744	0.0229
RESID(-1)^2	0.080407	0.026746	3.006251	0.0026
GARCH(-1)	0.877380	0.036232	24.21561	0.0000

R-squared	-0.000420	Mean dependent var	0.015735
Adjusted R-squared	-0.003454	S.D. dependent var	1.301875
S.E. of regression	1.304121	Akaike info criterion	3.300572
Sum squared resid	1682.025	Schwarz criterion	3.320313
Log likelihood	-1634.734	Durbin-Watson stat	1.993215

Dependent Variable: R
Method: ML - ARCH (Marquardt) - Normal distribution

Sample (adjusted): 2 994
Included observations: 993 after adjustments
Convergence achieved after 11 iterations
Variance backcast: ON
GARCH = C(2) + C(3)*RESID(-1)^2 + C(4)*GARCH(-1)

	Coefficient	Std. Error	z-Statistic	Prob.
C	0.042397	0.040573	1.044951	0.2960
		Variance Equation		
C	0.073836	0.025873	2.853797	0.0043
RESID(-1)^2	0.080407	0.015193	5.292469	0.0000
GARCH(-1)	0.877380	0.026154	33.54611	0.0000

R-squared	-0.000420	Mean dependent var	0.015735
Adjusted R-squared	-0.003454	S.D. dependent var	1.301875
S.E. of regression	1.304121	Akaike info criterion	3.300572
Sum squared resid	1682.025	Schwarz criterion	3.320313
Log likelihood	-1634.734	Durbin-Watson stat	1.993215

(f) The GARCH models can be easily estimated to obtain AIC and SIC in EViews. The AIC and SIC for GARCH(1,1), GARCH(2,1), GARCH(1,2) are GARCH(2,2) are presented in the bar chart below (AIC on the left and SIC on the right). Clearly, both AIC and SIC select GARCH(1,1).