#### Stochastic volatility

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# Volatility and applications Evidence of non-constant volatility Model and its estimation Extensions, possible work

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Evidence of non-constant volatility

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#### Model for stock price

Price of the stock at time t is  $X_t$  governed by geometric Brownian motion

$$d(\log X_t) = \mu dt + \sigma dB_t$$

Here  $\mu dt$  is the deterministic component and  $\sigma dB_t$  is the stochastic component.

 $B_t$  is Brownian motion:

 $dB_t$  is Normal with mean 0 and st.dev.  $\sqrt{dt}$ .

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Volatility  $\sigma$  determines the amplitude of the process fluctuations.

Other applications: commodities, foreign currency exchange rate etc.



assessment etc

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#### Applications

Volatility forecasting: important for portfolio management, risk assessment etc

Black-Scholes: A formula to obtain an Option price

Call Option is a contract to buy a security at time T (= maturity time) for the price S (=strike price).

Value of the call option:

$$C(X_t, t, T, S) = \Phi(d_1)X_t - \Phi(d_2)Se^{-r(T-t)}$$

where

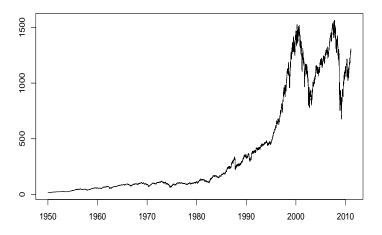
$$d_{1,2} = \frac{\log(X_t/S) + (r \pm \sigma^2/2)(T-t)}{\sigma\sqrt{T-t}}$$

r is the risk-free rate (at which you can borrow money) and  $\Phi$  is the Normal CDF.

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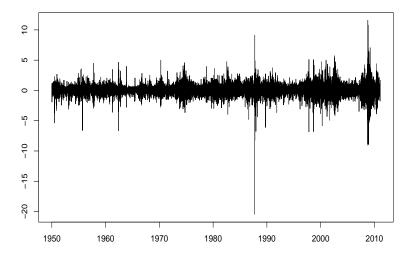
#### Evidence of non-constant volatility

#### S&P500 index

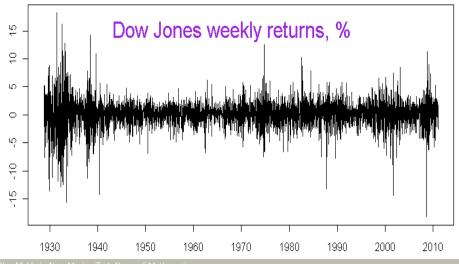


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S&P500 index daily returns  $Y_t = (X_t - X_{t-1})/X_t$ , in %



#### Evidence of non-constant volatility



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#### State-space model

- $Y_t = \beta \exp(h_t/2)\varepsilon_t$
- $h_t = rh_{t-1} + \sigma_\eta \eta_t$ , t = 2, ..., T

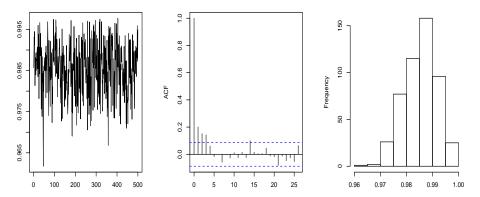
Hidden state  $h_t$  is log volatility and it follows an autoregressive model (r = correlation between today's state and yesterday's state).

 $\varepsilon_t$  and  $\eta_t$  are uncorrelated, standard Normal shocks

Efficient estimation methods since late 90's: Markov Chain Monte Carlo. Alternates between simulating from distribution of  $h_t$  and other unknown parameters  $(\beta, r, \sigma_\eta)$ . Represents distribution of  $log(Y_t^2)$  (which is not Normal) as a mixture of Normals.

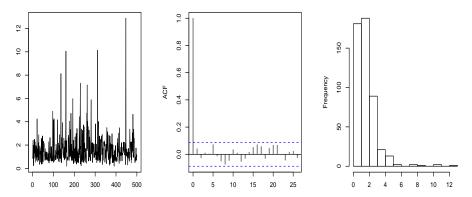
#### Estimation results

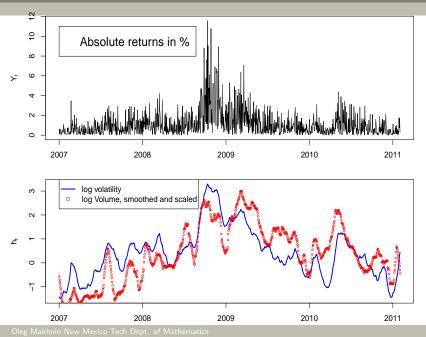
#### MCMC output for parameters: r (autocorrelation)



#### Estimation results

MCMC output for parameters:  $\beta$  (mean absolute return)



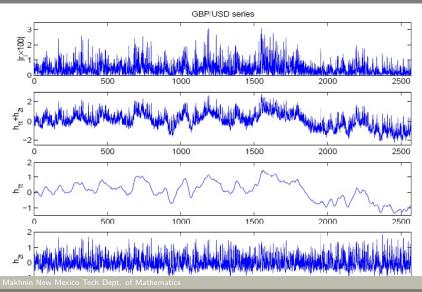


#### Extensions

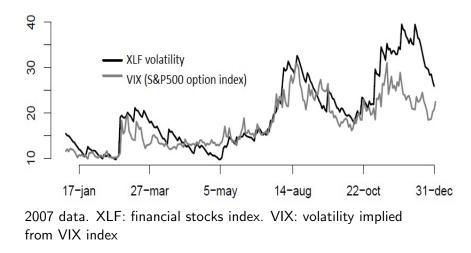
Rich, exponentially growing literature, including:

- Continuous/intraday trading
- Non-symmetry of returns
- Non-normal increments
- Models with jumps
- Multivariate: looking at several stocks at once
- Dimension reduction: hidden factor models (a few factors to explain SV behavior of several stocks)

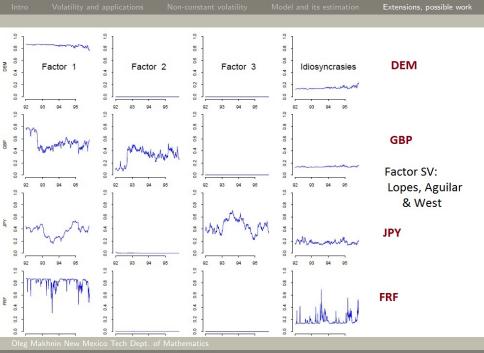
#### Multiscale model: Molina, Han & Fouque



#### Implied volatility, jumps: Lopes & Polson



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Hidden factor models:

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- Predictability (maybe use multiscale models)
- Development of particle-filtering methods (active area of research)
- Use in trading

#### Bibliography

• Kim, Shephard & Chib, 1998. Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models, Review of Economic Studies, vol. 65(3), 361-93

• Stochastic Volatility: Selected Readings, edited by N.Shephard, Oxford, 2005

• Lopes & Polson Bayesian Inference for S.V. modeling, in Bocker, K. (Ed.) Rethinking Risk Measurement and Reporting: Uncertainty, Bayesian Analysis and Expert Judgement, 2010, 515-551

• Lopes & Polson Extracting S&P500 and NASDAQ volatility: The Credit Crisis of 2007-2008 in The Handbook of Applied Bayesian Analysis, Oxford 2009

		Extensions, possible work

## **QUESTIONS?**

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### THANK YOU!

### see www.nmt.edu/~olegm/talks/SV

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