

Lecture Note of Bus 41202, Spring 2006: Multivariate Volatility Models

Multivariate Volatility Models

How do the correlations between asset returns change over time?

Focus on two series (Bivariate)

Two asset return series:

$$\mathbf{r}_t = \begin{bmatrix} r_{1t} \\ r_{2t} \end{bmatrix}.$$

Data: $\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_T$.

Basic concept

Let F_{t-1} denote the information available at time $t - 1$.

Partition the return as

$$\mathbf{r}_t = \boldsymbol{\mu}_t + \mathbf{a}_t, \quad \mathbf{a}_t = \boldsymbol{\Sigma}_t^{1/2} \boldsymbol{\epsilon}_t$$

where $\boldsymbol{\mu}_t = E(\mathbf{r}_t | F_{t-1})$ is the predictable component, and

$$\text{Cov}(\mathbf{a}_t | F_{t-1}) = \boldsymbol{\Sigma}_t = \begin{bmatrix} \sigma_{11,t} & \sigma_{12,t} \\ \sigma_{21,t} & \sigma_{22,t} \end{bmatrix},$$

$\{\boldsymbol{\epsilon}_t\}$ are iid 2-dimensional random vectors with mean zero and identity covariance matrix.

Multivariate volatility modeling

Study time evolution of $\{\Sigma_t\}$.

Σ_t is symmetric, i.e. $\sigma_{12,t} = \sigma_{21,t}$

There are 3 variables in Σ_t .

If k asset returns, Σ_t has $k(k+1)/2$ variables.

Requirement

Σ_t must be positive definite for all t ,

$$\sigma_{11,t} > 0, \quad \sigma_{22,t} > 0, \quad \sigma_{11,t}\sigma_{22,t} - \sigma_{12,t}^2 > 0.$$

The time-varying correlation between r_{1t} and r_{2t} is

$$\rho_{12,t} = \frac{\sigma_{12,t}}{\sqrt{\sigma_{11,t}\sigma_{22,t}}}.$$

Some complications

- Positiveness requirement is not easy to meet
- Too many series to model

Some simple models available

- Exponentially weighted covariance
- Diagonal model
- BEKK model
- Others, e.g. Dynamic correlation models

Exponentially weighted model

$$\Sigma_t = (1 - \lambda)\mathbf{a}_{t-1}\mathbf{a}'_{t-1} + \lambda\Sigma_{t-1},$$

where $0 < \lambda < 1$. That is,

$$\Sigma_t = (1 - \lambda) \sum_{i=1}^{\infty} \lambda^{i-1} \mathbf{a}_{t-i}\mathbf{a}'_{t-i}.$$

```
cov1 = EWMA.cov(rtn, lambda=0.96) % lambda given.
```

```
cov2 = mgarch(rtn~1,~ewma1,trace=F) % Estimate lambda
```

Diagonal VEC model

May not be positive definite.

Model elements of Σ_t separately

For instance, DVEC(1,1) model

$$\sigma_{11,t} = c_{11} + \alpha_{11}a_{1,t-1}^2 + \beta_{11}\sigma_{11,t-1}$$

$$\sigma_{12,t} = c_{12} + \alpha_{12}a_{1,t-1}a_{2,t-1} + \beta_{11}\sigma_{12,t-1}$$

$$\sigma_{22,t} = c_{22} + \alpha_{22}a_{2,t-1}^2 + \beta_{22}\sigma_{22,t-1}$$

In S-Plus, c is called “A”, α is ARCH(1), β is GARCH(1).

```
fit = mgarch(rtn~1,~dvec(1,1))
```

```
summary(fit)
```

```
names(fit) % see what are stored.
```

```
%In particular, fit$R.t stores correlations
```

BEKK model Engle and Kroner (1995)

Simple BEKK(1,1) model

$$\Sigma_t = \mathbf{A}_0 \mathbf{A}'_0 + \mathbf{A}_1 (\mathbf{a}_{t-1} \mathbf{a}'_{t-1}) \mathbf{A}'_1 + \mathbf{B}_1 \Sigma_{t-1} \mathbf{B}'_1$$

where \mathbf{A}_0 is a lower triangular matrix, \mathbf{A}_1 and \mathbf{B}_1 are square matrices without restrictions.

Pros: positive definite

Cons: Many parameters, dynamic relations require further study

```
fit2=mgarch(rtn~1,~bekk(1,1))
```

```
summary(fit2)
```

```
names(fit2)
```

Consider the monthly log returns of GM stock and the S&P500 index from 1950 to 2002 for 638 data points.

*** Demonstration of S-Plus commands for Chapter 9

```
> gm=gmspln5002$gm
```

```
> sp=gmspln5002$sp
```

```
> par(mfcol=c(2,1))
```

```
> plot(gm,type='l')
```

```
> plot(sp,type='l')
```

```
> gmsp=cbind(gm,sp) % create a 2-dim return series.
```

```
> fit1=mgarch(gmsp~1,~dvec(1,1),trace=F)
```

```
> summary(fit1)
```

```
mgarch(formula.mean=gmsp~1,formula.var=~dvec(1,1),trace=F)
```

Mean Equation: gmsp ~ 1

Conditional Variance Equation: \sim dvec(1, 1)

Conditional Distribution: gaussian

Estimated Coefficients:

Value Std.Error t value Pr(>|t|)

C(1)	0.0104749	0.00243210	4.307	1.919e-005
C(2)	0.0068800	0.00153509	4.482	8.790e-006
A(1, 1)	0.0001400	0.00004496	3.113	1.933e-003
A(2, 1)	0.0001073	0.00004952	2.168	3.055e-002
A(2, 2)	0.0001033	0.00003944	2.619	9.018e-003
ARCH(1; 1, 1)	0.0831688	0.01826946	4.552	6.367e-006
ARCH(1; 2, 1)	0.0385129	0.01622698	2.373	1.792e-002
ARCH(1; 2, 2)	0.0802303	0.02089382	3.840	1.355e-004
GARCH(1; 1, 1)	0.8916125	0.02274390	39.202	0.000e+000
GARCH(1; 2, 1)	0.9029094	0.03801639	23.751	0.000e+000
GARCH(1; 2, 2)	0.8656909	0.03383195	25.588	0.000e+000

AIC(11) = -4269.022

BIC(11) = -4220.015

Normality Test:

Jarque-Bera P-value Shapiro-Wilk P-value

gm	44.42	2.266e-010	0.9869	0.6761
sp	21.52	2.122e-005	0.9892	0.8954

Ljung-Box test for standardized residuals:

	Statistic	P-value	Chi ² -d.f.
gm	19.67	0.07364	12
sp	19.98	0.06740	12

Ljung-Box test for squared standardized residuals:

	Statistic	P-value	Chi ² -d.f.
gm	15.652	0.2077	12
sp	4.999	0.9580	12

Lagrange multiplier test:

	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
gm	-0.06115	-0.2803	-1.4642	-0.4926	1.1335	-1.6898
sp	-0.02731	-0.4904	-0.5857	-0.9897	0.5748	0.0973

	Lag 7	Lag 8	Lag 9	Lag 10	Lag 11	Lag 12	C
gm	-0.2745	1.2502	0.9645	-0.8264	2.1744	0.08219	0.4325
sp	-0.1627	0.4246	0.3809	1.4249	0.2165	0.12434	0.5229

	TR ²	P-value	F-stat	P-value
gm	15.035	0.2395	1.4006	0.2743
sp	4.739	0.9661	0.4341	0.9909

```
> fit2=mgarch(gmsp~1,~bekk(1,1)) % BEKK model
> summary(fit2)
mgarch(formula.mean=gmsp~1,formula.var=~bekk(1,1))
```

Mean Equation: gmsp ~ 1

Conditional Variance Equation: \sim bekk(1, 1)

Conditional Distribution: gaussian

Estimated Coefficients:

Value Std.Error t value Pr(>|t|)

C(1)	0.0101123	0.002697	3.74967	1.934e-004
C(2)	0.0065510	0.001697	3.86051	1.248e-004
A(1, 1)	0.0119214	0.007089	1.68176	9.311e-002
A(2, 1)	0.0146959	0.004269	3.44261	6.143e-004
A(2, 2)	0.0007941	0.056368	0.01409	9.888e-001
ARCH(1; 1, 1)	0.3348499	0.052971	6.32135	4.910e-010
ARCH(1; 2, 1)	0.0814715	0.039972	2.03820	4.195e-002
ARCH(1; 1, 2)	-0.3081572	0.078010	-3.95023	8.690e-005
ARCH(1; 2, 2)	0.1630736	0.054573	2.98816	2.916e-003
GARCH(1; 1, 1)	0.9237848	0.020397	45.29098	0.000e+000
GARCH(1; 2, 1)	-0.0280710	0.016658	-1.68515	9.245e-002
GARCH(1; 1, 2)	0.0710387	0.047735	1.48818	1.372e-001
GARCH(1; 2, 2)	0.9304805	0.031737	29.31835	0.000e+000

AIC(13) = -4241.851

BIC(13) = -4183.933

Normality Test:

Jarque-Bera P-value Shapiro-Wilk P-value

gm	41.87	8.086e-010	0.9901	0.9418
sp	36.84	1.001e-008	0.9868	0.6660

Ljung-Box test for standardized residuals:

	Statistic	P-value	Chi ² -d.f.
gm	21.68	0.04123	12
sp	20.98	0.05067	12

Ljung-Box test for squared standardized residuals:

	Statistic	P-value	Chi ² -d.f.
gm	20.540	0.05754	12
sp	7.639	0.81264	12

Lagrange multiplier test:

	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
gm	0.09856	-0.1232	-1.1413	-0.4392	1.279	-1.6702	-0.2185
sp	0.77406	-0.4373	-0.4633	-0.2767	1.181	-0.2194	0.6637

	TR ²	P-value	F-stat	P-value
gm	19.903	0.06895	1.8690	0.1201
sp	6.963	0.86002	0.6402	0.8942

```
>fit3=mgarch(gmsp~1,~ccc(1,1)) %Constant correlations!  
>summary(fit3)  
mgarch(formula.mean = gmsp ~ 1,formula.var=~ccc(1,1))
```

Mean Equation: gmsp ~ 1

Conditional Variance Equation: ~ ccc(1, 1)

Conditional Distribution: gaussian

Estimated Coefficients:

	Value	Std.Error	t value	Pr(> t)
C(1)	0.01049566	0.00241094	4.353	1.564e-005
C(2)	0.00735053	0.00152773	4.811	1.876e-006
A(1, 1)	0.00007338	0.00004950	1.482	1.387e-001
A(2, 2)	0.00007252	0.00003277	2.213	2.727e-002
ARCH(1; 1, 1)	0.11404920	0.02685448	4.247	2.493e-005
ARCH(1; 2, 2)	0.09837054	0.02328916	4.224	2.755e-005
GARCH(1; 1, 1)	0.88296850	0.02786099	31.692	0.000e+000
GARCH(1; 2, 2)	0.86944221	0.02880646	30.182	0.000e+000

Estimated Conditional Constant Correlation Matrix:

	gm	sp
gm	1.0000	0.6482
sp	0.6482	1.0000

Standard Errors:

	gm	sp
gm	NA	0.01906
sp	0.01906	NA

AIC(8) = -4238.222

BIC(8) = -4202.58

Normality Test:

	Jarque-Bera	P-value	Shapiro-Wilk	P-value
gm	35.44	2.015e-008	0.9867	0.6564
sp	36.80	1.022e-008	0.9852	0.4492

Ljung-Box test for standardized residuals:

```
-----
```

	Statistic	P-value	Chi ² -d.f.
gm	18.05	0.11415	12
sp	22.72	0.03016	12

Ljung-Box test for squared standardized residuals:

```
-----
```

	Statistic	P-value	Chi ² -d.f.
gm	16.98	0.1504	12
sp	16.66	0.1627	12

Lagrange multiplier test:

```
-----
```

	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
gm	-0.3586	-0.69005	-1.81246	-0.7803	0.6568	-1.8299
sp	1.3149	-0.06239	-0.04997	-0.1384	0.8093	0.3792

	TR ²	P-value	F-stat	P-value
gm	16.28	0.1788	1.520	0.2214
sp	14.64	0.2618	1.363	0.2937

```
> fit4=mgarch(gmsp~1,~egarch(1,1),leverage=T)
```

```
> summary(fit4)
```

```
mgarch(formula.mean = gmsp ~ 1,formula.var=~egarch(1,1),
```

leverage = T)

Mean Equation: gmsp ~ 1

Conditional Variance Equation: ~ egarch(1, 1)

Conditional Distribution: gaussian

Estimated Coefficients:

Value Std.Error t value Pr(>|t|)

C(1)	0.009157	0.003196	2.865	0.0043037
C(2)	0.006447	0.002157	2.988	0.0029151
A(1, 1)	-0.415912	0.158767	-2.620	0.0090141
A(2, 2)	-0.719478	0.364322	-1.975	0.0487219
ARCH(1; 1, 1)	0.219687	0.064281	3.418	0.0006724
ARCH(1; 2, 2)	0.169399	0.075000	2.259	0.0242454
GARCH(1; 1, 1)	0.954872	0.023042	41.440	0.0000000
GARCH(1; 2, 2)	0.907813	0.051497	17.629	0.0000000
LEV(1; 1, 1)	-0.136060	0.107624	-1.264	0.2066189
LEV(1; 2, 2)	-0.374486	0.224256	-1.670	0.0954339

AIC(10) = -3910.694

BIC(10) = -3866.142

Normality Test:

Jarque-Bera P-value Shapiro-Wilk P-value

gm	28.43	6.717e-007	0.9893	0.9011985
sp	222.96	0.000e+000	0.9762	0.0007066

Ljung-Box test for standardized residuals:

	Statistic	P-value	Chi ² -d.f.
gm	19.568	0.07572	12
sp	9.854	0.62873	12

Ljung-Box test for squared standardized residuals:

	Statistic	P-value	Chi ² -d.f.
gm	19.683	0.07332	12
sp	5.395	0.94346	12

Lagrange multiplier test:

	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6
gm	-0.05071	-0.24765	-1.6586	-0.5954	0.906238	-1.718
sp	-0.23843	0.08391	-0.4111	-0.4491	0.009386	-1.073

	TR ²	P-value	F-stat	P-value
gm	18.667	0.0969	1.7493	0.1475
sp	5.123	0.9538	0.4695	0.9832

*** Demonstration of forecasts

> predict(fit2,5)

\$series.pred:

	gm	sp
[1,]	0.01011233	0.006550963
[2,]	0.01011233	0.006550963
[3,]	0.01011233	0.006550963

```
[4,] 0.01011233 0.006550963
[5,] 0.01011233 0.006550963
```

\$sigma.pred:

```
          gm          sp
[1,] 0.1161069 0.05758898
[2,] 0.1149695 0.05642254
[3,] 0.1138556 0.05538088
[4,] 0.1127669 0.05445162
[5,] 0.1117043 0.05362331
```

\$R.pred:

```
, , gm
      gm          sp
[1,]  1 0.5406667
[2,]  1 0.5322805
[3,]  1 0.5243709
[4,]  1 0.5169547
[5,]  1 0.5100440
```

```
, , sp
          gm sp
[1,] 0.5406667  1
[2,] 0.5322805  1
[3,] 0.5243709  1
[4,] 0.5169547  1
[5,] 0.5100440  1
```