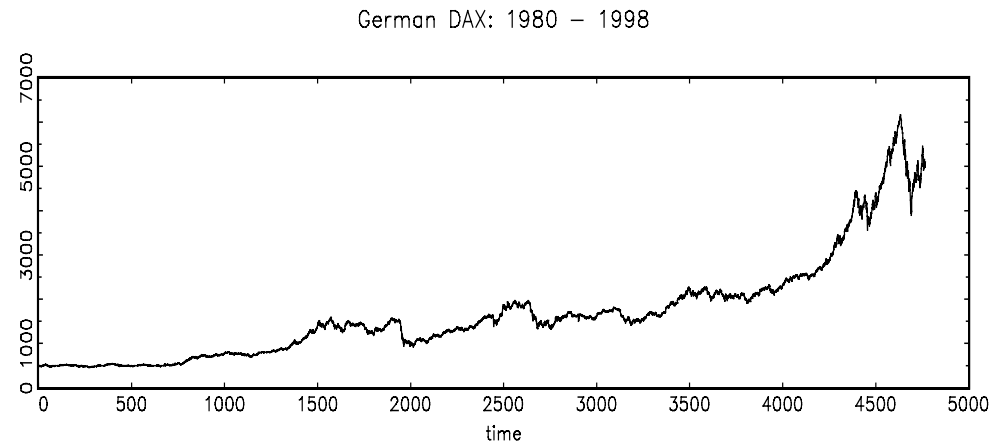
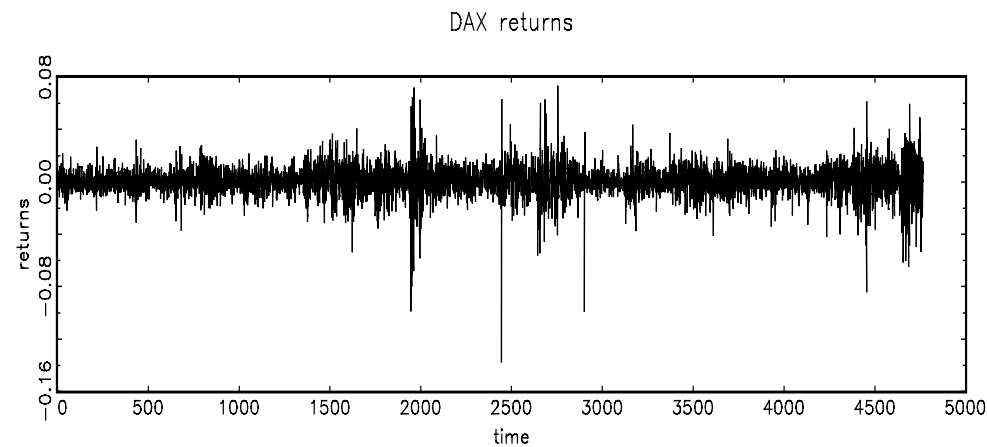


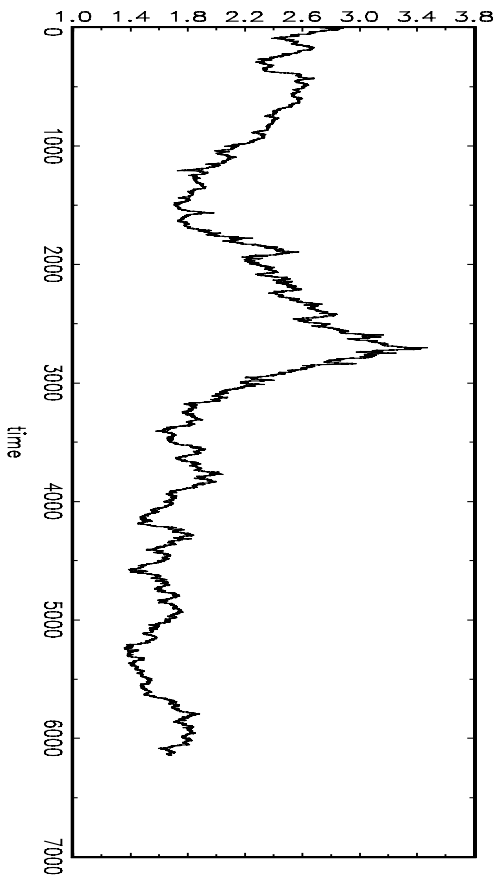
The stylized facts: some typical time series



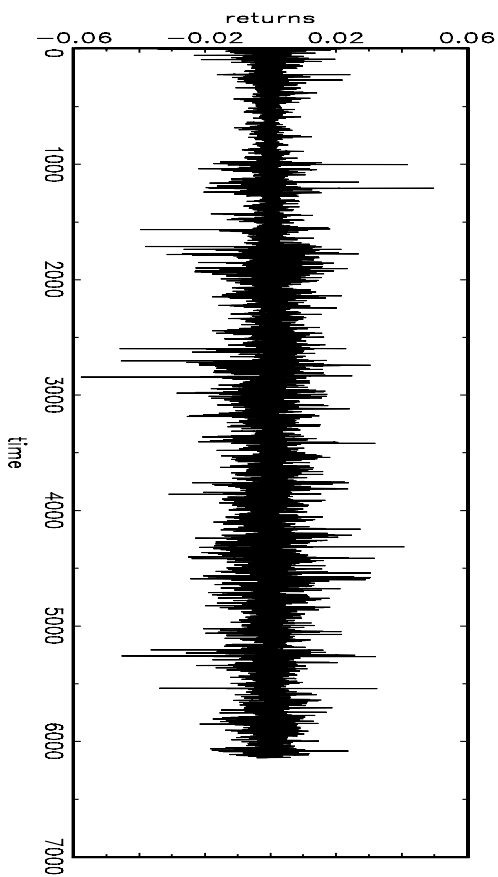
returns =
 $\ln(p_t) - \ln(p_{t-1})$



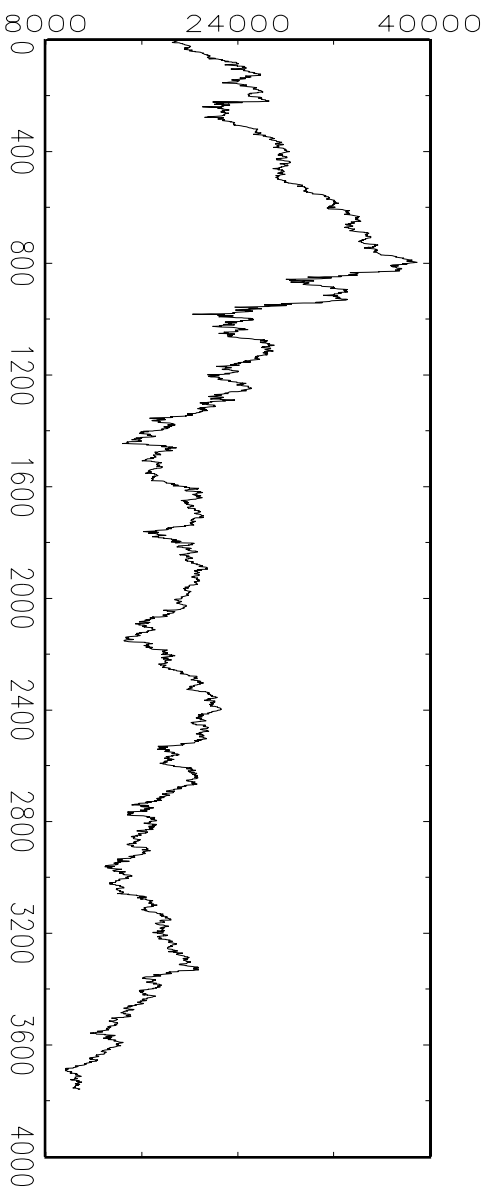
DM/U.S.\$ exchange rate: 1974 - 1998



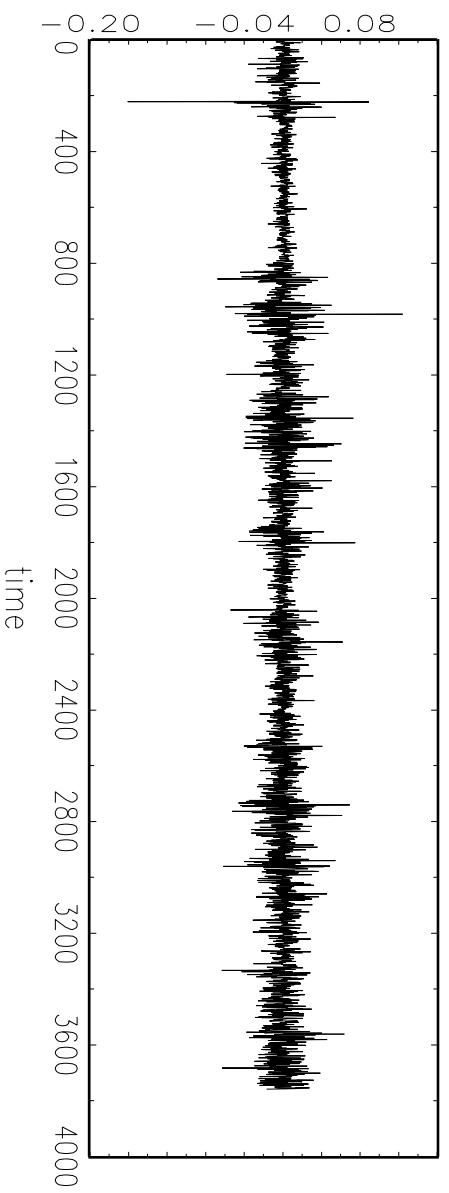
Relative daily changes of DM/U.S.\$ exchange rate



Nikkei index, 1987 – 2001



Daily returns



'Stylized Facts': Most Elementary and Universal Time Series Characteristics

- Random walk (martingal) property of prices
- Fat tails of returns
- Clusters of volatility
- Volume-volatility correlation

Fact 1: Random Walk (Martingal) Property of Prices

Prices (or their logs) look like realizations of a simple process:

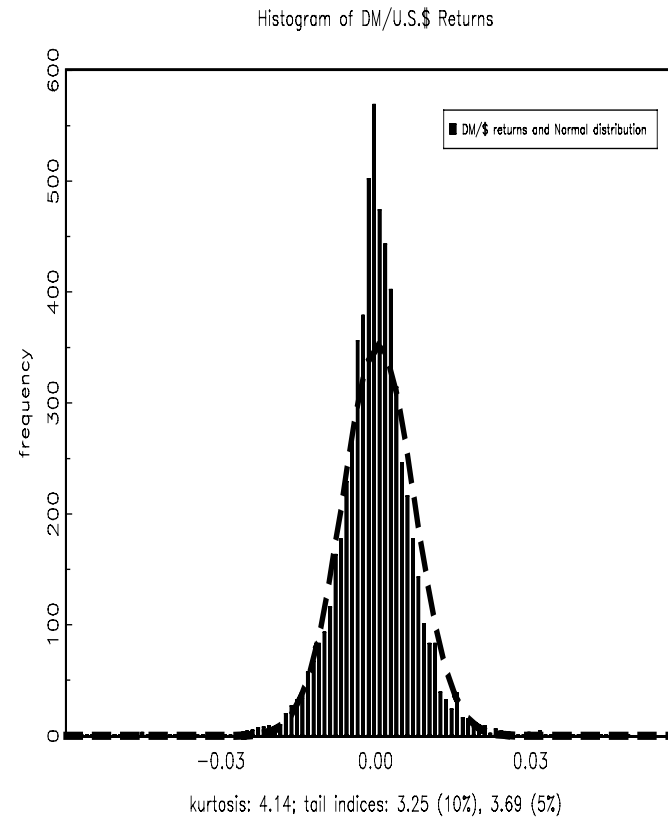
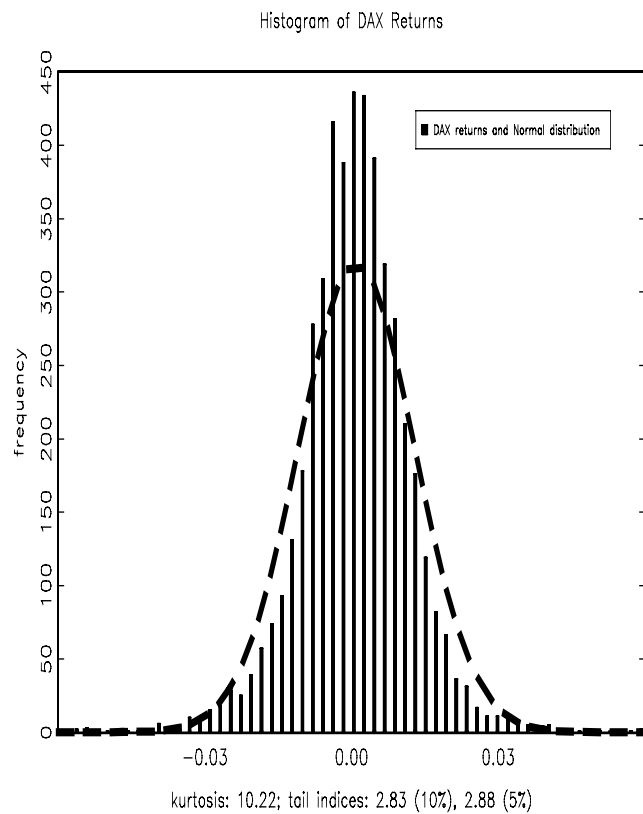
$$p_t = p_{t-1} + \varepsilon_t \quad \text{with } E[\varepsilon_t] = 0$$

if ε_t is drawn from a fixed distribution, one speaks of a *random walk*, if no further assumptions are made other than $E[\varepsilon_t] = 0$, one speaks of a *martingal* (note that this allows for dependence in the variance \Leftrightarrow volatility clustering)

random walk (martingal) implies:

- absence of autocorrelations in returns (relative price changes),
- no predictability of future price developments,
- **efficient** price formation

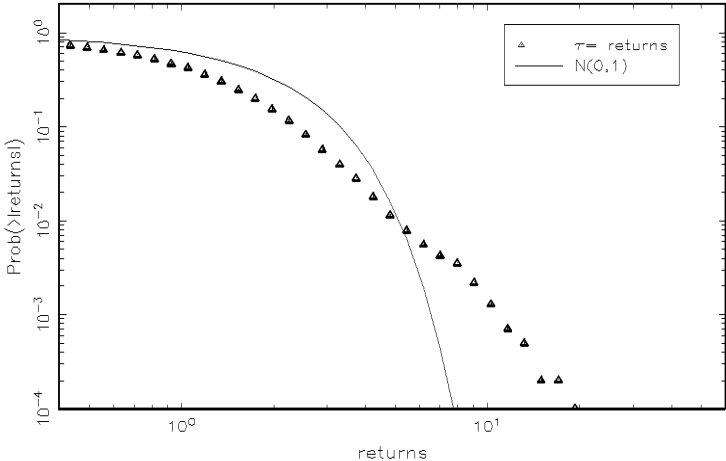
Fact 2: Fat Tails (Leptokurtosis) of the Distribution of Returns: Typical Histograms



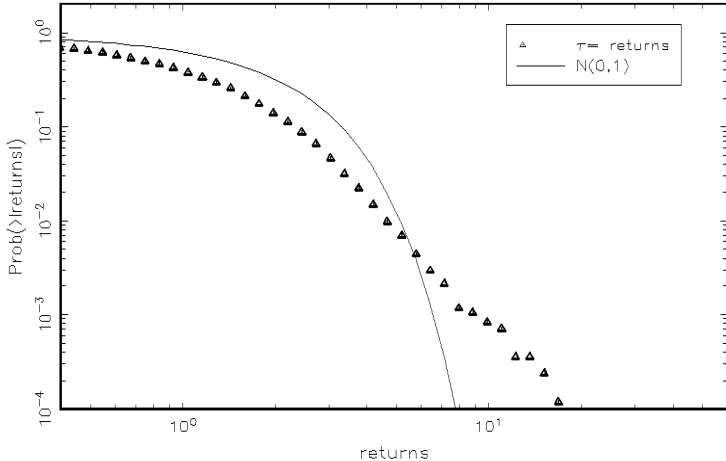
Fat tails are more clearly visible in logarithmic representation of the histogram:

probability for large returns: $\text{Prob}(\text{ret.} > x) \sim x^{-\alpha}$ with $\alpha \in [2,5]$

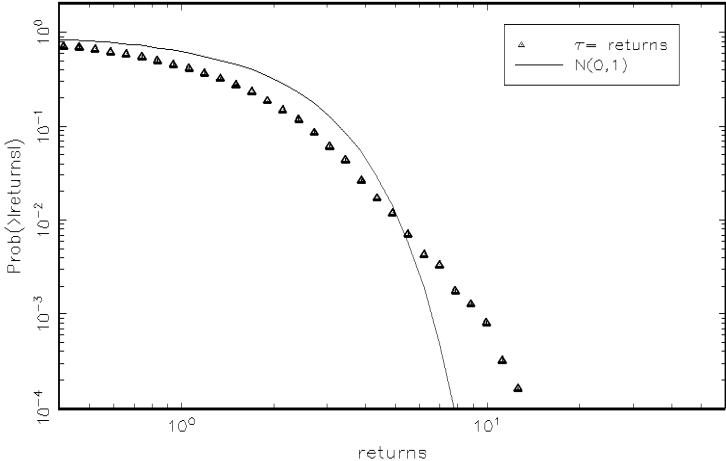
German share price index DAX, daily returns 1959 – 1998



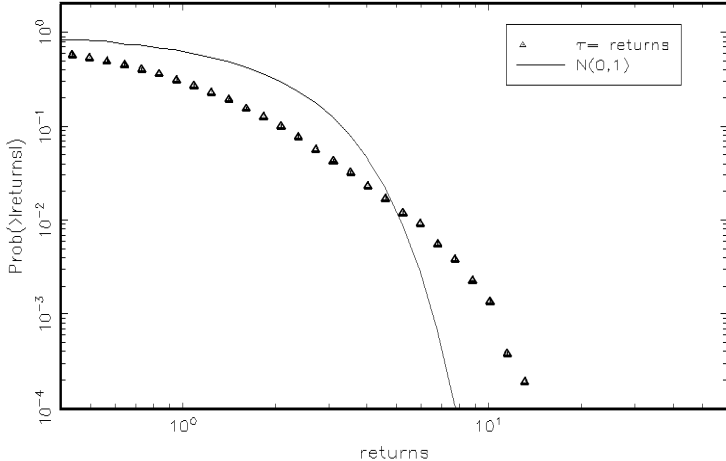
New York Stock Exchange Composite Index, daily returns 1966 – 1998



U.S.\$-DEM exchange rate, daily returns 1974 – 1998



Gold, daily returns 1978 – 1998



Heavy Tails: History of Thoughts

- Daily returns exhibit *leptokurtosis*: probability of large realizations is *always much* higher than under a Normal distribution
- Puzzling, because returns are summable and should, therefore, follow the *Central Limit Law* -> convergence to Normality (Bachelier, 1900)
- Mandelbrot/Fama (1963): *Generalized Central Limit Law*
-> hypothesis: convergence to Levy Stable Distributions
- Recently emerging consensus: daily returns follow *neither Normal nor Levy Stable* distribution
- convergence to Normal only with low-frequency data (e.g., monthly returns)

Levy Stable Distributions

The so-called Levy Stable distributions are the *limiting distributions of sums of random variables*.

Drawback: no general analytical solution is known, Levy distributions can only be described by their characteristic function (only for illustration, you don't have to learn this formula):

$$\log E(e^{ixt}) = \begin{cases} i\delta t - |c t| \alpha_s [1 - i\beta \operatorname{sgn}(t) \tan(\alpha_s/2)] & \text{if } \alpha_s \neq 1 \\ i t - |c t| [1 + i\beta (2/\pi) \operatorname{sgn}(t) \log |c t|] & \text{if } \alpha_s = 1. \end{cases}$$

Parameters: β , c , δ : parameters for skewness, scale and location,

α_s : characteristic exponent, $\alpha_s \in (0,2]$, parameter for *tail behavior*

$\alpha_s = 2$: Normal distribution, $\alpha_s < 2$: Levy distributions with *infinite variance*

Advantages: *stability under aggregation, bellshape, leptokurtosis*

Mandelbrot (1971): Most successful model in economics

Basics of Extreme Value Theory

The *tail behavior of most continuous distributions can be described by one of only three types of behavior:*

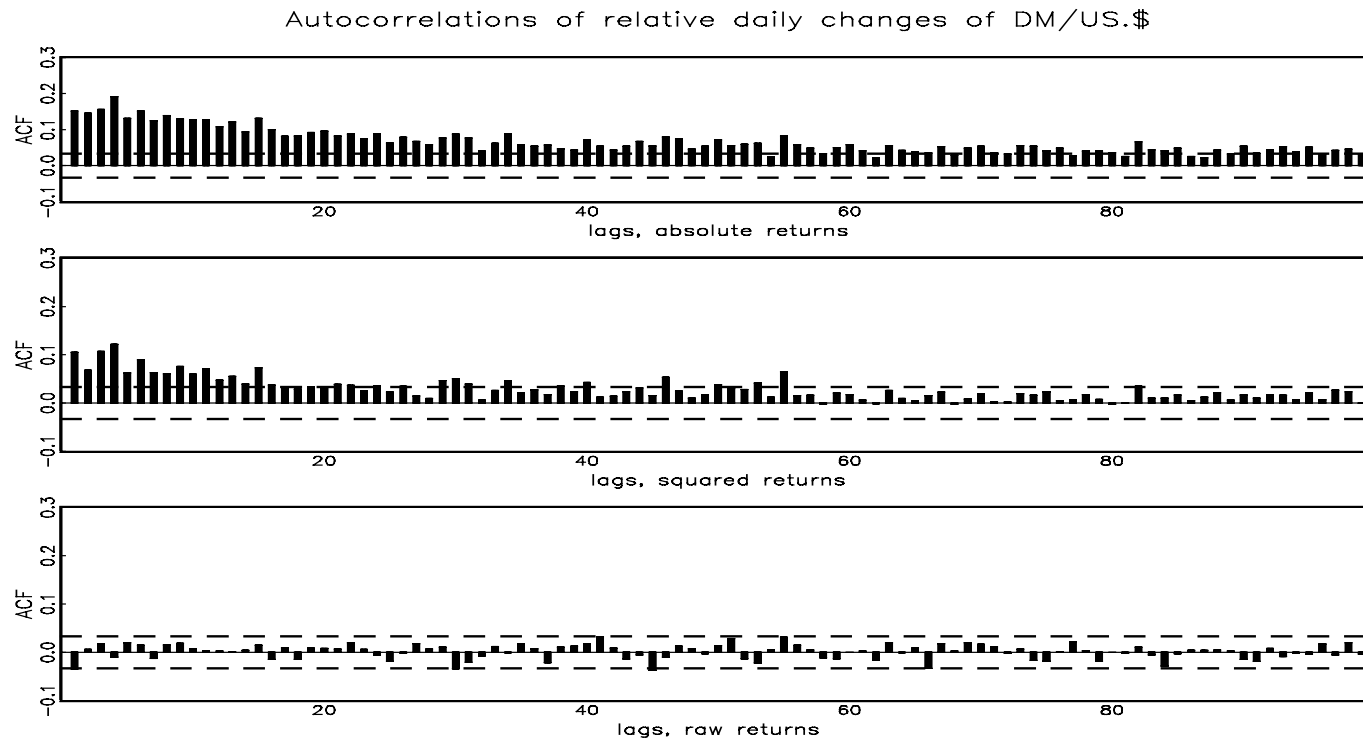
- *Finite endpoint (e.g., a uniform distribution over a finite interval)*
- *Exponential decline à la: $F(x) = 1 - \exp(-x)$ (e.g., the Normal distribution)*
- *Power-law decline à la: $F(x) = 1 - x^{-\alpha}$ (e.g., the Student t distribution)*

α : tail index (the lower, the slower the decay in the tail, i.e., the more large realizations occur)

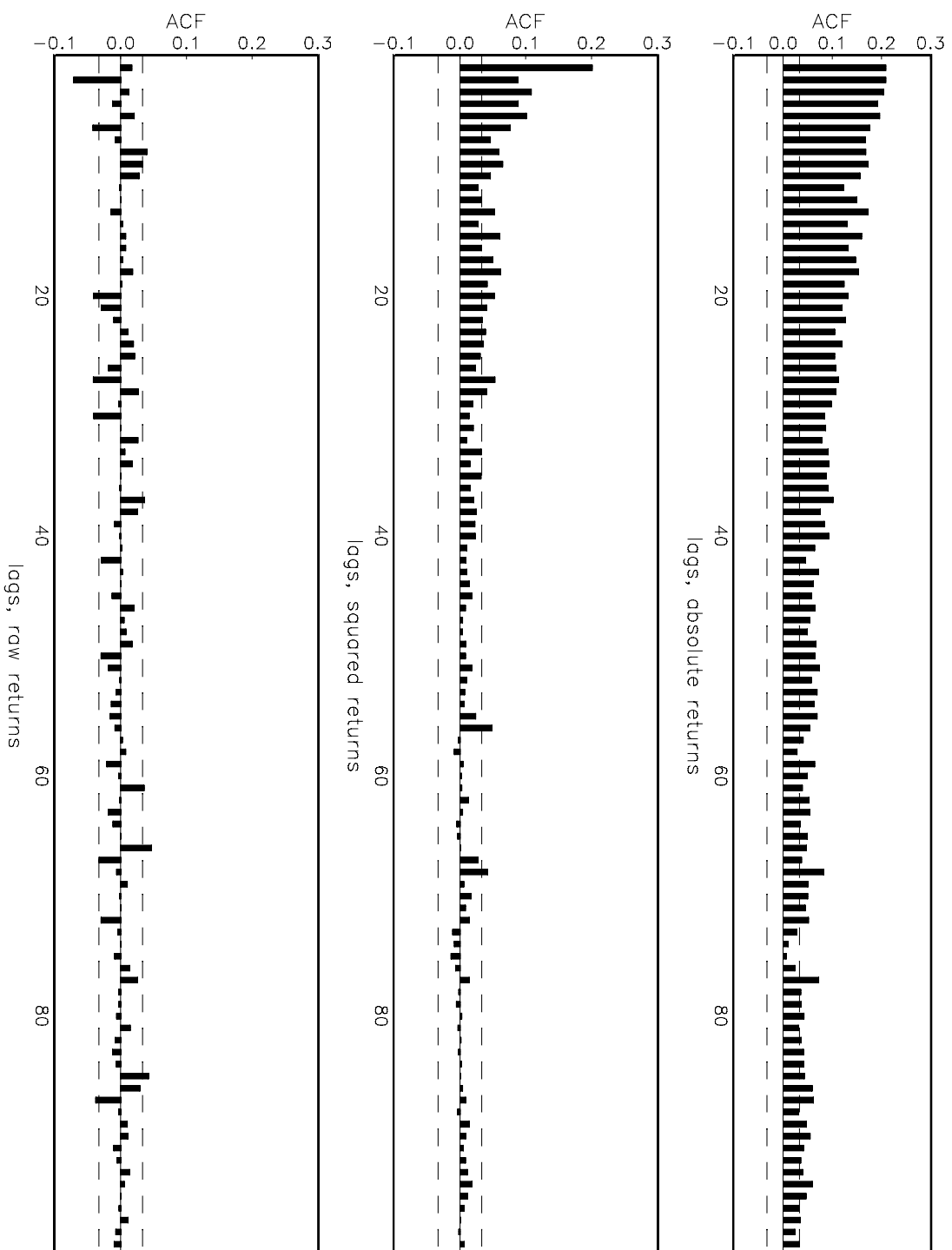
Empirical results for returns: power-law behavior with $\alpha \approx 3$ (cf. the values noted below the histograms)

Consequences: one rejects the Levy ($\alpha = \alpha_s \leq 2$) as well as the Normal distribution

Fact 3: Volatility clustering: **autocorrelation in all measures of volatility**, e.g. ret^2 , $\text{abs}(\text{ret})$ etc.
despite absence of autocorrelation in raw returns



Autocorrelations of relative daily changes of Nikkei index



The Baseline Stochastic Model for Volatility Clustering:

GARCH: Generalized Autoregressive Conditional Heteroscedasticity

returns follow: $r_t = \varepsilon_t$ with $\varepsilon_t \sim N(0, h_t)$

$$\text{with } h_t = \alpha_0 + \sum_{i=1}^p \alpha_i r_{t-i}^2 + \sum_{j=1}^q \beta_j h_{t-j} \quad (\text{Engle, 1982; Bollerslev, 1986})$$

Usual results:

- GARCH(1,1) is sufficient to capture the volatility dynamics
- high persistence: $\alpha_1 \approx 0.1$, $\beta_1 \approx 0.9$
- process is close to the non-stationary case, i.e. $\alpha_1 + \beta_1 \approx 1$

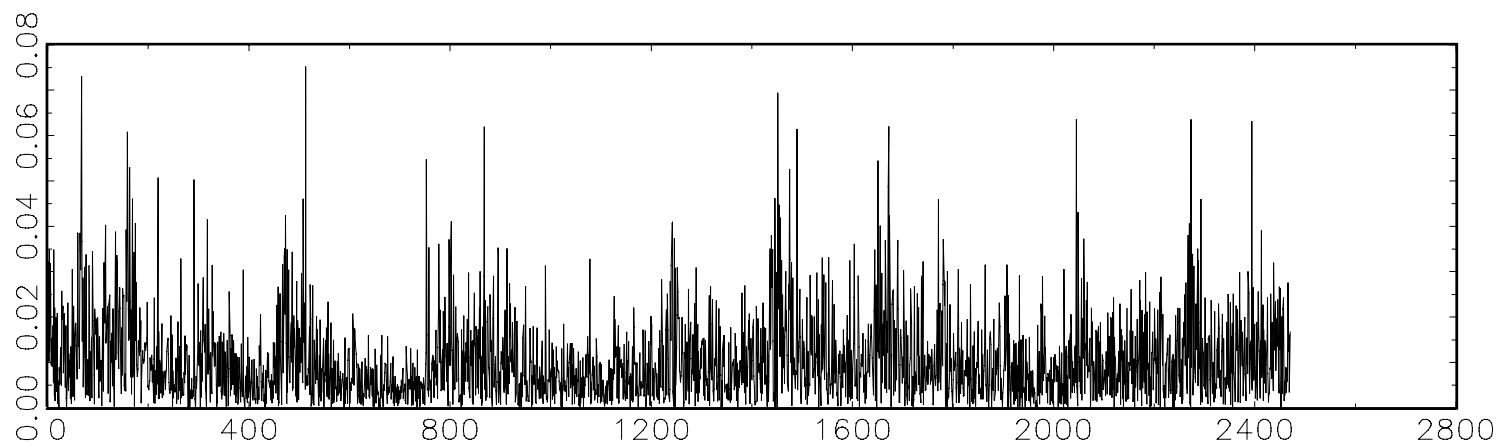
Example: Typical GARCH Estimates for Daily Returns

Data	α_0	α_1	β_1
DAX (1959 – 1998)	4.14×10^{-6} (5.07)	0.1520 (7.61)	0.8186 (49.86)
NYCI (1966 – 1998)	1.04×10^{-6} (4.44)	0.0787 (3.81)	0.9093 (48.18)
US\$-DM (1974 – 1998)	8.50×10^{-7} (3.74)	0.1049 (8.26)	0.8836 (80.45)
Gold (1978 – 1998)	1.14×10^{-6} (2.46)	0.1023 (6.78)	0.8853 (54.25)

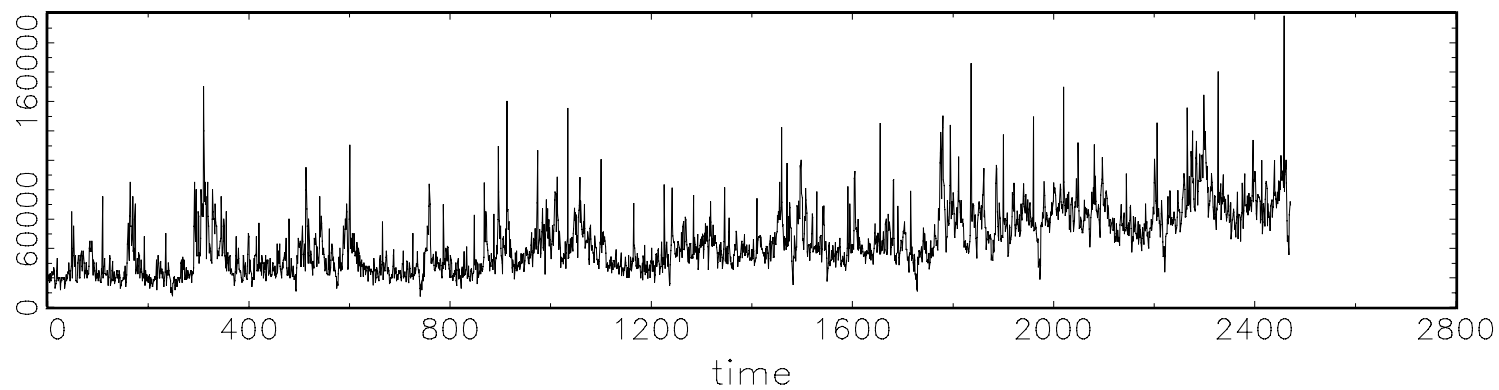
t-values of the GARCH parameters are given in parenthesis.

Fact 4: Correlation between Volatility and Volume

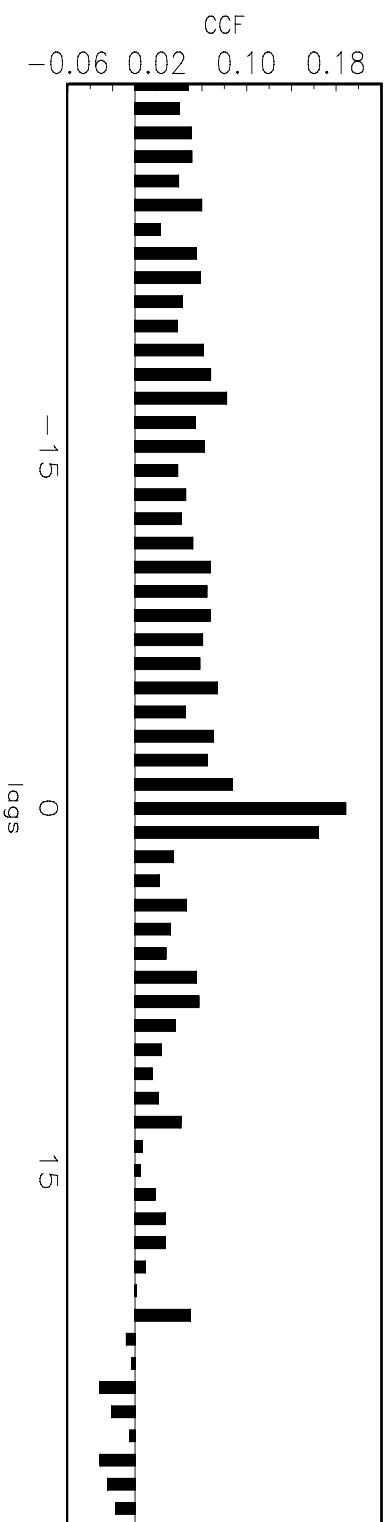
Nikkei daily volatility (absolute returns), 1992 – 2001



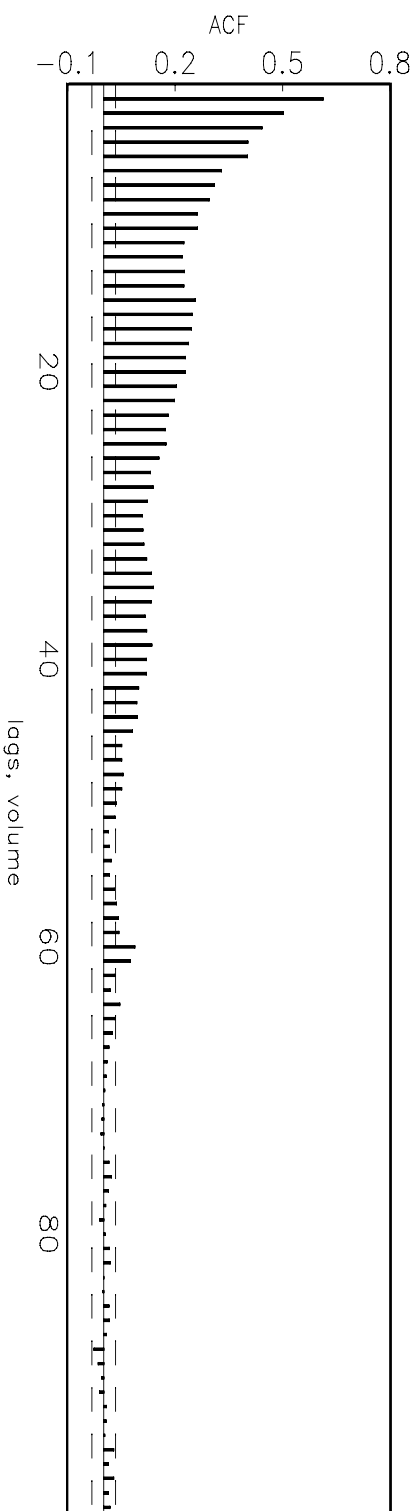
Daily trading volume



Crosscorrelation between Volume and Volatility: Nikkei, 1992 – 2001



Autocorrelation of Volume: Nikkei, 1992 – 2001 (detrended)



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