

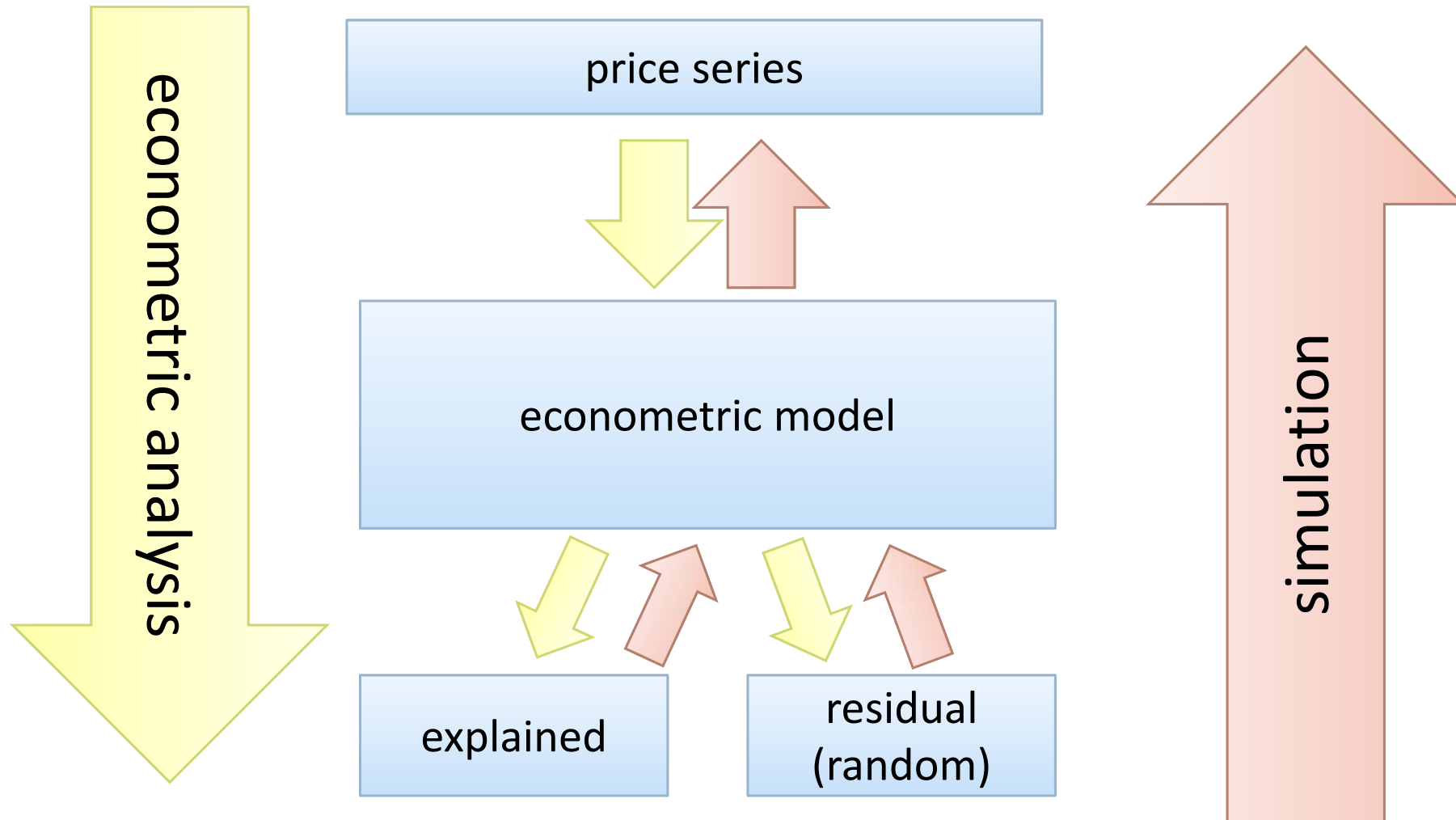
# Simulation (part 2)

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# simulation with econometric models

## ▶ econometric modelling



# simulation with econometric models

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## ▶ assumptions about stock prices

- ▶ past return:  $r_t = \ln(S_t/S_{t-1})$
- ▶ follow a stochastic process
  - ▶  $S_{t+1} = S_t \exp(r_{t+1})$
  - ▶  $r_{t+1}$  is a „random variable“

## ▶ simplest case

- ▶ normal distribution
  - ▶ mean and volatility are sufficient
  - ▶ return for 1 period:  $r_{t+1} \sim N(\mu, \sigma)$
  - ▶ return for T periods:  $r_{t+T} \sim N(\mu T, \sigma \sqrt{T})$
  - ▶ expected price:  $E(S_{t+T}) = S_t \exp((\mu + \sigma^2/2)T)$

# simulation with econometric models

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## econometric model

$$S_t = S_{t-1} \cdot e^{r_t}, r_t \sim \text{niid}(\mu, \sigma^2)$$

$$r_t = \mu + \varepsilon_t, \varepsilon_t \sim \text{niid}(0, \sigma^2)$$

$$\varepsilon_t = z_t \cdot \sigma, z_t \sim \text{niid}(0; 1)$$

## MC simulation

- ① simulate  $\tilde{z}_t$
- ② compute  $\tilde{\varepsilon}_t = \tilde{z}_t \cdot \sigma$
- ③ compute  $\tilde{r}_t = \mu + \tilde{\varepsilon}_t$
- ④ compute  $\tilde{S}_t = S_{t-1} \cdot e^{\tilde{r}_t}$

# simulation with econometric models

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## ▶ some simple return processes

- ▶ returns follow a random walk:

$$r_t = \mu + \epsilon_t \quad \epsilon_t \sim N(0, \sigma_\epsilon)$$

- ▶ are driven by some factor:

$$r_t = \alpha + \beta r_{f,t} + \epsilon_t$$



- ▶ have some memory (auto regressive):

$$r_t = \mu + \gamma r_{t-1} + \epsilon_t \quad r_t = \mu + \theta_1 e_{t-1} + e_t$$

## ▶ time varying volatility

- ▶ **Generalized AutoRegressive Heteroskedasticity (GARCH)**

$$r_t = \mu + \epsilon_t, \quad \epsilon_t \sim N(0; \sigma_t^2), \quad \sigma_t^2 = \alpha_0 + \sum_{i=1}^q \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^p \beta_j \sigma_{t-j}^2$$

# generating multivariate random numbers

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## ▶ example: multivariate normal distribution

- ▶ assume  $\mathbf{X}$  is centered, i.e.,  $E(\mathbf{X}) = 0$ , and normally distributed with  $\text{cov}(\mathbf{X}) = \mathbf{C}$
- ▶ let  $\mathbf{C}^{-0.5} = (\mathbf{C}^{0.5})^{-1}$  and  $(\mathbf{C}^{0.5})' \mathbf{C}^{0.5} = \mathbf{C}$
- ▶ to get  $\mathbf{C}^{0.5}$ , use, e.g., the Cholesky decomposition
- ▶ then  $\mathbf{Z} = \mathbf{X} \mathbf{C}^{-0.5}$  is white noise with  $\text{cov}(\mathbf{Z}) = \mathbf{I}$
- ▶ likewise,  $\text{cov}(\mathbf{Z} \mathbf{C}^{0.5}) = \text{cov}(\mathbf{X} \mathbf{C}^{-0.5} \mathbf{C}^{0.5}) = \text{cov}(\mathbf{X}) = \mathbf{C}$
- ▶  $\text{cov}(\mathbf{X} \mathbf{C}^{-0.5}) = \mathbf{I}$  where  $\mathbf{C}^{-0.5} = (\mathbf{C}^{0.5})^{-1}$  and  $(\mathbf{C}^{0.5})' \mathbf{C}^{0.5} = \mathbf{C}$

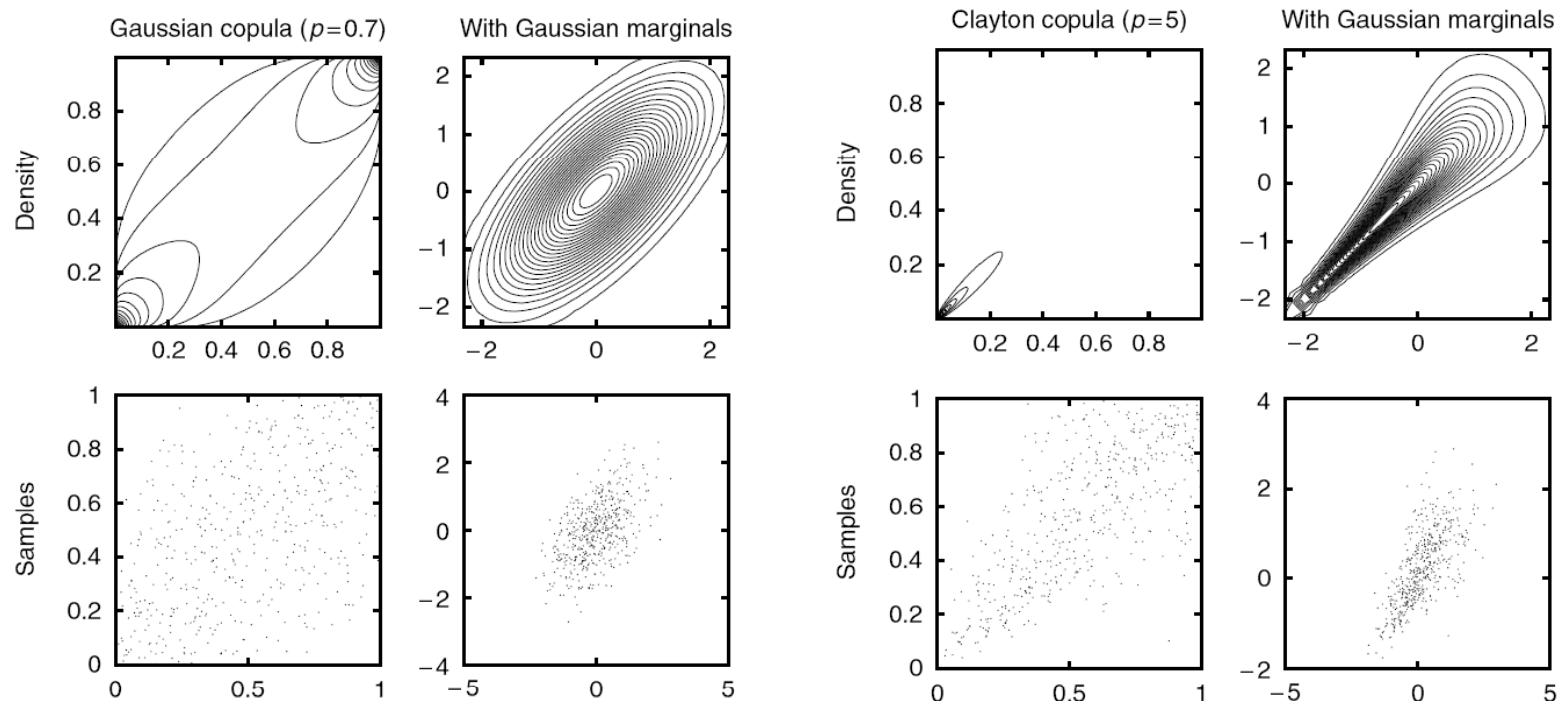
## ▶ in Matlab

- ▶ given: number of variables  $n$ , covariance matrix  $\mathbf{C}$  ( $n \times n$ ), number of samples  $S$
- ▶  $\mathbf{X} = \text{randn}(S, n) * \text{chol}(\mathbf{C})$

# generating multivariate random numbers

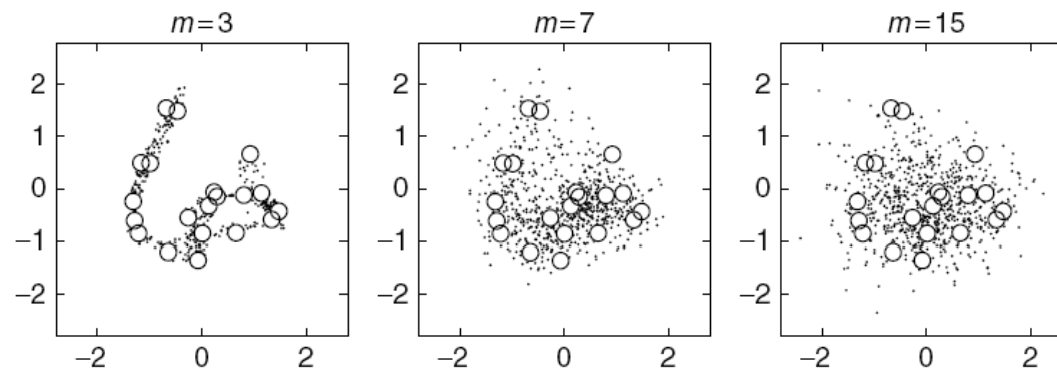
## ▶ example: copulas

- ▶ background for arbitrary distribution, if  $X \sim F$ , then  $F(X) \sim U(0,1)$
- ▶ copula = joint density of uniform variables (i.e., of quantiles)
- ▶ Sklar's theorem:  $F(X,Y) = C(F(X), F(Y))$



# generating multivariate random numbers

- ▶ example: arbitrary mv parametric distributions
  - ▶ individual samples: e.g., acceptance/rejection
  - ▶ sequences of samples: e.g., Metropolis(-Hastings), Gibbs-Sampler
- ▶ example: empirical distribution
  - ▶ e.g., semi-parametric: multivariate kernel density estimation
  - ▶ e.g., Taylor-Thompson:
    - randomly pick one observation and its  $(m-1)$  nearest neighbours  $x_{j_1}, \dots, x_{j_m}$
    - new sample = linear combination of  $m$  points, randomly weighted



**Figure 6.7** Samples generated with the Taylor–Thompson algorithm; original observations (circles) from a  $(0,1)$  Gaussian distribution.

$$\bar{x}_s = \frac{1}{m} \sum_i x_{j_i}$$

$$u_i \sim U(-1, +1)$$

$$w_i = \frac{1 + \sqrt{3(m-1)}u_i}{m}$$

$$x_s = \bar{x}_s + \sum_i w_i (x_{j_i} - \bar{x}_s)$$



# literature

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## ▶ additional reading

- ▶ J Gentle (2009), *Computational Statistics*, Springer.
- ▶ Gilli, M., Maringer, D., and Schumann, E. (2011), *Numerical Methods and Optimization in Finance*, Academic Press.
- ▶ O Jones, R Maillardet, A Robinson (2009), *Scientific Programming and Simulation Using R*, CRC Press.