

# Fokker-Planck description from empirical data

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# OUTLINE

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➤ *Motivation*

➤ *Systems of interest*

➤ *Theoretical background*

*Kramers-Moyal description*

➤ *Evolution equation from data*

*Fokker-Planck equation*

*Linear-quadratic FPE*

➤ *Difficulties: finite-time effects*

# MOTIVATION

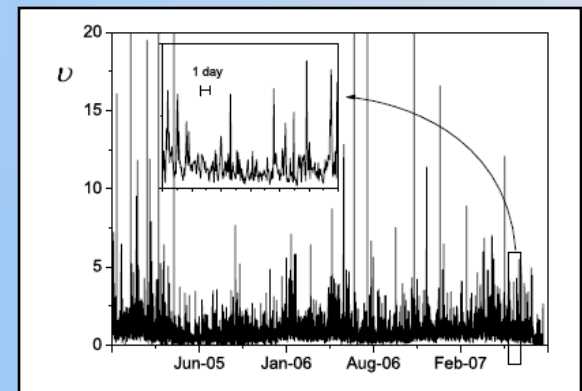
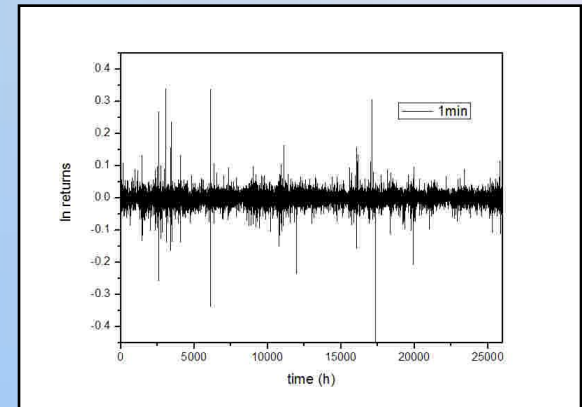
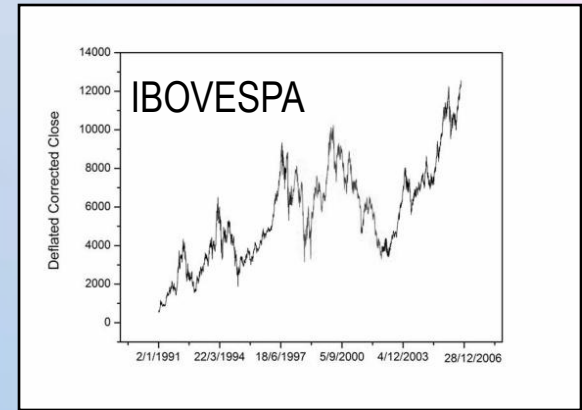
➤ *to model the dynamics of fluctuating observables*

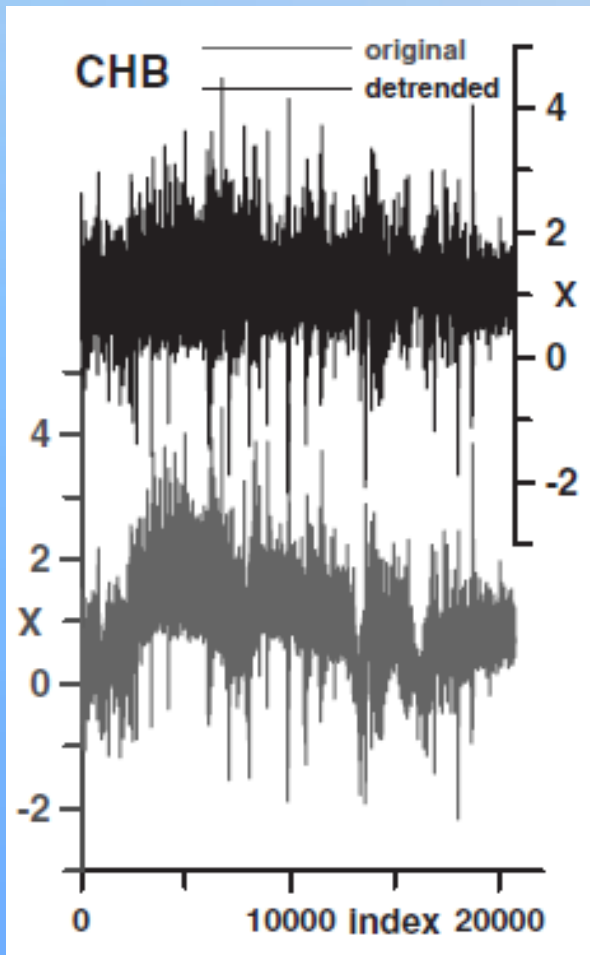
$x(t)$  = stock index at time  $t$

returns at different time scales  $\Delta t$  :

$$r(t) = \log x(t+\Delta t) - \log x(t)$$

$V(t)$  = volume of shares traded in  $\Delta t$  at time  $t$





- heart rate variability
- EEG timeseries
- atmospheric data
- turbulence

## Phenomenological models

- *generalized Fokker-Planck (nonlinear)*

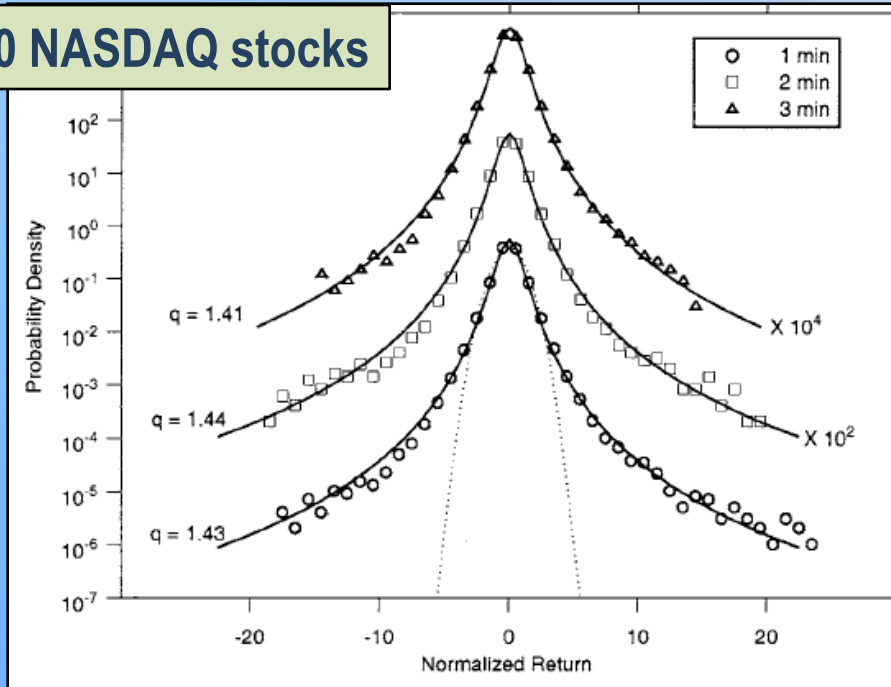
$$\partial_t P(z, t) = D \partial_{zz} [P(z, t)]^{\nu}$$

- *generalized Langevin*

$$\dot{z} = f(z, t) + g(z, t)\eta(t)$$

➤ returns

10 NASDAQ stocks



PDFs of returns at timelags  $\Delta t$

Tsallis, Anteneodo, Borland, Osorio; *Physica A* (2003)

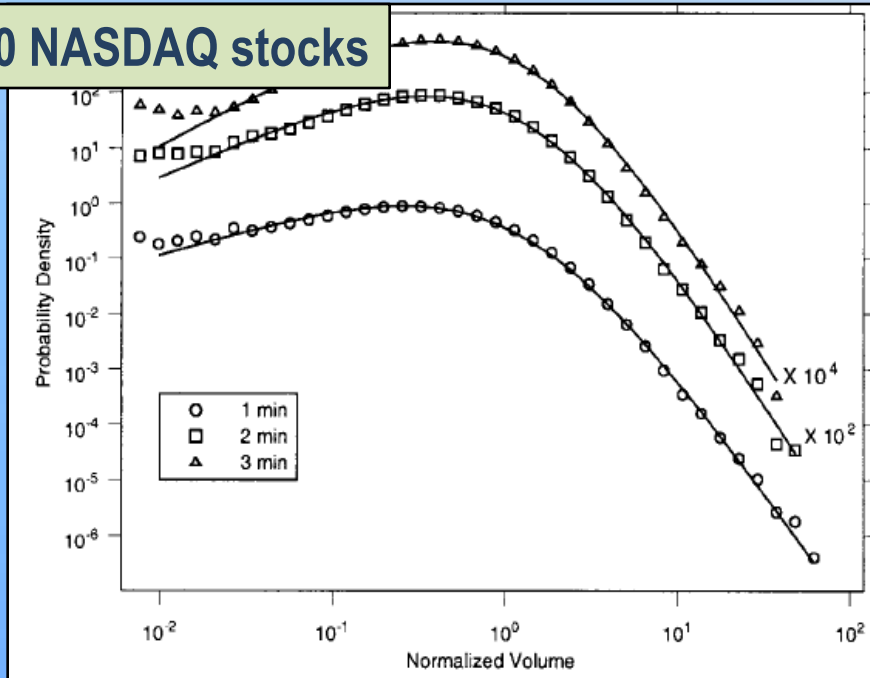
Borland; *PRE* (1998); *PRL* (2002)

$$\dot{x} = \mu + \sqrt{D} [P(x,t)]^{(v-1)/2} \eta(t)$$

$$\partial_t P(x,t) = -\partial_x [\mu P(x,t)] + D \partial_{xx} [P(x,t)]^v$$

➤ volumes

10 NASDAQ stocks



Queiros; *EPL* (2005)

Queiros, Tsallis; *EPJB* (2005)

...

$$\dot{v} = -\gamma(v - \alpha) + \beta\sqrt{v}\eta(t)$$

with fluctuating  $\alpha$

PDFs of volumes at aggregation times  $\Delta t$

Tsallis, Anteneodo, Borland, Osorio; *Physica A* (2003)



→ *reproduce (1time) distributions*

*Difficulties: higher order statistics?  
correlations?  
non unique  
parameter meaning?*

positivity, mean reversion

➤ volumes or volatility

$$\dot{x} = -\gamma(x - \theta)x^{r-1} + \mu x^s \eta(t)$$

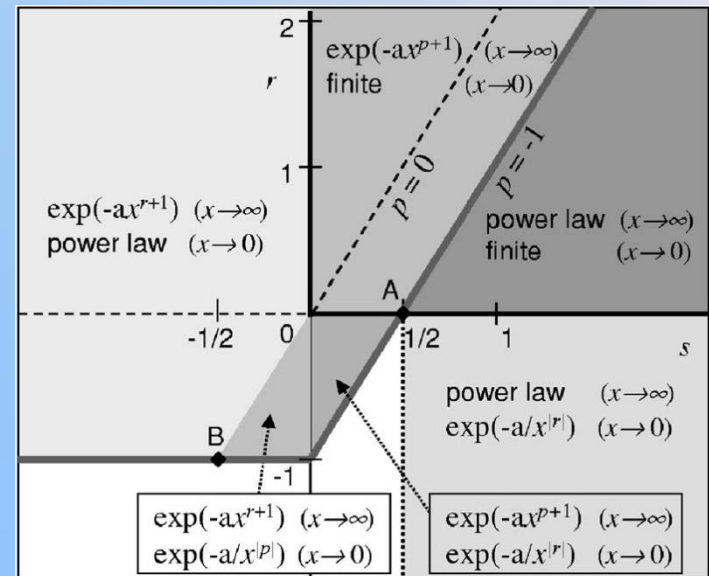
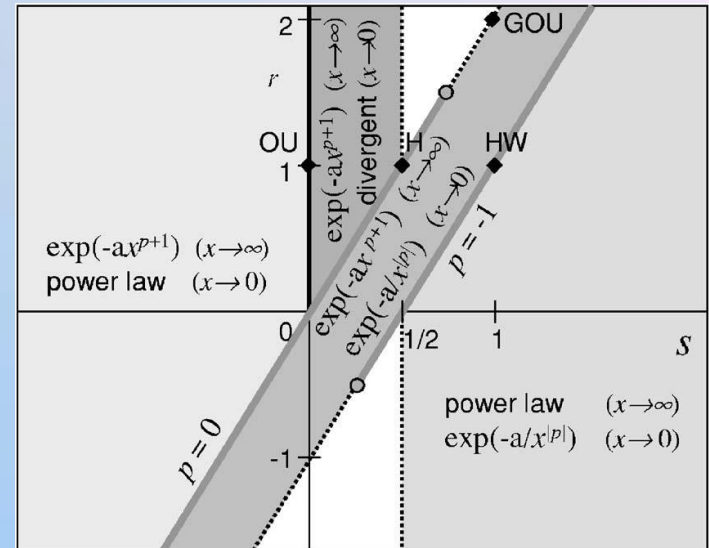
*OU* (1,0)

*GOU* (2,1)

*Hull-White* (1,1)

*Heston* (1,1/2)

$$\dot{x} = -\gamma(x - \theta)x^{r-1} + \mu x^s \eta_1(t) + \alpha \eta_2(t)$$



Anteneodo, Riera; *PRE* (2005)

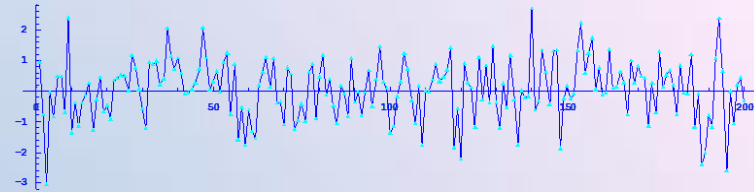
# OBJECTIVE

- *determine the dynamics directly from the data series*

# SYSTEMS/PROCESSES

- *Markovian*

# Markov processes



$$P_n(x_1, t_1; x_2, t_2; \dots; x_n, t_n) \equiv P_n(X_{t_1} = x_1; \dots; X_{t_n} = x_n)$$

para  $n$  valores arbitrários de  $t$ , com  $n = 1, 2, \dots$

Purely random

( $n > 1$ )

$$P_{1|n-1}(x_n, t_n | x_1, t_1; x_2, t_2; \dots; x_{n-1}, t_{n-1}) = P_1(x_n, t_n)$$

Markovian

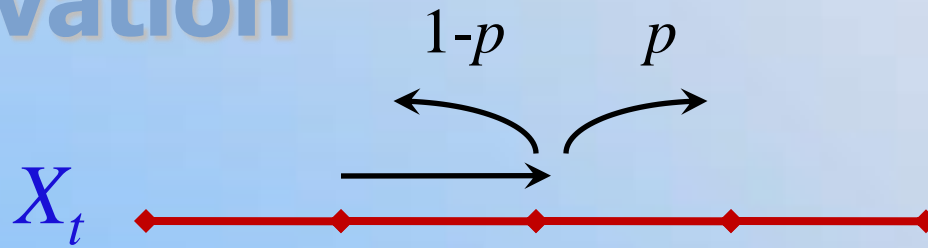
for any set  $t_1 < t_2 < \dots < t_n$ ,  $n > 1$

$$P_{1|n-1}(x_n, t_n | x_1, t_1; x_2, t_2; \dots; x_{n-1}, t_{n-1}) = P_{1|1}(x_n, t_n | x_{n-1}, t_{n-1})$$

More general

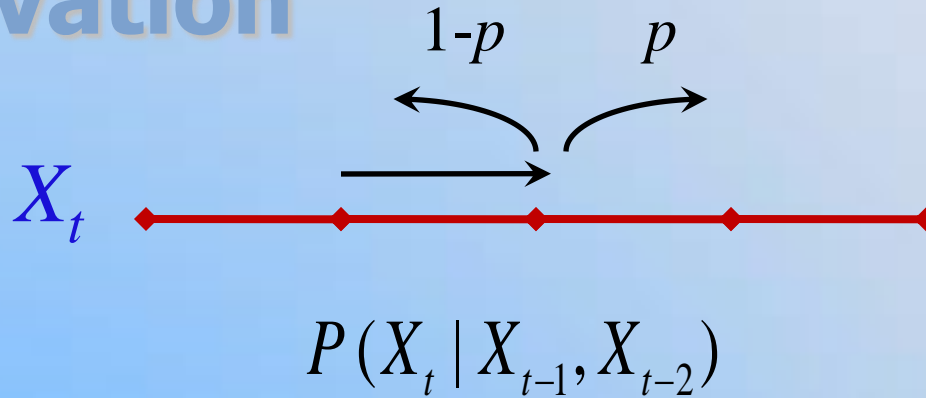
$$P_{1|n-1}(x_n, t_n | x_1, t_1; x_2, t_2; \dots; x_{n-1}, t_{n-1})$$

# Observation



$$P(X_t | X_{t-1}, X_{t-2})$$

# Observation



Cure:  $(X_t, X_{t-1})$

$$P(s_1, s_2; t | r_1, r_2; t-1) = \delta_{s_2 r_1} [p \delta_{s_1 - s_2, r_1 - r_2} + (1-p) \delta_{s_1 r_2}]$$

Except if ALL steps (e.g., SAW)

# Markov processes

$$P_{1|n-1}(x_n, t_n | x_1, t_1; x_2, t_2; \dots; x_{n-1}, t_{n-1}) = P_{1|1}(x_n, t_n | x_{n-1}, t_{n-1})$$

# Markov processes

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$$\begin{aligned} P_3(x_1, t_1; x_2, t_2; x_3, t_3) &= P_{1|2}(x_3, t_3 | x_1, t_1; x_2, t_2) P_2(x_1, t_1; x_2, t_2) \\ &= P_{1|1}(x_3, t_3 | x_2, t_2) P_{1|1}(x_2, t_2 | x_1, t_1) P_1(x_1, t_1) \end{aligned}$$



# Markov processes

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Integration in  $x_2$ :

$$P_2(x_1, t_1; x_3, t_3) = P_1(x_1, t_1) \int dx_2 P_{1|1}(x_3, t_3 | x_2, t_2) P_{1|1}(x_2, t_2 | x_1, t_1)$$

# Markov processes

$$P_{1|n-1}(x_n, t_n | x_1, t_1; x_2, t_2; \dots; x_{n-1}, t_{n-1}) = P_{1|1}(x_n, t_n | x_{n-1}, t_{n-1})$$

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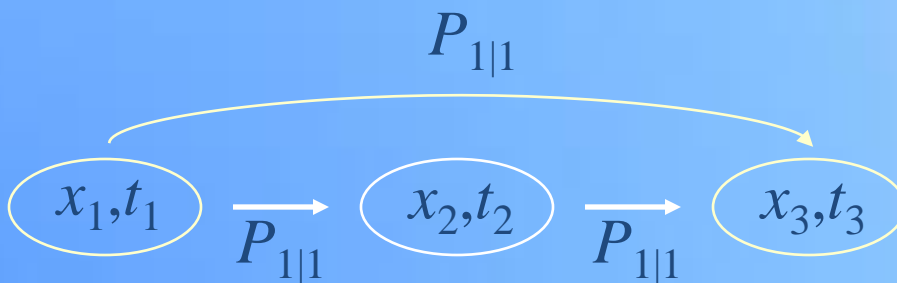
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Division by  $P_1(x_1, t_1)$ :

$$P_{1|1}(x_3, t_3 | x_1, t_1) = \int dx_2 P_{1|1}(x_3, t_3 | x_2, t_2) P_{1|1}(x_2, t_2 | x_1, t_1)$$

Chapman-Kolmogorov



# Kramers-Moyal (KM) expansion

general evolution equation for the PDFs of Markovian processes

$$\frac{\partial}{\partial t} P(x, t) = \sum_{k \geq 1} \left[ -\frac{\partial}{\partial x} \right]^k D^{(k)}(x, t) P(x, t)$$

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$$M^{(k)} = \int dx' (x' - x)^k P(x', t + \Delta t | x, t)$$

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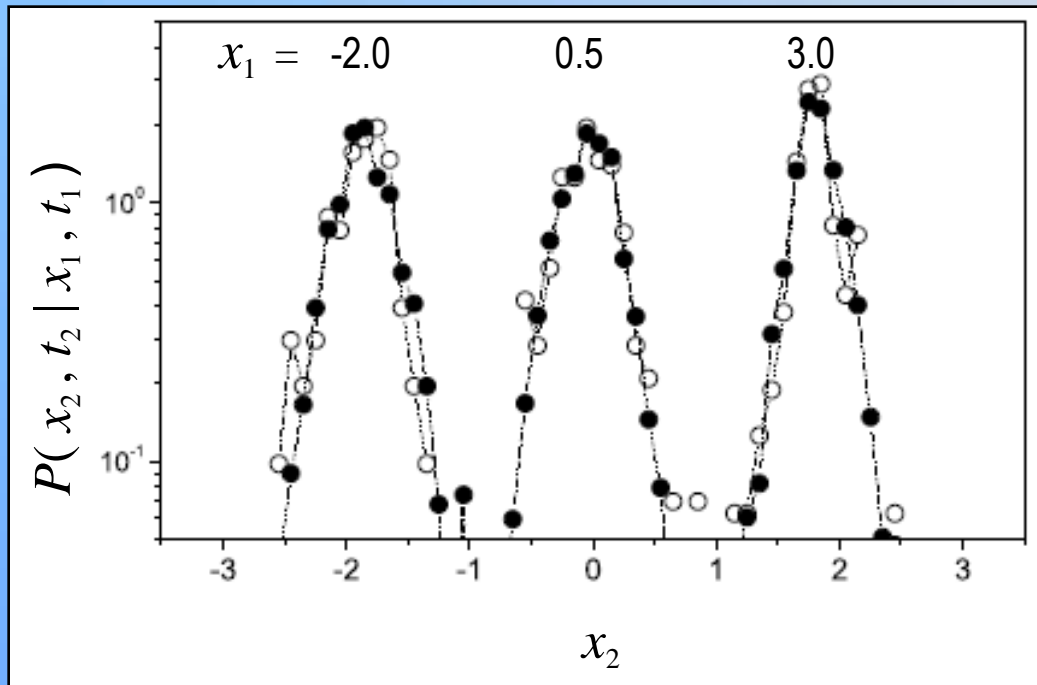
$$\tilde{D}^{(k)}(x, t, \Delta t) = \frac{1}{k!} \frac{M^{(k)}(x, t, \Delta t)}{\Delta t}$$

$$D^{(k)}(x, t) = \lim_{\Delta t \rightarrow 0} \tilde{D}^{(k)}(x, t, \Delta t)$$

# Markovianity check

evaluation of the Chapman-Kolmogorov equation:

$$P(x_2, t_2 | x_1, t_1) = \int dx' P(x_2, t_2 | x', t') P(x', t' | x_1, t_1) \quad t_1 < t' < t_2$$

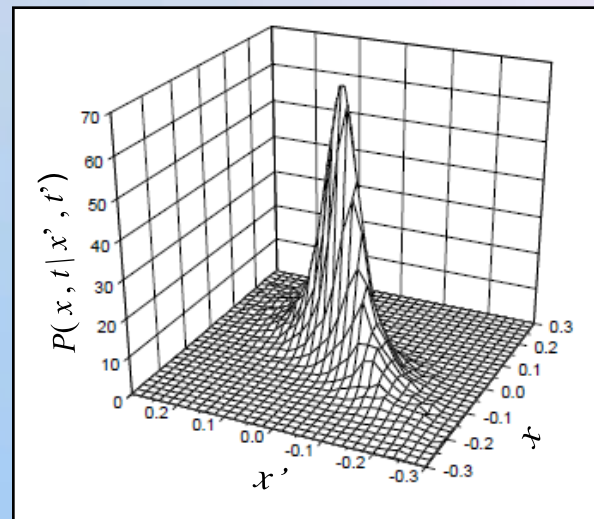


# Computation of KM coefficients

$$M^{(k)}(x, t, \Delta t) = \int dx' (x' - x)^k P(x', t + \Delta t | x, t)$$

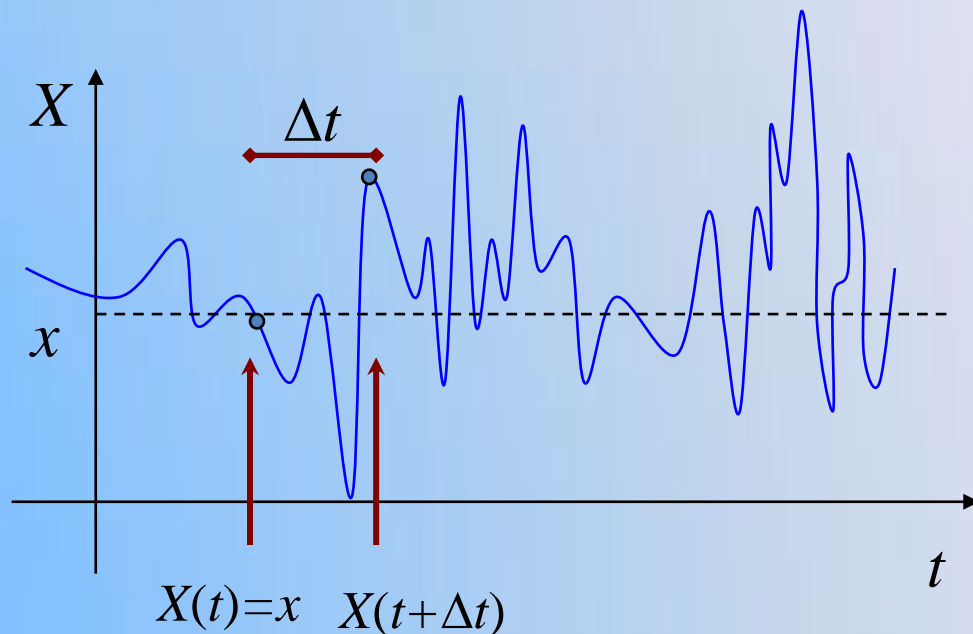
Conditional probabilities

$$P(x', t + \Delta t | x, t) = P(x', t + \Delta t; x, t) / P(x, t)$$



or equivalently

$$M^{(k)} = \left\langle (X(t + \Delta t) - X(t))^k \right\rangle_{|_{X(t)=x}}$$



$$\frac{\partial}{\partial t} P(x, t) = \sum_{k \geq 1} \left[ -\frac{\partial}{\partial x} \right]^k D^{(k)}(x, t) P(x, t)$$

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---

Important case: Fokker-Planck equation

$$\frac{\partial}{\partial t} P(x, t) = \left[ -\frac{\partial}{\partial x} D^{(1)}(x, t) + \frac{\partial^2}{\partial x^2} D^{(2)}(x, t) \right] P(x, t)$$

drift coefficient  
(deterministic)

diffusion coefficient  
(random)



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drift coefficient  
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Itô-Langevin dynamics

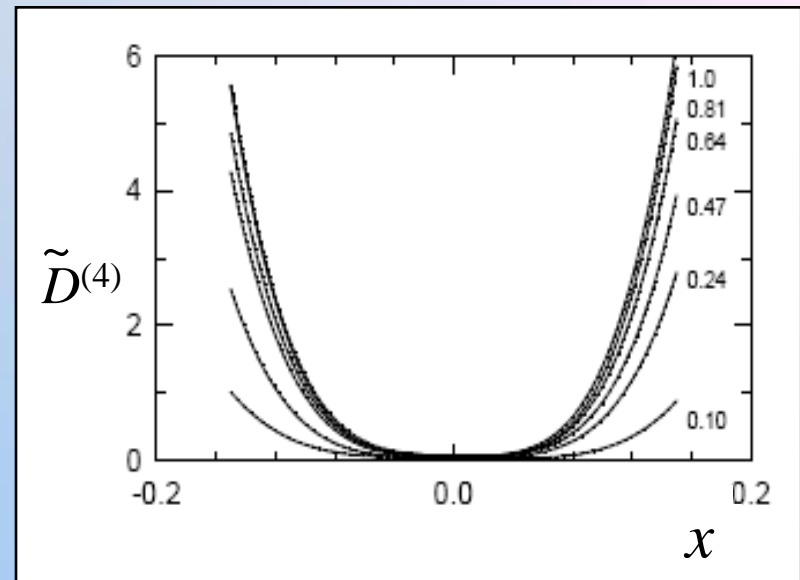
$$\dot{x} = D^{(1)}(x, t) + \sqrt{D^{(2)}(x, t)} \eta(t)$$



$$\begin{cases} \langle \eta(t) \rangle = 0 \\ \langle \eta(t) \eta(t') \rangle = 2\delta(t - t') \\ \text{Gaussian} \end{cases}$$

# Pawula theorem

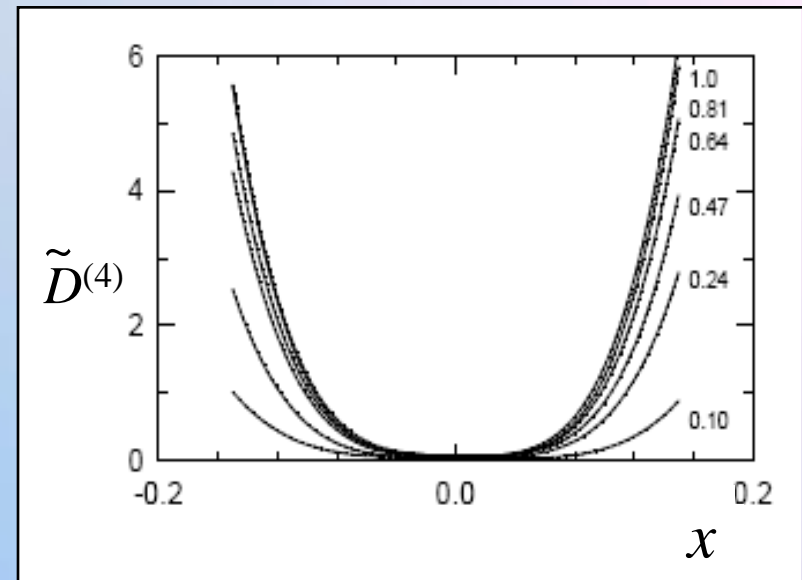
null 4th order coefficient  $D^{(4)}$   
→ truncate KM expansion at 2nd order,  
reducing to a **Fokker-Planck equation**



consistent with  $D^{(4)}(x, t) = 0$

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$$\left[ \int f(x)g(x)P(x)dx \right]^2 \leq \int f^2(x)P(x)dx \int g^2(x)P(x)dx$$

Schwartz

$\left\{ \begin{array}{l} \text{arbitrary } f, g \\ \text{non-negative } P \end{array} \right.$

$$\iint [f(x)g(y) - f(y)g(x)]^2 P(x)P(y)dxdy \geq 0$$

$$f(x) = (x - x')^n$$

$$g(x) = (x - x')^{n+m}$$

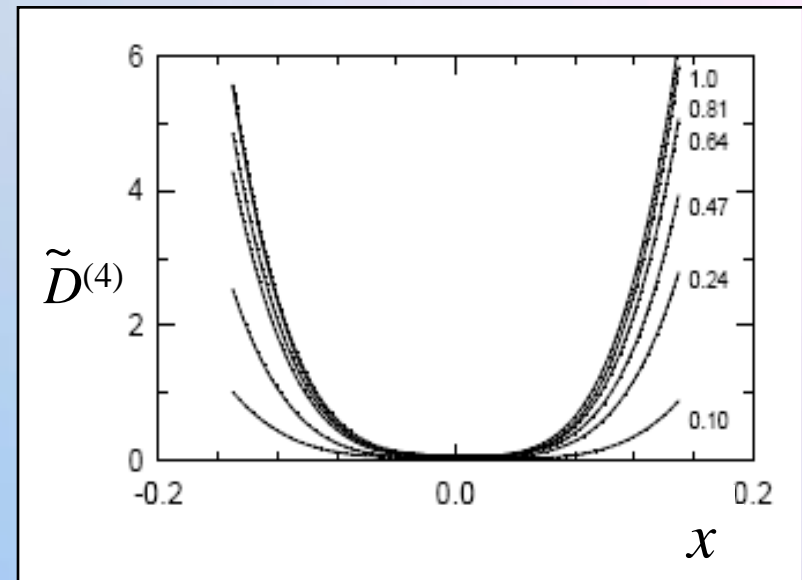
$$P(x) = P(x, t + \tau | x', t')$$



$$M_{2n+2m}^2 \leq M_{2n} M_{2n+2m} \quad n, m \geq 0$$

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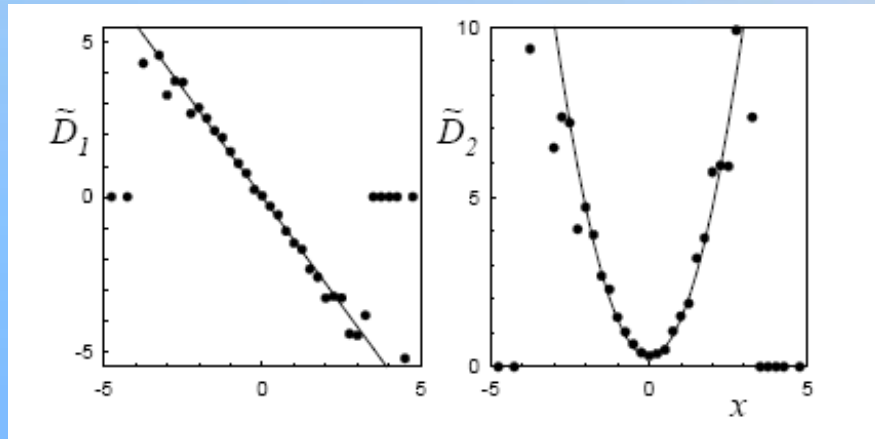


$$M_{2n+m}^2 \leq M_{2n} M_{2n+2m} \quad n, m \geq 0$$



$$D_{2n+m}^2 \leq cte D_{2n} D_{2n+2m} \quad n, m \geq 1$$

# Exemplo 1



$$\tilde{D}^{(1)} \rightarrow D^{(1)}$$

$$\tilde{D}^{(2)} \rightarrow D^{(2)}$$

$$\tilde{D}^{(4)} \rightarrow 0$$

$$\Delta t \rightarrow 0$$

$$\partial_t P(x,t) = \left[ -\partial_x D^{(1)}(x,t) + \partial_{xx} D^{(2)}(x,t) \right] P(x,t)$$

$$\dot{x} = -D^{(1)}(x) + \sqrt{D^{(2)}(x)} \eta(t)$$

$$\langle \eta(t) \rangle = 0$$

$$\langle \eta(t) \eta(t') \rangle = 2\delta(t-t')$$

Gaussian

# Exemplo 2

Poisson process

$$\dot{P}(m,t) = \lambda P(m-1,t) - \lambda P(m,t)$$

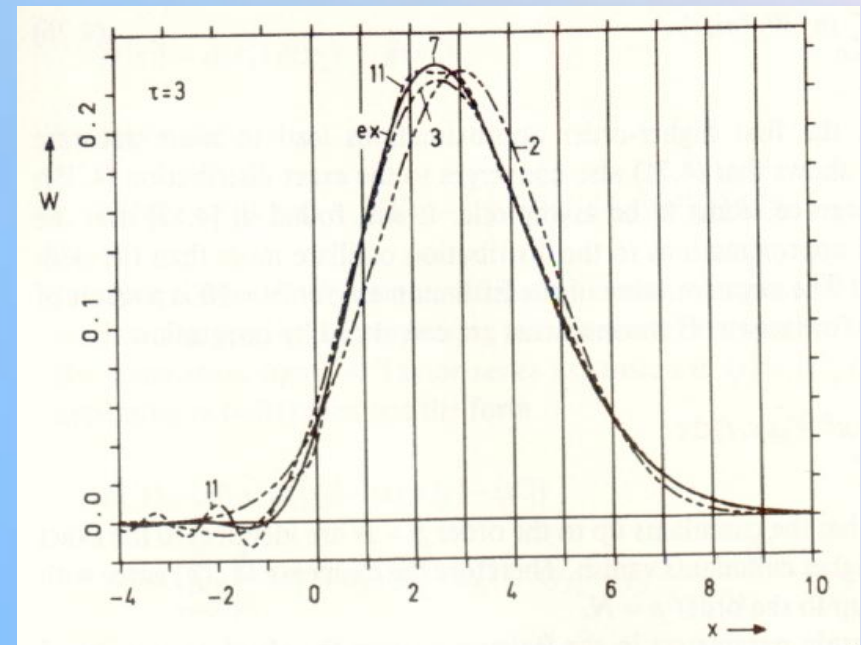
$$m \rightarrow x$$

$$\partial_t P(x,t) = \sum_{n \geq 1} \lambda [-\partial_x]^n P(x,t) / n!$$

$$P(x,t) = \lambda^x e^{-\lambda} / \Gamma(x+1)$$

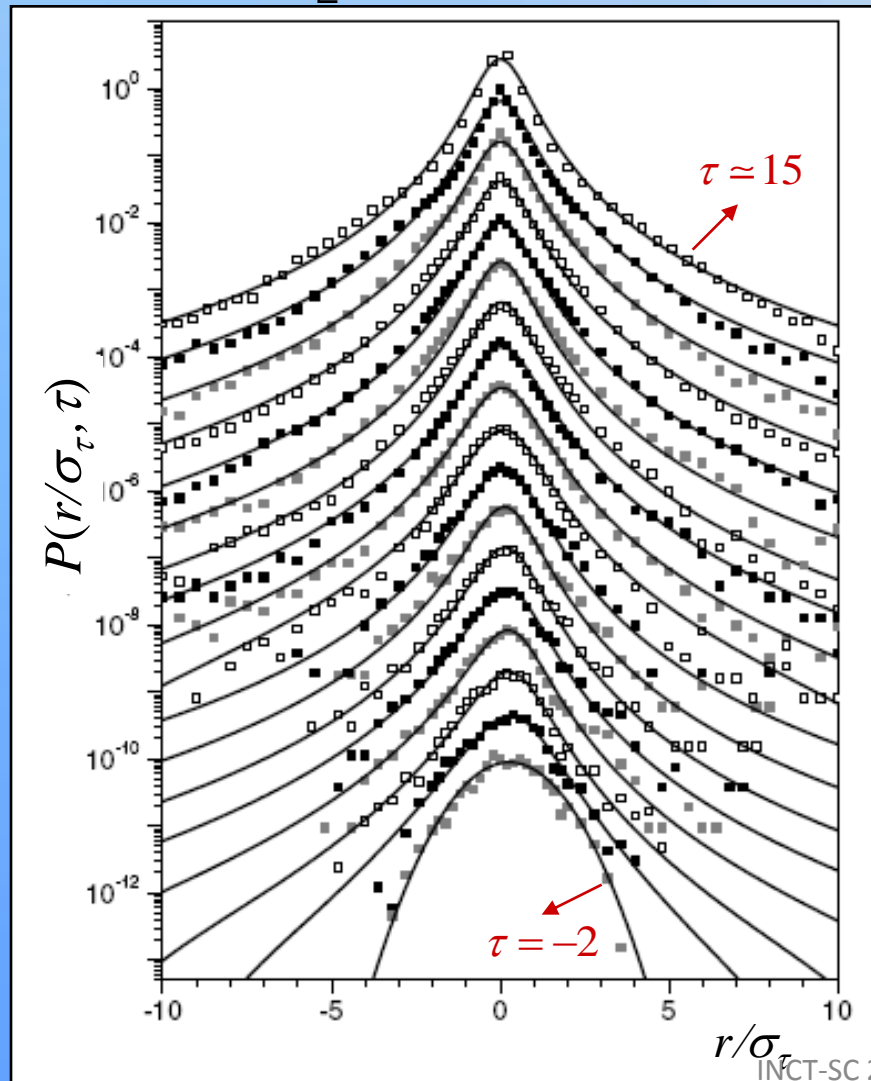
$$\partial_t P_N(x,t) = \sum_{n=1}^N \lambda [-\partial_x]^n P_N(x,t) / n!$$

$$P_N(x,t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} e^{ikx + \sum_{n=1}^N [-ik]^n \lambda t / n!} dk$$



# Applications: IBOVESPA

$$\partial_{\tau} P(r, \tau) = \left[ -\partial_r D^{(1)}(r, \tau) + \partial_{rr}^2 D^{(2)}(r, \tau) \right] P(r, \tau)$$



$$(\tau = -\log \Delta t / \Delta t_0)$$

➤ **Unified description**

Cortines, Riera, Anteneodo; *EPJB* (2007)

# Applications: Worldwide markets

➤  $D^{(1)} = -a_1 r$      $D^{(2)} = b_2 r^2 + b_0$

*universal  $r$ -dependence* for all analyzed markets at the monthly/weekly timescales

- $D^{(1)}$  and  $D^{(2)}$  reveal market inner mechanisms
  - $a_1$  (restoring force) *without significant differences* across markets, meaning similar deterministic rules constrain the dynamics of markets
  - $b_0$  (additive noise) *measure of market efficiency*
  - $b_2$  (multiplicative noise) main determining factor of the power-law exponents of the *tails of the PDFs*, has a wide relative variation for different markets

Cortines, Anteneodo, Riera; *EPJB* (2008)



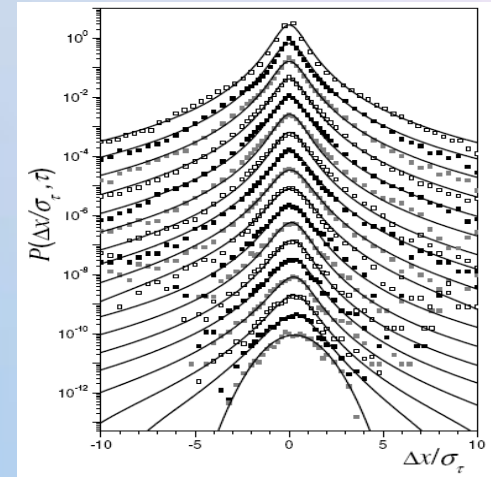
# Observation

returns at different lags  $\Delta t$  :

$$r(t) = \log x(t+\Delta t) - \log x(t)$$

$$\partial_\tau P(r, \tau) = \left[ -\partial_r D^{(1)}(r, \tau) + \partial_{rr}^2 D^{(2)}(r, \tau) \right] P(r, \tau)$$

$$\tau = -\log \Delta t / \Delta t_0$$



# Observation

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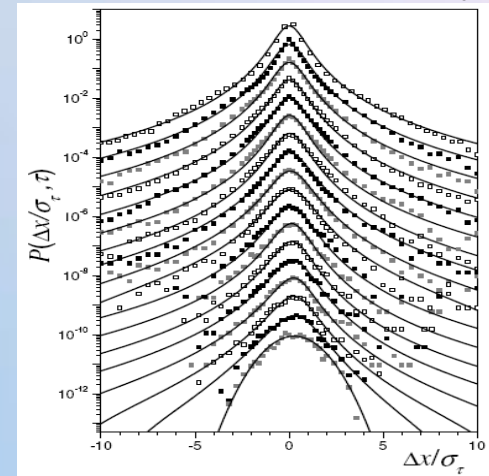
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$\Delta\tau \rightarrow 0$

$$\tilde{D}^{(k)}(r, \tau, \Delta\tau)$$

$$\tau = -\log \Delta t / \Delta t_0$$



# Observation

returns at different lags  $\Delta t$  :

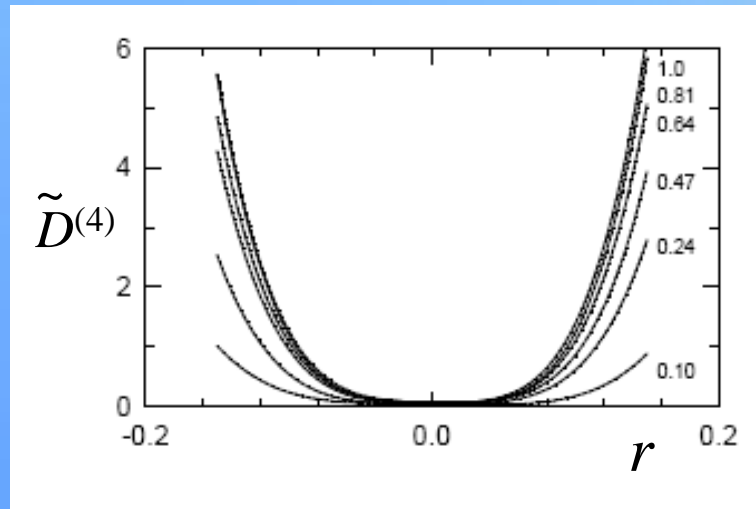
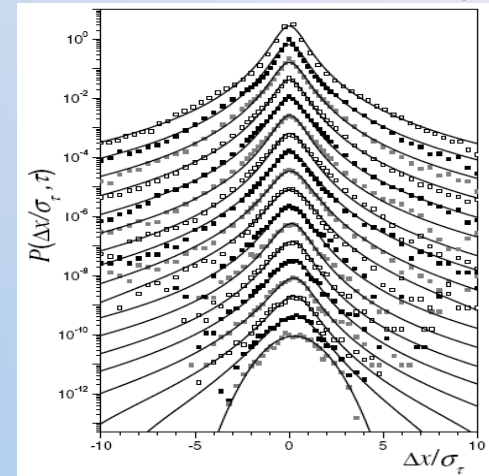
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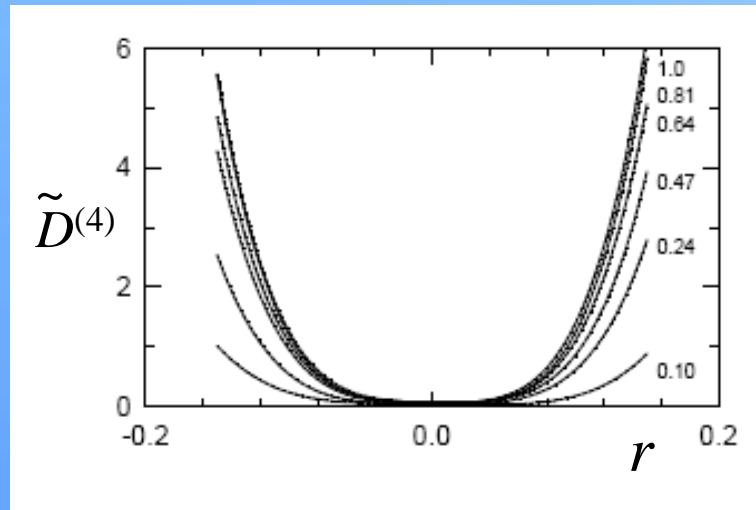
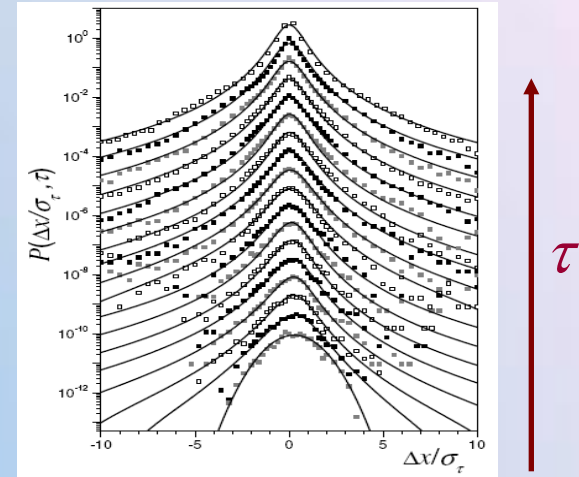
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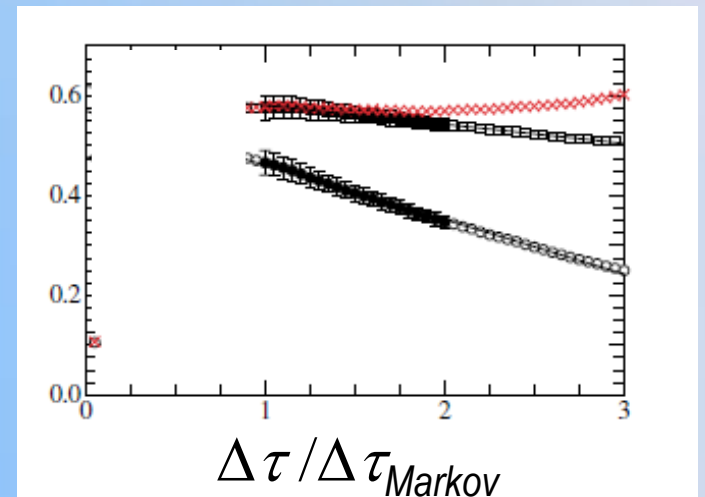
$$\Delta\tau \rightarrow 0$$

$$\tilde{D}^{(k)}(r, \tau, \Delta\tau)$$

$$\tau = -\log \Delta t / \Delta t_0$$



$$\tilde{D}^{(4)}(r, \tau, \Delta\tau) = a_{\tau, \Delta\tau} r^4 + b_{\tau, \Delta\tau} r^2 + c_{\tau, \Delta\tau}$$



# Observation

returns at different lags  $\Delta t$  :

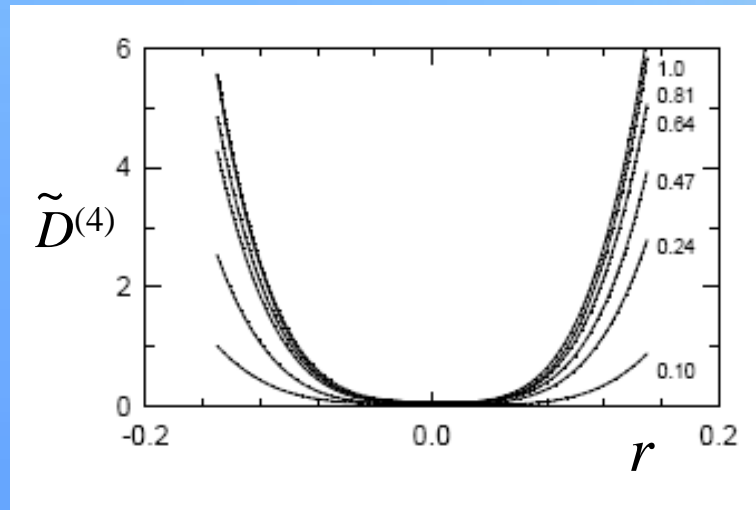
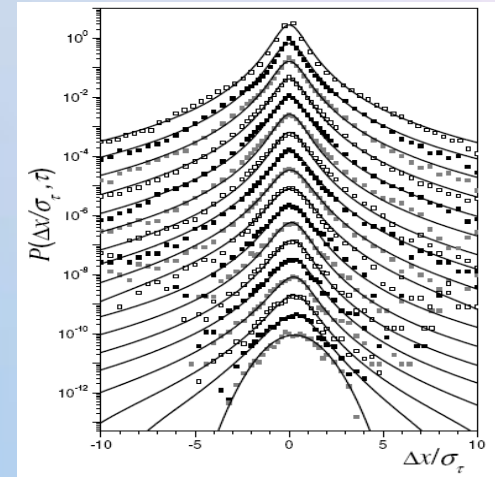
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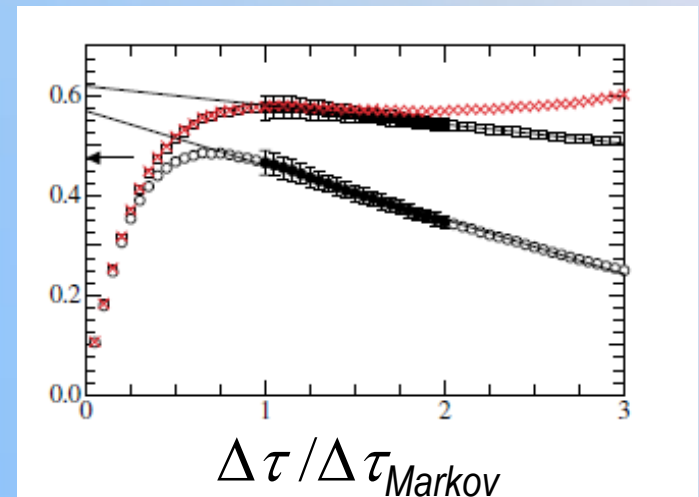
$$\Delta\tau \rightarrow 0$$

$$\tilde{D}^{(k)}(r, \tau, \Delta\tau)$$

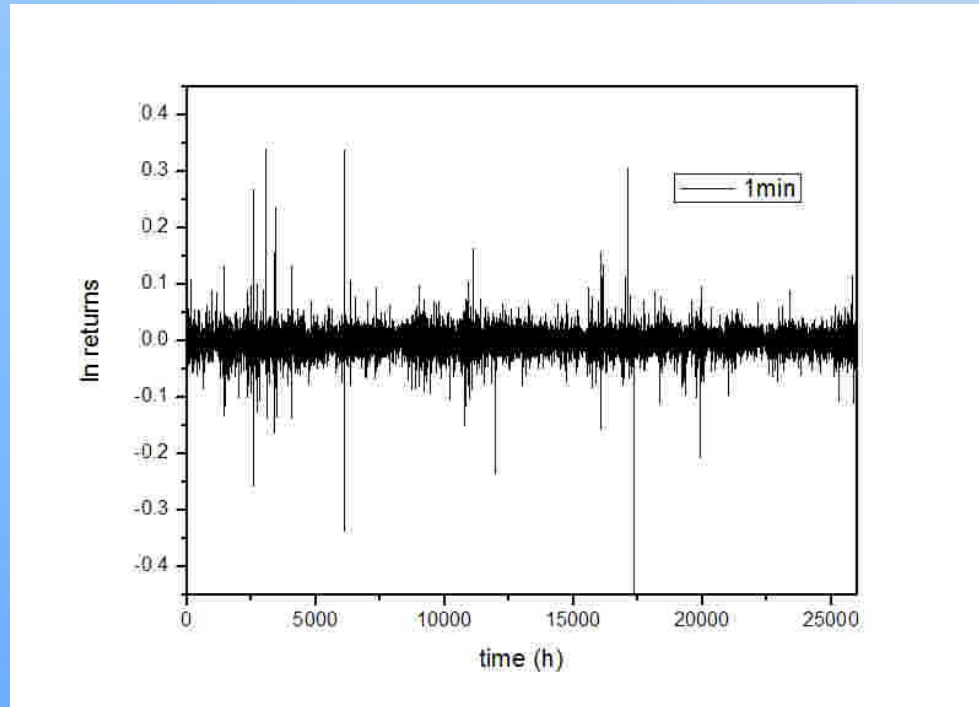
$$\tau = -\log \Delta t / \Delta t_0$$



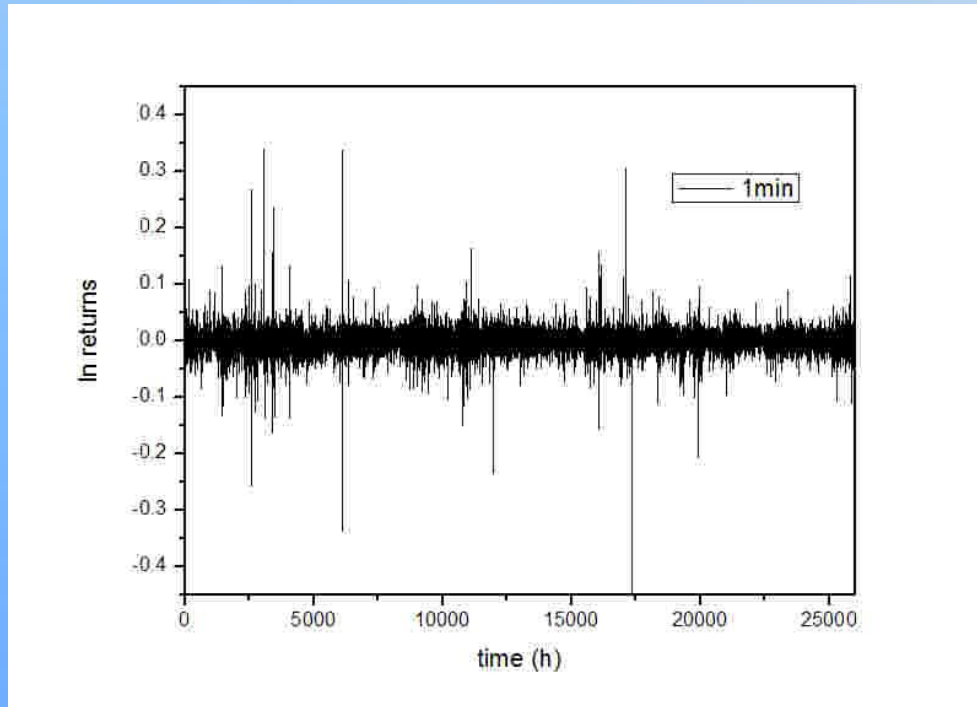
$$\tilde{D}^{(4)}(r, \tau, \Delta\tau) = a_{\tau, \Delta\tau} r^4 + b_{\tau, \Delta\tau} r^2 + c_{\tau, \Delta\tau}$$



Now: timescale  $t$  (given fixed lag “ $\Delta t$ ”)



Now: timescale  $t$  (given fixed lag “ $\Delta t$ ”)



$$D^{(k)}(x, t) = \lim_{\Delta t \rightarrow 0} \tilde{D}^{(k)}(x, t, \Delta t)$$

$\Delta t \rightarrow 0 ?$

$\Delta t_{min} \equiv 1/\text{data rate}$

$\Delta t_{max} \ll t_{char}$

# Applications

I

VOLUME 78, NUMBER 5

PHYSICAL REVIEW LETTERS

3 FEBRUARY 1997

## Description of a Turbulent Cascade by a Fokker-Planck Equation

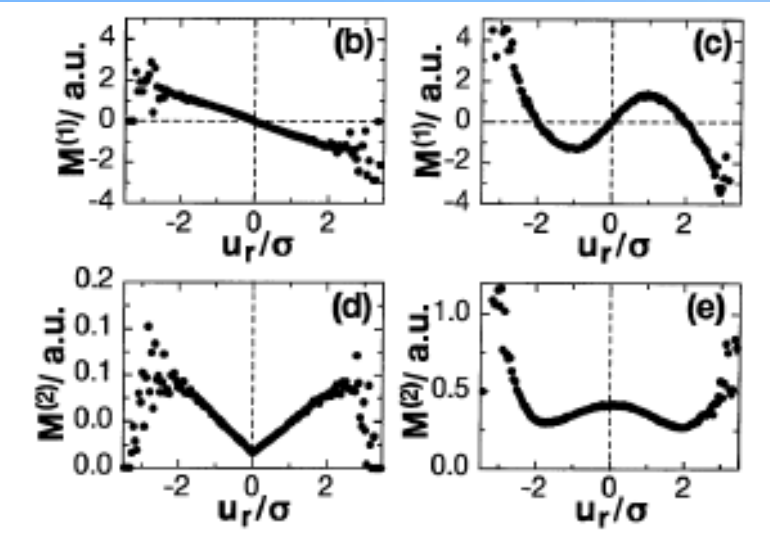
R. Friedrich

*Institut für Theoretische Physik und Synergetik, Universität Stuttgart, D-70550 Stuttgart, Germany*

J. Peinke

*Experimentalphysik II, Universität Bayreuth, D-95447 Bayreuth, Germany*

(Received 1 July 1996)



VOLUME 83, NUMBER 26

PHYSICAL REVIEW LETTERS

27 DECEMBER 1999

## Uniform Statistical Description of the Transition between Near and Far Field Turbulence in a Wake Flow

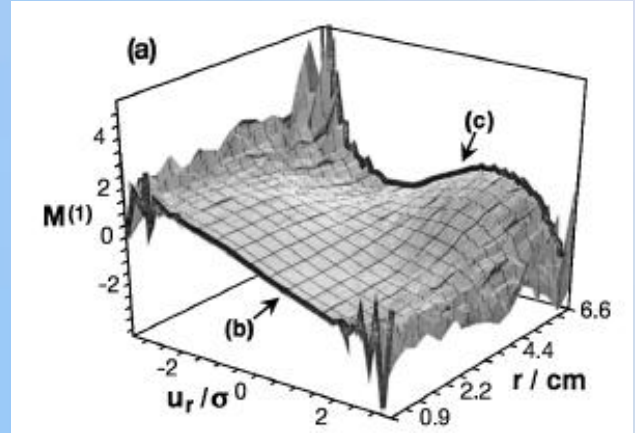
St. Lütk and J. Peinke

*Fachbereich Physik, Universität Oldenburg, D-26111 Oldenburg, Germany*

R. Friedrich

*Institut für theoretische Physik, Universität Stuttgart, D-70569 Stuttgart, Germany*

(Received 4 February 1999)





PHYSICAL REVIEW E 75, 060102(R) (2007)

## Markov analysis and Kramers-Moyal expansion of nonstationary stochastic processes with application to the fluctuations in the oil price

Fatemeh Ghasemi,<sup>1</sup> Muhammad Sahimi,<sup>2,\*</sup> J. Peinke,<sup>3</sup> R. Friedrich,<sup>4</sup> G. Reza Jafari,<sup>5</sup> and M. Reza Rahimi Tabar<sup>3,6,7,†</sup>

<sup>1</sup>*The Max Planck Institute for the Physics of Complex Systems, Nöthnitzer Strasse 38, D-01187 Dresden, Germany*

<sup>2</sup>*Mork Family Department of Chemical Engineering & Materials Science, University of Southern California, Los Angeles, California 90089-1211, USA*

<sup>3</sup>*Carl von Ossietzky University, Institute of Physics, D-26111 Oldenburg, Germany*

<sup>4</sup>*Institute for Theoretical Physics, University of Münster, D-48149 Münster, Germany*

<sup>5</sup>*Department of Physics, Shahid Beheshti University, Evin, Tehran 19839, Iran*

<sup>6</sup>*Department of Physics, Sharif University of Technology, Tehran 11365, Iran*

<sup>7</sup>*CNRS UMR 6529, Observatoire de la Côte d'Azur, BP 4229, 06304 Nice Cedex 4, France*

(Received 10 January 2007; revised manuscript received 9 May 2007; published 18 June 2007)

$$D^{(1)}(y) = -1.09y,$$

$$D^{(2)}(y) = 0.0033 - 0.003y + 0.716y^2$$

## Stochastic Qualifiers of Epileptic Brain Dynamics

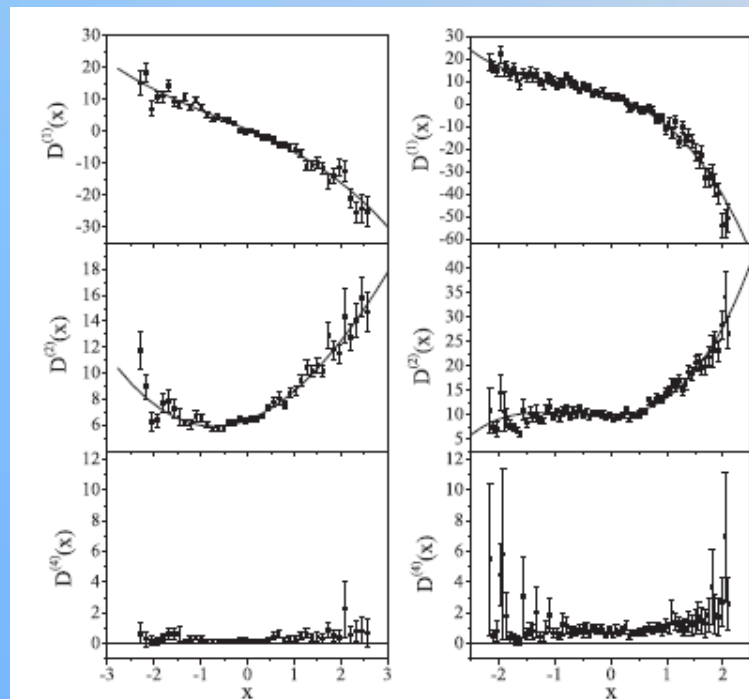
Jens Prusseit<sup>1,2,\*</sup> and Klaus Lehnertz<sup>1,2,3,†</sup>

FIG. 1. Estimated coefficients  $D^{(1)}$ ,  $D^{(2)}$ , and  $D^{(4)}$  for exemplary EEG time series (left: from a distant brain region; right: from within the epileptic focus). Shown are estimates for time

PHYSICAL REVIEW E **80**, 031127 (2009)

## Kramers-Moyal coefficients in the analysis and modeling of heart rate variability

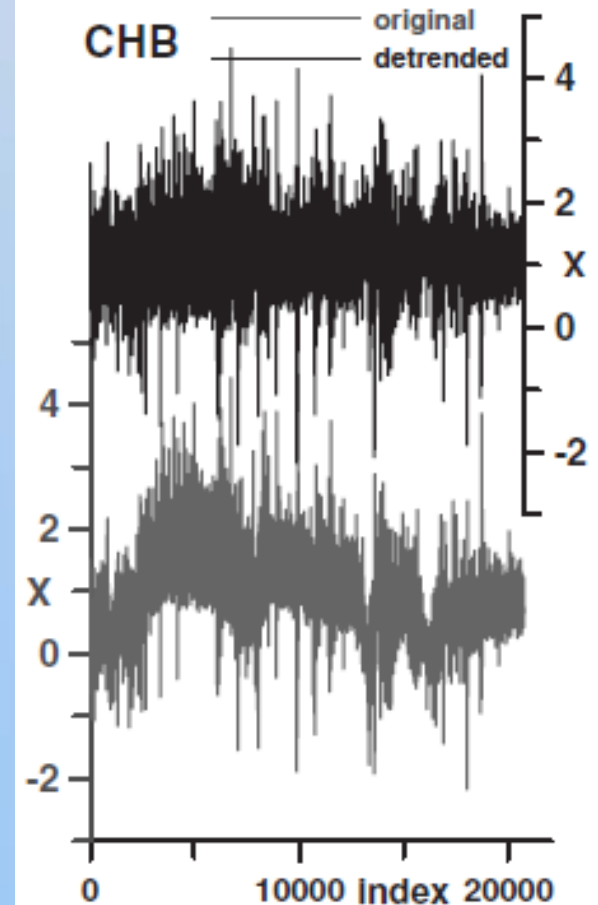
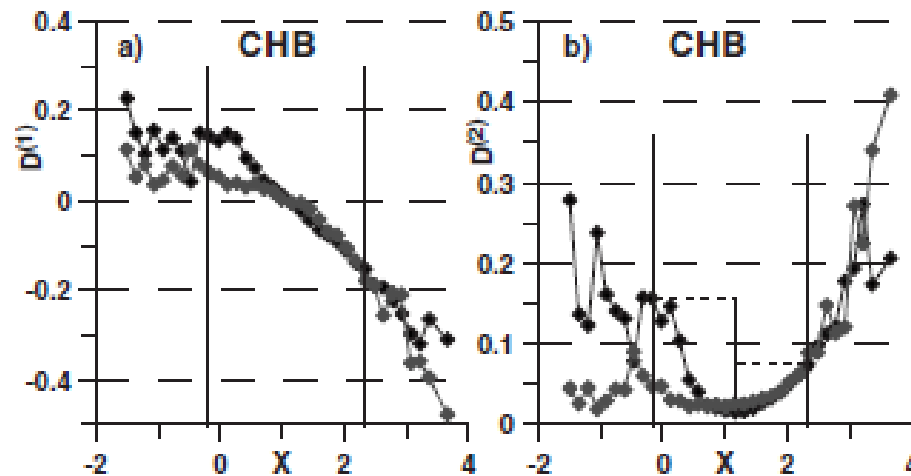
M. Petelczyc\* and J. J. Żebrowski†

*Faculty of Physics, Warsaw University of Technology, Koszykowa 75, 00-662 Warsaw, Poland*

R. Baranowski‡

*National Institute of Cardiology, Alpejska 42, 04-628 Warsaw, Poland*

(Received 8 February 2009; revised manuscript received 25 May 2009; published 18 September 2009)



# HOWEVER ...

$$D^{(k)}(x, t) = \lim_{\Delta t \rightarrow 0} \tilde{D}^{(k)}(x, t, \Delta t)$$

$\Delta t \rightarrow 0 ?$

\*  $\Delta t_{min}$

\* Finite time corrections  
(first order)

# Observation



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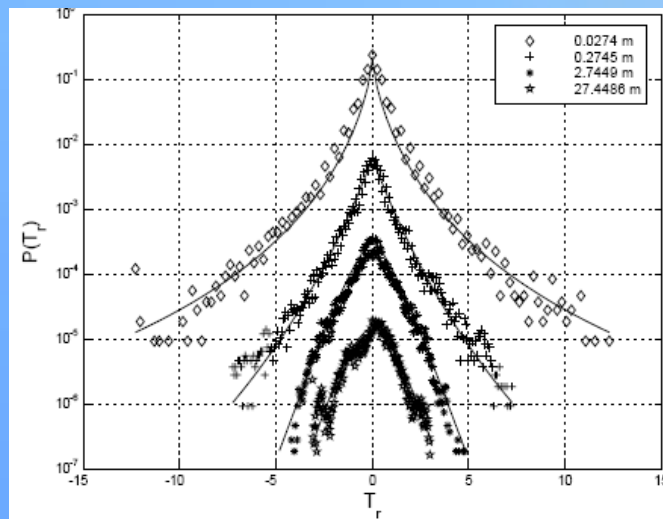
## Atmospheric turbulence within and above an Amazon forest

Fernando Manuel Ramos<sup>a,\*</sup>, Maurício José Alves Bolzan<sup>b</sup>,  
Leonardo Deane Abreu Sá<sup>a,c</sup>, Reinaldo Roberto Rosa<sup>a</sup>

<sup>a</sup> Instituto Nacional de Pesquisas Espaciais, INPE, São José dos Campos, SP, Brazil

<sup>b</sup> Universidade do Vale do Paraíba, UNIVAP, São José dos Campos, SP, Brazil

<sup>c</sup> Museu Paraense Emílio Goeldi (Campus de Pesquisa), Coordenação de Ciências da Terra e Ecologia (CCTE),  
Escritório do CPTEC/INPE, Belém, PA, Brazil



# Observation



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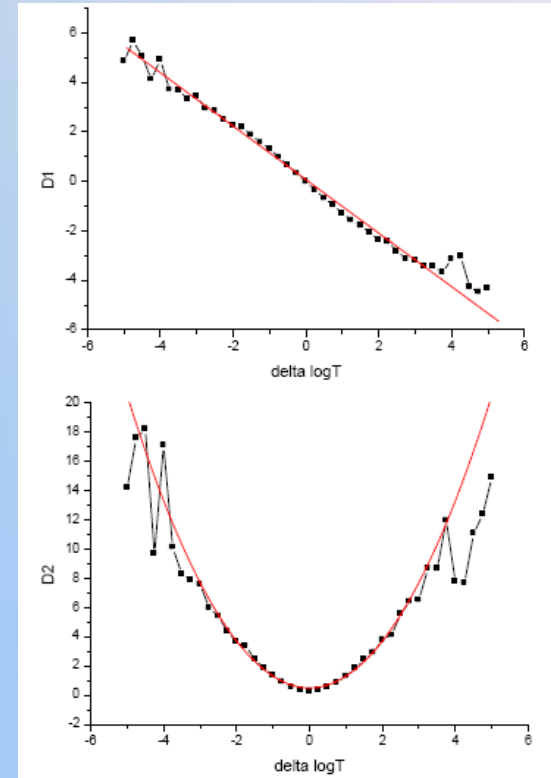
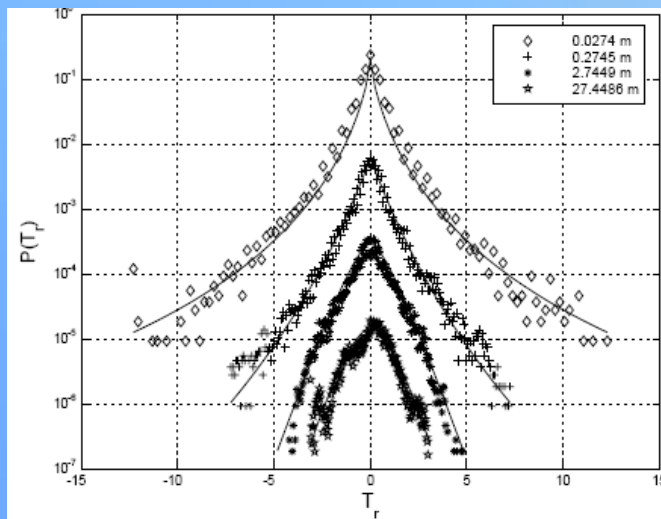
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<sup>a</sup> Instituto Nacional de Pesquisas Espaciais, INPE, São José dos Campos, SP, Brazil

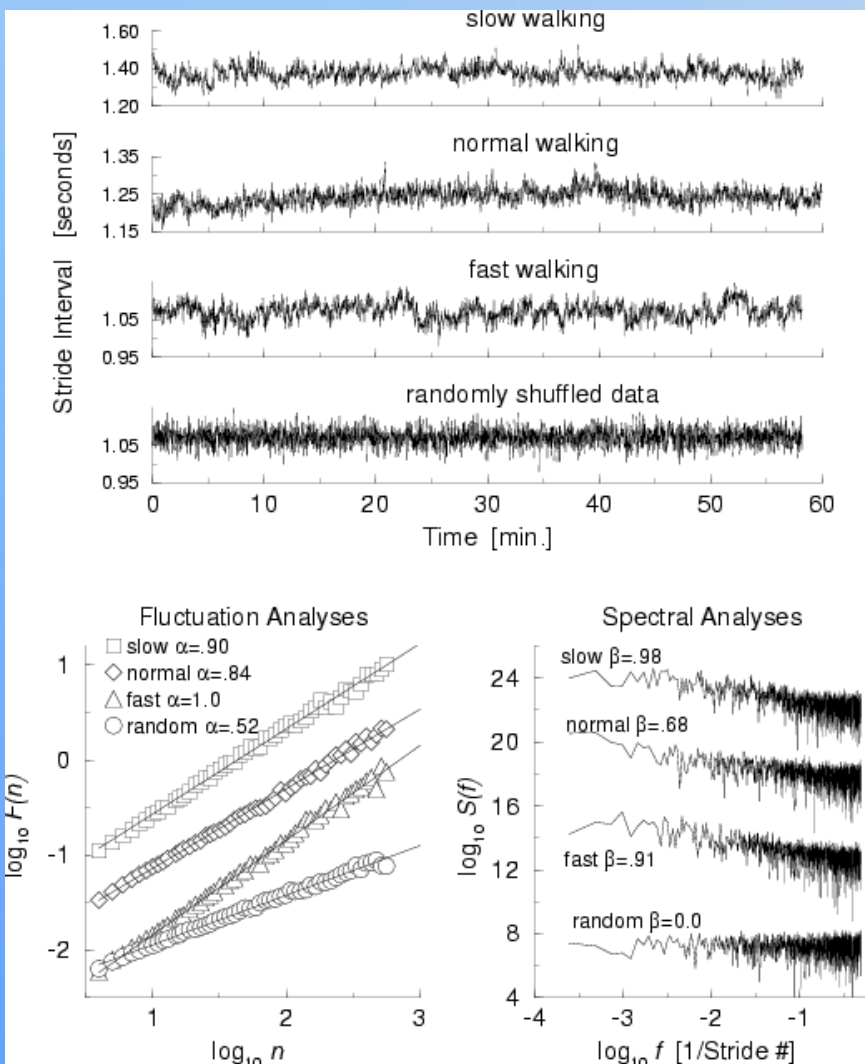
<sup>b</sup> Universidade do Vale do Paraíba, UNIVAP, São José dos Campos, SP, Brazil

<sup>c</sup> Museu Paraense Emílio Goeldi (Campus de Pesquisa), Coordenação de Ciências da Terra e Ecologia (CCTE),  
Escritório do CPTEC/INPE, Belém, PA, Brazil



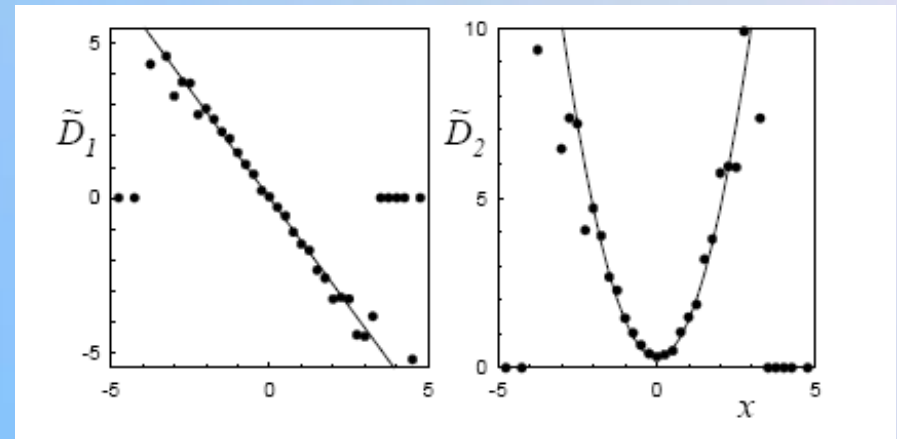
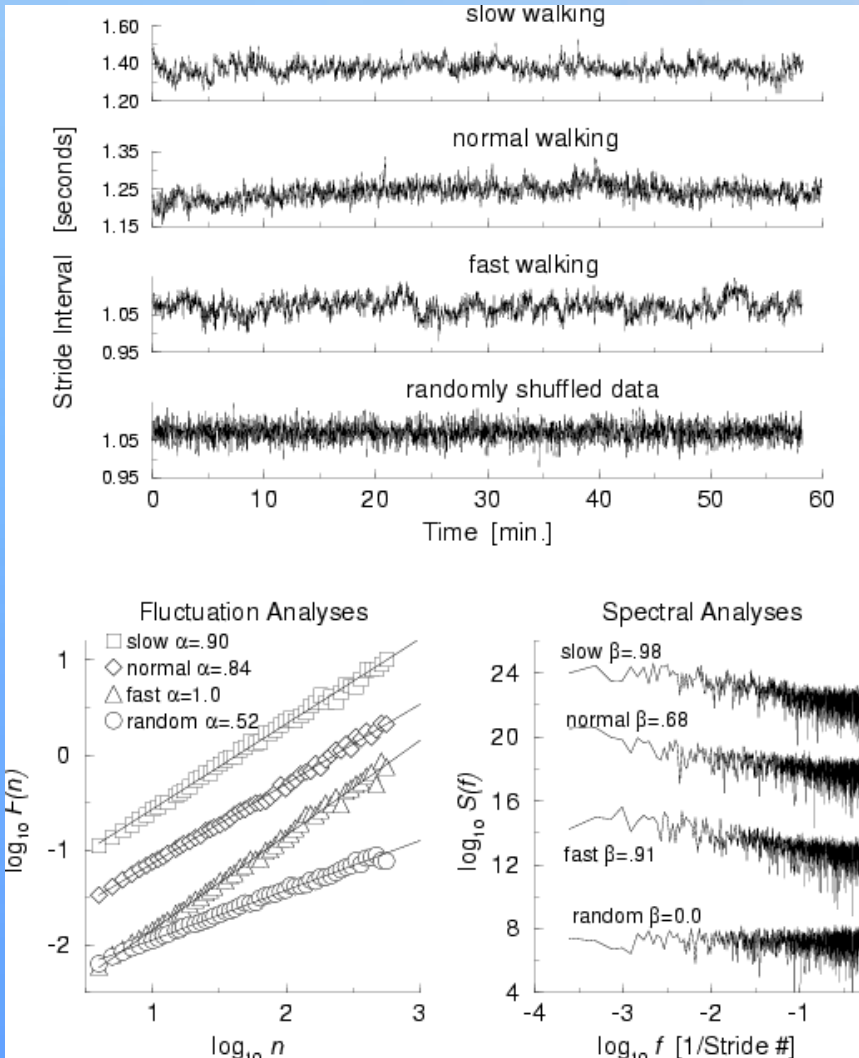
## Long-term Recordings of Gait Dynamics: Unconstrained and Metronomic Walking

Hausdorff et al.; *J Appl Physiol* 8(1996)



## Long-term Recordings of Gait Dynamics: Unconstrained and Metronomic Walking

Hausdorff et al.; *J Appl Physiol* 8(1996)





$$\partial_t P(z,t) = \left[ \underbrace{-\partial_z D^{(1)}(z,t)}_{-a_1(t)z} + \underbrace{\partial_{zz} D^{(2)}(z,t)}_{[b_0(t) + b_2(t)z^2]} \right] P(z,t)$$

$$\dot{z} = D^{(1)}(z,t) + \sqrt{D^{(2)}(z,t)} \boldsymbol{\eta}(t)$$

Itô-Langevin dynamics

$$\dot{z} = -a_1(t)z + \sqrt{b_0(t) + b_2(t)z^2} \boldsymbol{\eta}(t)$$

$$\left\{ \begin{array}{l} \langle \boldsymbol{\eta}(t) \rangle = 0 \\ \langle \boldsymbol{\eta}(t) \boldsymbol{\eta}(t') \rangle = 2\boldsymbol{\delta}(t-t') \\ \text{Gaussian} \end{array} \right.$$

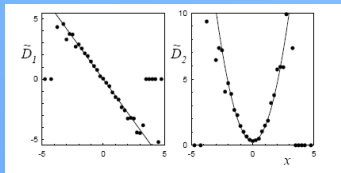
$$\dot{z} = -a_1(t)z + \sqrt{b_0(t)} \boldsymbol{\eta}_1(t) + \sqrt{b_2(t)} z \boldsymbol{\eta}_2(t)$$

$\boldsymbol{\eta}_1, \boldsymbol{\eta}_2$ : independent

Anteneodo, Tsallis, *JMP* (2003)  
Anteneodo, *Physica A* (2005)

➤ *Finite-time effects*

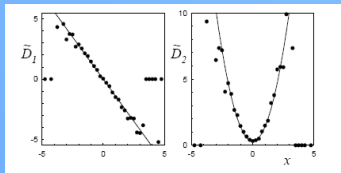
➤ *Linear-quadratic*



*Exact corrections*

➤ *Finite-time effects*

➤ *Linear-quadratic*



*Exact corrections*

➤ *See next talk*