MS&E 444: Investment Practice

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General

- Admissions form due Thu 1:30pm in the box outside Terman 418
- We will review the forms and get back by the end of the week
- Office hours: Tuesday 3-4:30pm and by appointment
- Ben's office hours: Monday 4-6:30
- Contact at EvA: Lisa Borland, **lecture April 11**
- Data: WRDS database (access details after teams have formed)
- Background material: course website
  `http://www.stanford.edu/~barmbrus/2007msande444/`

Project 1

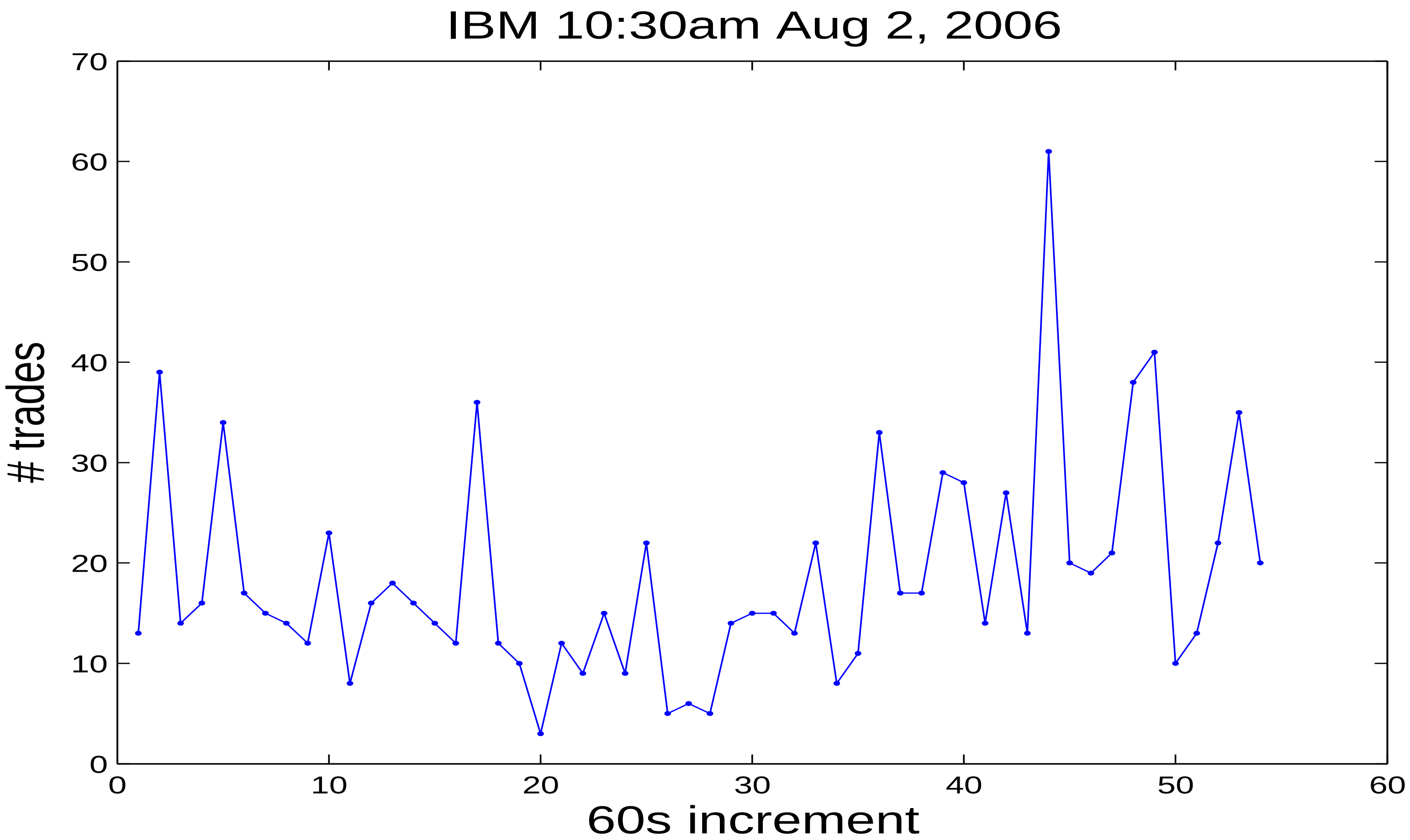
Modeling and predicting the arrival of buy and sell orders

- Goal: forecast the conditional distribution of future trades and volumes given past trade arrivals and other co-variates
- Important stylized fact: trade times, price changes are **clustered**
- Model arrival times (T^k) as a **self-affecting point process**

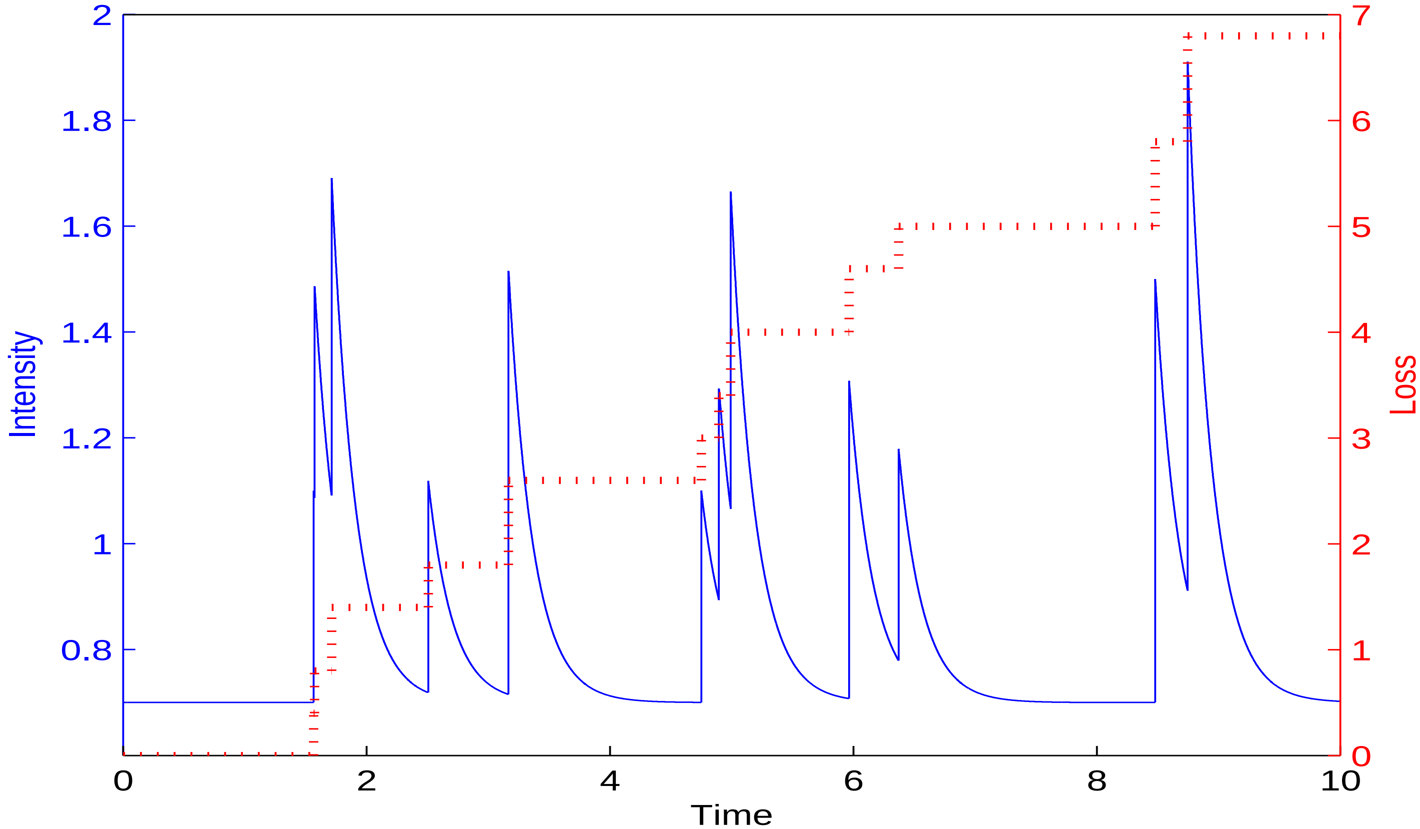
$$N_t = \sum_k 1_{\{T^k \leq t\}}$$

- Examples: intensity λ of N responds to arrivals
  - Birth process: $d\lambda_t = \delta dN_t$
  - Hawkes process: $d\lambda_t = \kappa(\lambda_\infty - \lambda_t)dt + \delta dN_t$
  - Generalized process: $d\lambda_t = \kappa(\lambda_\infty - \lambda_t)dt + \sigma\sqrt{\lambda_t}dW_t + \delta dN_t$

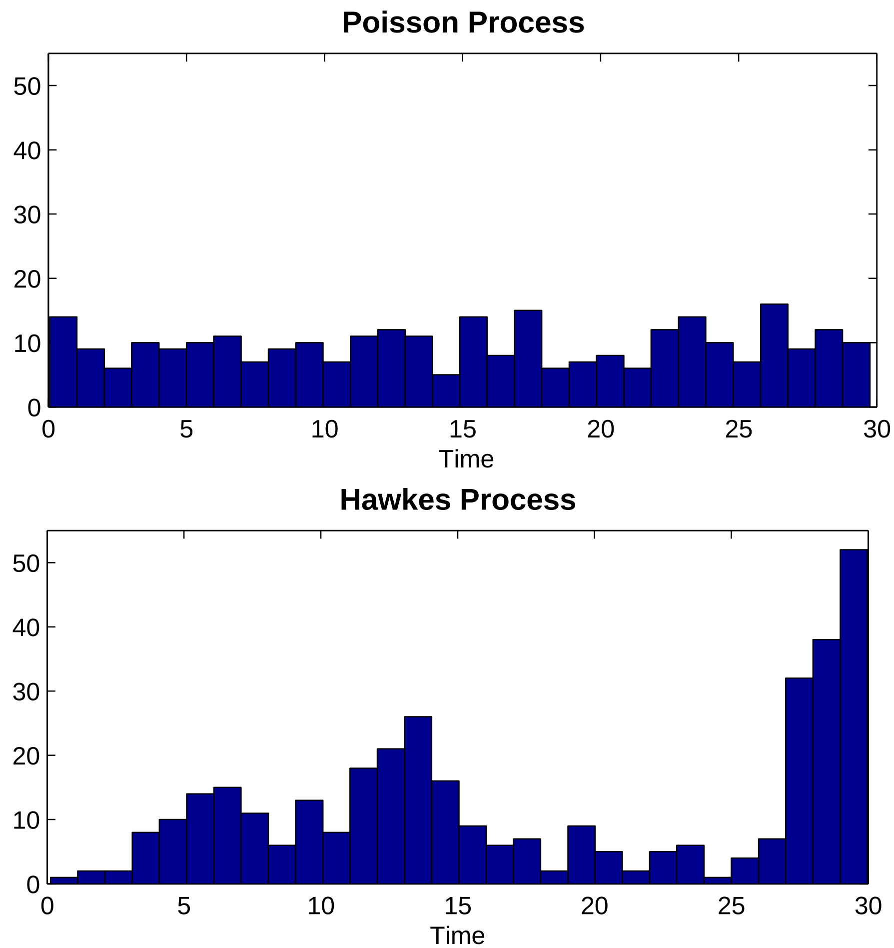
Frequency of trades



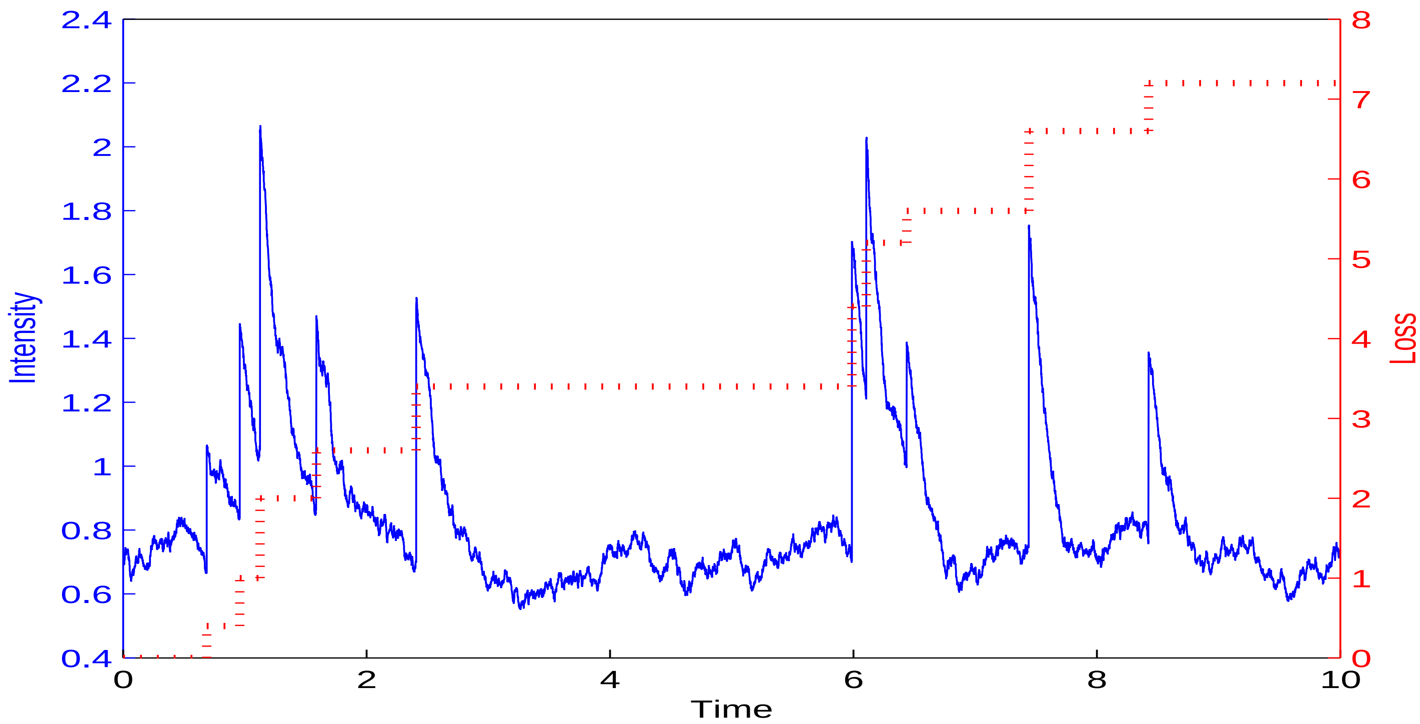
Simulated Hawkes process with $\lambda_\infty = 0.7$, $\delta = 1$, $\kappa = 5$ and jump size uniform on $\{0.4, 0.6, 0.8, 1\}$



Arrivals of Poisson and Hawkes processes with $\lambda_\infty = 1$, $\delta = 2$, $\kappa = 1.5$ and jump size uniform on $\{0.4, 0.6, 0.8, 1\}$



Simulated general process with $\lambda_\infty = 0.7$, $\delta = 1$, $\kappa = 5$, $\sigma = 0.2$ and jump size uniform on $\{0.4, 0.6, 0.8, 1\}$



Project 1

Modeling and predicting the arrival of buy and sell orders

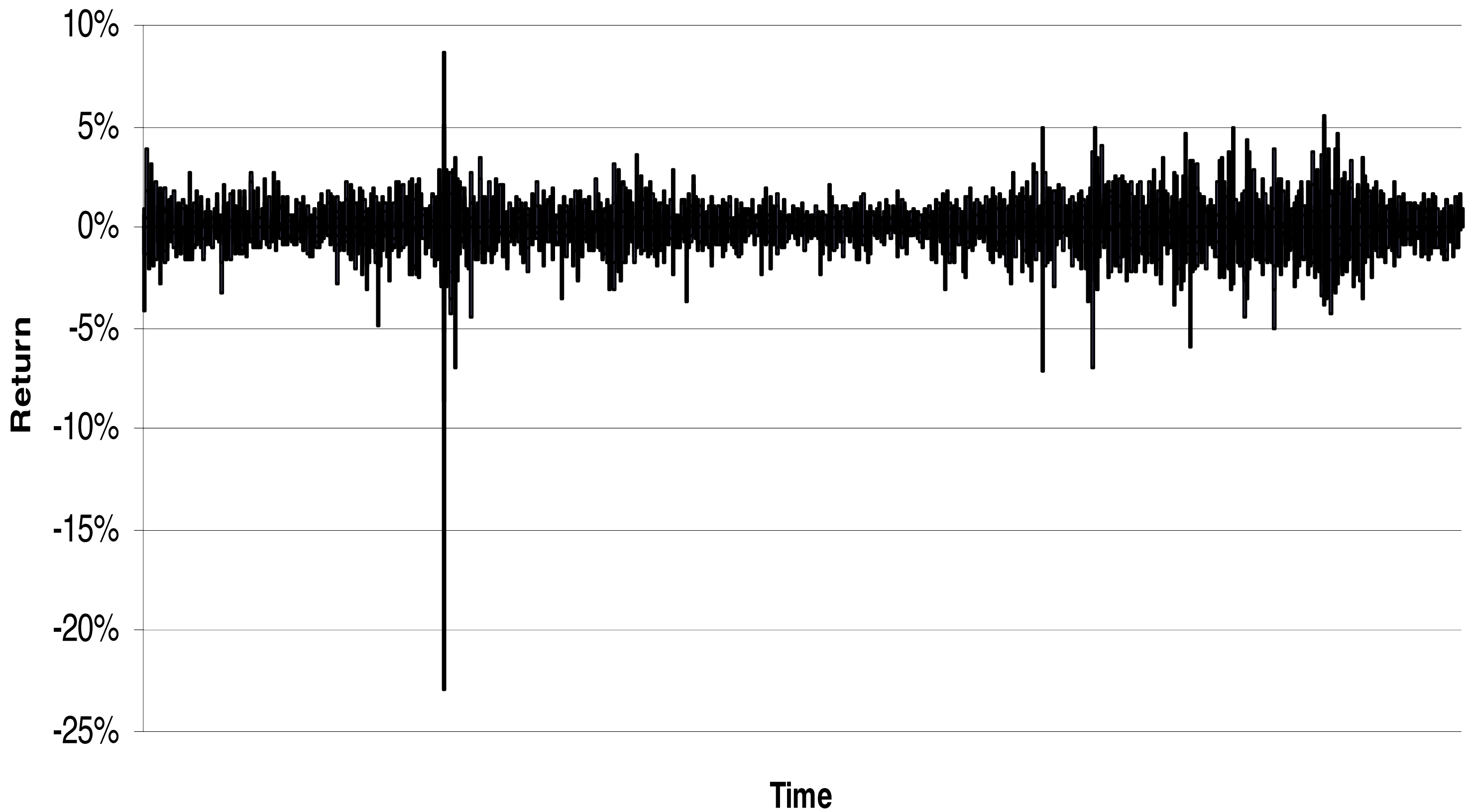
- Estimate parametric intensity model from observed arrivals using maximum likelihood, for example
- Obtain forecast conditional distribution by inverting the characteristic function $E[e^{iv(N_s-N_t)} \mid \mathcal{F}_t]$, which we know for a broad class of self-affecting intensity models
  - Used in portfolio credit risk
- Develop and test program trading strategy
- Develop optimal execution strategy, see Hewlett (2006)
  - Trader's dilemma: market impact vs. adverse price movements

Project 2

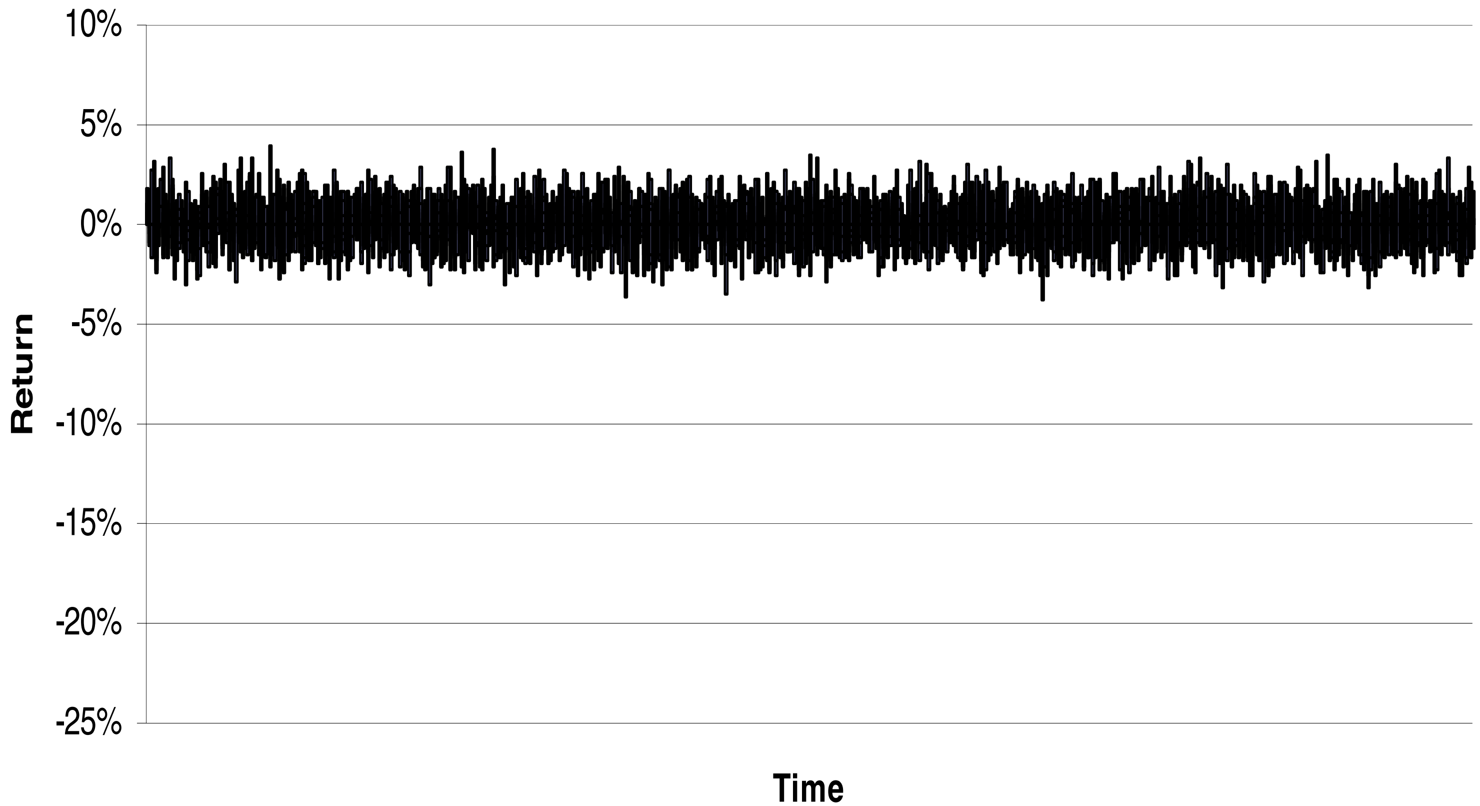
Modeling and predicting volatility

- Volatility is a measure of the degree of fluctuation of a security price around its mean; it is the main driver of option prices
- Goal: Forecast the conditional distribution of future security price volatility given past prices and other co-variates
- Well known stylized facts of empirical asset returns
  - Fat tails relative to the Gaussian distribution: power law
  - Volatility clustering: long range memory in volatility; auto correlation follows power law
  - Leverage effect: vol is correlated with price changes

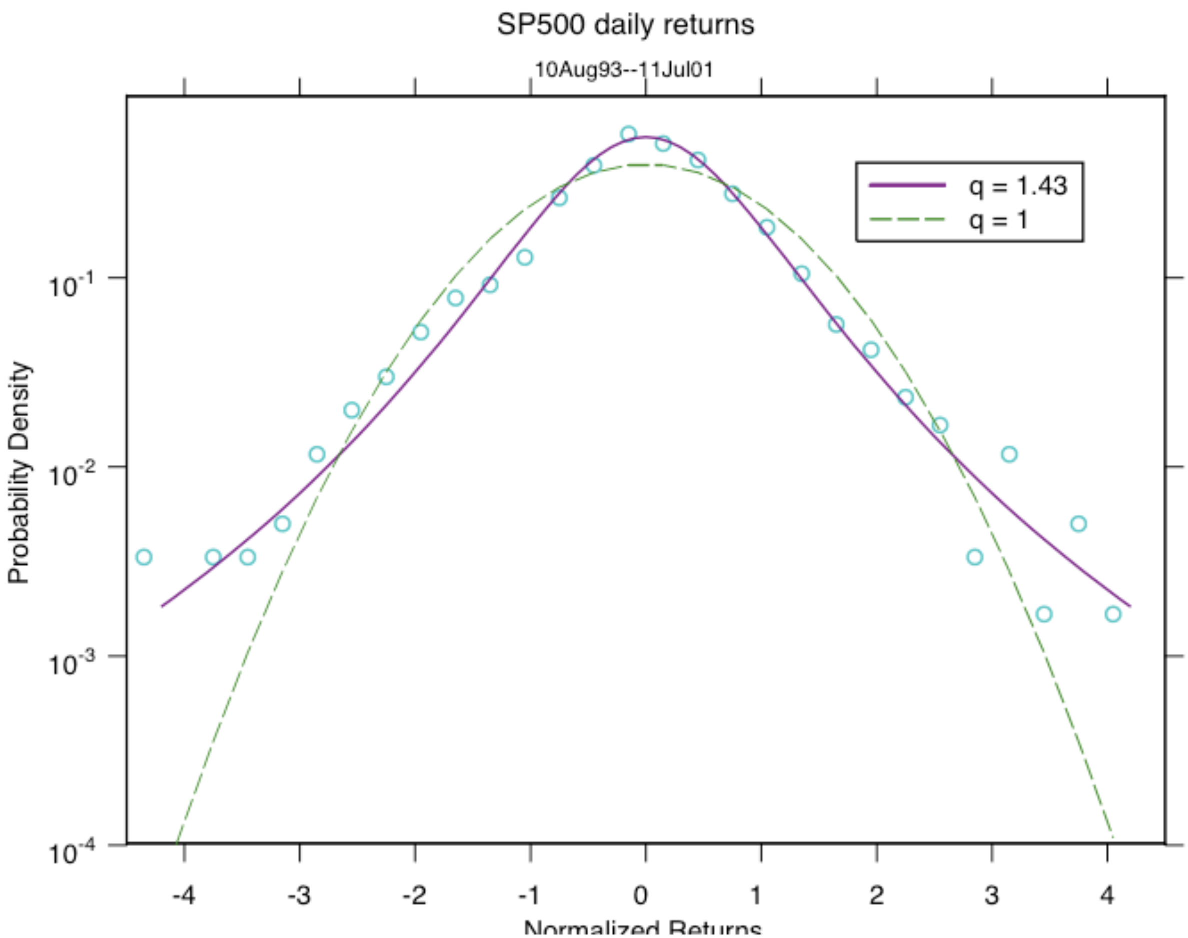
Daily S&P 500 log-returns October ’82 to November ’04: skewed and leptokurtic



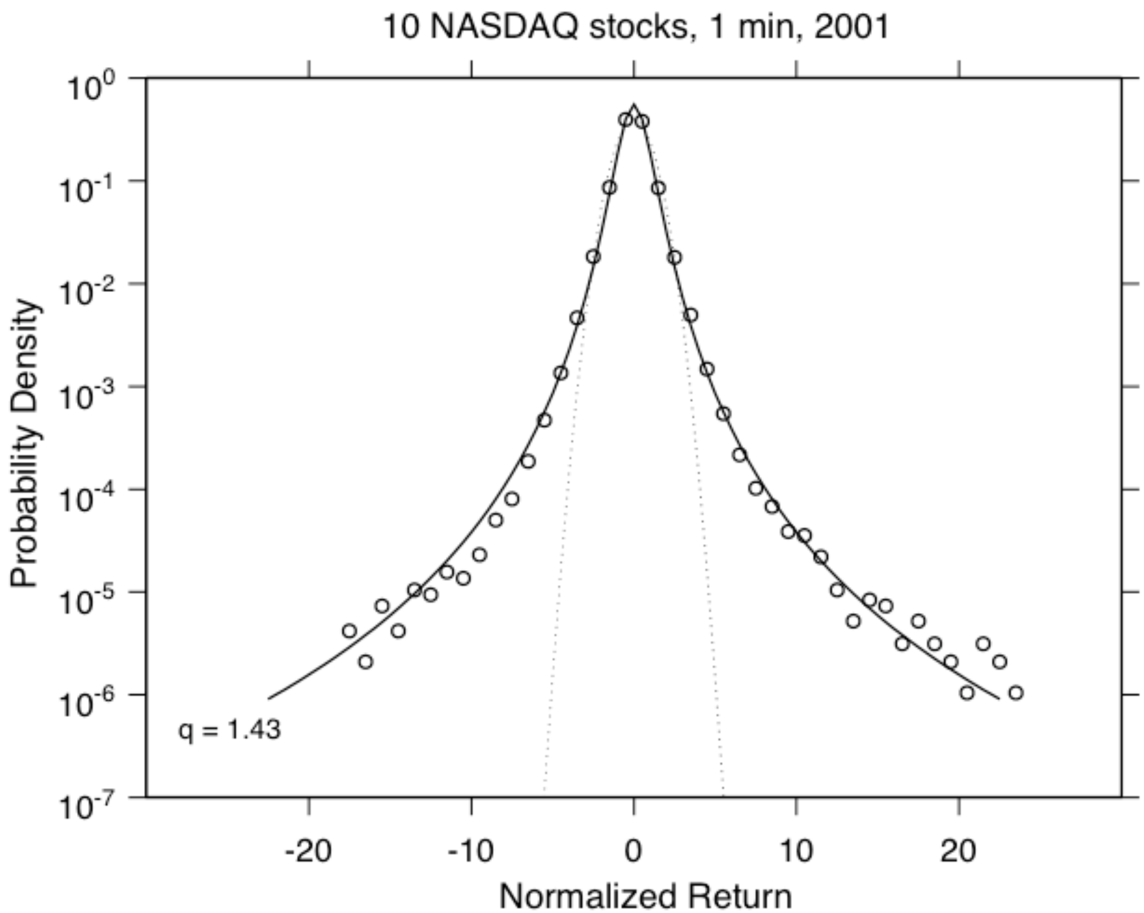
Daily log-returns simulated from $N(0.00038, 0.0107^2)$



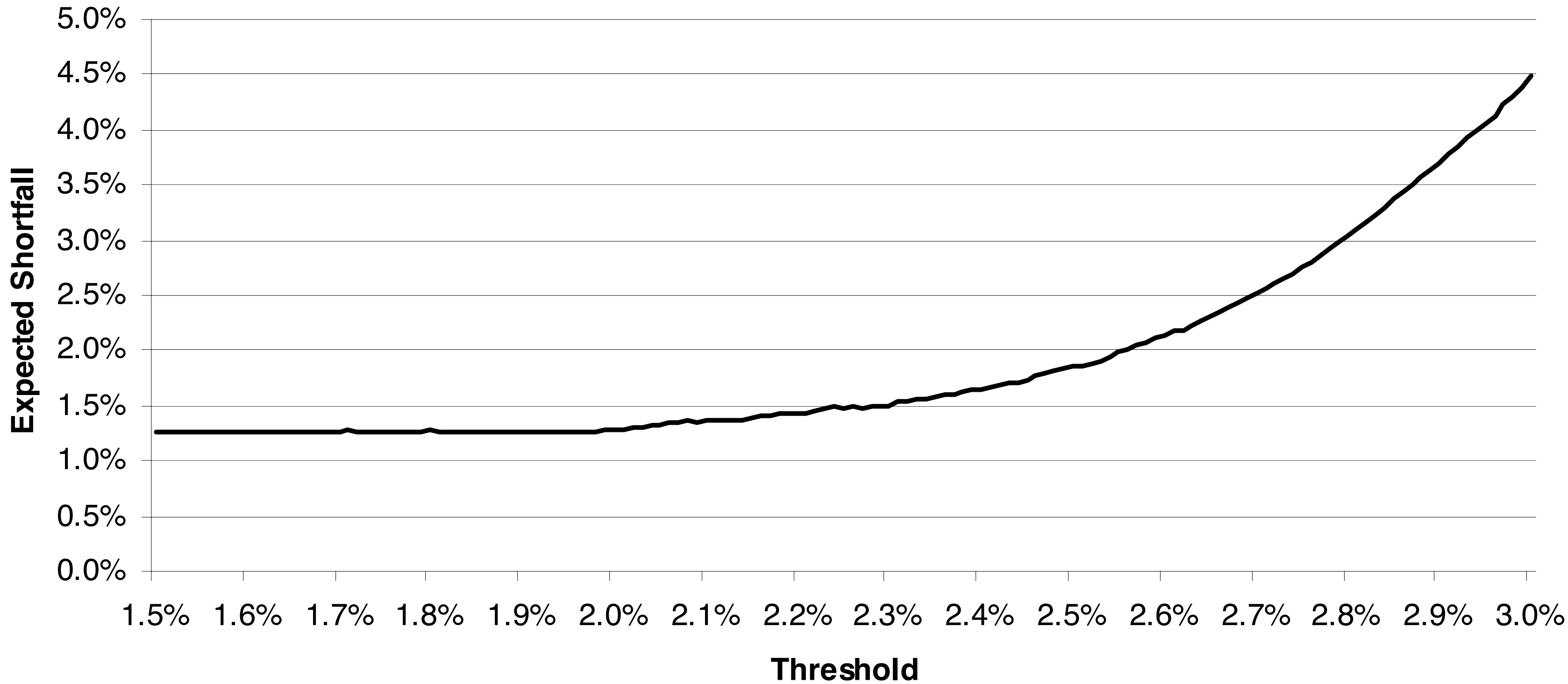
Empirical daily S& P 500 return distribution



Empirical Nasdaq return distribution



Mean excess $\frac{1}{\sum_{i=1}^{n} 1_{\{r_i \leq q\}}} \sum_{i=1}^{n}(q - r_i)^+$ as a function of $-q$ for the daily S& P 500 returns



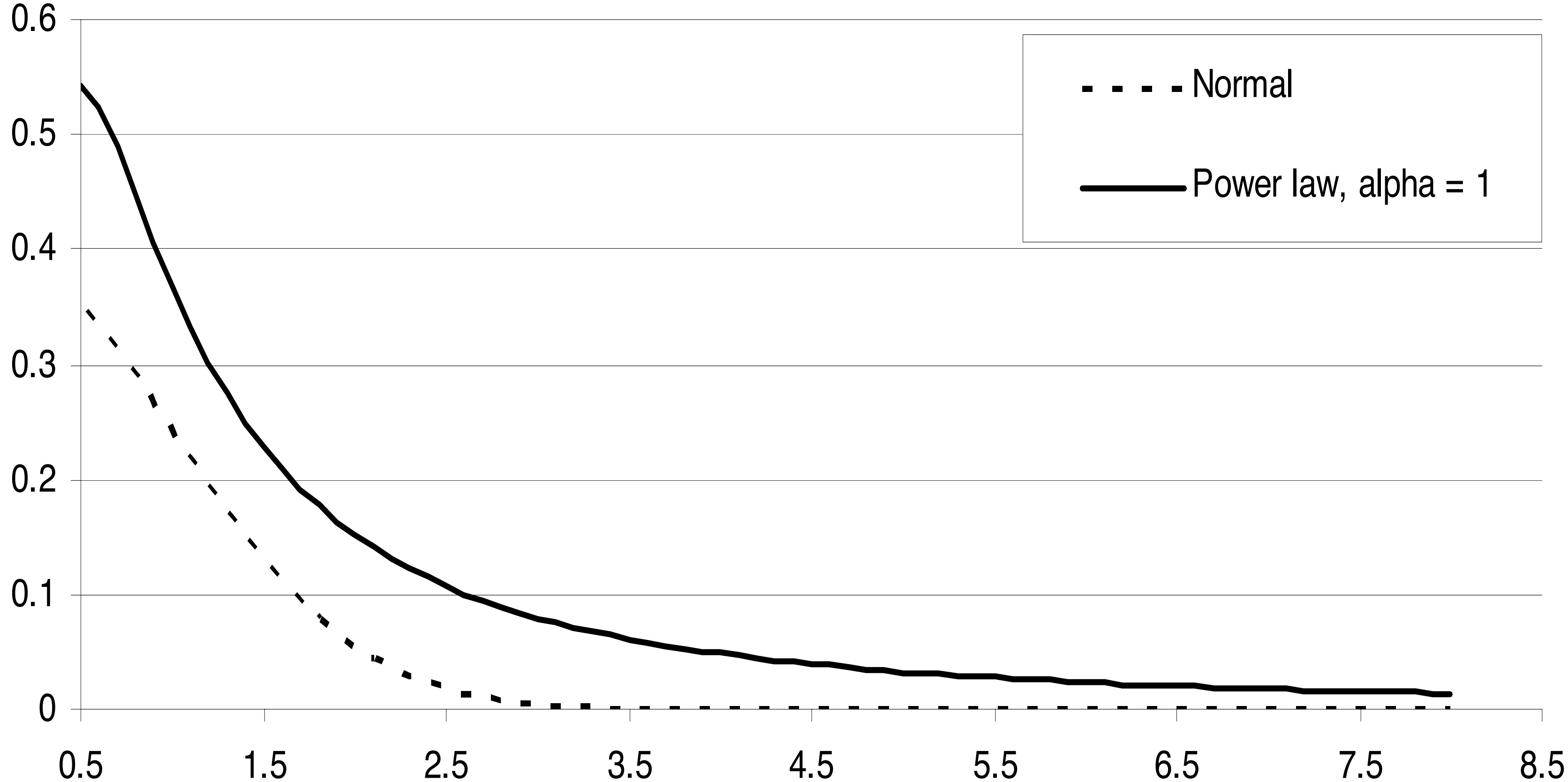
Power laws

- The empirical mean excess return grows with the negative value of the threshold
- Intuitively, the more infrequent an event, the higher is the loss: the data shows that there very few but extreme return fluctuations
- A much better model for the daily return is thus a **power law**
- A random variable X with distribution function F_X follows a power law with exponent α if

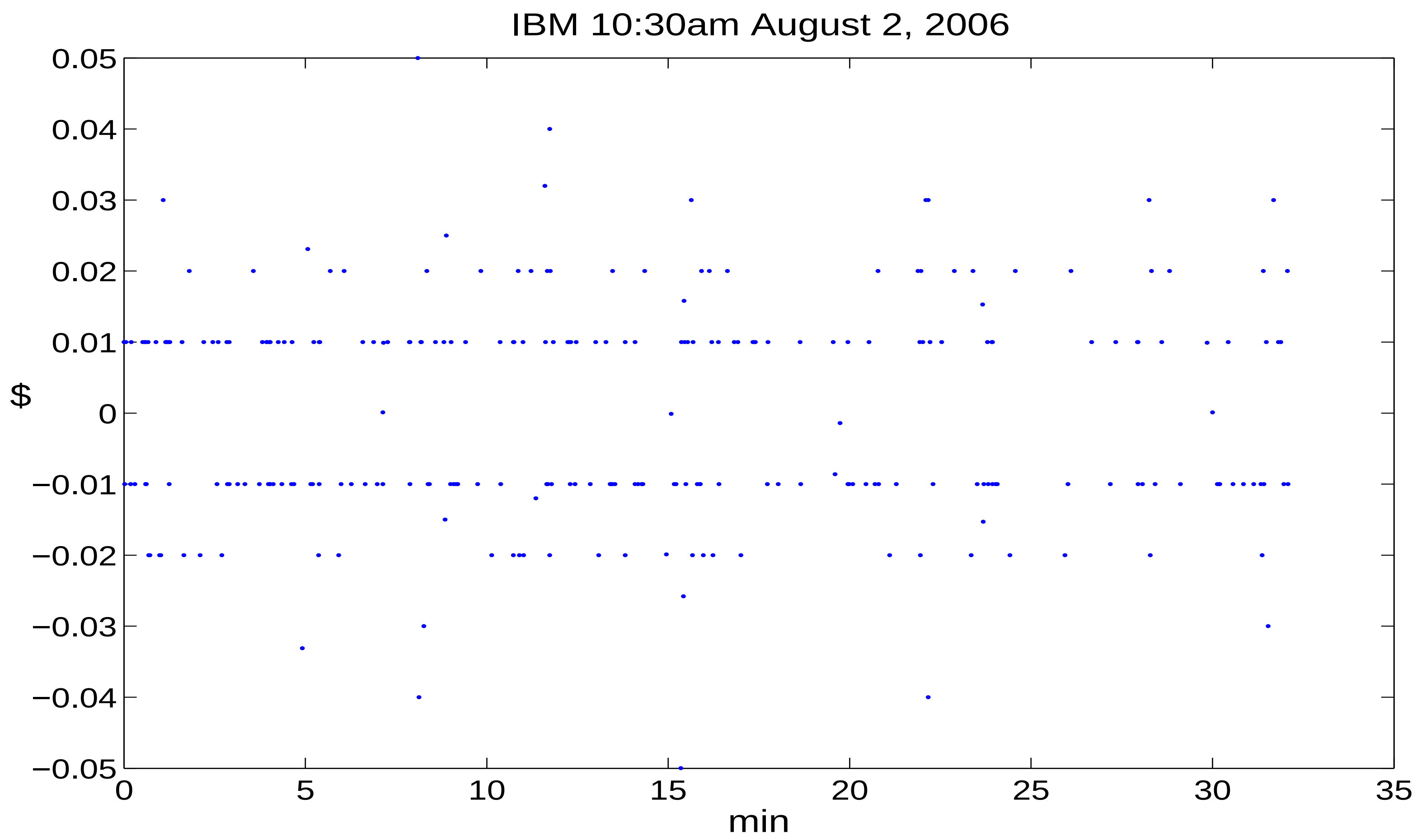
$$(1 - F_X(x)) \sim x^{-\alpha}$$

  That is, the survival probability $P[X > x]$ is asymptotically proportional to $x^{-\alpha}$: the tail of the distribution decays like $x^{-\alpha}$

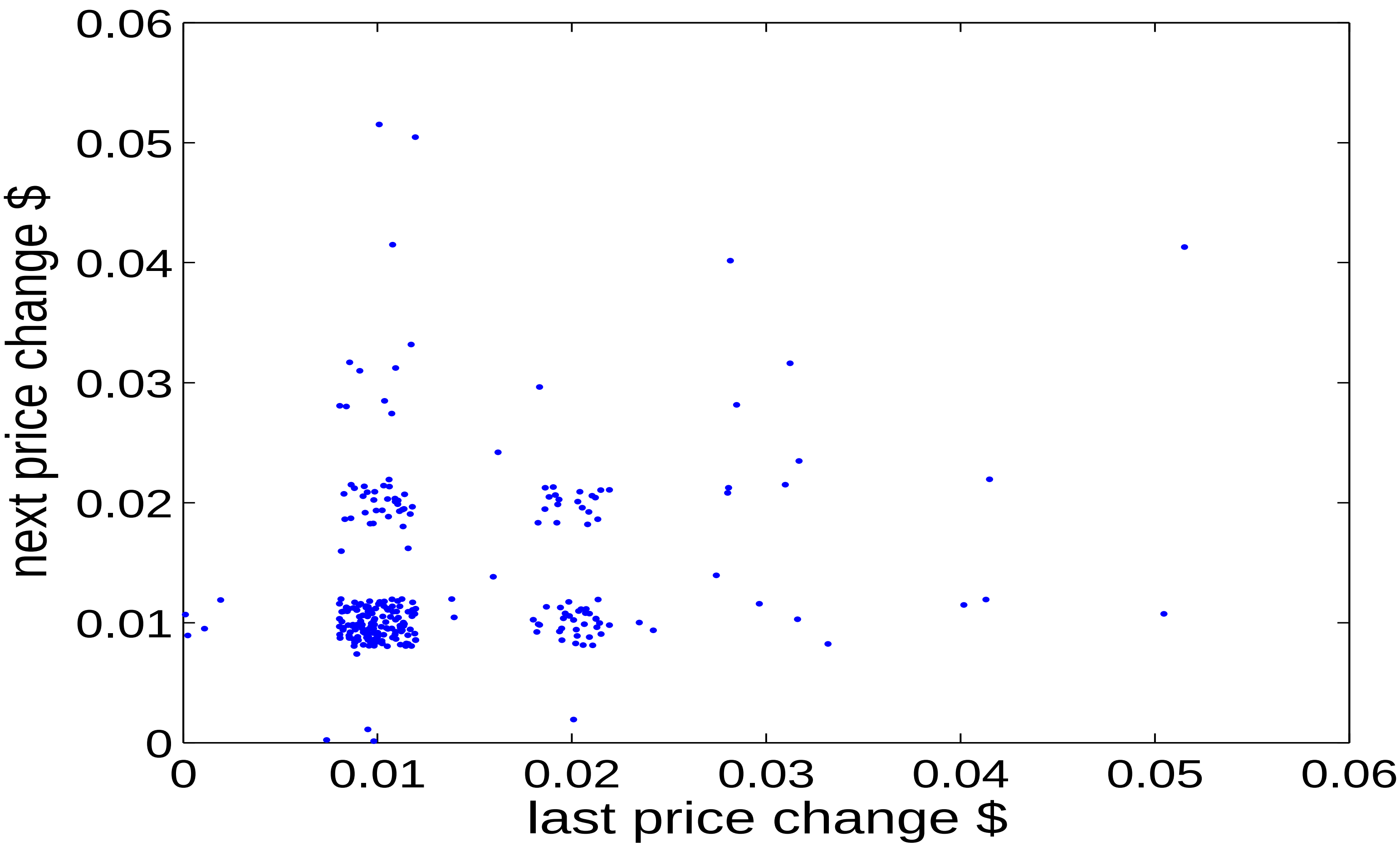
Densities of the Normal and the Power law with $\alpha = 1$



IBM price changes



IBM price changes



Project 2

- A price event arrives when the price change exceeds some threshold α
- The sequence of price events forms a point process that is self-affecting if the volatility clusters
- The intensity or conditional event arrival rate of this process measures the volatility
- How good is this measure? Relate it to realized volatility
- What are the properties of this volatility measure?
  - Clustering
  - Distribution of future volatility roughly log-normal
  - Higher moments exhibit multi-fractal scaling: $E[r(\ell)^n] = c_n \ell^{b_n}$
  - Volatility shock decays like a power law
  - Leverage effect

Project 3

Capital structure arbitrage

- Goal: design and test a trading strategy that exploits relative mis-pricing in credit and equity markets
- EvA has developed an option pricing model that incorporates the stylized facts of empirical asset returns discussed above
- Can calibrate this model to market option prices of a given name
- What does the calibrated model imply for the price of a credit swap referenced on that name?
- Need to model default of the firm along with an equity option: domain of structural credit models, in which a firm defaults when its assets hit a lower barrier and the equity of a firm is an option on firm value

Project 4

Effect of earnings announcements

- Realized volatility of stock prices rises significantly on the day that a company reports its earnings
- Option prices (implied volatility) anticipate this increase prior to the announcement, and then fall as soon as the stock price absorbs the new information
- Can we validate this pattern statistically based on past earnings announcements and the corresponding option implied volatilities?
- If so, we can exploit the pattern with a trading strategy

Project 4

Effect of earnings announcements

- Suppose a hedge fund manager has insider information about negative news
- The manager would leverage this information by taking positions in out of the money options
- Can we infer the presence of insider information from the distribution of the underlying implied by the listed option prices?
- Can compare the shape of the tail of the distribution with subsequent realized performance

Project 5

Detecting takeovers and mergers

- Goal: detect likely candidates from typical patters in market prices
- Related to Mike Lipkin's talk last December in the Financial Math Seminar: corporate insiders choose a certain strategy to leverage their information, and we can link that strategy to patterns in the implied volatility surface
- Of interest are general signatures that dominate the noise