

# Overview

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- Volatility Clustering
- GARCH Model is widely applied in the financial industry
- High-dimension models have not well developed

# Notations

Consider a financial time series  $\{y_t\}_{t=1}^T$ ,

$$\begin{aligned}y_t &= \mu_t(\theta) + \varepsilon_t, \quad t = 1, \dots, T \\ \varepsilon_t &= H_t^{1/2}(\theta)z_t, \quad t = 1, \dots, T\end{aligned}$$

where  $\theta$  is an information variable,  $y_t$  is an  $p \times 1$  vector,  $E_{t-1}(y_t) = \mu_t(\theta)$  and we assuming the mean and variance of the normal random variable  $z_t$  as following.

$$E(z_t) = 0$$

$$\text{Var}(z_t) = I_N$$

Therefore, the covariance matrix of  $y_t$  can be expressed in the following way,

$$\begin{aligned}\text{Var}(y_t \mid I_{t-1}) &= \text{Var}_{t-1}(y_t) = \text{Var}_{t-1}(\varepsilon_t) \\ &= H_t^{1/2} \text{Var}_{t-1}(z_t) \left(H_t^{1/2}\right)'\end{aligned}$$

,the matrix  $H_t$  is positive definite.

# Bollerslev's VEC Model

The VEC (1,1) model is defined as,

$$h_t = c + A\eta_{t-1} + Gh_{t-1}$$

where,

$$h_t = \text{vech}(H_t)$$

$$\eta_t = \text{vech}(\varepsilon_t \varepsilon_t')$$

$$\text{eigen}(A + G) < 1$$

# General Form

$$\text{vech}(H_t) = \text{vech}(C^*) + \sum_{i=1}^q A_i \text{vech}(\varepsilon_{t-i} \varepsilon'_{t-i}) + \sum_{j=1}^p B_j \text{vech}(H_{t-j})$$

$A_i$  and  $B_j$  are square parameter matrices of order  $(N+1)N/2$  and  $C^*$  is a  $(N+1)N/2 \times 1$  parameter vector.

$$\begin{aligned} \text{num}(VEC) &= \text{num}(C^*) + \text{num}(A_i) + \text{num}(B_j) \\ &= \tilde{N}/2 + \tilde{N}^2/4 + \tilde{N}^2/4 \\ &= N(N+1)(N(N+1)+1)/2 \end{aligned}$$

# Our Improvements

$$\begin{aligned} L(\zeta, \theta; \Lambda) = & \frac{1}{T} \sum_{t=1}^T \log |H_t(\theta)| + \frac{1}{T} \sum_{t=1}^T \text{tr} (H_t^{-1}(\theta) R_t) \lambda_1 + \sum_{Z=A,B,C} \|Z_L\|_* \\ & + \lambda_2 \sum_{Z=A,B,C} |Z_D|_1 - \sum_{Z=A,B,C} \langle \Lambda_{Z_L}, \zeta_{Z_L} - Z_L \rangle \\ & - \sum_{Z=A,B,C} \langle \Lambda_{Z_D}, \zeta_{Z_D} - Z_S \rangle \\ & + \sum_{Z=A,B,C} \frac{1}{2\mu_{Z_L}} \|\zeta_{Z_L} - Z_L\|_F^2 + \sum_{Z=A,B,C} \frac{1}{2\mu_{Z_D}} \|\zeta_{Z_D} - Z_S\|_F^2 \end{aligned}$$

# Application

$$\begin{array}{ll} \min & w' \Sigma w \\ \text{w.r.t} & w' 1 = 1 \end{array}$$

Take the partial derivatives,

$$\begin{aligned} \frac{\partial}{\partial w} w' \Sigma w + \lambda (w' 1 - 1) \\ 2 \Sigma w + \lambda 1 = 0 \end{aligned}$$

Then the result is below and  $\Sigma$  can be estimated by  $\{H_t\}$ .

$$w = - \frac{\Sigma^{-1} 1}{1' \Sigma^{-1} 1}$$

# Snapshot of Data Results

	LW	ISEE	UT	AT	MT	DCC	VEC
annual volatility	0.3280	0.3587	0.3286	0.336311	0.3588	0.3570	0.1845
sharpe ratio	0.2313	0.2018	0.2327	0.2100	0.2015	0.2065	0.4187

<sup>1</sup> In the above table LW is Ledoit and Wolf; DCC is Dynamic Conditional Covariance; DCP is Dynamic Conditional Precision; ISEE is Innovated Scalable Efficient Estimation; UT is Universal Thresholding; AT is Adaptive Thresholding; MT is Multiple Testing.

<sup>2</sup> Since the data is S&P 100 component stock price from 2008 to 2018, we rebalance the portfolio in every 2 years.