

3 Empirical properties of financial data

3.1 Stylized facts of financial return series

3.2 Multivariate stylized facts

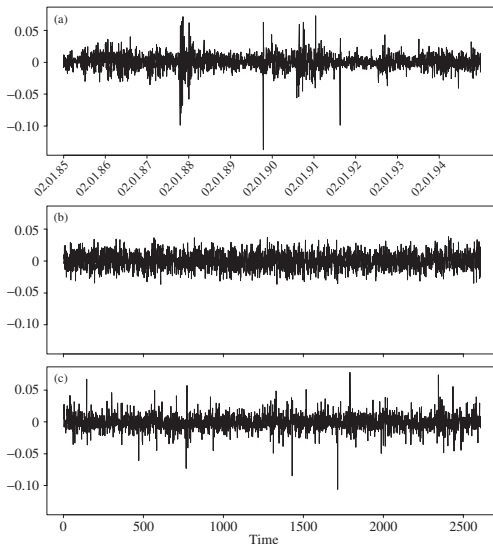
3.1 Stylized facts of financial return series

- The **stylized facts** are a collection of **empirical observations** and **related inferences**, which apply to many time series of risk-factor changes (e.g. log-returns on equities, indices, exchange rates, commodity prices).
- The best-known stylized facts **apply to daily log-returns** (also to intra-daily, weekly, monthly). Tick-by-tick (**high-frequency**) data **have their own stylized facts** (not discussed here) and annual return (**low-frequency**) data **are more difficult** to investigate (**data sparseness**; non-stationarity).
- Consider **discrete-time risk-factor changes** $X_t = Z_t - Z_{t-1}$ for a log-price or rate $Z_t = \log S_t$. In this case

$$X_t = \log(S_t/S_{t-1}) \approx S_t/S_{t-1} - 1 = (S_t - S_{t-1})/S_{t-1};$$

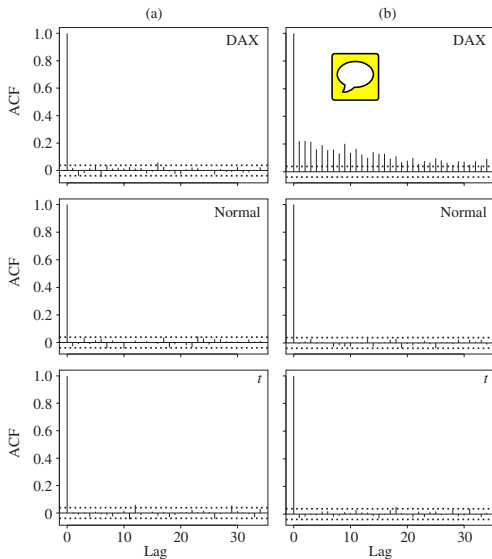
the former is often called a **(log-)return**, the latter a **relative return**.

3.1.1 Volatility Clustering



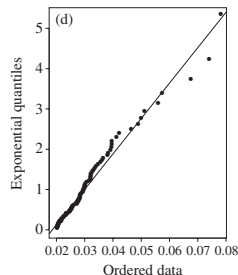
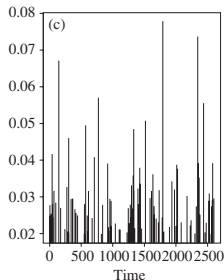
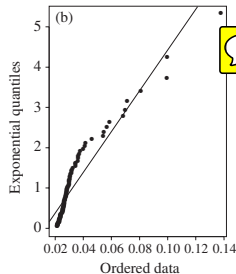
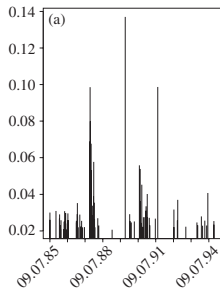
- (a) Log-returns for the DAX index from 1985-01-02 to 1994-12-30 ($n = 2608$).
- (b) Simulated iid data from a fitted normal with $\hat{\mu} = \bar{X}_n$, $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (X_i - \bar{X}_n)^2$ show too few extremes.
- (c) Simulated iid data from a fitted $t_{3.8}$. Better range of values but still no volatility clustering (= tendency for extreme returns to be followed by extreme returns).

Estimated *autocorrelation function (ACF)* $\rho(h) = \text{corr}(X_0, X_h), h \in \mathbb{Z}$



- Estimated
 (a) ACF of $(X_t)_{t \in \mathbb{Z}}$
 (b) ACF of $(|X_t|)_{t \in \mathbb{Z}}$
- Non-zero ACF at lag 1 implies a tendency for a return to be followed by a return of equal sign; not the case here.
 \Rightarrow Predicted return ≈ 0
- For iid process $(X_t)_{t \in \mathbb{Z}}$
 $\rho_X(h) = \rho_{|X|}(h) = I_{\{h=0\}}$;
 not the case here. (Can confirm with Ljung–Box tests.)
- $(Z_t)_{t \in \mathbb{Z}}$ not a random walk
 $(S_t)_{t \in \mathbb{Z}}$ not GBM.

Concerning clustering of extremes, consider the 100 largest losses of the ...



- (a) ... DAX index
(c) ... simulated fitted $t_{3.8}$
- (b), (d) Q-Q plots of waiting times between these large losses (should be $\text{Exp}(\lambda)$ for iid data; see EVT chapter).
- The DAX data shows shorter and longer waiting times than the iid data
 \Rightarrow clustering of extremes.



3.1.2 Non-normality and heavy tails

Formal statistical tests of normality

- For general univariate df F :

- ▶ Kolmogorov–Smirnov (test statistic $T_n = \sup_x |\hat{F}_n(x) - F(x)|$)
- ▶ Cramér–von Mises ($T_n = n \int_{-\infty}^{\infty} (\hat{F}_n(x) - F(x))^2 dF(x)$)
- ▶ Anderson–Darling ($T_n = n \int_{-\infty}^{\infty} \frac{(\hat{F}_n(x) - F(x))^2}{F(x)(1-F(x))} dF(x)$; recommended by D’Agostino and Stephens (1986))

- For $F = N(\mu, \sigma^2)$:

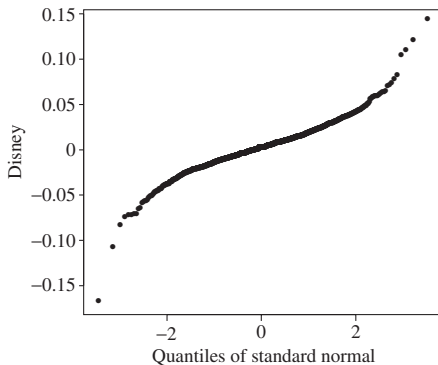
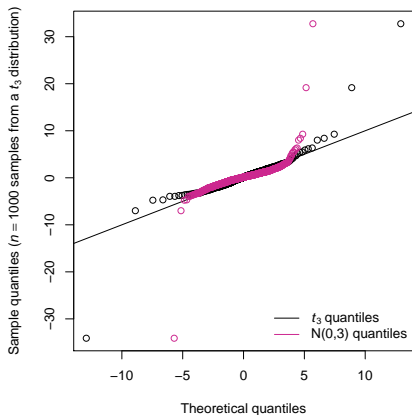
- ▶ Shapiro–Wilk  idea: quantify Q-Q plot in one number)
- ▶ D’Agostino (based on skewness and kurtosis as Jarque–Bera)
- ▶ Jarque–Bera test  Compares skewness $\beta = \frac{\mathbb{E}((X-\mu)^3)}{\sigma^3}$ and kurtosis $\kappa = \frac{\mathbb{E}((X-\mu)^4)}{\sigma^4}$ with sample versions. The test statistic is

$$T_n = \frac{n}{6} \left(\hat{\beta}^2 + \frac{1}{4} (\hat{\kappa} - 3)^2 \right) \overset{H_0}{\underset{n \text{ large}}{\rightarrow}} \chi^2_2.$$

Graphical tests

- Suppose we want to **graphically test whether $X_1, \dots, X_n \sim F$ for some df F** based on realizations of iid X_1, \dots, X_n .
- Let $X_{(1)} \leq \dots \leq X_{(n)}$ denote the corresponding **order statistics** and note that $\hat{F}_n(x) = \frac{1}{n} \sum_{i=1}^n I_{\{X_i \leq x\}} = \frac{1}{n} \sum_{i=1}^n I_{\{X_{(i)} \leq x\}}$, $x \in \mathbb{R}$, i.e. the order statistics contain all relevant information about X_1, \dots, X_n .
- Possible graphical tests (see also the appendix):
 - ▶ **P-P plot**: Plot $\{(p_i, F(X_{(i)})) : i = 1, \dots, n\}$, where $p_i \stackrel{n > 10}{=} \frac{i-1/2}{n} \approx \frac{i}{n} \approx \hat{F}_n(X_{(i)})$. If $F \approx \hat{F}_n$, the points lie roughly on a **line with slope 1**; this also applies to Q-Q plots.
 - ▶ **Q-Q plot**: Plot $\{(F^{\leftarrow}(p_i), X_{(i)}) : i = 1, \dots, n\}$ (tail differences better visible).

Interpreting Q-Q plots (**S-shape** hints at **heavier tails** than $N(\mu, \sigma^2)$):



Daily returns typically have kurtosis $\kappa > 3$ (**leptokurtic**; narrower center, heavier tails than $N(\mu, \sigma^2)$ for which $\kappa = 3$). They have **power-like tails** rather than exponential.

3.1.3 Longer-interval return series

- By going from daily to weekly, monthly, quarterly and yearly data, these effects become less pronounced (returns look more iid, less heavy-tailed).
- The (non-overlapping) h -period log-return at $t \in \{h, 2h, \dots, \lfloor \frac{n}{h} \rfloor h\}$ is

$$X_t^{(h)} = \log\left(\frac{S_t}{S_{t-h}}\right) = \log\left(\frac{S_t}{S_{t-1}} \frac{S_{t-1}}{S_{t-2}} \dots \frac{S_{t-h+1}}{S_{t-h}}\right) = \sum_{k=0}^{h-1} X_{t-k}$$

A Central Limit Theorem (CLT) effect takes place (less heavy-tailed, less evidence of serial correlation).

- Problem: the larger h , the less data are available.
- Possible remedy: Consider overlapping returns

$$\left\{ X_t^{(h)} : t \in \left\{ h, h+k, \dots, h + \left\lfloor \frac{n-h}{k} \right\rfloor k \right\} \right\}, \quad 1 \leq k < h.$$

⇒ More data but serially dependent now.

To summarize, we can infer the following stylized facts about univariate financial return series:

- (U1) Return series are not iid although they show little serial correlation;
- (U2) Series of absolute or squared returns show profound serial correlation;
- (U3) Conditional expected returns are close to zero;
- (U4) Volatility (conditional standard deviation) appears to vary over time;
- (U5) Extreme returns appear in clusters;
- (U6) Return series are leptokurtic or heavy-tailed (power-like tail).

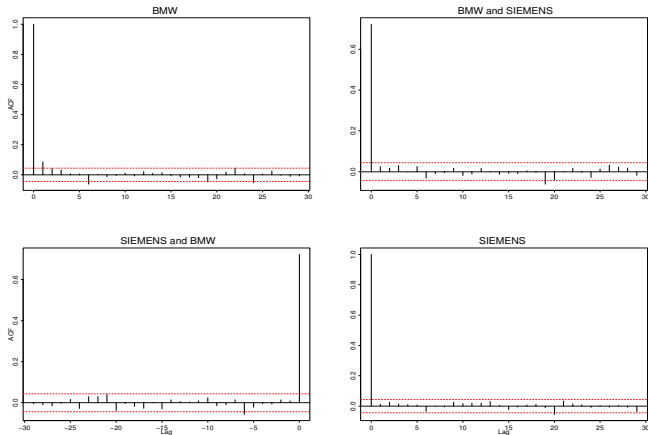
3.2 Multivariate stylized facts

Consider **multivariate** log-return data X_1, \dots, X_n .

3.2.1 Correlation between series

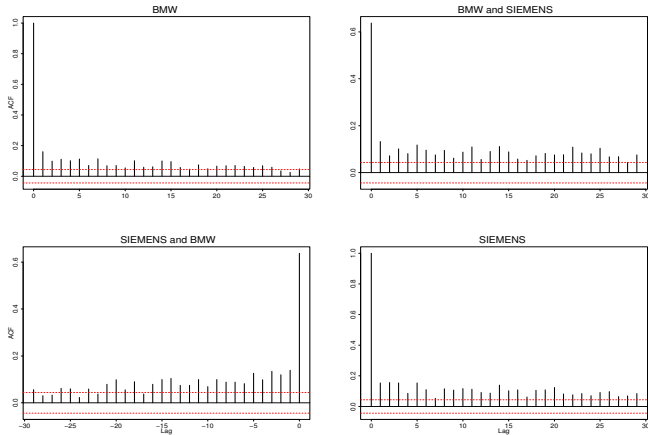
- By (U1), the **returns of stock A at t and $t + h$ show little correlation**. The same applies to the returns of stock A at t and stock B at $t + h$, $h > 0$. Stock **A and stock B on day t may be correlated** due to factors that affect the whole market (*contemporaneous dependence*).
- **Correlations of returns at t vary over time** (difficult to detect whether changes are continual or constant within regimes; fit different models for changing correlation, then make a formal comparison).
- **Periods of high/low volatility** are typically **common to more than one stock** \Rightarrow Returns of large magnitude in A at t may be followed by returns of large magnitude in A and B at $t + h$.

Estimated correlations between/within series:



2000 values from period 1985-01-23 to 1994-09-22

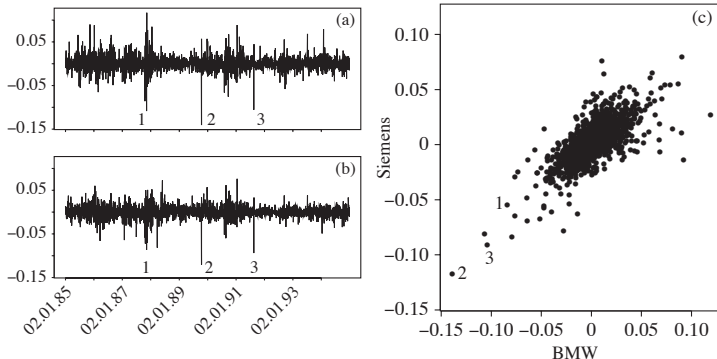
Estimated correlations between/within series of absolute values:




2000 values from period 1985-01-23 to 1994-09-22

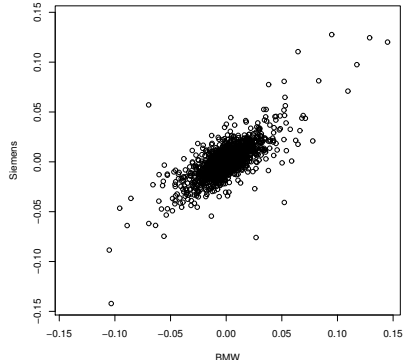
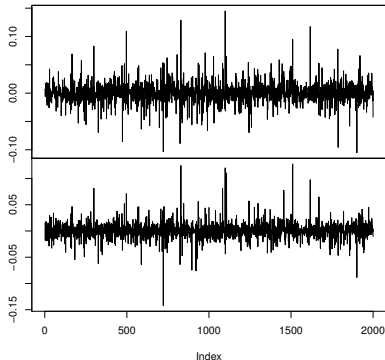
3.2.2 Tail dependence

(BMW, Siemens) log-returns from 1985-01-23 to 1994-09-22 ($n = 2000$)



In **volatile/extreme periods**, dependence is **stronger** (1: 1987-10-19  **Black Monday** (DJ drop by 22%); 2: 1989-10-16 **Monday demonstrations in Leipzig** (Wende); 3: 1991-08-19 **coup against soviet president M. Gorbachev**).

Simulated log-returns from a fitted bivariate t distribution ($n = 2000$; $\rho = 0.72$, $\nu = 2.8$ both fitted to (BMW, Siemens))



- The multivariate t distribution can replicate joint large gains/losses but in a symmetric way.
- The multivariate normal distribution cannot replicate such behaviour, known as tail dependence; see Chapter 7.

To summarize, we can infer the following **stylized facts** about **multivariate** financial return series:

- (M1) **Multivariate return series** show **little** evidence of **cross-correlation**, **except** for **contemporaneous returns** (i.e. at the same t);
- (M2) Multivariate series of **absolute returns** show **profound cross-correlation**;
- (M3) **Correlations** between contemporaneous returns **vary over time**;
- (M4) **Extreme returns** in one series **often coincide with extreme returns** in several **other series** (e.g. tail dependence).