FAKULTÄT FÜR PHYSIK

UNIVERSITÄT DUISBURG ESSEN

Econophysics II:

Detailed Look at Stock Markets and Trading

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Let’s Face Chaos through Nonlinear Dynamics, Maribor 2011

Outline

- stock markets and trading in reality
- two extreme model scenarios: Efficient Market Hypothesis, Zero Intelligence Trading
- large scale data analysis reveals non–Markovian features
- artifical stock market to encircle mechanisms
- trading strategies and temporal correlations

Stock Market Trading in Reality

Clearing House and Orders

trading via clearing house, buy and sell offers/orders (bids and asks)

limit order: bid or ask for a specific volume at a specific price within a certain time window,

best ask $a(t)$, best bid $b(t)$, always $a(t) \geq b(t)$

if equal $\longrightarrow$ trade, price $S(t) = a(t) = b(t)$ immediately thereafter

market order: buy or sell immediately what is offered,
$S(t) = b(t)$ or $S(t) = a(t)$

Order Book

make public to provide all traders with same information

XETRA | DEUTSCHE BÖRSE GROUP

Bid/Ask-Overview

Bid	Bid Qty	Ask Qty	Ask
44.020	1,845	675	44.040
44.015	577	2,444	44.045
44.010	1,195	2,121	44.050
44.005	1,016	685	44.055
44.000	921	592	44.060
43.995	685	184	44.065
43.990	2,022	184	44.070
43.985	699	103	44.075
43.980	1,146	1,026	44.080
43.975	1,011	380	44.090

limit orders appear in the order book, market orders do not

Midpoint, Bid–ask Spread, Trade Sign

in between trades, there is no price !

bid–ask spread $\quad s(t) = b(t) - a(t) < 0$

the higher the trading frequency, the smaller is $s(t)$

midpoint $\quad m(t) = \dfrac{a(t) + b(t)}{2}$

immediately after a trade, define trade sign

$$\vartheta(t) = \begin{cases} +1 & \text{if } S(t) \text{ is higher than the last } m(t) \\ -1 & \text{if } S(t) \text{ is lower than the last } m(t) \end{cases}$$

positive, if trade was triggered by a market order to buy
negative, if trade was triggered by a market order to sell

Traders and Liquidity

market is liquid, if there are always enough shares at a “reasonable” price to ensure that every planned trade can be carried out and if the trading happens continuously

small bid–ask spread $s(t) = b(t) - a(t)$ is indicator

limit orders make a market liquid $\longleftrightarrow$ liquidity providers

market orders absorb liquidity $\longleftrightarrow$ liquidity takers (“informed”)

liquidity providers and takers are not static populations, these rôles change constantly

Model Scenarios

First Extreme Model Scenario — EMH

Efficient Market Hypothesis

Traders always act fully rationally. Market price results from consensus between the traders about the “fair” price. It always exists and reflects quantifiable economic value of asset. Deviation of market price from “fair” price $\longrightarrow$ arbitrage $\longrightarrow$ disappears. Consensus comes about, because group of traders processed all available information. Price can only change if new information arrives. The new information is totally random.

Second Extreme Model Scenario — ZIT

Zero Intelligence Trading

Individual trader is irrational and acts fully randomly. The other traders do not know that and interpret the buy and sell decisions made by others as potentially information driven. Price change is not attributed to new information, it automatically follows from the fact that trading takes place $\longrightarrow$ demand and supply. There is no fair price, midpoint $m(t)$ moves as well. Traders immediately accept the new midpoint as the new reference point about which they send out their random buy and sell orders.

Where is the Truth ?

both scenarios lead to a Markovian random walk model for price !

both partly compatible with reality, but there are objections:

EMH: “fair” price deeply obscure $\longrightarrow$ what is then rational ? — high volatilities incompatible with rational pricing — time scales of trading not consistent with those of information flow

ZIT: irrationality not realistic either, traders use information

truth is somewhere in between $\longrightarrow$ need detailed data analysis

Collecting Emipirical Information

Data Analysis

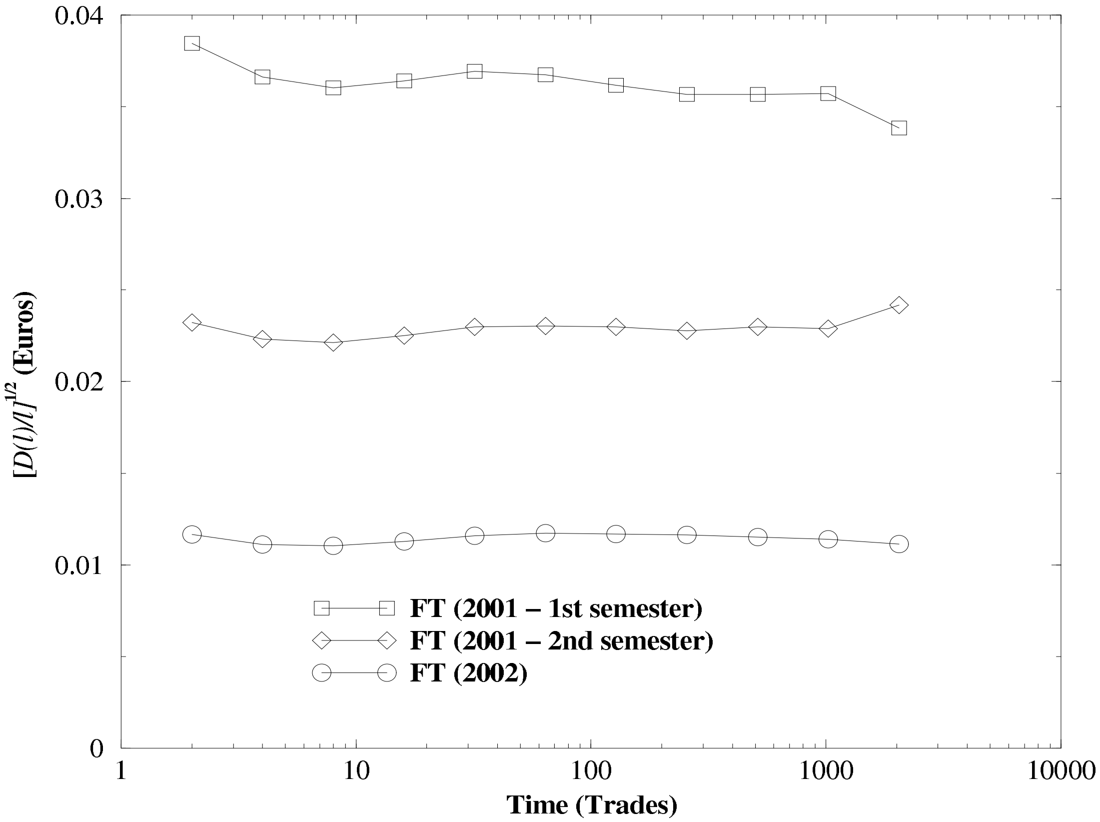
Bouchaud, Gefen, Potters and Wyart, Quantitative Finance 4 (2004) 176

- fully electronically traded French stocks 2001–2002
- intraday
- high frequency, up to 10000 trades/day
- volumes between a few and 80000 shares
- trade time instead of real time

Volatility and Diffusion

substract drift from $S(t) \longrightarrow$ detrended price $Z(t)$

diffusion function $D(\tau) = \left\langle \left(Z(t+\tau) - Z(t)\right)^2 \right\rangle$



largely constant
volatility function

$$\sqrt{D(\tau)/\tau}$$

for France–Telecom

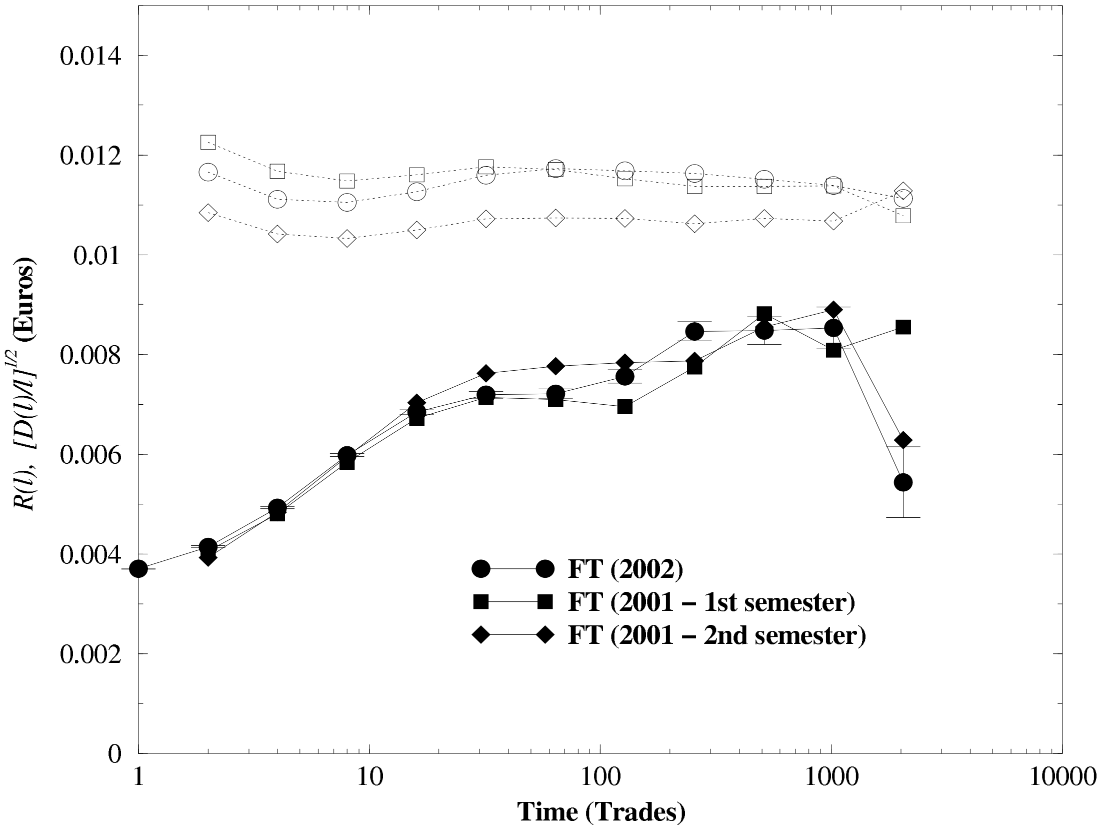
diffusive motion !

Average Response to Trading

response function $R(\tau) = \langle (Z(t+\tau) - Z(t))\, \vartheta(t) \rangle$

average impact of trading at t on subsequent price changes

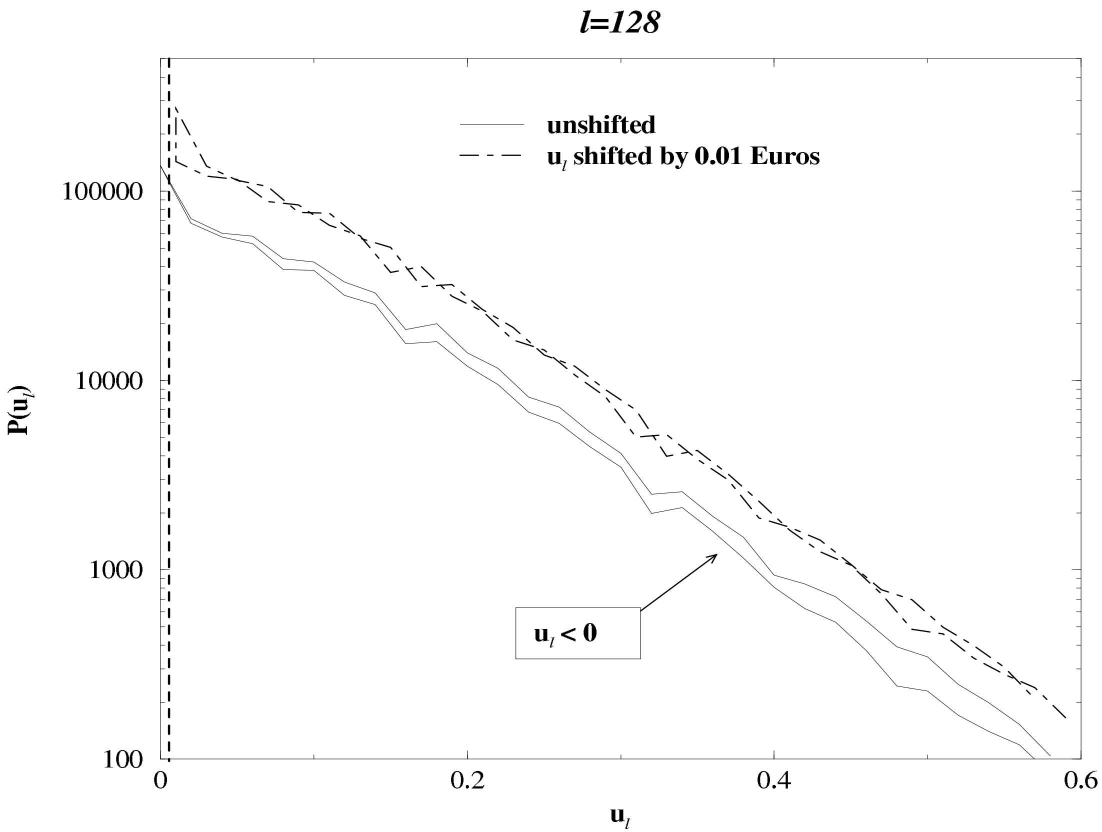
non–zero empirical result proves non–Markovian behavior !



Distribution of Sign Supplemented Price Changes

sign supplemented price changes $u(t,\tau) = (Z(t+\tau) - Z(t))\,\vartheta(t)$

response $R(\tau) = \langle u(t,\tau)\rangle$, diffusion function $D(\tau) = \langle u^2(t,\tau)\rangle$



distribution $p(u(t,\tau))$
for $\tau = 128$

moment $R(128) > 0$

small arbitrage

truly informed traders

Power Law Autocorrelations in Trade Signs

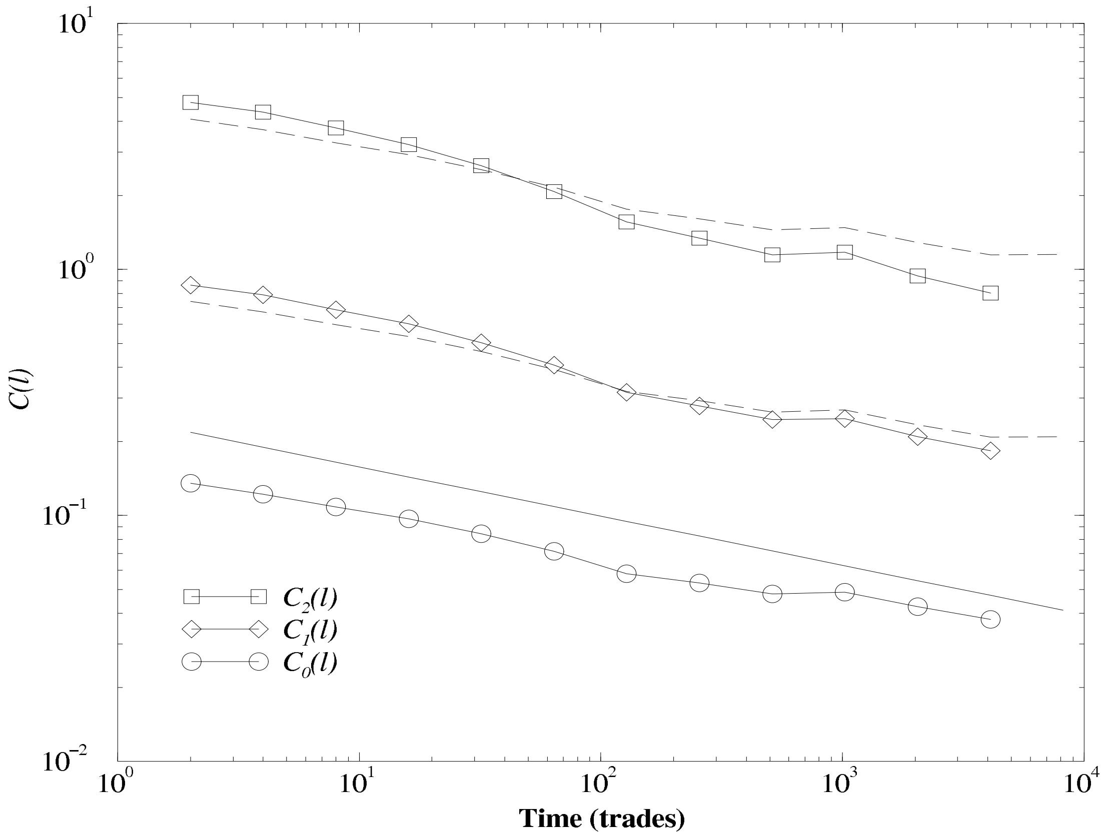
trade sign autocorrelation $\Theta(\tau) = \langle \vartheta(t+\tau)\vartheta(t) \rangle - \langle \vartheta(t) \rangle^2$

power law

$$\Theta(\tau) \sim \frac{1}{\tau^{\gamma}}$$

with $\gamma < 0$

non–Markovian,
outrules ZIT idea !



Modeling the Price Dynamics

Non–Markovian Model

$$Z(t) = \sum_{t'=1}^{t} G_0(t-t')\vartheta(t')\ln V(t') + \sum_{t'=1}^{t} \varepsilon(t')$$

first term non–Markovian, second Markovian

ansatz for bare impact function $G_0(\tau) \sim \dfrac{1}{(1+\tau/\tau_0)^\beta}$

$\longrightarrow \quad D(\tau) \sim \tau^{2-2\beta-\gamma},$ critical exponent $\beta_c = \dfrac{1-\gamma}{2}$

$\beta = \beta_c$ diffusive, $\beta > \beta_c$ sub–diffusive, $\beta < \beta_c$ super–diffusive

possible to reproduce empirical $R(\tau)$ for $\beta \approx \beta_c$ and $\tau_0 \approx 20$

Bouchaud, Gefen, Potters, Wyart (2004)

Liquidity Takers versus Liquidity Providers

Reality is non–Markovian, interpreted as a competition: Consider trader who is “informed” that price of a company will go up. He wants to buy shares, likely by market orders $\longrightarrow$ liquidity taker. Not be wise to place big offer, because this would alert liquidity providers who emit the limit orders to sell (“knows something”). They would place their limit orders at higher price. Liquidity taker is aware $\longrightarrow$ divides his market order into smaller chunks which he places one after the other $\longrightarrow$ introduces temporal autocorrelations $\Theta(\tau)$. Liquidity providers want to mean revert price $\longrightarrow R(\tau) \to 0$ for large τ. They do that slowly, because they do not know whether liquidity taker’s information becomes true $\longrightarrow$ maximum of $R(\tau)$. $\longrightarrow$ Persistence: liquidity providers do not sufficiently mean revert the price $\longrightarrow$ super–diffusive. Antipersistence: they mean revert too strongly $\longrightarrow$ sub–diffusive. $\longrightarrow$ Subtle balance between sub– and super–diffusive $\longrightarrow$ effectively diffusive. Compares to balancing a stick on the palm.

Artifical Stock Market

Agent Based Modeling

financial markets are complex systems: many degrees of freedom, non–linear effects, basic processes and time evolution governed by probabilistic rules, not by deterministic equations

top–down approach: schematic models, stochastic processes
$\longrightarrow$ successes and limitations

bottom–up approach: artificial stock market on computer with virtual traders $\longrightarrow$ agent based modeling

- set up system microscopically and let evolve
- price dynamics and all other macroscopic observables result
- identify crucial mechanisms by encircling them

various examples in biology, social sciences, economics, one of the first is Conway's Game of Life (1970)

Wigner's Caveat

"It is nice to know that the computer understands the problem. But I would like to understand it too."

Eugene Paul Wigner, 1902–1995

Impact of Trading Strategies

introduce different types of traders traders $\longrightarrow$ top–down element in an otherwise bottom–up approach, not adaptive

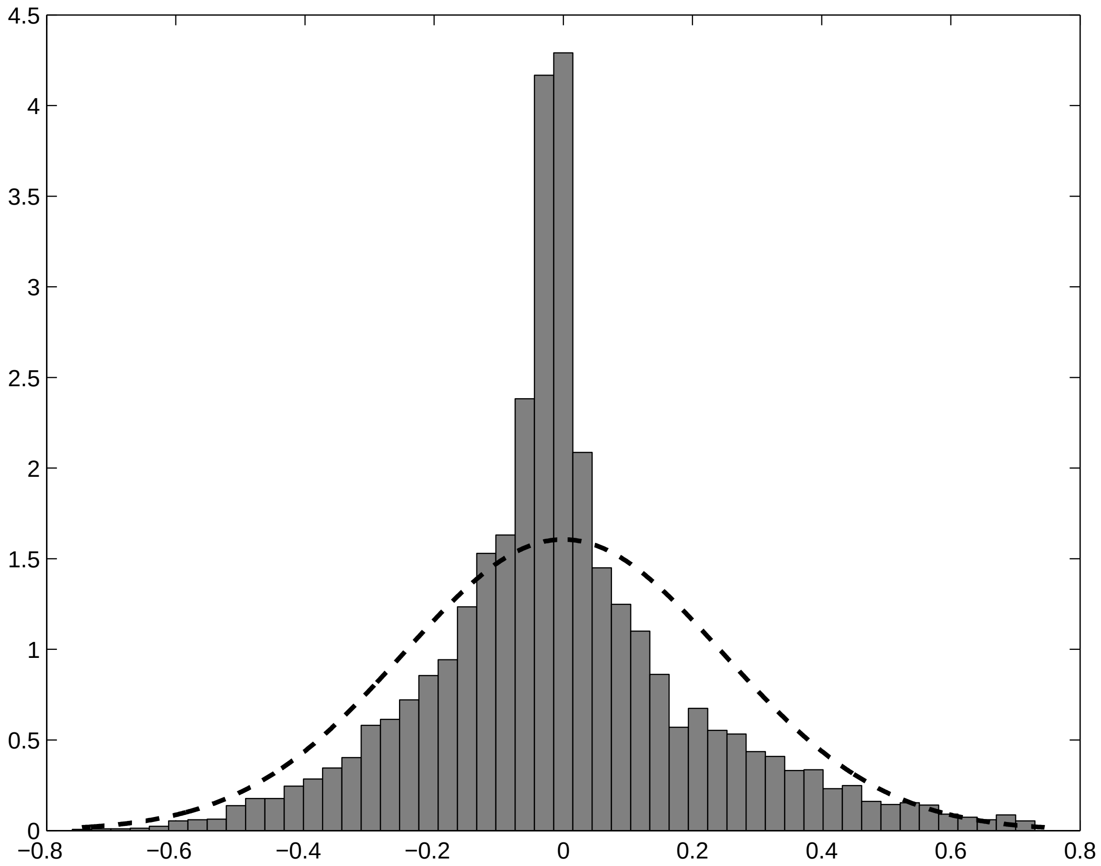
- ZeroIntelligenceTrader
- RandomTrader
- EagerTrader
- LiquidityProvider
- RandomInformedTrader
- SerialTrader
- ExpectingTrader

let evolve and see what happens !

Berseus, Schäfer, Guhr (2007)

Zero Intelligence Trading

population of 300 ZeroIntelligenceTraders
return distribution after 10000 trades



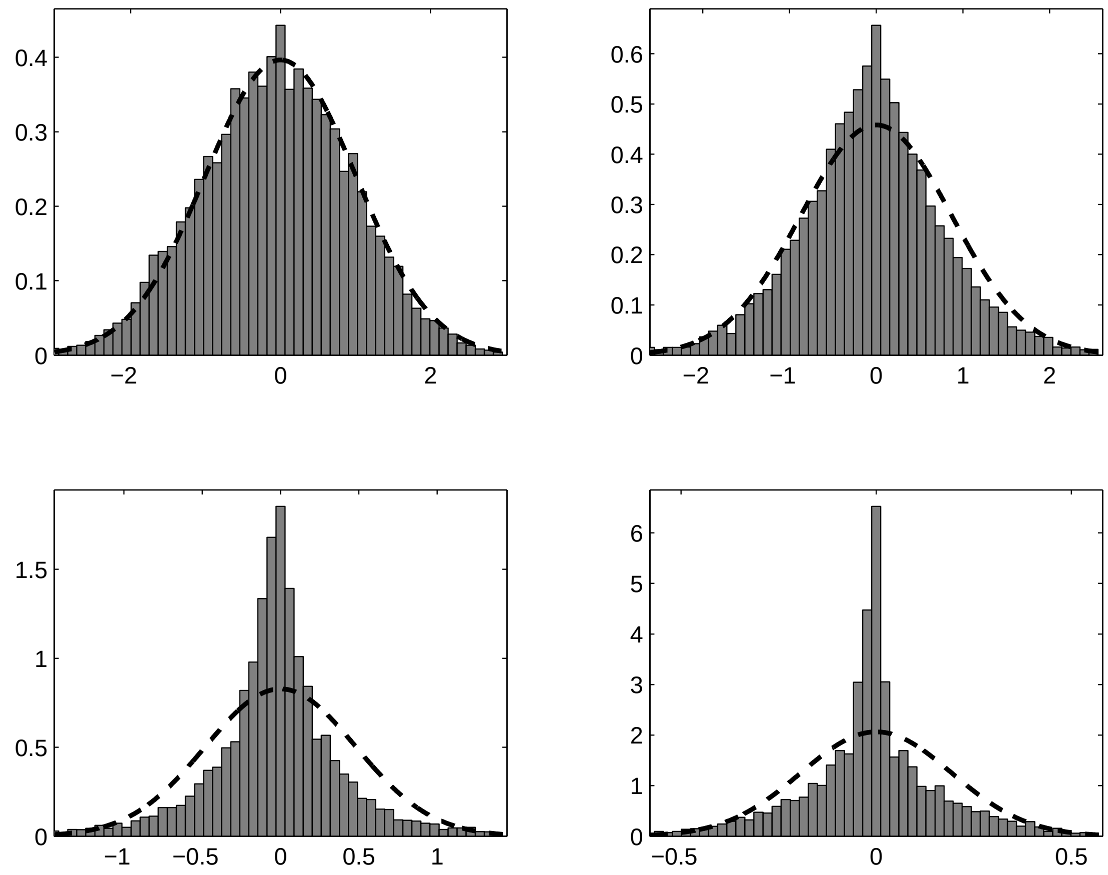
non–Gaussian,

heavy tails !

Heavy Tails and Order Book

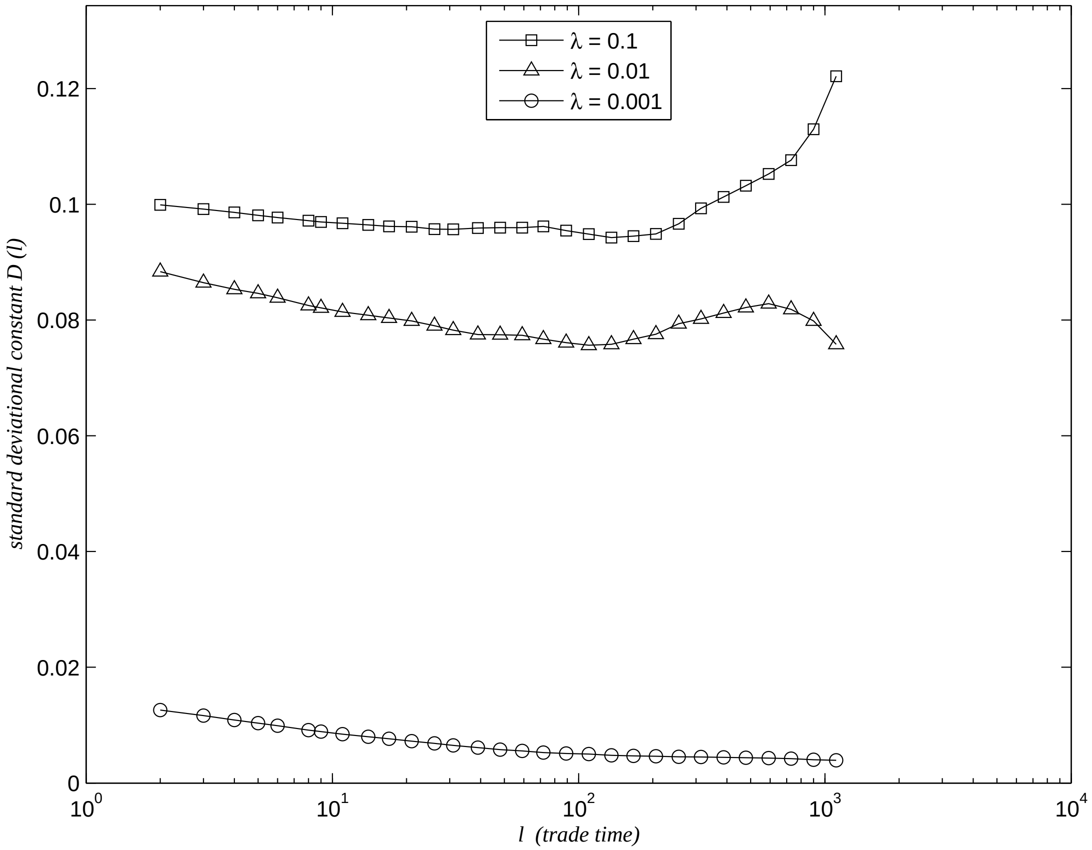
population of 300 traders, distributions of price differences
EagerTraders and three versions of RandomTraders

non–Gaussian
when order book
becomes
more important



Mixed Populations — Volatility Function

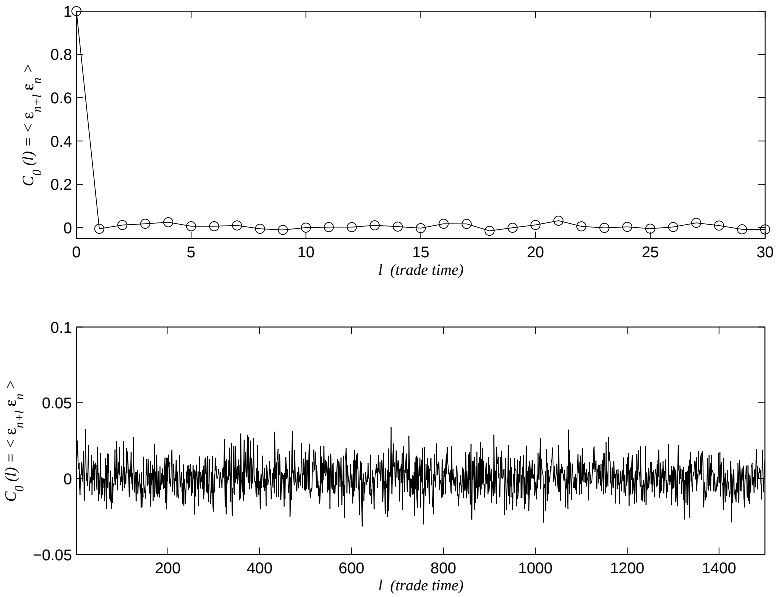
LiquidityProvider and three versions of RandomInformedTraders



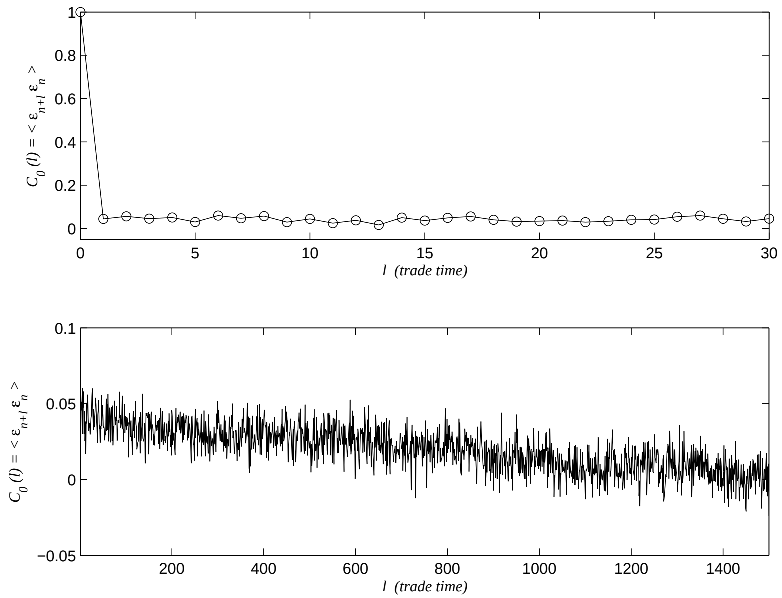
largely diffusive

depends sensitively on likeliness to emit market orders

Mixed Populations — Trade Sign Autocorrelations



LiquidityProviders,
SerialTraders



LiquidityProviders,
ExpectingTraders

ExpectingTrader waits for gap between $m(t)$ and “fair” price,
Serial Trader does not $\longrightarrow$ trade sign autocorrelations

Summary and Conclusions

- stock markets and trading in reality
- two extreme model scenarios: Efficient Market Hypothesis, Zero Intelligence Trading
- large scale data analysis reveals non–Markovian features
- schematic top–down stochastic model
- artifical stock market as bottom–down approach
- heavy tails are order book effect
- trading strategies sensitively determine temporal correlations