统计物理学在金融动力学中的应用

-- 经验规律与唯象模型

郑波

浙江大学物理系

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物理学家为什么对经济金融系统感兴趣?

- 经济金融是显而易见重要的，定性学科的定量化是必由之类，而金融首当其冲

- 几百年历史的物理学拥有成熟而先进的思维方法，拓广研究领域是必由之路，金融是“不能重复”的实验，具有极大的挑战性，而且高度贴近生活

现 状

- 所谓的“经济金融物理学”(Econophysics)还没有成为物理学成熟的分支，因为目前而言她对经济金融的意义大于对物理学。

- 领头羊是Boston大学的Stanley，其他研究组、包括欧洲的法、英、德、以色列，亚洲的日本、韩国、印度、台湾、香港，我国大陆的浙江大学、复旦大学、华东理工大学、北京师范大学、中国科技大学等

- 广义的Econophys范围更广，包括博弈论、网络等

- 南京大学都有为院士主编的《物理学大辞典》将编录《经济物理学分册》

现 状

- 物理学的发展道路：观测自然现象，开展实验研究，积累观测和实验数据，唯象模型和局部的经验理论，微观模型和统一的基本理论，近年来的数值模拟。

- 金融物理学的发展道路：观测金融现象，积累观测数据，唯象模型和局部的经验规律，数值模拟方法，微观模型和统一的微观理论，开展实验研究。

Financial dynamics

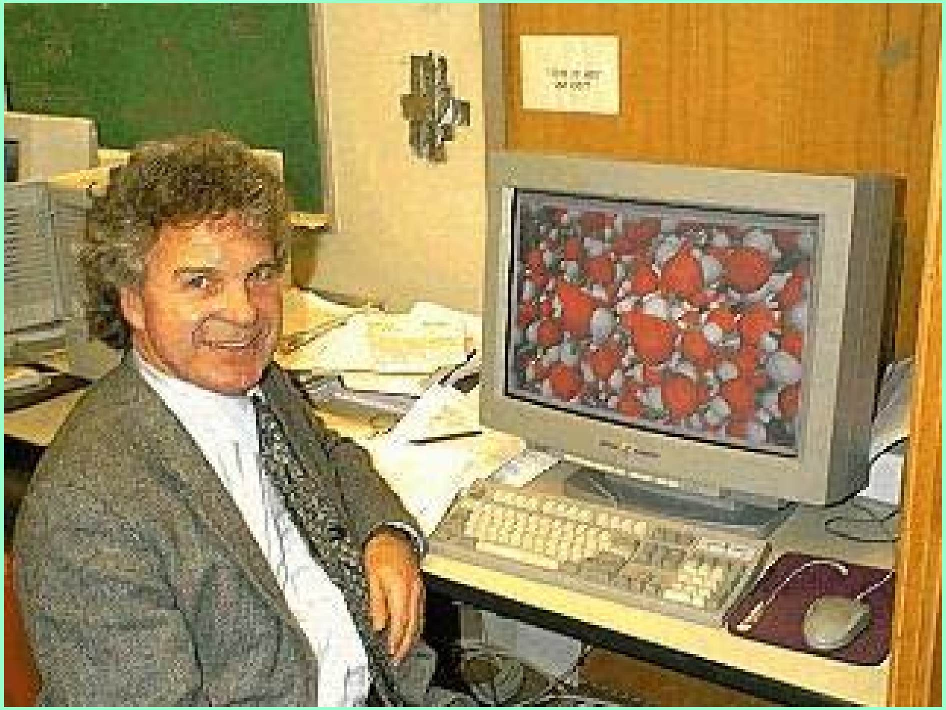
2. J.J. Chen and B. Zheng, Agent-based model with asymmetric trading and herding in complex financial dynamics, submitted to Plos One, 2013
3. X.F. Jiang and B. Zheng, Interaction structure of communities in complex financial systems, submitted to PRE, 2013
4. X.F. Jiang, B. Zheng and J. Shen, Time reversal asymmetry in financial markets, Physica A, 2013
5. X.F. Jiang and B. Zheng, Anti-correlations and subsectors in financial systems, **EPL 97** (2012) 48006
6. T. Qiu and B. Zheng, Network structure of financial dynamics, **New J. Phys. 12** (2010) 043057
7. J. Shen and B. Zheng, On return-volatility correlation in financial dynamics, **Europhys. Lett. 88** (2009) 28003.
8. J. Shen and B. Zheng, Cross-correlation in financial dynamics, **Europhys. Lett. 86** (2009) 48005
8. T. Qiu, B. Zheng, F. Ren and S. Trimper, Return-volatility correlation in financial dynamics, **Phys. Rev. E73** (2006) 065103(R)
9. F. Ren, B. Zheng, T. Qiu and S. Trimper, Minority games with score-dependent and agent-dependent payoffs, **Phys. Rev. E74** (2006) 041111

Publications

9. 郑波，金融动力学的时空关联与大波动特性
   -- 兼谈中西方金融市场的对比研究，
   《物理》第39卷（2010年）第95页.
10. 郑波，金融市场的微观动力学及其数值模拟研究，
   《管理学报》第6卷（2009年）第1608页

美国Boston Univ., HE Stanley

Citation is within top 100



Contents

How to look at financial dynamics from the view of physicists?

Good variable: price return $R_i(t)$

- **Probability distributions**
- **Temporal and spatial correlations**
- **Non-stationary dynamics**
- **Micro- or meso-scopic modeling**

Complexity in modeling or human experiment

$$\dot{R}_i(t) = D(\{R_j(t)\}, J_i) + \eta_i$$

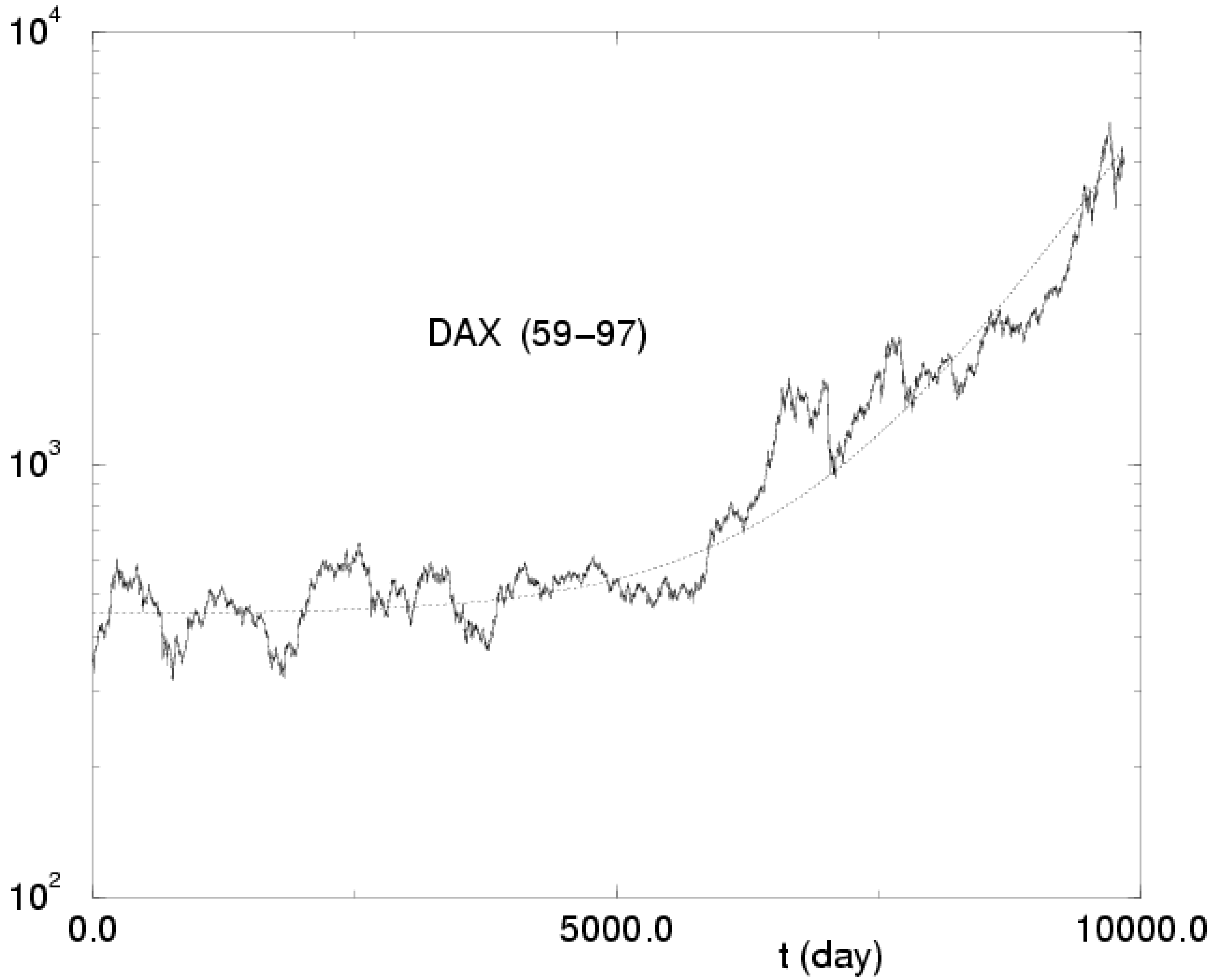
$$e.g., \qquad D(\ldots) = K \sum_{<ij>} R_j(t) + J_i$$

*** Irregular interactions**

*** Non-local interactions**

*** Time dependent interactions**

德国的 Financial index



Mantegna and Stanley, Nature 376 (1995)46

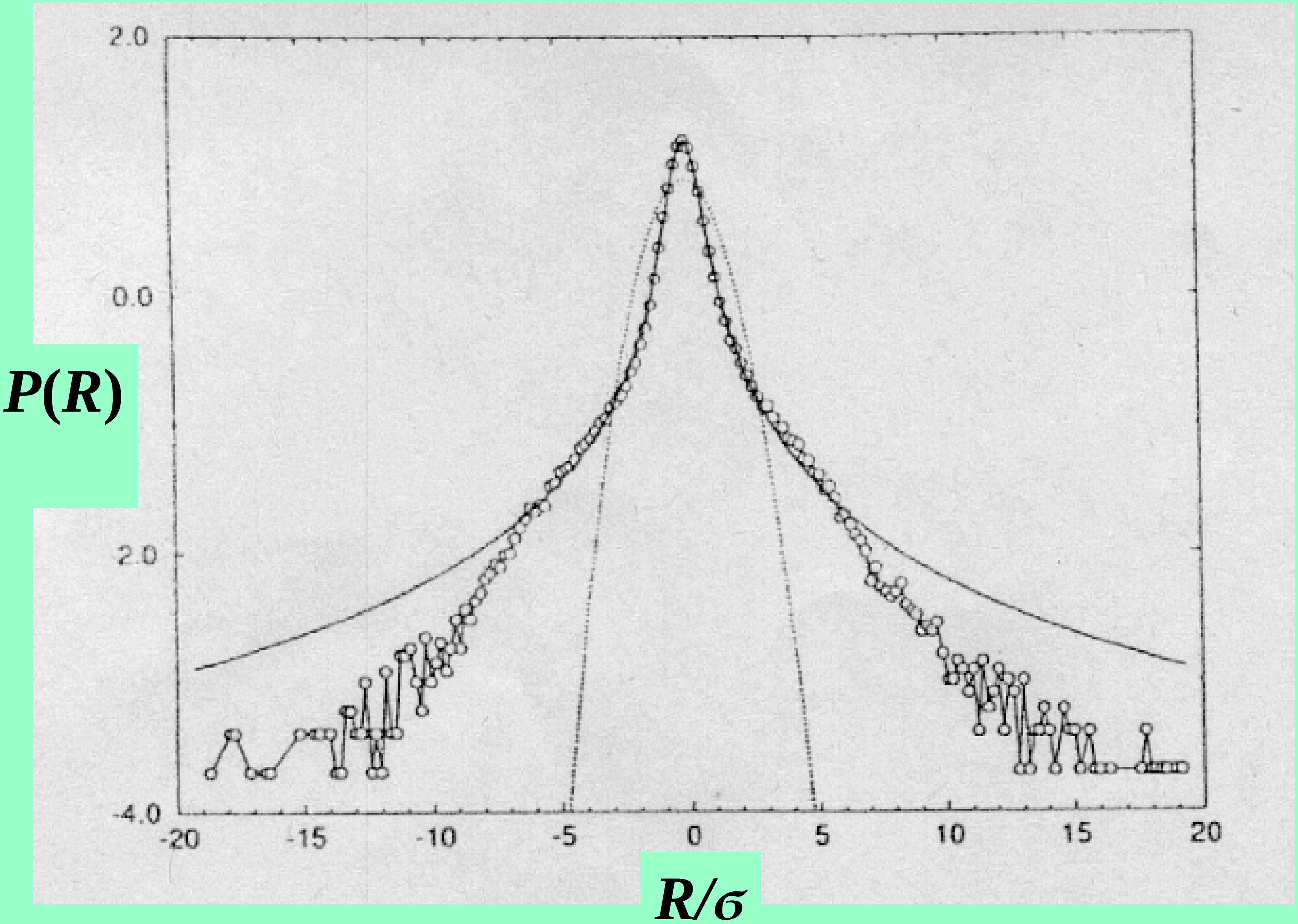
Financial index $Y(t')$

Return $R(t',\Delta t) = Y(t'+\Delta t) - Y(t')$

Probability distribution $P(R,\Delta t)$

shorter Δt **truncated Levy distribution**

longer Δt **Gaussian**



P(R)
R/σ
2.0
0.0
2.0
-4.0
-20
-15
-10
-5
0
5
10
15
20

Let $R(t') = \ln Y(t'+1) - \ln Y(t')$

Auto-correlation of *R*

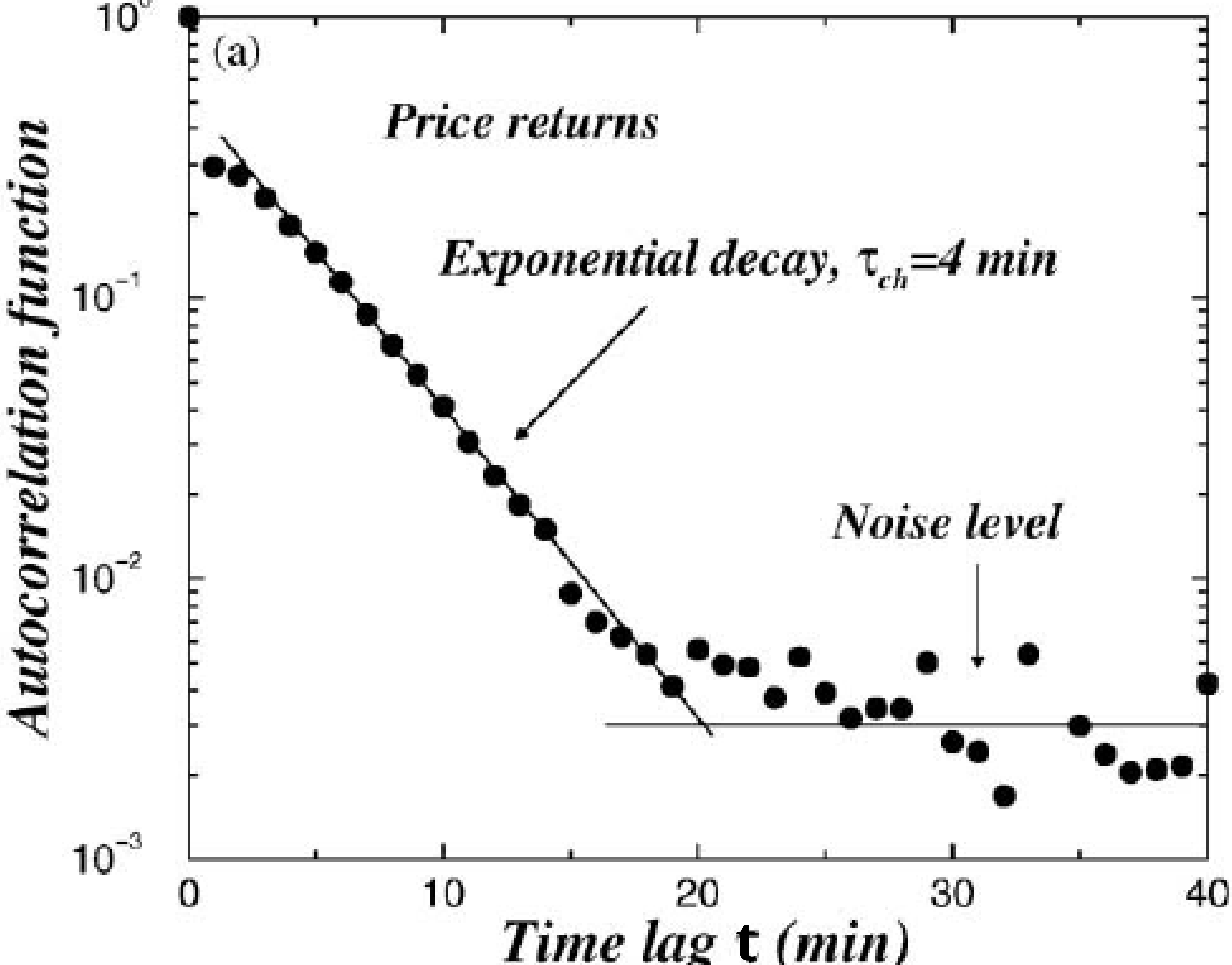
$$A(t) = < R(t'+t)R(t') > - < R(t') >^2$$

$$\propto e^{-\sigma t}$$ **exponentially decay**

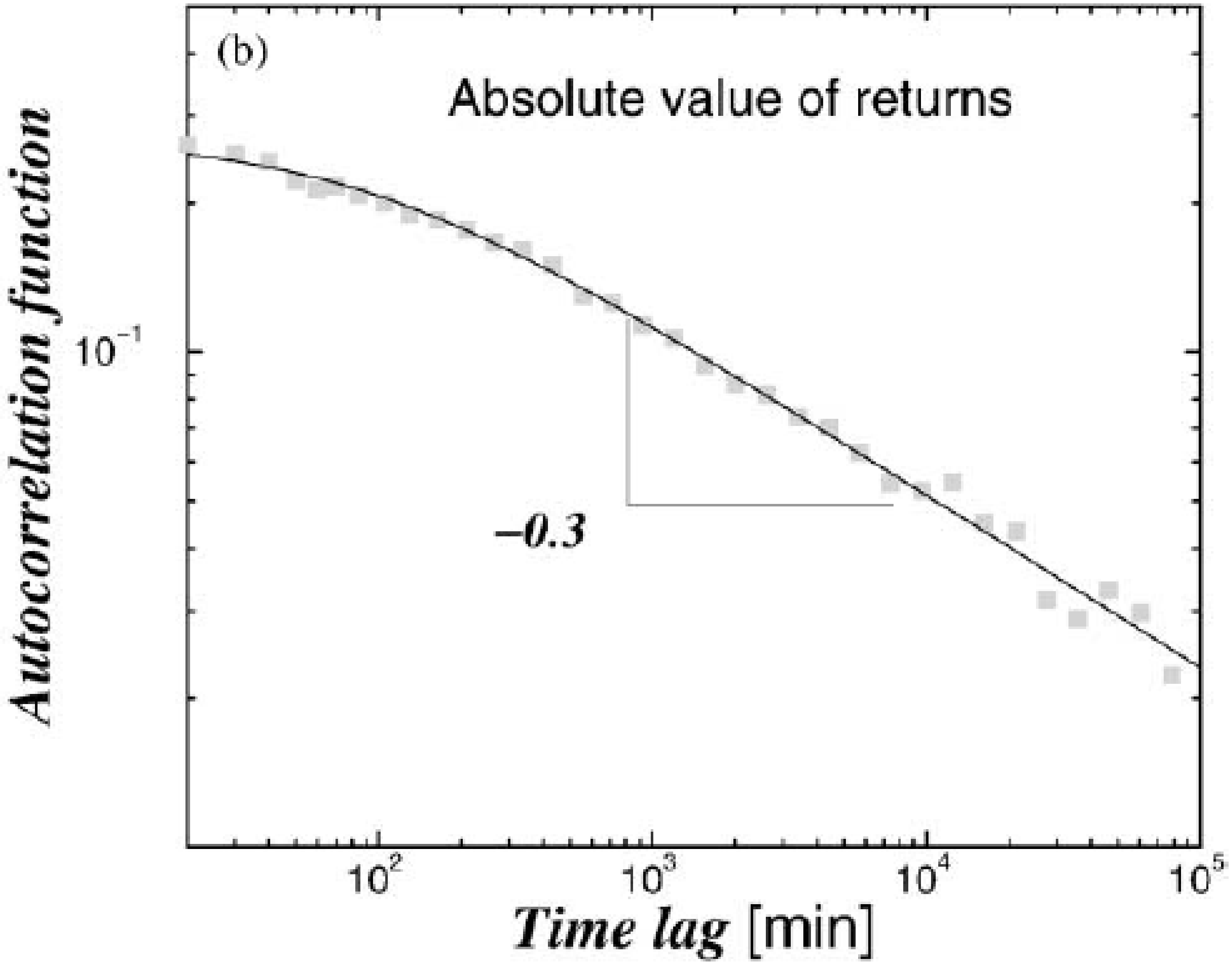
Auto-correlation of $|R|$

$$A(t) = <|R(t'+t)||R(t')|> - <|R(t')|>^2$$

$$\propto t^{-\gamma}$$ **power-law decay!!**



(a)
Price returns
Exponential decay, τ_{ch}=4 min
Noise level
Autocorrelation function
Time lag t (min)
10^0
10^{-1}
10^{-2}
10^{-3}
0
10
20
30
40


(b)
Absolute value of returns
Autocorrelation function
10^{-1}
−0.3
10^2
10^3
10^4
10^5
Time lag [min]

Summary

* 收益率***R(t')*** 是时间短程相关
* 波动率|***R(t')***| 是时间长程相关
* 胖尾分布 $P(Z,t) \propto Z^{-\beta}$ **for small *t***
* 高低不对称，时间反演不对称
* 股市的崩溃
* 时空结构

…….

前几年偏物理，近几年逐步偏金融，
侧重研究西方股票市场

研究思路

* 市场数据的唯象分析和经验模型

-- 不可重复的实验

* 微观模型的理论计算和数值模拟

* 真人实验

-- 极大的挑战，如何简化问题，又保留其核心与实质

统计物理学的方法

* 微观高频数据和定量分析
* 关联函数计算

* 微观多体模型

* 网络结构和动力学
* 实验研究

* **Others, e.g., symmetry analysis, phase transition, renormalization group method, etc**

微观多体模型

* 羊群模型

  股民结群，相互作用从简单到复杂，五花八门

* 多体博弈论

  多体不完全信息博弈，思路清晰，但是离真实市场有一定距离

* 订单模型

  出发点比较实际，但需要附加假设

* Ising类模型
* 随机过程模型

金融微观模型的现状

* 可以取得局部成功，但整体不令人满意。波动率的运动规律相对简单，而价格本身的运动规律极其艰难

* 微观多体模型加上经验参数较令人信服。例如Stanley等用市场数据确定模型参数

PNAS 109(2012)8388

Herd behavior in a complex adaptive system

Li Zhao[a], Guang Yang[a], Wei Wang[a], Yu Chen[b], J. P. Huang[a,1], Hirotada Ohashi[b], and H. Eugene Stanley[c,1]

[a]Department of Physics and State Key Laboratory of Surface Physics, Fudan University, Shanghai 200433, China; [b]Department of Systems Innovation, Graduate School of Engineering, University of Tokyo, 7-3-1 Hongo, Bunkyo-ku, Tokyo 113-8656, Japan; and [c]Center for Polymer Studies and Department of Physics, Boston University, Boston, MA 02215

Contributed by H. Eugene Stanley, April 7, 2011 (sent for review September 13, 2010)

In order to survive, self-serving agents in various kinds of complex adaptive systems (CASs) must compete against others for sharing limited resources with biased or unbiased distribution by conducting strategic behaviors. This competition can globally result in the balance of resource allocation. As a result, most of the agents and species can survive well. However, it is a common belief that the formation of a herd in a CAS will cause excess volatility, which can ruin the balance of resource allocation in the CAS. Here this belief is challenged with the results obtained from a modeled resource-allocation system. Based on this system, we designed and conducted a series of computer-aided human experiments including herd behavior. We also performed agent-based simulations and theoretical analyses, in order to confirm the experimental observations and reveal the underlying mechanism. We report that, as long as the ratio of the two resources for allocation is biased enough, the formation of a typically sized herd can help the system to reach the balanced state. This resource ratio also serves as the critical point for a class of phase transition identified herein, which can be used to discover the role change of herd behavior, from a ruinous one to a helpful one. This work is also of value to some fields, ranging from management and social science, to ecology and evolution, and to physics.

experimental econophysics | computational econophysics | market-directed resource-allocation game | minority game | agent-based model

allocation system. Accordingly, herd behavior is commonly seen as a tailor-made cause for explaining bubbles and crashes in a CAS with the existence of extremely high volatility. But is this "common sense" always right? Based on results of this study, we argue that herd behavior should not be labeled like the killer of balance and stability all the time. Here we focus on the effect of herding on the whole CAS for resource allocation, because it is most important for as many agents (involving human beings) as possible to survive in various kinds of CASs like social, ecological or biological systems. Therefore, we shall not study or consider the details on how to reach a herd through contagion and/or imitating. In fact, our results are not dependent on the process of herding formation.

Experiment

We design and conduct a series of computer-aided human experiments, on the basis of the resource-allocation system (4, 11–13), in order to study the necessary conditions for a CAS to reach the ideal balanced state. Using this kind of experimental settings will allow us to investigate the herd behavior in a well regulated abstract system for resource allocation, which reflects the fundamental characteristics of many CASs (14–17). Human participants of the resource-allocation experiment are students recruited from several departments of Fudan University. Before the start of experiments, a leaflet (as shown in *SI Text: Part I*) was provided which explains configurations of the experiment and

What are the (potential) contributions?

-- universal and quasi-universal behavior

- 所有或一类股票市场共有的性质
- 所有或一类个体股票共有的性质
- 全部或一段时间的统计性质

对物理学，目前并无概念上的实质发现；对经济金融学，主要是方法上的进展

与相关学科的比较（粗浅理解）

- 金融数学一类是金融问题提炼出来的数学，较宏观，另一类是优化算法，较具体
- 定量金融比较宏观，数学相对简单
- 行为金融以相对“简单”例子进行心理分析

我们的研究思路

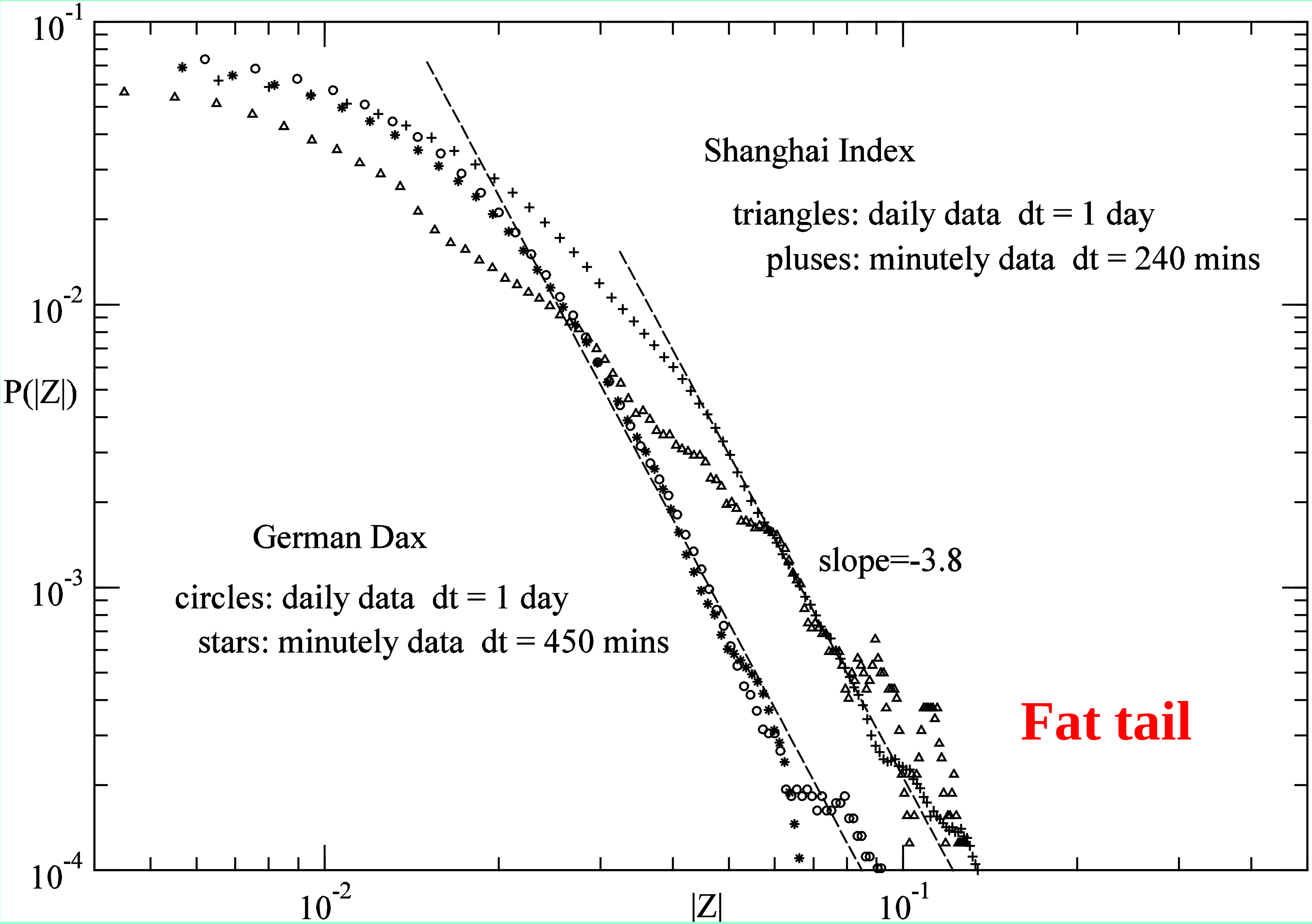
* 中西方金融市场的对比研究
* 发展和应用时间系列展开方法；强调时间非局域关联函数等
* 真人实验
* 如何赚钱

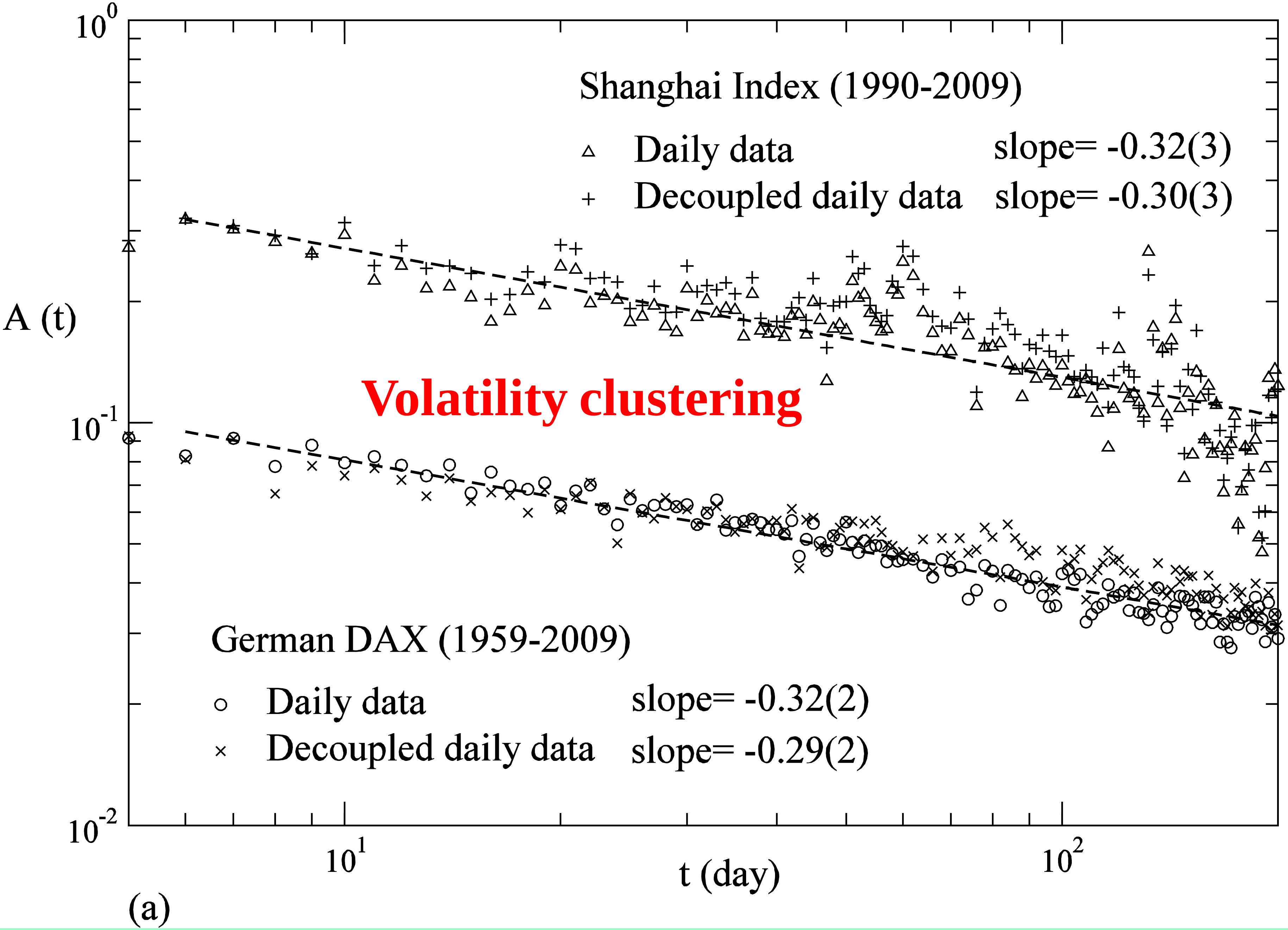
中西方金融市场对比研究

Chinese and western stock markets

share common basic features,
such as probability distribution of returns,
auto-correlations of returns and volatility

but not all characteristics, e.g.,
higher-order time correlations,
cross-correlations of returns
Non-stationary dynamic behavior


Shanghai Index
triangles: daily data dt = 1 day
pluses: minutely data dt = 240 mins
German Dax
circles: daily data dt = 1 day
stars: minutely data dt = 450 mins
slope=-3.8
Fat tail
P(|Z|)
|Z|
10^{-1}
10^{-2}
10^{-3}
10^{-4}
10^{-2}
10^{-1}



Shanghai Index (1990-2009)
Daily data slope= -0.32(3)
Decoupled daily data slope= -0.30(3)
Volatility clustering
German DAX (1959-2009)
Daily data slope= -0.32(2)
Decoupled daily data slope= -0.29(2)
A (t)
t (day)
10^0
10^{-1}
10^{-2}
10^1
10^2
(a)

Contents

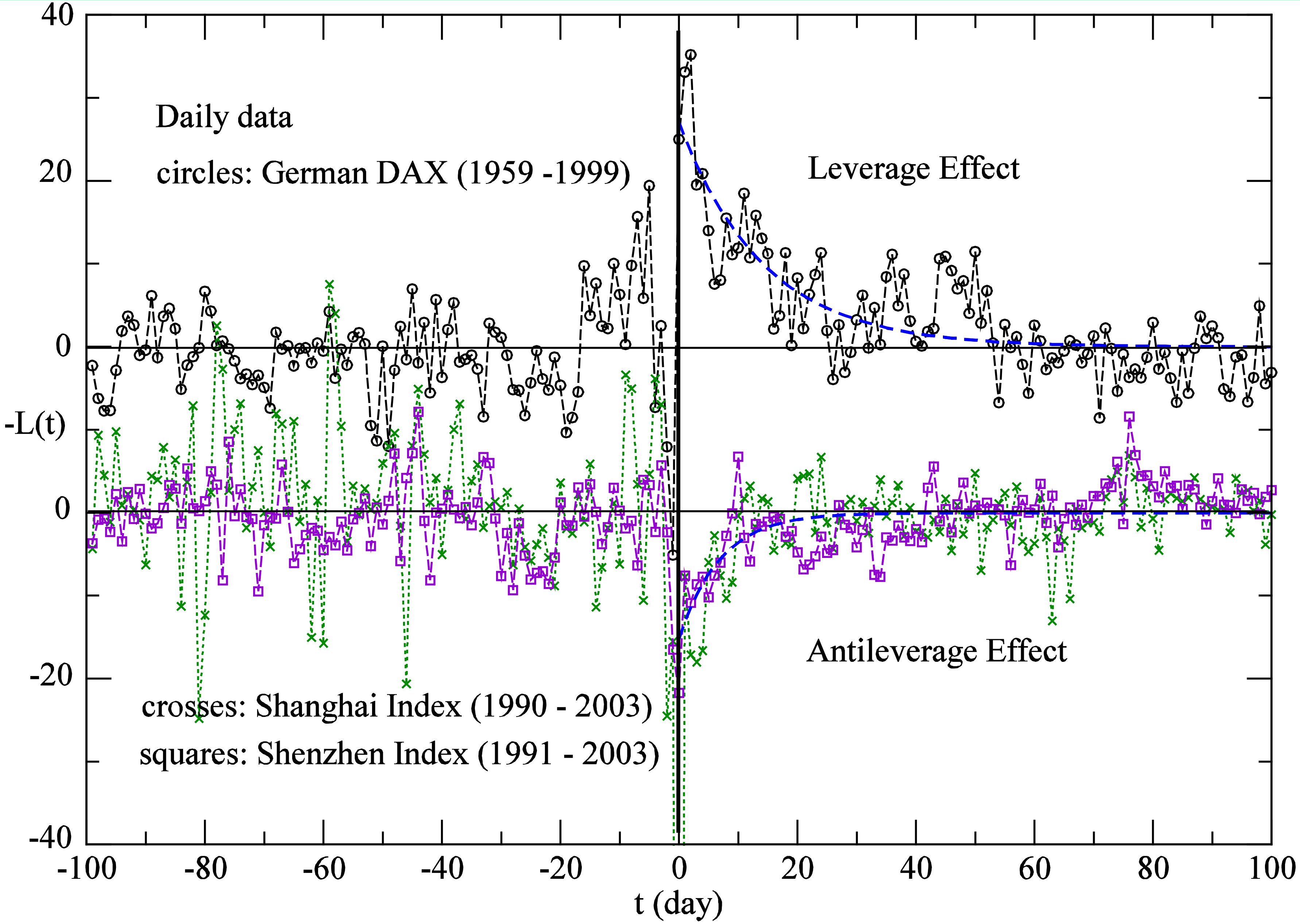
Leverage and anti-leverage effects

Return-volatility correlation

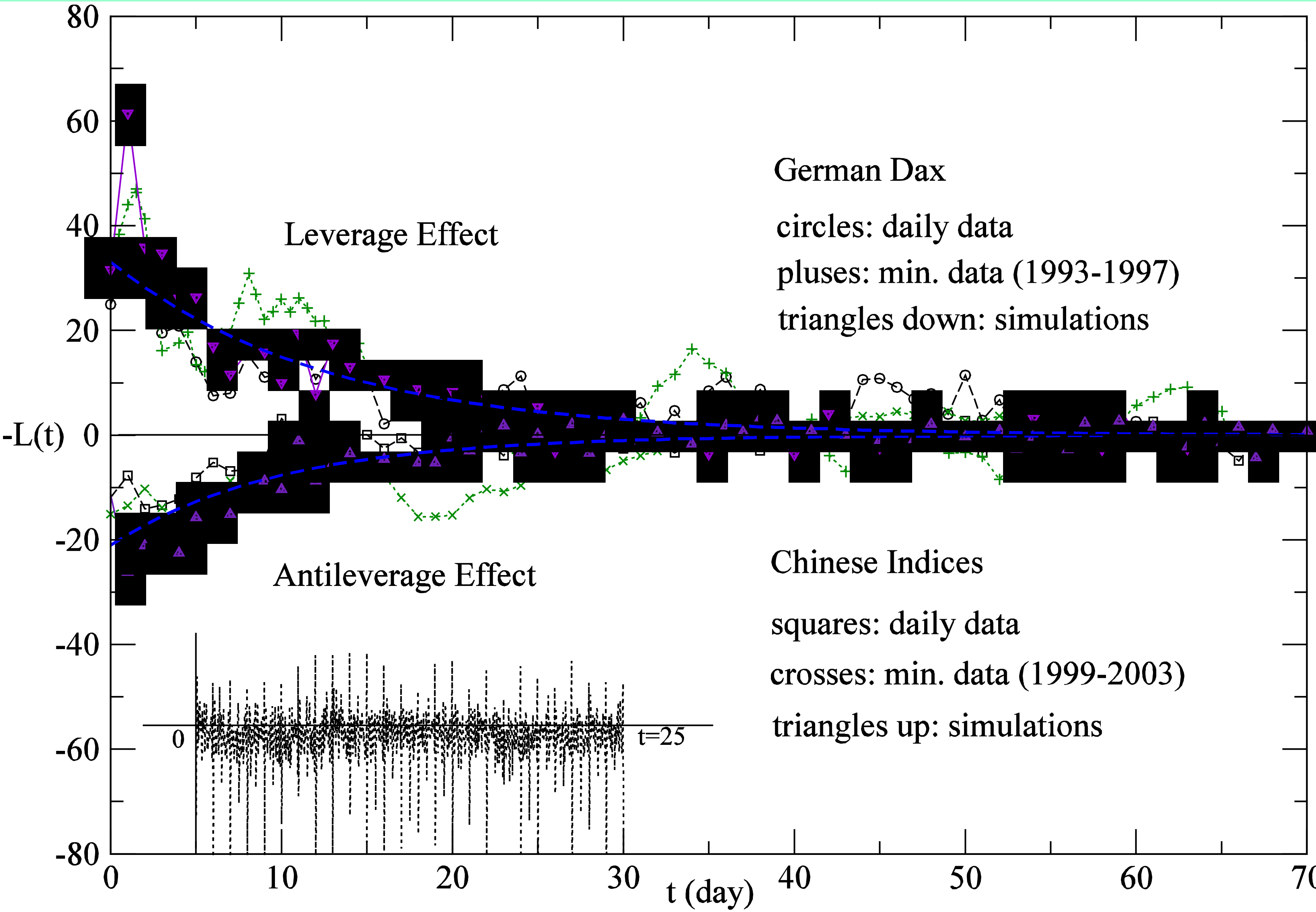
$$L(t) = < R(t') \, | R(t'+t) |^2 > - < R >< | R |^2 >$$

- **it measures the correlation between** $R(t')$ **and** $| R(t') |^2$
- **it is not time-reverse invariant**
- **it is important since the auto-correlation of returns is small**

Qiu, Zheng, **PRE73** (2006) 065103(R), Rapid Comm.
Shen, Zheng, **EPL 88** (2009) 28003



Daily data
circles: German DAX (1959 -1999)
Leverage Effect
Antileverage Effect
crosses: Shanghai Index (1990 - 2003)
squares: Shenzhen Index (1991 - 2003)
-L(t)
t (day)
40
20
0
0
-20
-40
-100
-80
-60
-40
-20
0
20
40
60
80
100



Leverage Effect
Antileverage Effect
German Dax
circles: daily data
pluses: min. data (1993-1997)
triangles down: simulations
Chinese Indices
squares: daily data
crosses: min. data (1999-2003)
triangles up: simulations
-L(t)
t (day)
t=25
0
80
60
40
20
-20
-40
-60
-80
10
30
50
70

How is non-zero return-volatility correlation created?

Is it induced by asymmetric *P(r)* and long-range time-correlation of volatility?

How does anti-leverage effect in China originate?

*** Economic, social and cultural systems**

*** Non-stationary dynamic effects**

A retarded interacting model

$$r_0(t') = [1 + \sum_{t=1}^{\infty} K(t) r(t'-t)] r(t')$$

$r(t') \equiv (R - \langle R \rangle)/\sigma$ is the normalized price-return

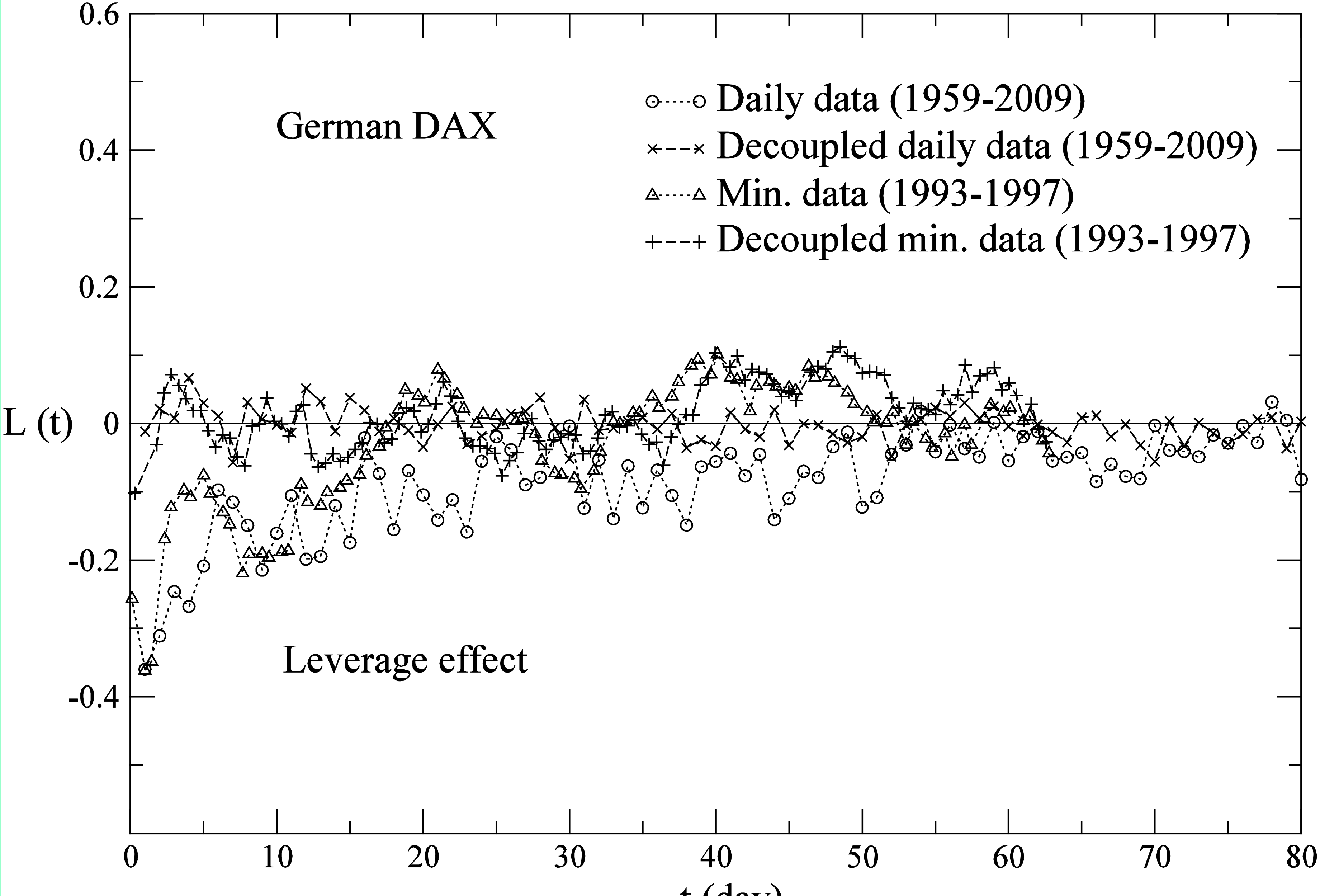
$r_0(t')$ is the decoupled price-return

$K(t)$ represents the retarded effect of the price return

In general

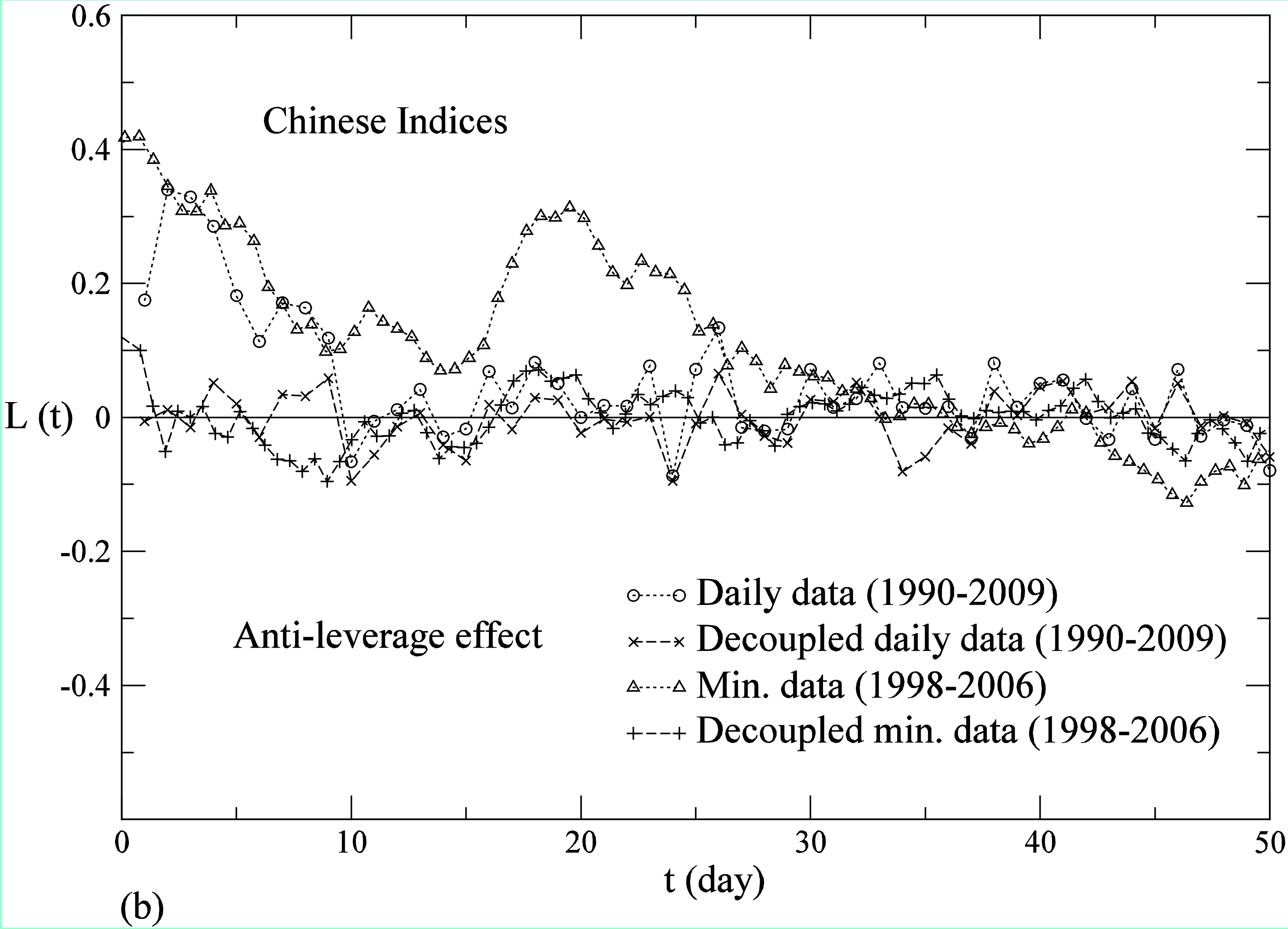
$$K(t) = -\frac{C}{2} L(t)$$

It may generate and remove leverage and anti-leverage effects

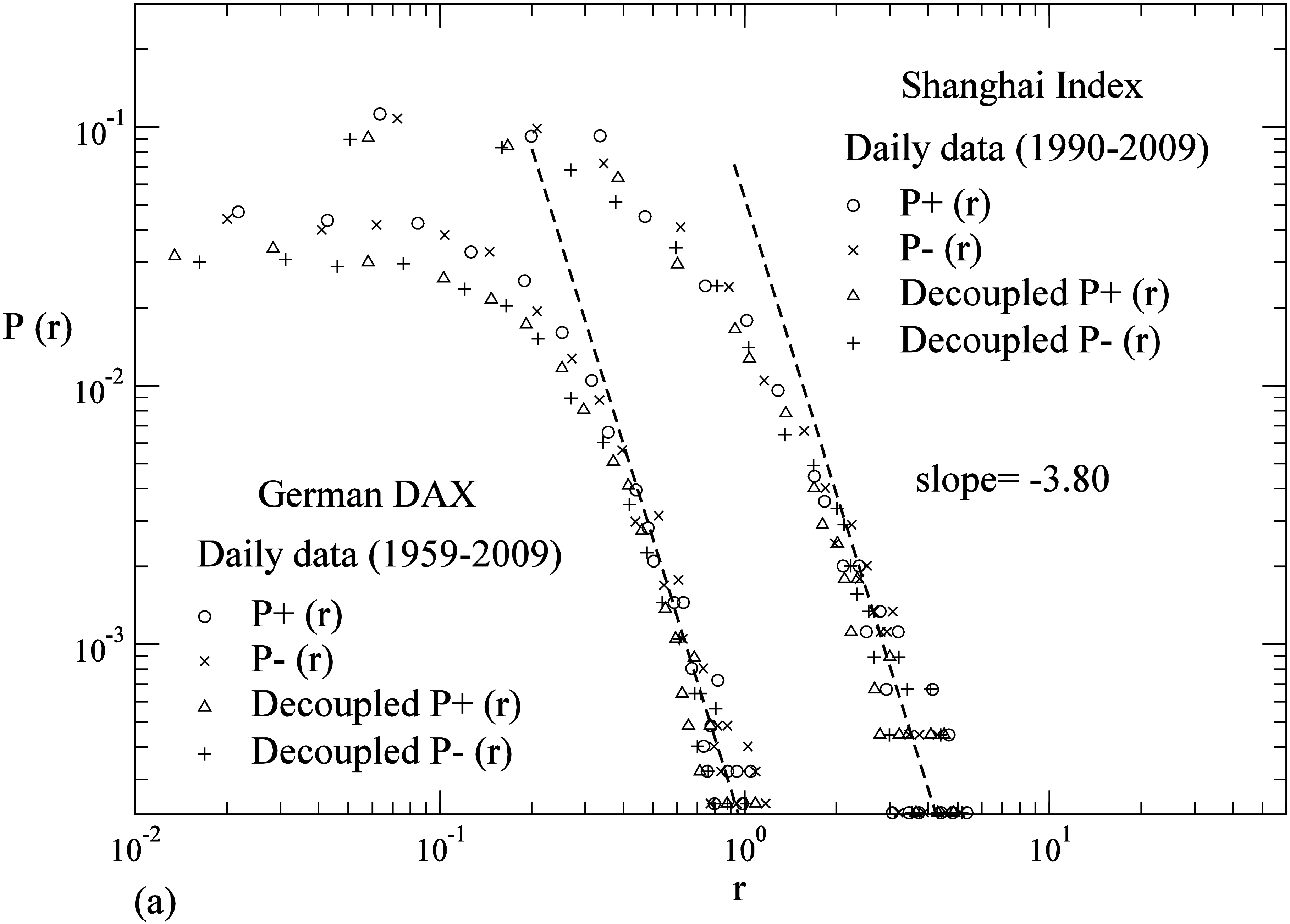


German DAX
Daily data (1959-2009)
Decoupled daily data (1959-2009)
Min. data (1993-1997)
Decoupled min. data (1993-1997)
Leverage effect
L (t)
t (day)
0.6
0.4
0.2
0
-0.2
-0.4
0
10
20
30
40
50
60
70
80

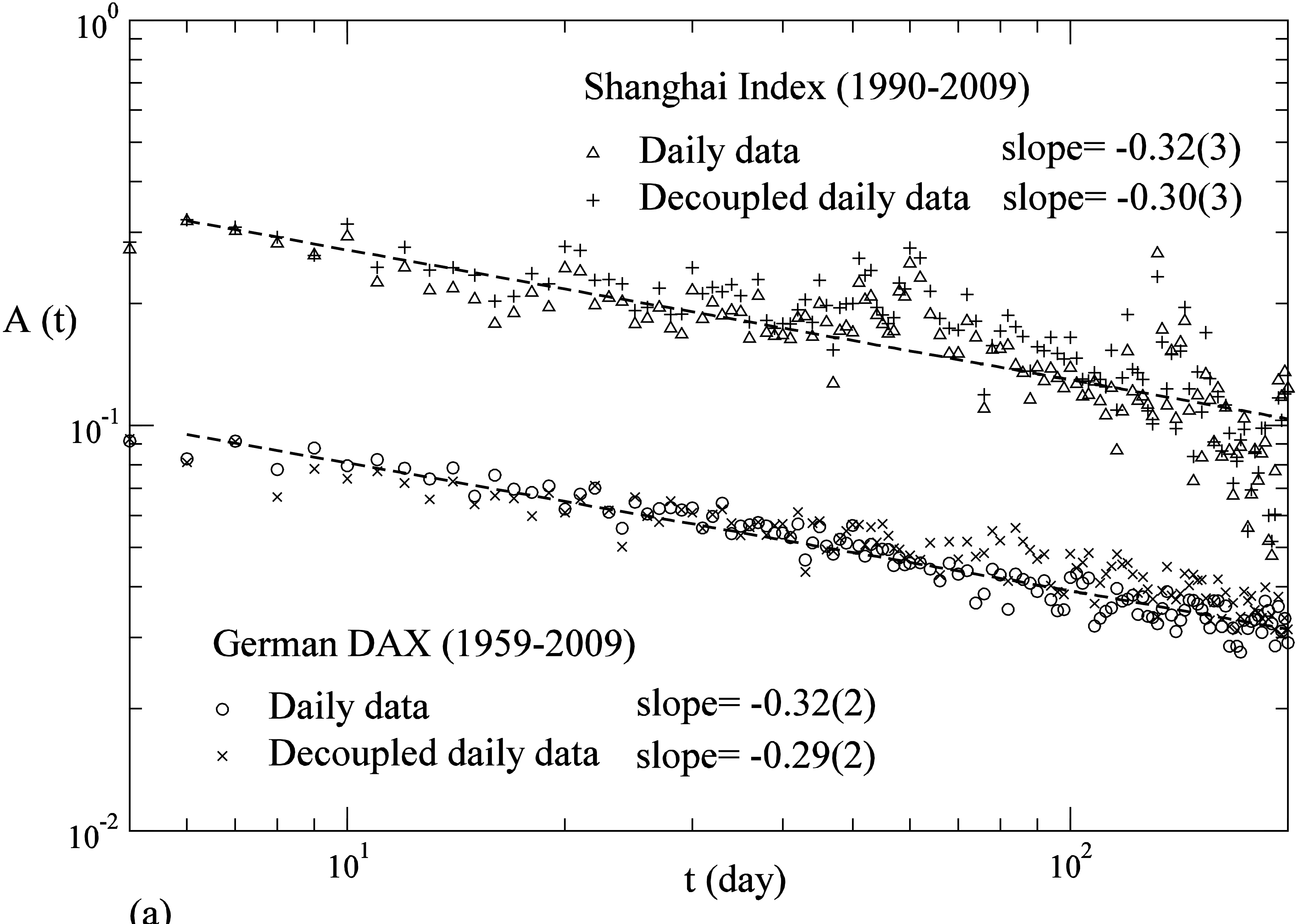
(a)



Chinese Indices
Anti-leverage effect
Daily data (1990-2009)
Decoupled daily data (1990-2009)
Min. data (1998-2006)
Decoupled min. data (1998-2006)
L (t)
t (day)
0.6
0.4
0.2
0
-0.2
-0.4
0
10
20
30
40
50
(b)



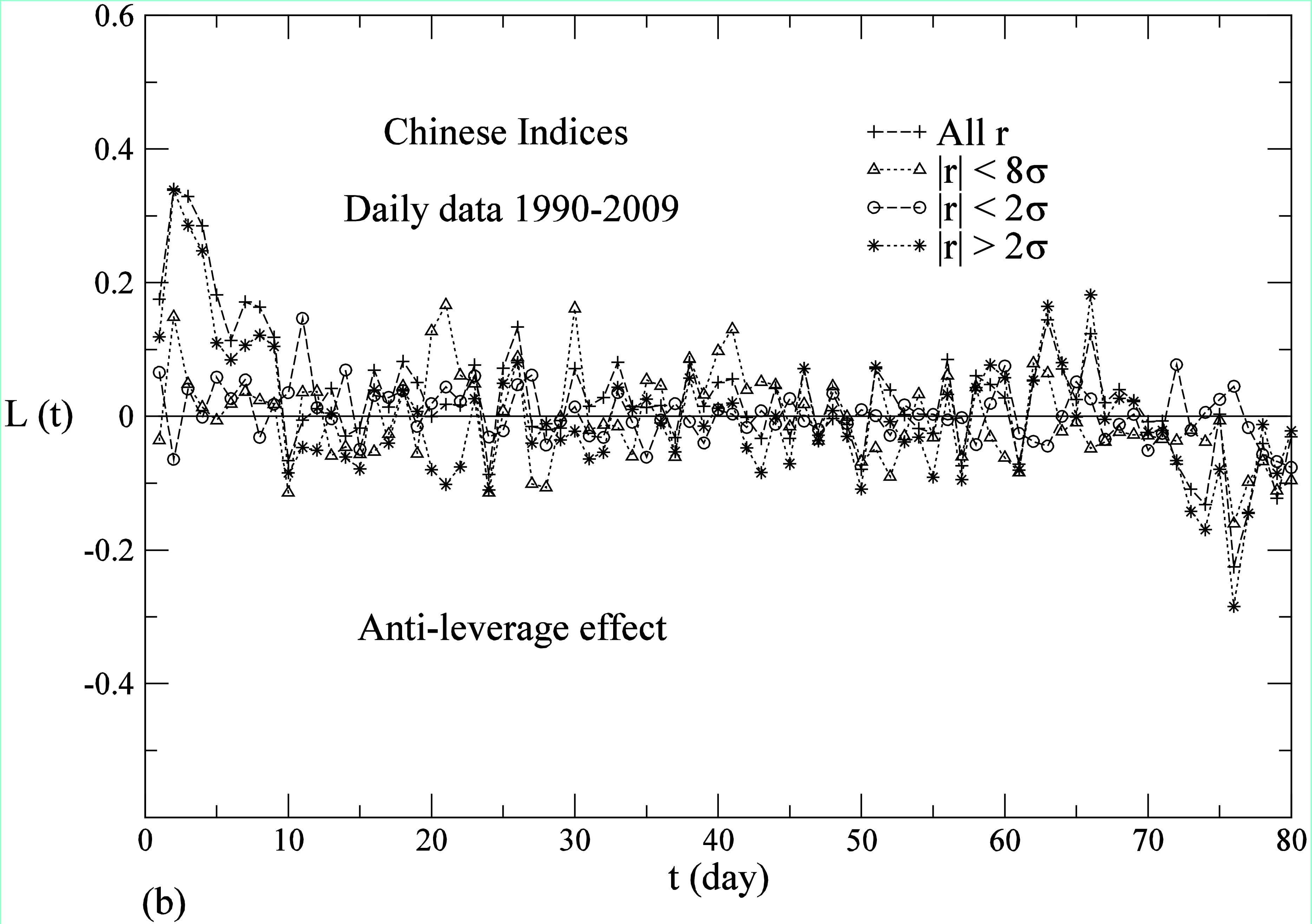
Shanghai Index
Daily data (1990-2009)
P+ (r)
P- (r)
Decoupled P+ (r)
Decoupled P- (r)
slope= -3.80
German DAX
Daily data (1959-2009)
P+ (r)
P- (r)
Decoupled P+ (r)
Decoupled P- (r)
P (r)
r
10^-1
10^-2
10^-3
10^-2
10^-1
10^0
10^1
(a)

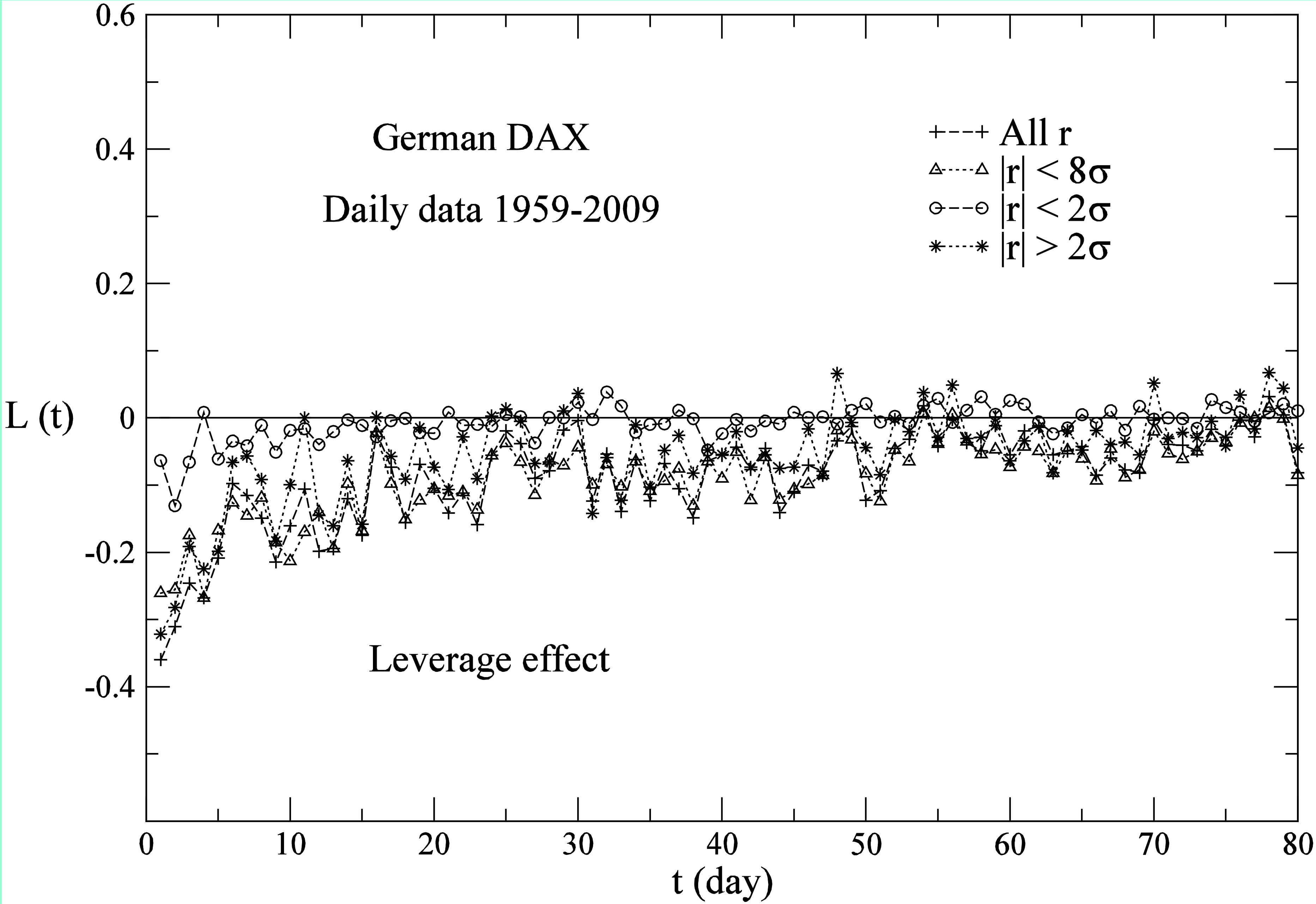


Shanghai Index (1990-2009)
Daily data slope= -0.32(3)
Decoupled daily data slope= -0.30(3)
German DAX (1959-2009)
Daily data slope= -0.32(2)
Decoupled daily data slope= -0.29(2)
A (t)
t (day)
10^0
10^-1
10^-2
10^1
10^2
(a)

Large volatilities dominate

the leverage and anti-leverage effects


Chinese Indices
Daily data 1990-2009
Anti-leverage effect
All r
|r| < 8σ
|r| < 2σ
|r| > 2σ
L (t)
t (day)
0.6
0.4
0.2
0
-0.2
-0.4
0
10
20
30
40
50
60
70
80
(b)


German DAX
Daily data 1959-2009
All r
|r| < 8σ
|r| < 2σ
|r| > 2σ
Leverage effect
L (t)
t (day)
0.6
0.4
0.2
0
-0.2
-0.4
0
10
20
30
40
50
60
70
80
(a)

New observation

In recent years, it has changed to the leverage effect in Chinese stock markets. This is similar to such a crossover for the bank interest rate in Western countries at the beginning of last century.

In fact,

1990-2000	Anti-leverage effect
2000-2005	zero effect
2005-	Leverage effect

Contents

Cross-correlations between stocks

The sector and subsector structure in Chinese stock markets is unusual

Cross-correlations of individual stocks

We define the normalized return

$$r_i(t', \Delta t) \equiv \frac{R_i - \langle R_i \rangle}{\sigma_i}$$

the cross-correlation

$$C_{ij} \equiv \langle r_i(t') r_j(t') \rangle$$

Compute probability distribution of C_{ij},

Eigenvalues and eigenvectors of $\{C_{ij}\}$

Shen, Zheng, **EPL 86** (2009) 48005
Qiu, Zheng, **NJP 12** (2010) 043057

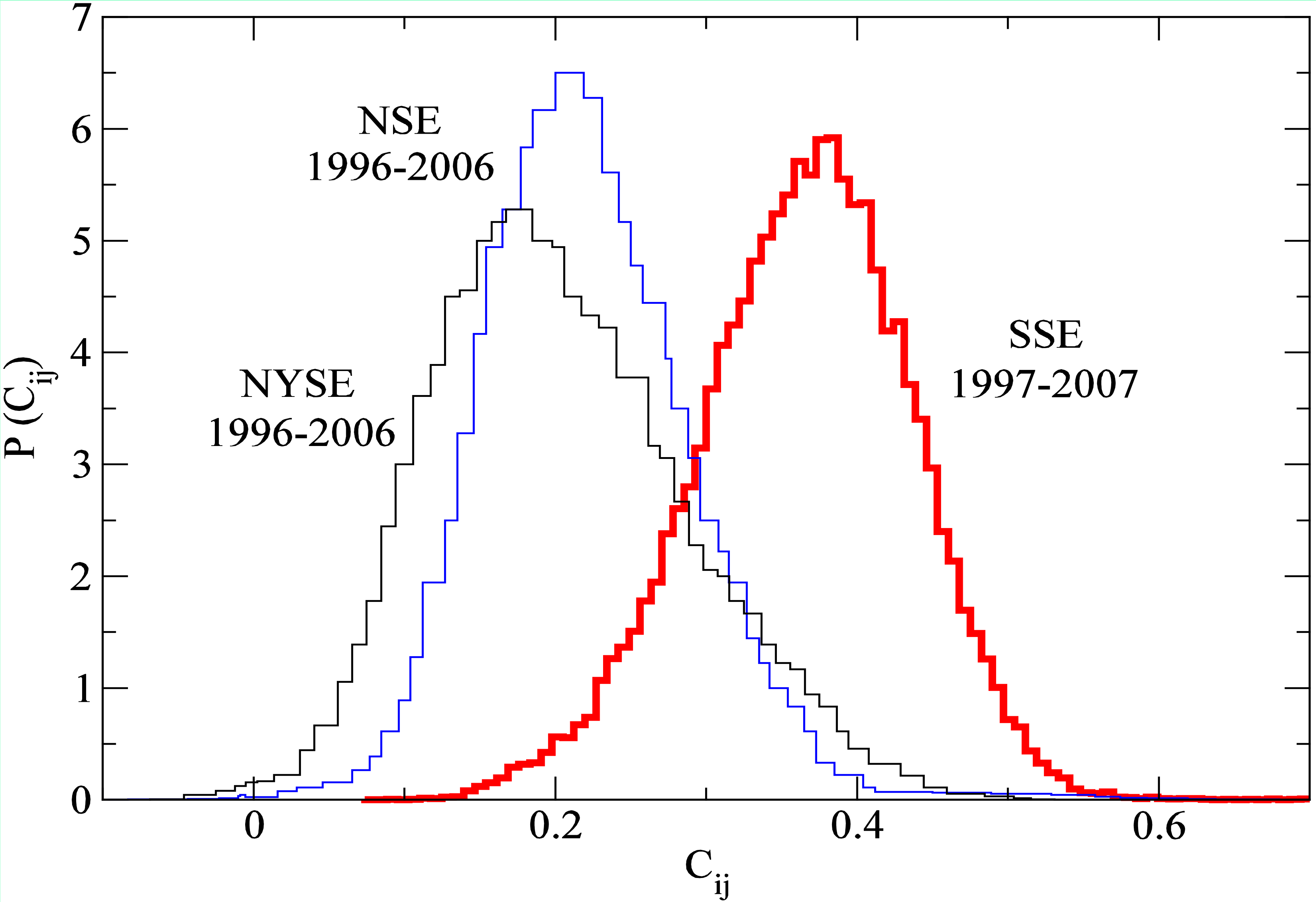
PHYSICAL REVIEW E **76**, 046116 (2007)

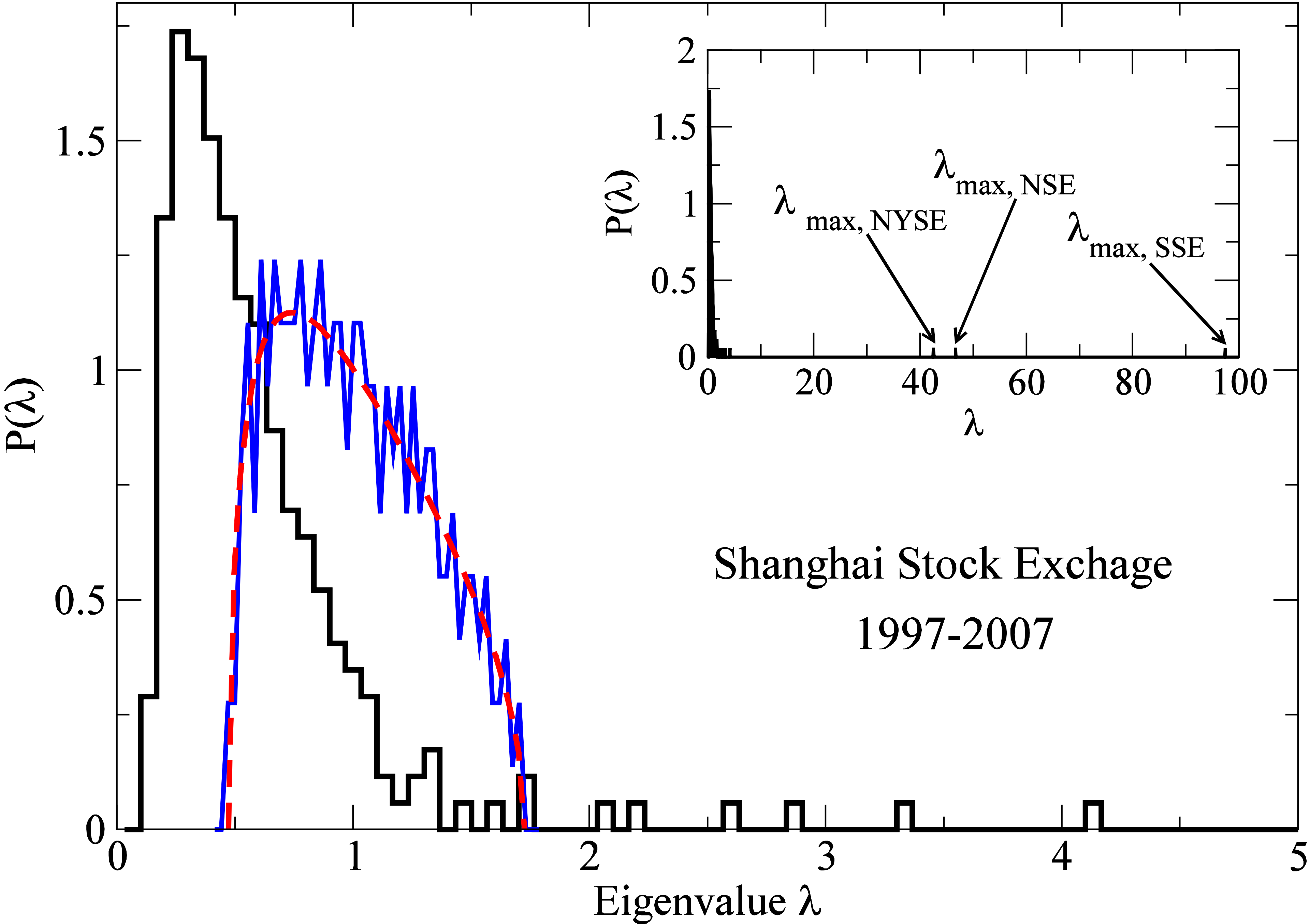
Collective behavior of stock price movements in an emerging market

Raj Kumar Pan[*] and Sitabhra Sinha[†]
The Institute of Mathematical Sciences, C. I. T. Campus, Taramani, Chennai 600 113, India
(Received 5 April 2007; revised manuscript received 5 July 2007; published 25 October 2007)

To investigate the universality of the structure of interactions in different markets, we analyze the cross-correlation matrix **C** of stock price fluctuations in the National Stock Exchange (NSE) of India. We find that this *emerging* market exhibits strong correlations in the movement of stock prices compared to *developed* markets, such as the New York Stock Exchange (NYSE). This is shown to be due to the dominant influence of a common market mode on the stock prices. By comparison, interactions between related stocks, e.g., those belonging to the same business sector, are much weaker. This lack of distinct sector identity in emerging markets is explicitly shown by reconstructing the network of mutually interacting stocks. Spectral analysis of **C** for NSE reveals that, the few largest eigenvalues deviate from the bulk of the spectrum predicted by random matrix theory, but they are far fewer in number compared to, e.g., NYSE. We show this to be due to the relative weakness of intrasector interactions between stocks, compared to the market mode, by modeling stock price dynamics with a two-factor model. Our results suggest that the emergence of an internal structure comprising multiple groups of strongly coupled components is a signature of market development.

Chinese market shows stronger correlations

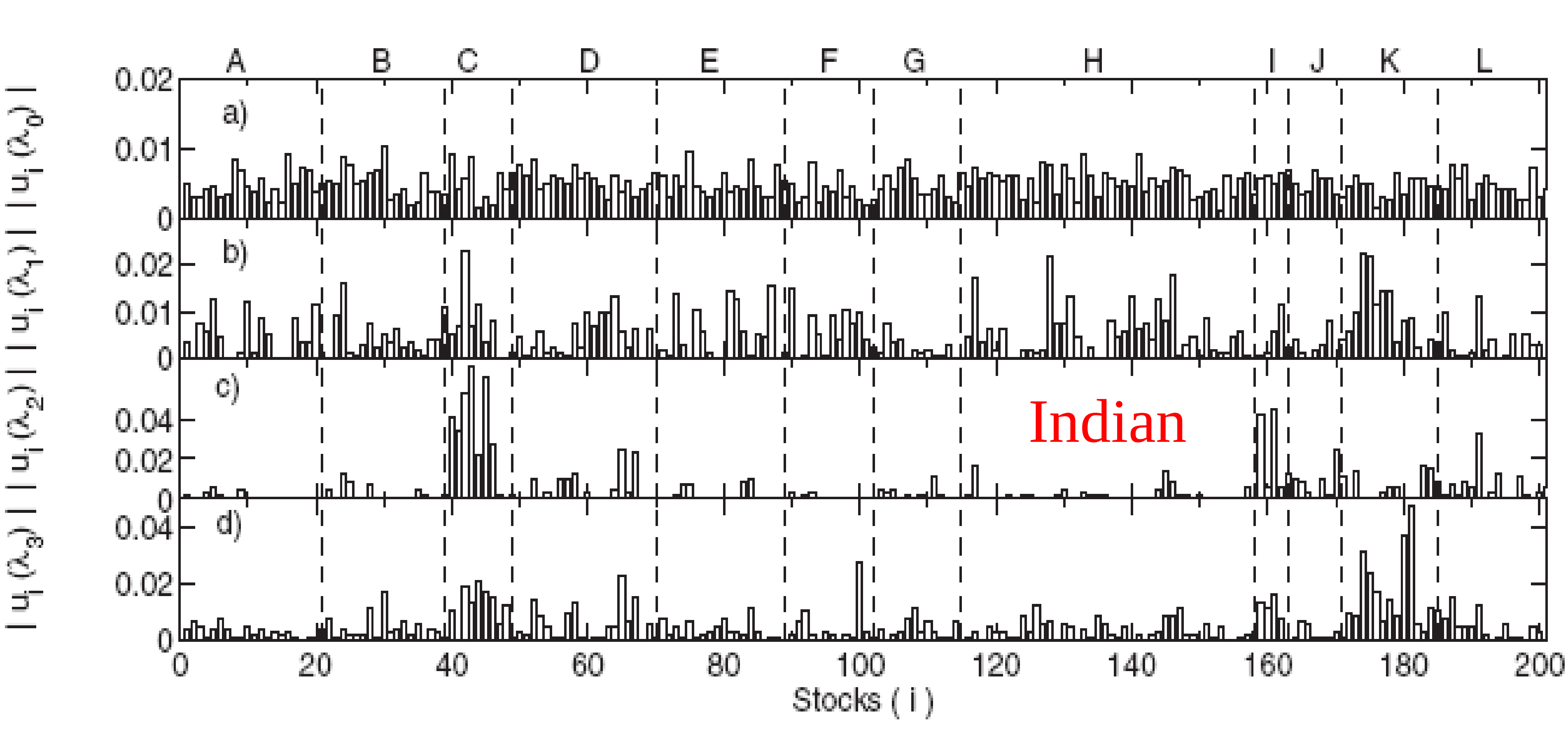


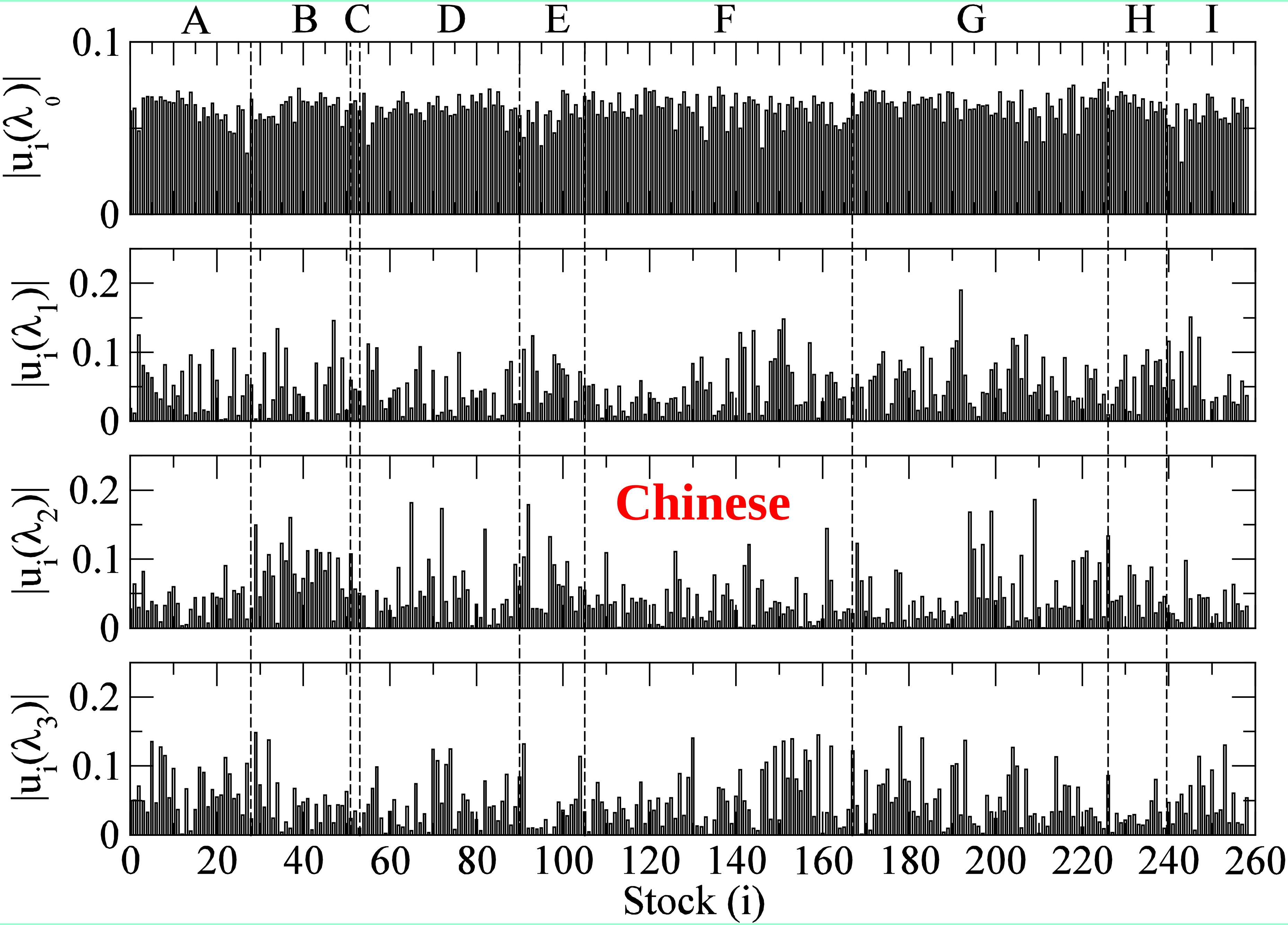


P(λ)
1.5
1
0.5
0
0
1
2
3
4
5
Eigenvalue λ
Shanghai Stock Exchage
1997-2007
2
1.5
1
0.5
0
0
20
40
60
80
100
λ
λ max, NYSE
λ max, NSE
λ max, SSE

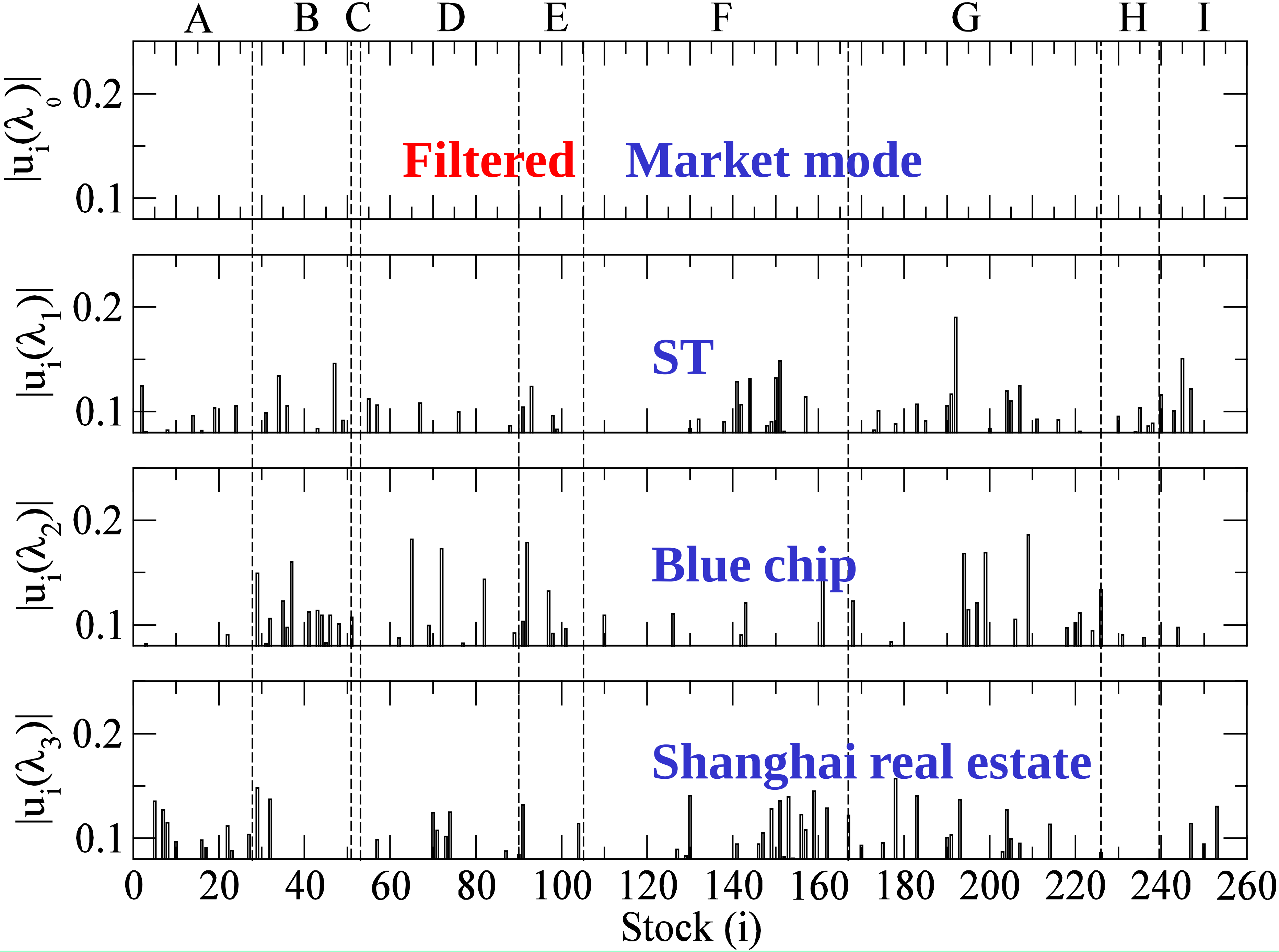
Indian market shows still group effect

Chinese market is much more emerging





A
B
C
D
E
F
G
H
I
$|u_i(\lambda_0)|$
$|u_i(\lambda_1)|$
$|u_i(\lambda_2)|$
$|u_i(\lambda_3)|$
Chinese
0.1
0.2
0
0
20
40
60
80
100
120
140
160
180
200
220
240
260
Stock (i)



A
B
C
D
E
F
G
H
I
Filtered
Market mode
ST
Blue chip
Shanghai real estate
$|u_i(\lambda_0)|$
$|u_i(\lambda_1)|$
$|u_i(\lambda_2)|$
$|u_i(\lambda_3)|$
0.1
0.2
0
20
40
60
80
100
120
140
160
180
200
220
240
260
Stock (i)

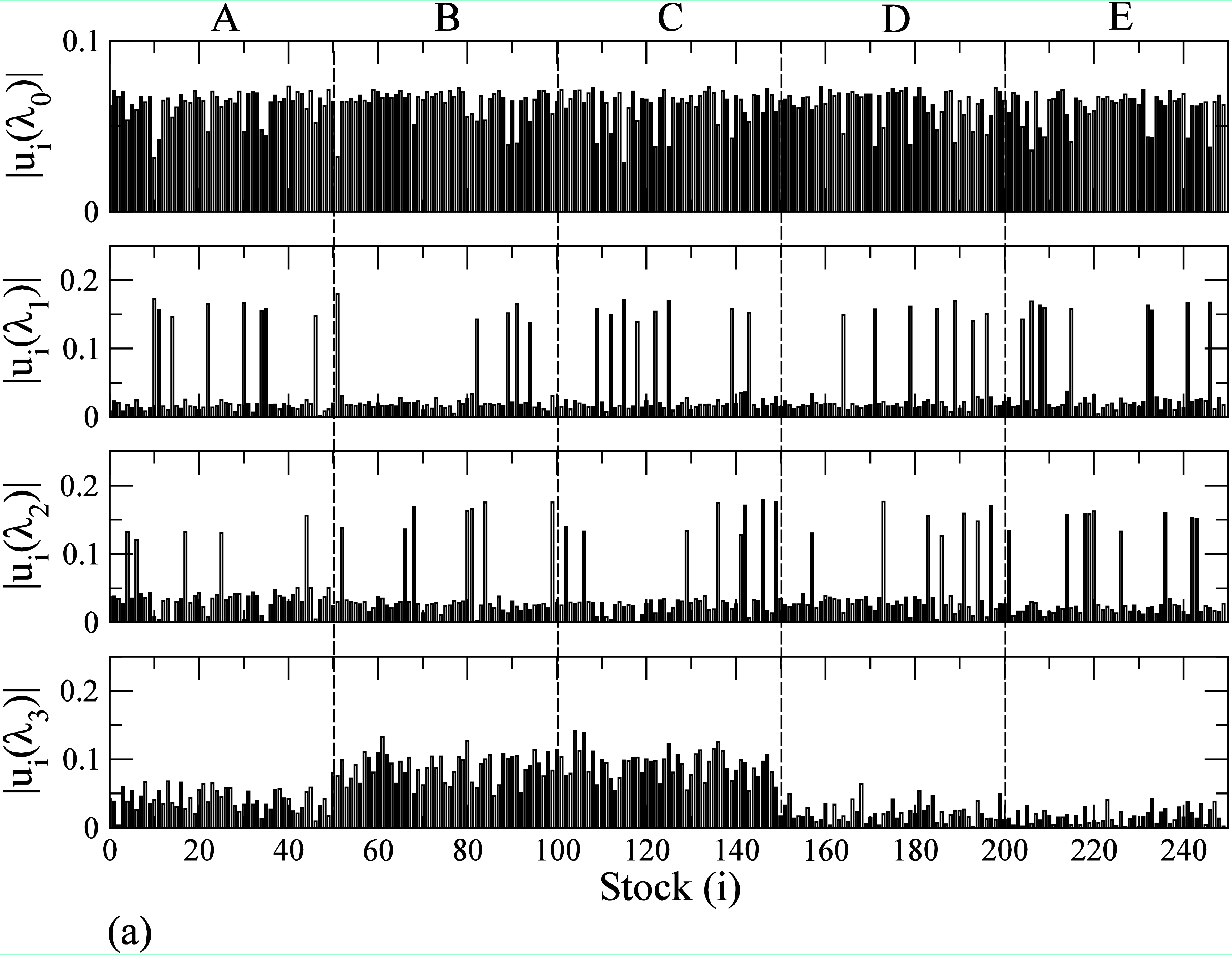
Variation of two-factor model

$$r_i^k(t) = \beta_i r_m(t) + \alpha_i^k r_g^k(t) + \alpha_i^p r_p(t) + \sigma_i \eta_i(t)$$

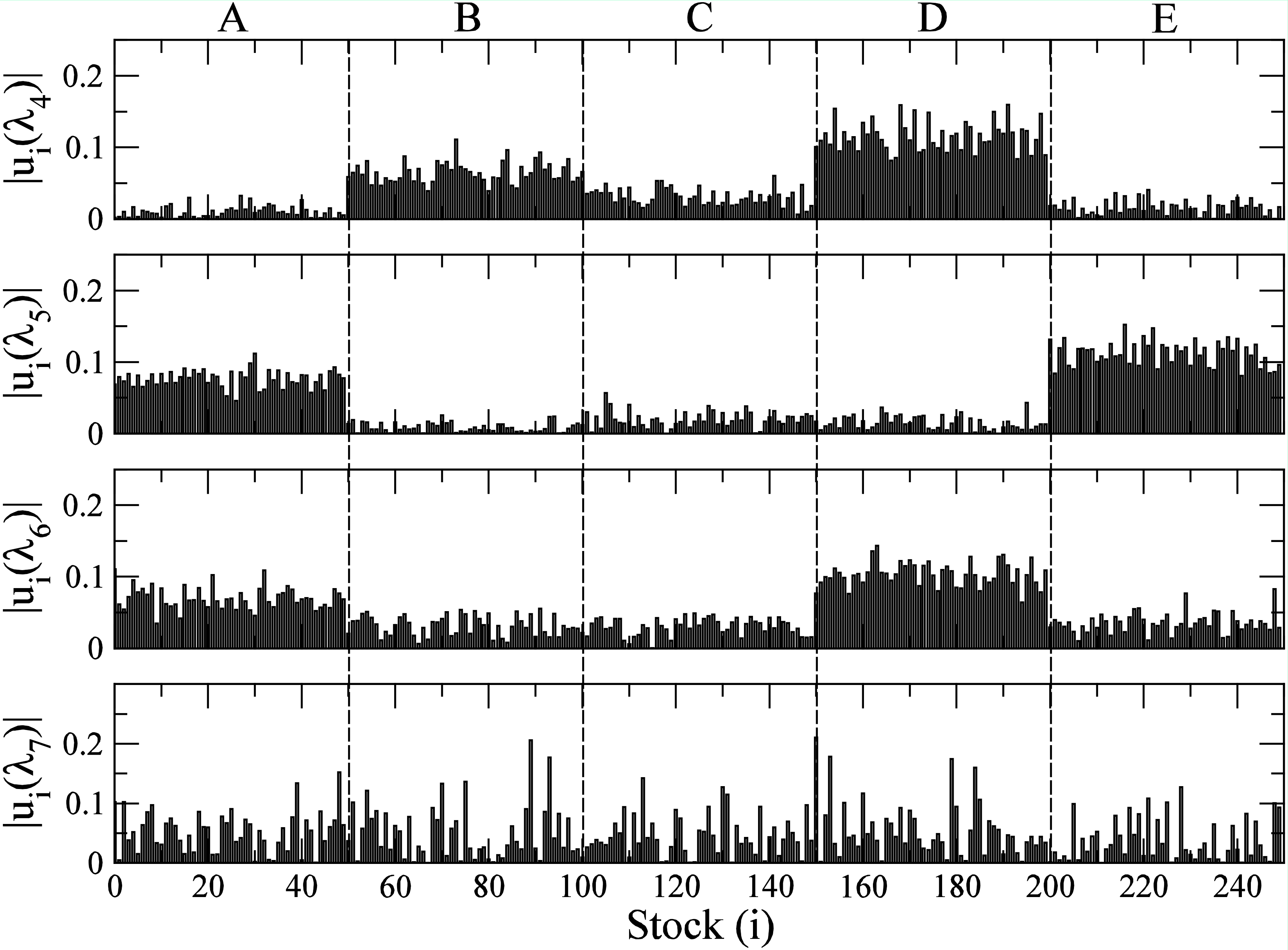
***m*: market mode**

***g*: group interaction**

***p*: profit-group interaction**



A
B
C
D
E
$|u_i(\lambda_0)|$
$|u_i(\lambda_1)|$
$|u_i(\lambda_2)|$
$|u_i(\lambda_3)|$
0
0.1
0.2
0
20
40
60
80
100
120
140
160
180
200
220
240
Stock (i)
(a)



A
B
C
D
E
$|u_i(\lambda_4)|$
$|u_i(\lambda_5)|$
$|u_i(\lambda_6)|$
$|u_i(\lambda_7)|$
0
0.1
0.2
0
20
40
60
80
100
120
140
160
180
200
220
240
Stock (i)

(b)

From the signs of the components in the eigenvectors, we may detect subsectors.

The subsector structure is stronger in the Chinese stock market

The positive and negative subsectors are anti-correlated each other

$$C_{ij} = \sum_{\alpha=1}^{N} \lambda_\alpha C_{ij}^\alpha, \quad C_{ij}^\alpha = u_i^\alpha u_j^\alpha$$

	λ_1		λ_2		λ_3		λ_4	
Sign	$+$	$-$	$+$	$-$	$+$	$-$	$+$	$-$
Sector	Null	ST	Trad	Tech	ST	SHRE	Weak	Stro
$u_c^{\pm} = \pm 0.08$	26	31/35	22/23	23/25	24/27	27/27	23/26	24/26
$u_c^{\pm} = \pm 0.10$	7	20/23	16/17	12/13	11/12	20/20	13/15	15/16
	λ_5		λ_6					
Sign	$+$	$-$	$+$	$-$				
Sector	Fin	Null	IG	Null				
$u_c^{\pm} = \pm 0.08$	14/18	25	15/17	25				
$u_c^{\pm} = \pm 0.10$	10/14	17	8/9	18				

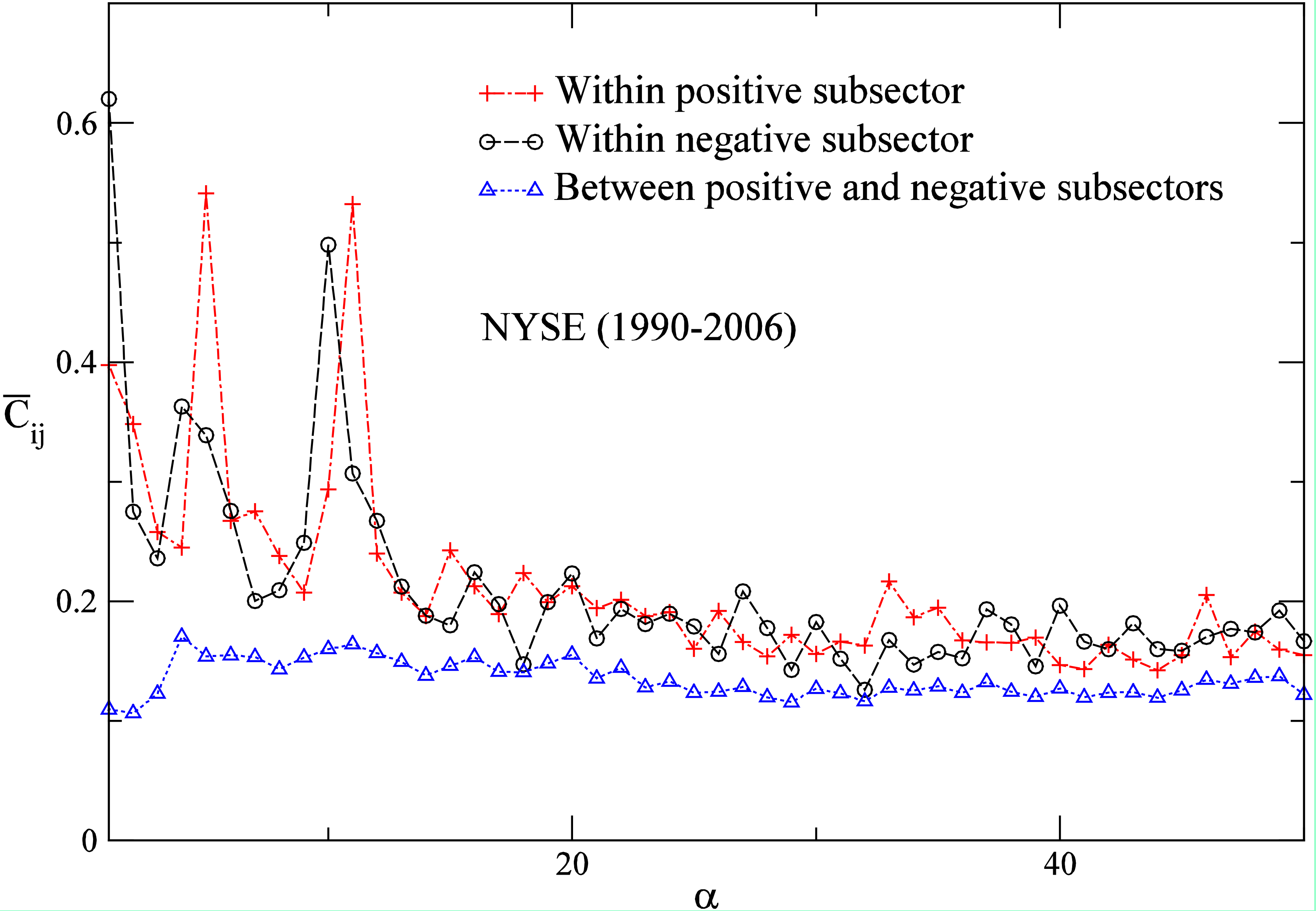
Table 3. The sectors and subsectors in the SSE. The fraction is the number of stocks in the subsector over the total number of stocks. Null: no obvious category; ST: specially treated; Trad: traditional industry; Tech: high technology; SHRE: Shanghai real estate; Weak: weakly cyclical industry; Stro: strongly cyclical industry; Fin: finance; IG: industrial goods; Util: utility; Basic: basic materials; Heal: health care;

λ_i	λ_1		λ_2		λ_3		λ_4	
Sign	+	−	+	−	+	−	+	−
Sector	Util	Tech	CG	Basi	Tech	CG	Null	Null
$u_c^{\pm} = \pm 0.08$	26/26	3/4	9/16	23/26	15/26	14/32	26	25
$u_c^{\pm} = \pm 0.10$	25/25	0/0	0/0	19/21	6/13	13/19	18	12
$u_c^{\pm} = \pm 0.12$	21/21	0/0	0/0	19/21	5/7	5/6	7	6
λ_i	λ_5		λ_6		λ_7		λ_8	
Sign	+	−	+	−	+	−	+	−
Sector	Basi	Null	Null	Fin	Tech	Serv	Serv	Heal
$u_c^{\pm} = \pm 0.08$	6/6	9	14	16/20	11/24	12/29	9/19	9/16
$u_c^{\pm} = \pm 0.10$	0/0	8	8	16/18	7/13	10/18	8/11	8/13
$u_c^{\pm} = \pm 0.12$	0/0	4	2	8/11	4/7	8/11	5/5	7/7

Table 4. The sectors and subsectors in the NYSE. The abbreviations can be seen in the caption of table 3.

	Sign		Area
λ_0		VLIC XMI DJA DJI DJT DJX IIX IXIC MID NDX NWX	US
		OEX PSE RUA RUI RUT SML SPC ***GDAXI GSPTSE***	
λ_1		AORD HSI HSNC HSNF HSNP HSNU JKSE KS11 N225	Asia
		NZ50 PSI STI ***ATX***	
λ_2		bond6mo bond1yr bond2yr bond3yr bond5yr bond7yr	Bond
		bond10yr bond20yr	
λ_3	+	AEX BFX FCHI FTSE GDAXI MIBTEL SSMI	EU
	-	SHA SZA SHB SZB	China
λ_4	+	HSI HSNC HSNP	HK
	-	AEX BFX FCHI FTSE GDAXI MIBTEL SSMI	EU
		SHA SZA SHB SZB	
λ_5	+	IIX IXIC NDX NWX PSE SOXX	US
	-	XMI DJA DJI DJU DJX ***bond3mo***	US
λ_6	+	bond3mo bond6mo bond1yr	Bond
	-	bond7yr bond10yr bond20yr ***HSNU***	Bond
λ_7	+	AORD JKSE KS11 N225 NZ50 PSI TWII	Asia
	-	HSI HSNC HSNF HSNP HSNU ***bond3mo***	HK
λ_8		BVSP IPSA MERV MXX ***XAX GSPTSE***	North America

Table 5. The sector and subsector structure in the GMI . The thresholds are $u_c^{\pm} = \pm 0.15$. The bold Italic items are those which do not belong to the areas.



Within positive subsector
Within negative subsector
Between positive and negative subsectors
NYSE (1990-2006)
$\overline{C}_{ij}$
0
0.2
0.4
0.6
20
40
α

股票价格运动粗略分解为：

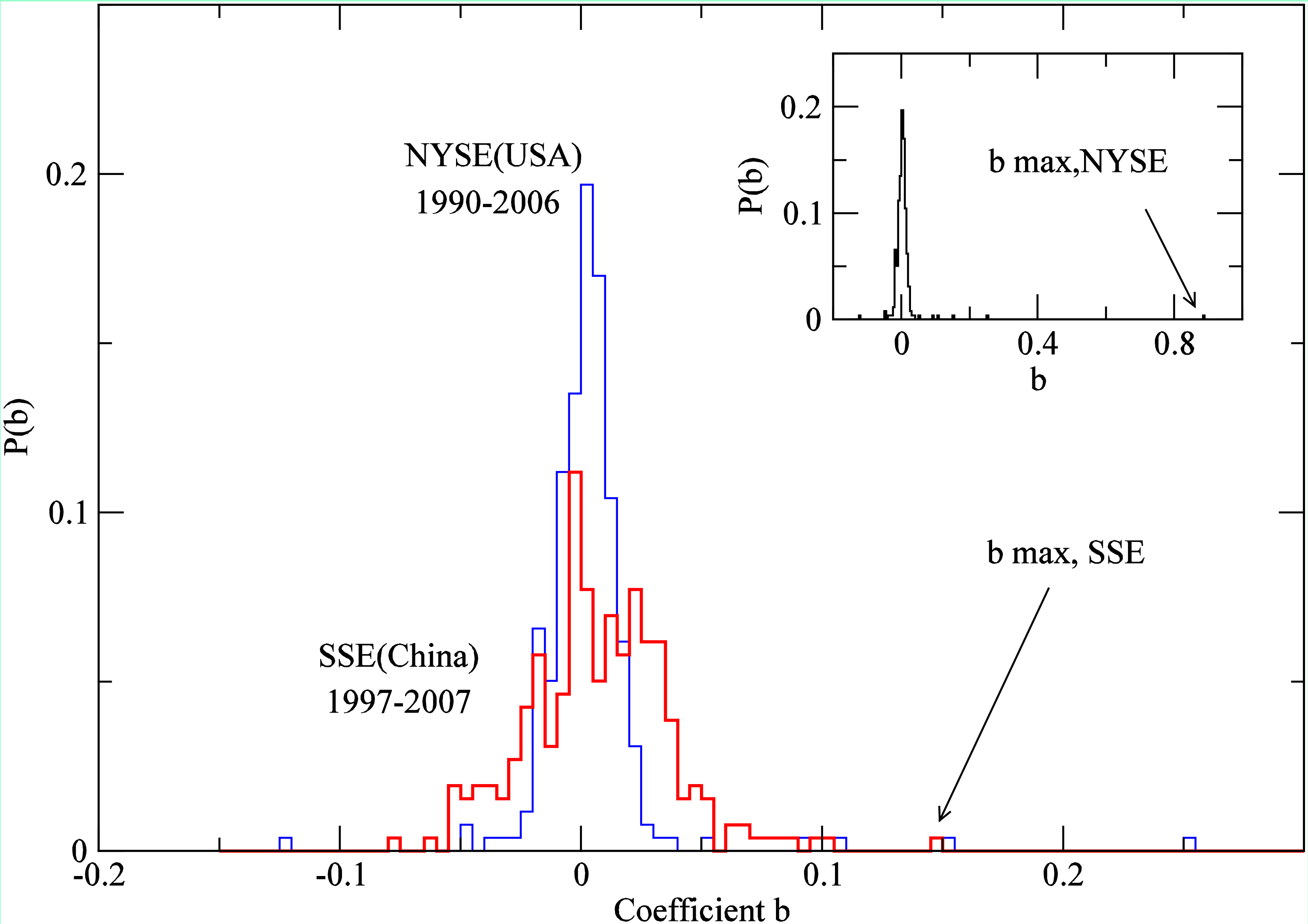
* 股票整体运动 – market mode

* 股票局域运动 – group modes

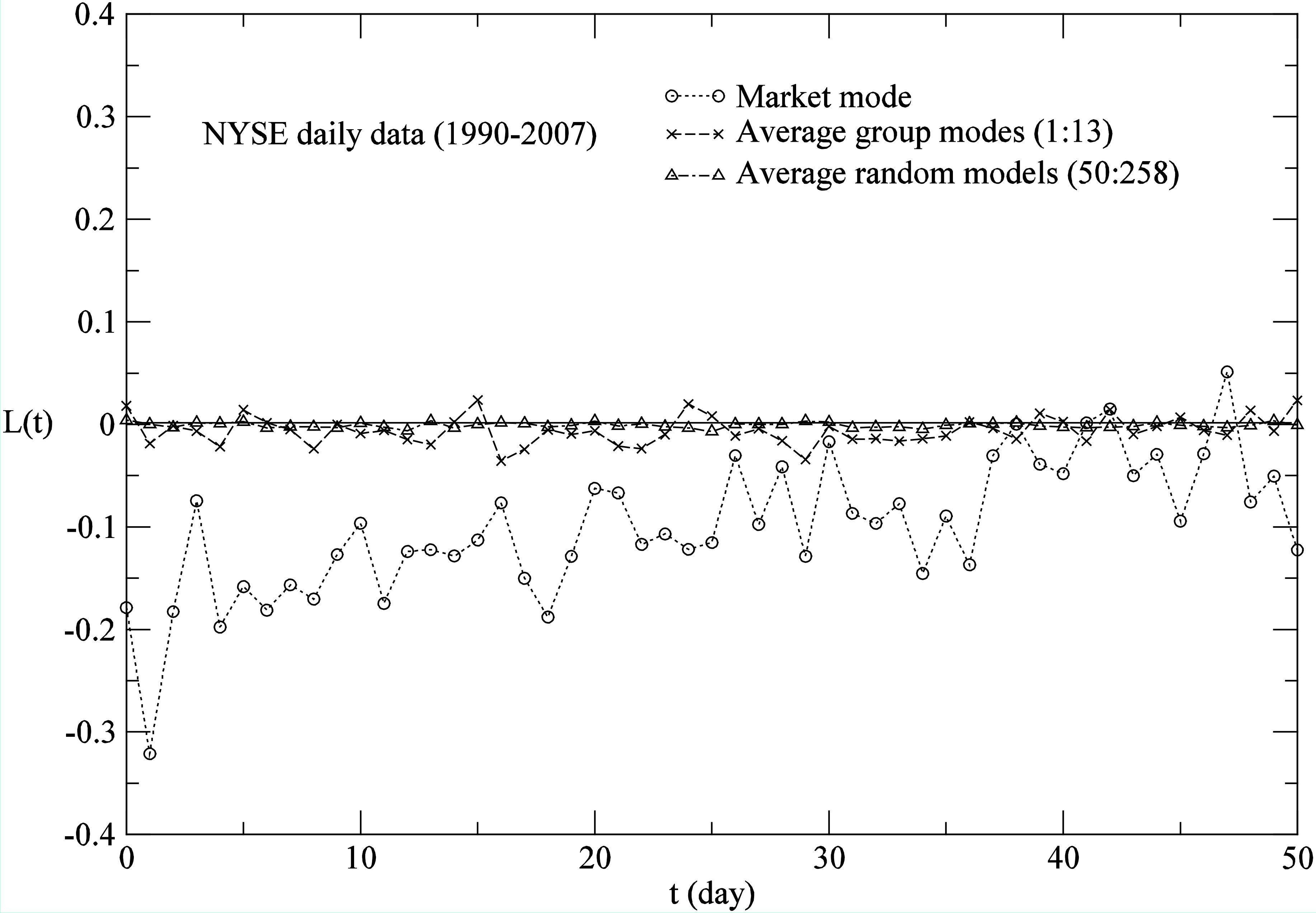
* 准随机运动 – quasi-random modes

大盘指数和个体股票价格可以按模式展开

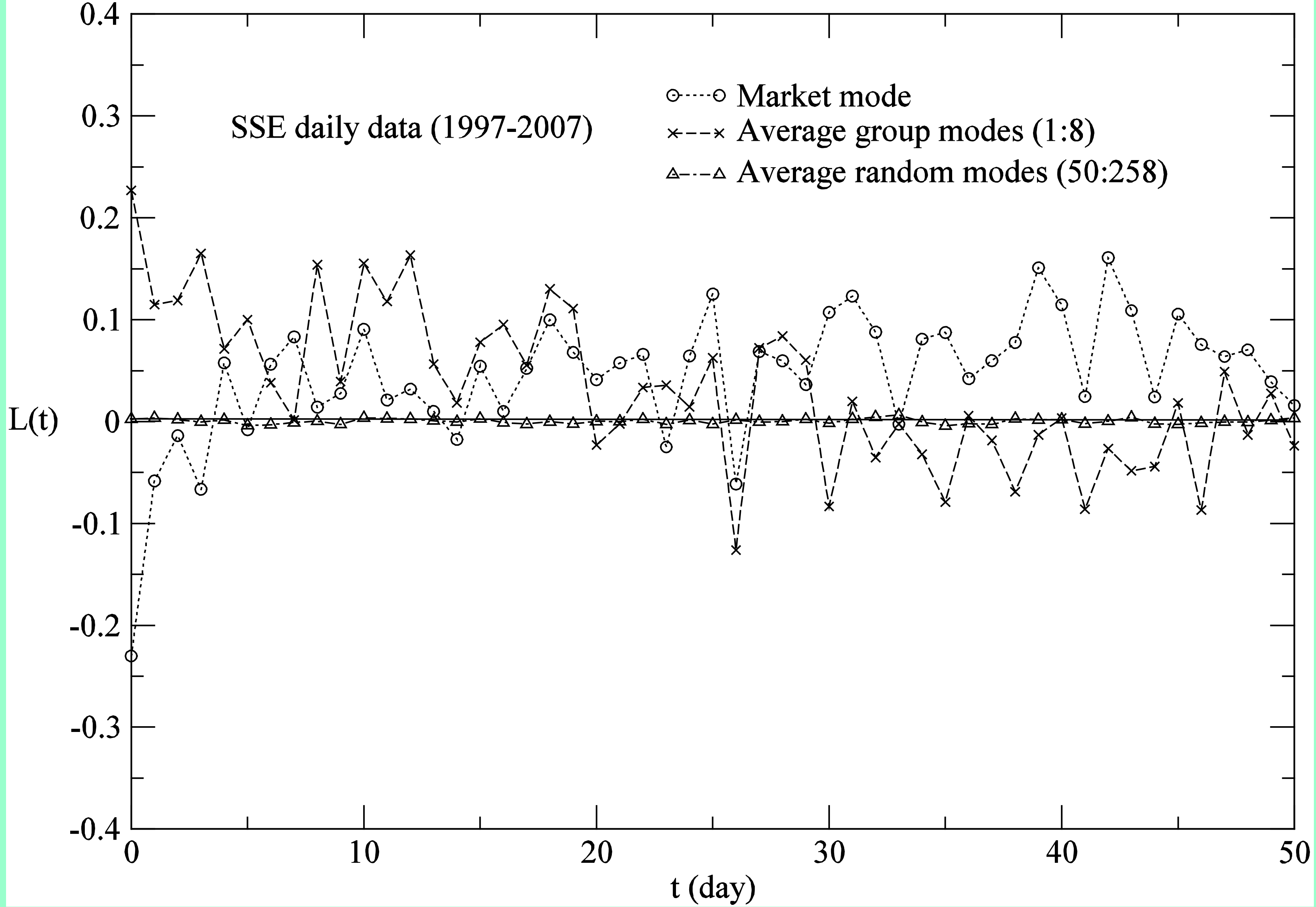
模式之间可以相干，如中国
也可以不相干，如美国



NYSE(USA)
1990-2006
SSE(China)
1997-2007
b max, SSE
P(b)
0.2
0.1
0
-0.2
-0.1
0
0.1
0.2
Coefficient b
b max,NYSE
P(b)
0.2
0.1
0
0
0.4
0.8
b



NYSE daily data (1990-2007)
Market mode
Average group modes (1:13)
Average random models (50:258)
L(t)
t (day)
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
0
10
20
30
40
50



SSE daily data (1997-2007)
Market mode
Average group modes (1:8)
Average random modes (50:258)
L(t)
t (day)
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
0
10
20
30
40
50

板块的相互作用

* 网络方法，如最小生成树、平面极大网络图

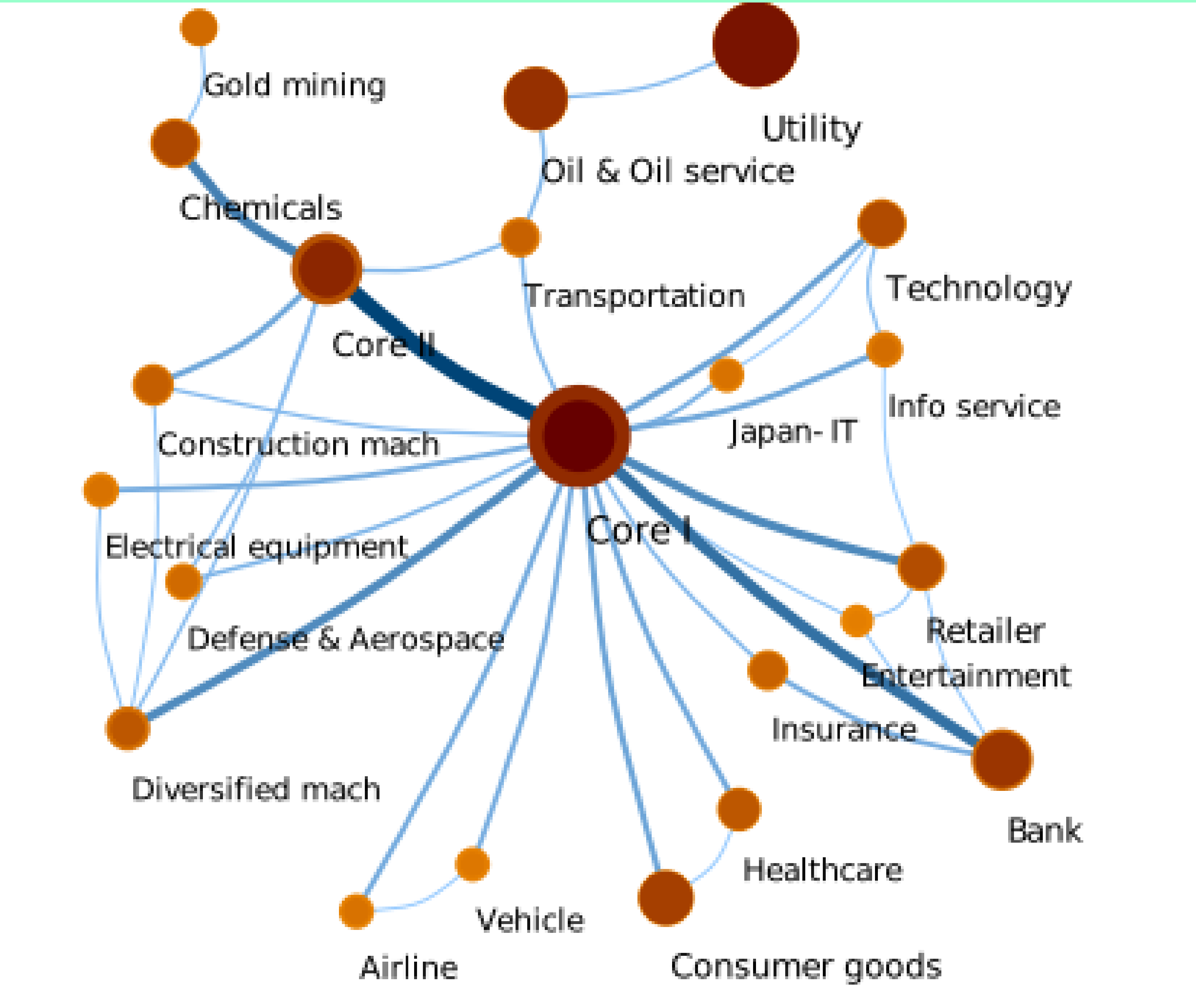
* 信息图方法

* 关联模式展开

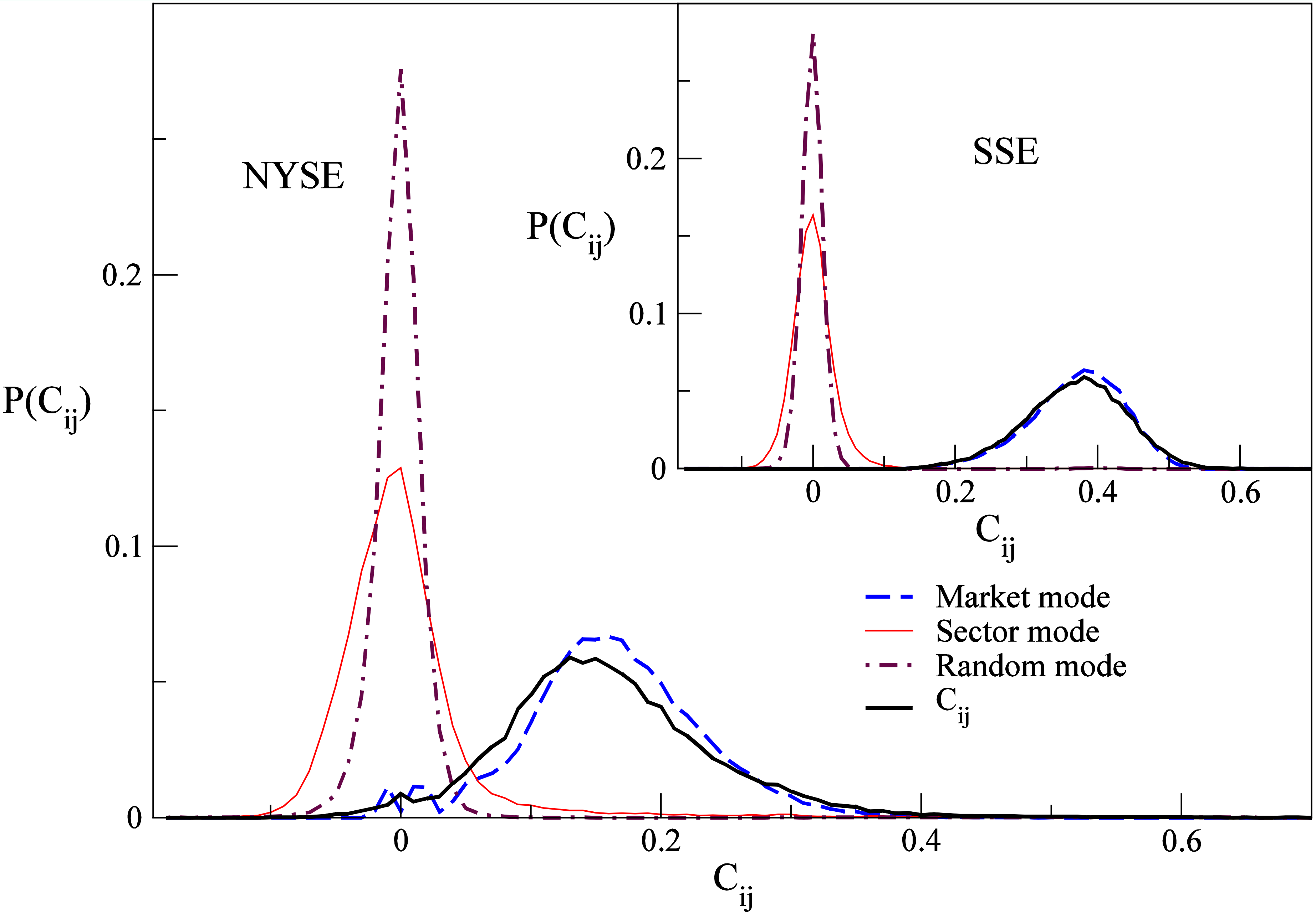
--真正的板块作用来自板块模式

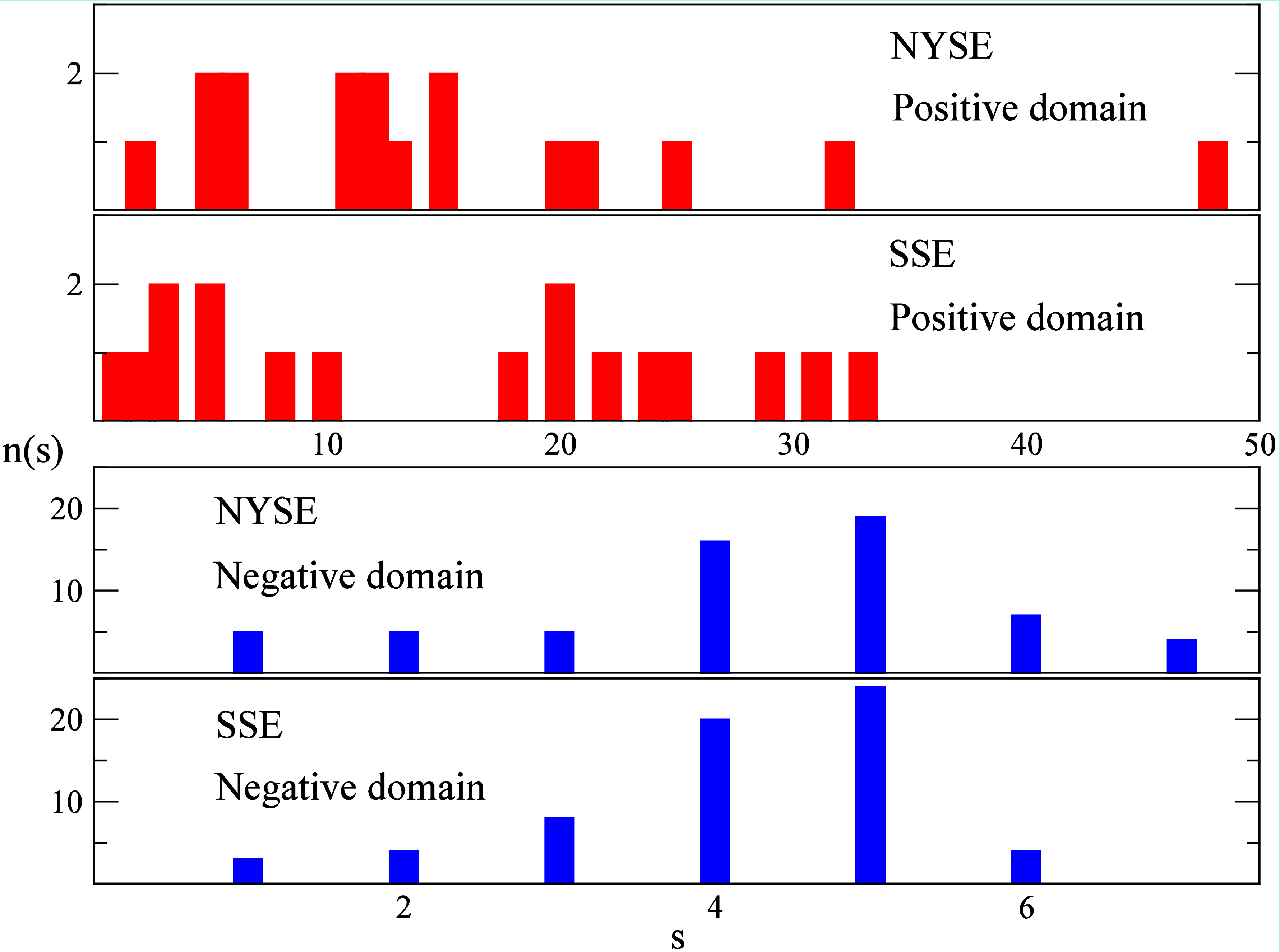
PNAS 102(2005)10421

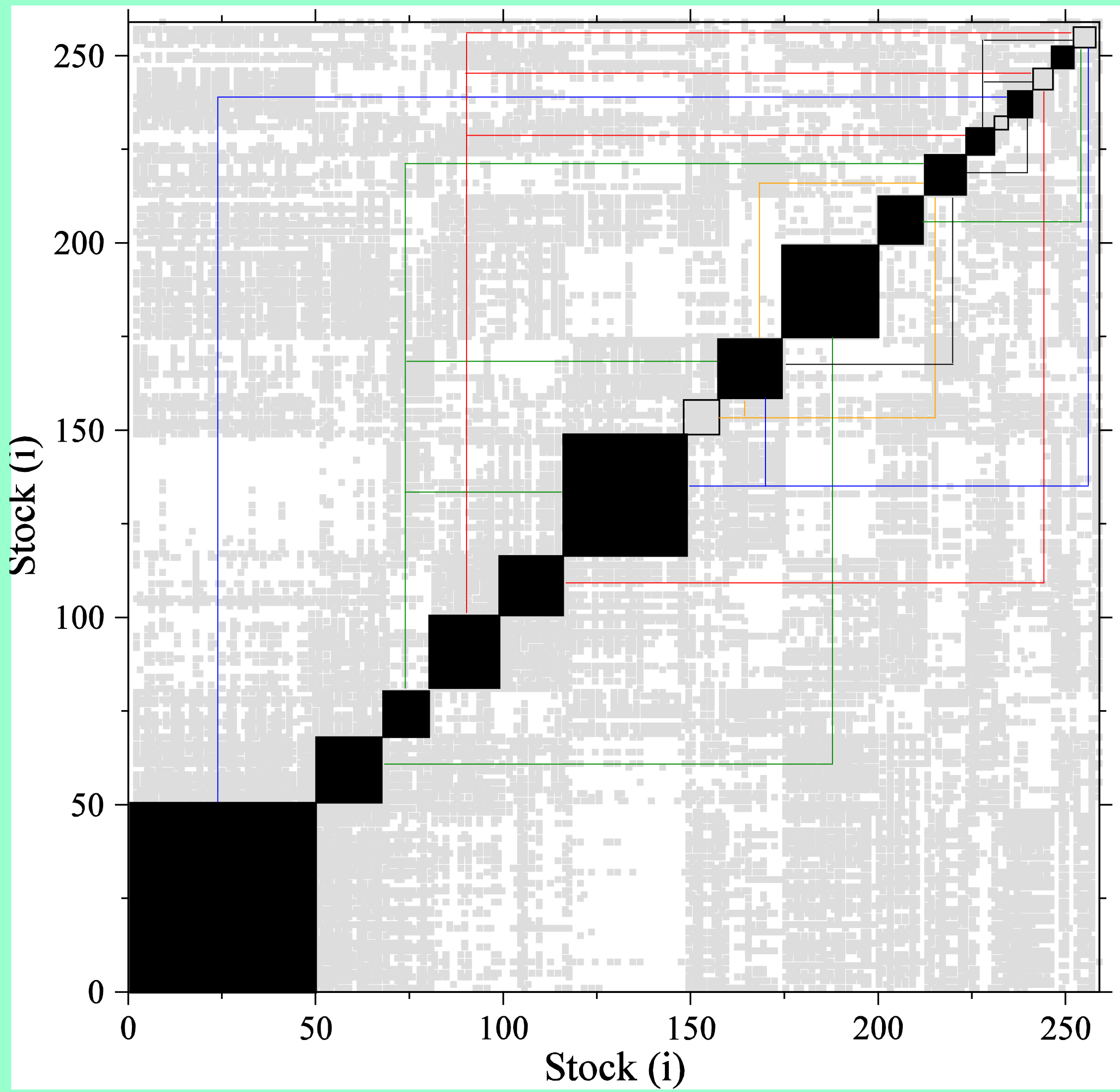
PMFG graph of New York market



		$\overline{C}_{ij}$	$\overline{C}_{ij}^{in}$	$\overline{C}_{ij}^{be}$	$\overline{C}_{ij}^{li}$	$\overline{C}_{ij}^{de}$	$\overline{C}_{ij}^{+-}$
NYSE	RMT	0.16	0.33	0.16			0.15
	MST	0.16	0.49	0.16	0.19	0.12	
	PMFG	0.16	0.46	0.15	0.18	0.13	
SSE	RMT	0.37	0.40	0.34			0.32
	MST	0.37	0.48	0.36	0.39	0.31	
	PMFG	0.37	0.43	0.36	0.38	0.32	

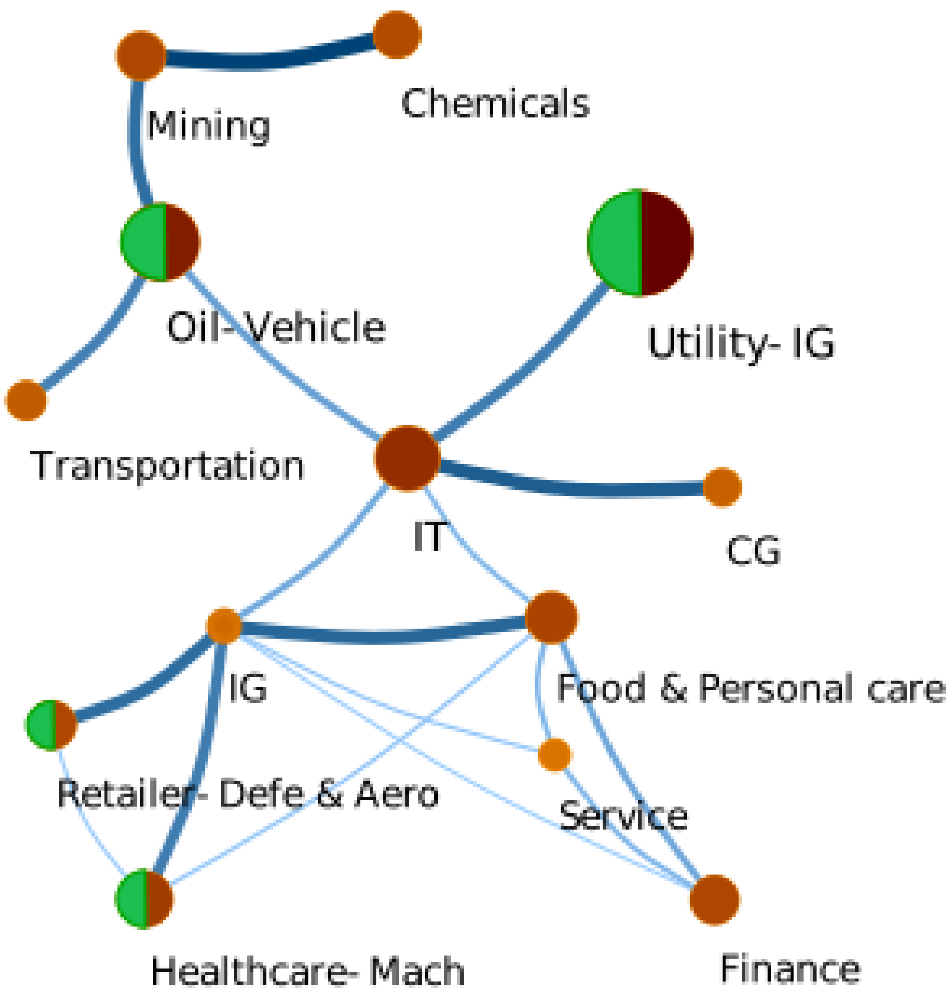

NYSE
P(C_ij)
0.2
0.1
0
0
0.2
0.4
0.6
C_ij
SSE
P(C_ij)
0.2
0.1
0
0
0.2
0.4
0.6
C_ij
Market mode
Sector mode
Random mode
C_ij


NYSE
Positive domain
2
SSE
Positive domain
2
n(s)
10
20
30
40
50
NYSE
Negative domain
20
10
SSE
Negative domain
20
10
2
4
6
s



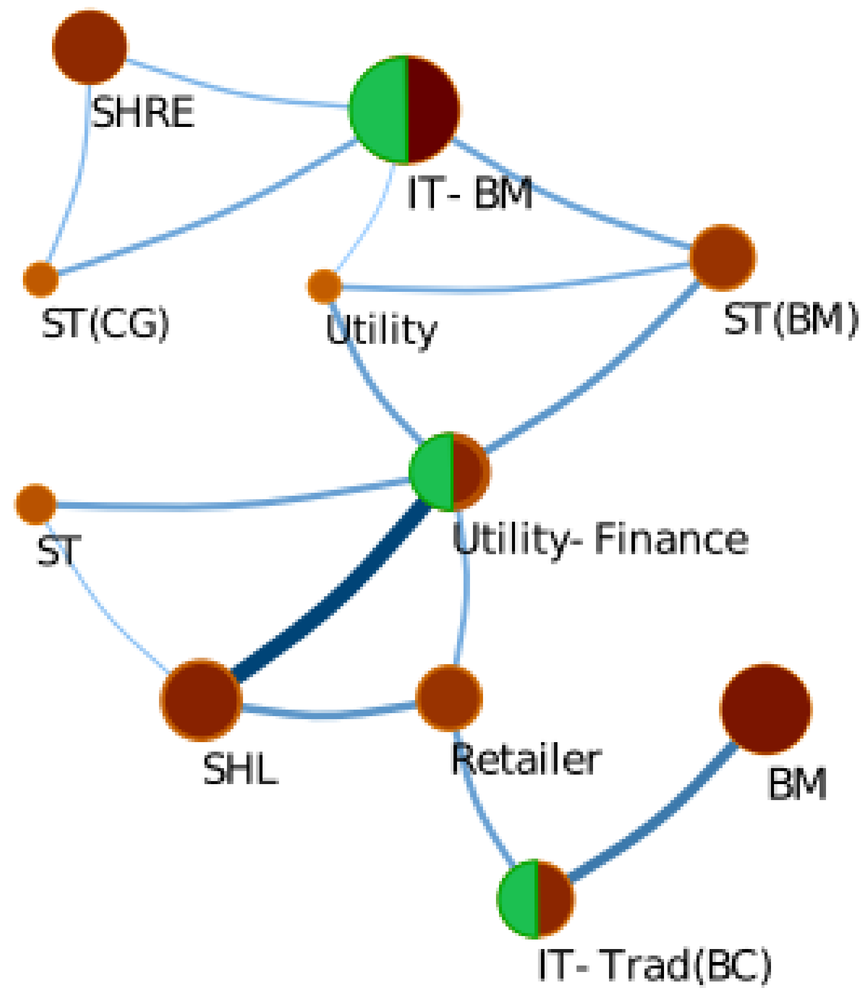
Stock (i)
Stock (i)
0
50
100
150
200
250
0
50
100
150
200
250

New York



(a)

Shanghai



(b)

		$\overline{C}_{ij}$	$\overline{C}_{ij}^{in}$	$\overline{C}_{ij}^{be}$	$\overline{C}_{ij}^{li}$	$\overline{C}_{ij}^{de}$	$\overline{C}_{ij}^{+-}$
NYSE	$\lvert C_{sec}\rvert$	3.2	9.7	2.5	2.8	2.4	2.3
	C_{sec}	0	7.4	−0.7	−0.4	−0.8	−0.9
SSE	$\lvert C_{sec}\rvert$	2.1	3.8	1.9	2.3	1.8	1.7
	C_{sec}	0	1.3	−0.2	−0.1	−0.2	−0.2

Contents

Large-volatility dynamics

It is time-reversal symmetric in the time scale of minutes, while asymmetric in the daily scale

The asymmetry is induced by external forces, which are accidental in Germany, while market-policy changing in China

Remanent and anti-remanent volatilities

$$v_{\pm}(t) = \frac{1}{Z}[<| R(t'+t) |>_{c} - \sigma]$$

The average is over the events

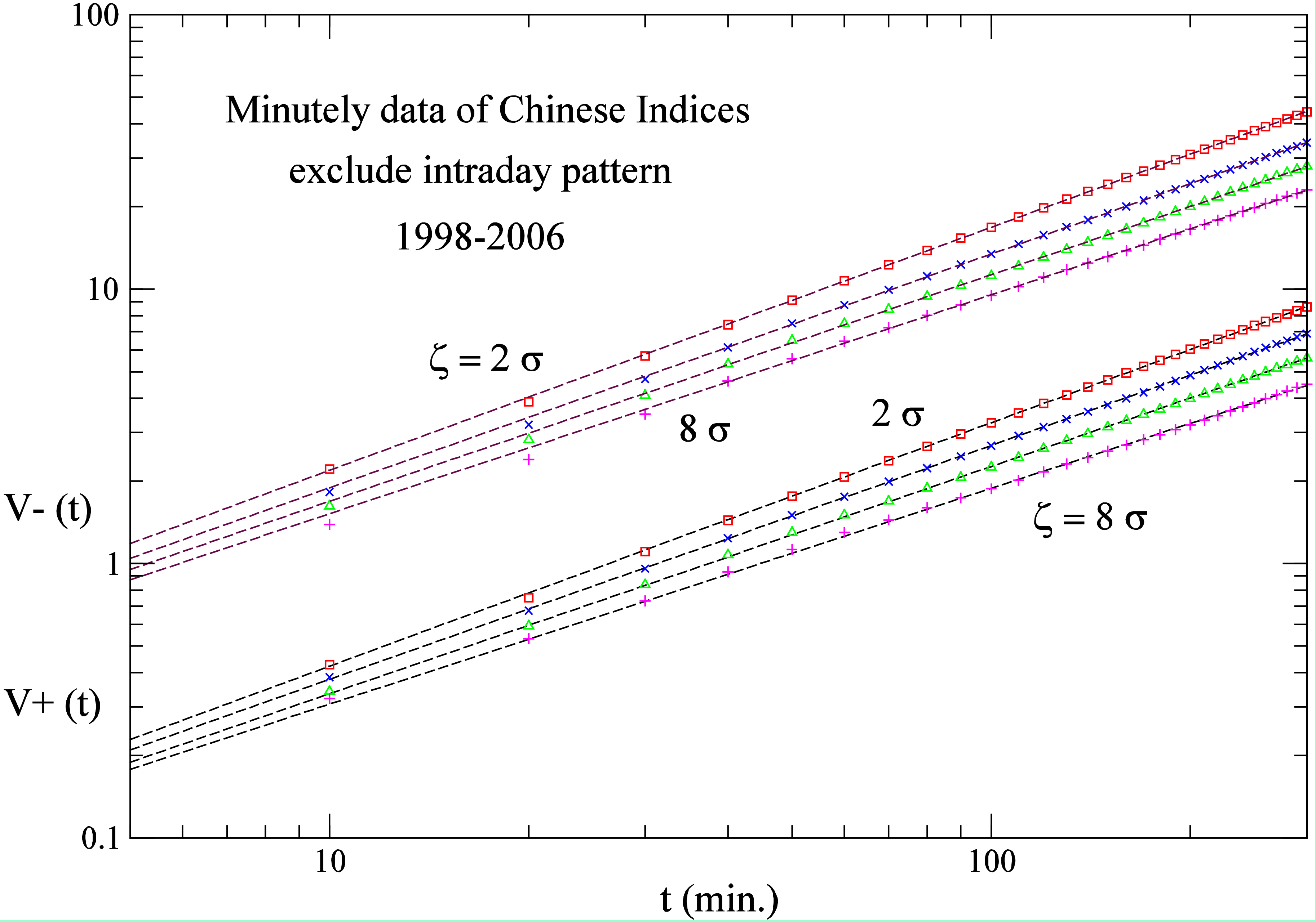
$$| R(t'+t) |> \zeta = 2\sigma,\ 4\sigma\ ,6\sigma\ ,8\varsigma$$

The power law

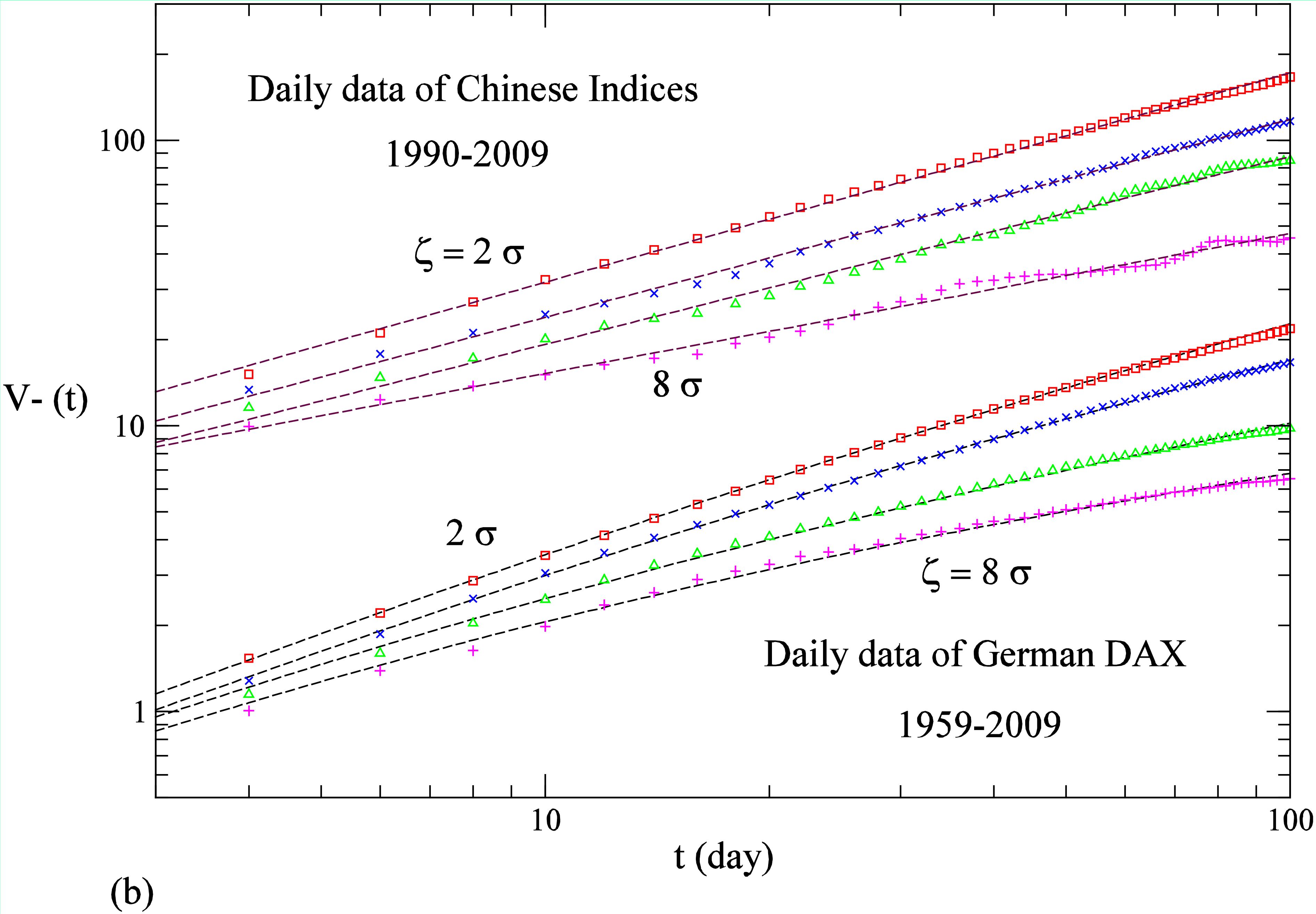
$$v_{\pm}(t) \propto (t+\tau)^{-p_{\pm}}$$

$$V(t) = \int_{0}^{t} v(t')dt' = (t+\tau)^{1-p} - \tau^{1-p}$$

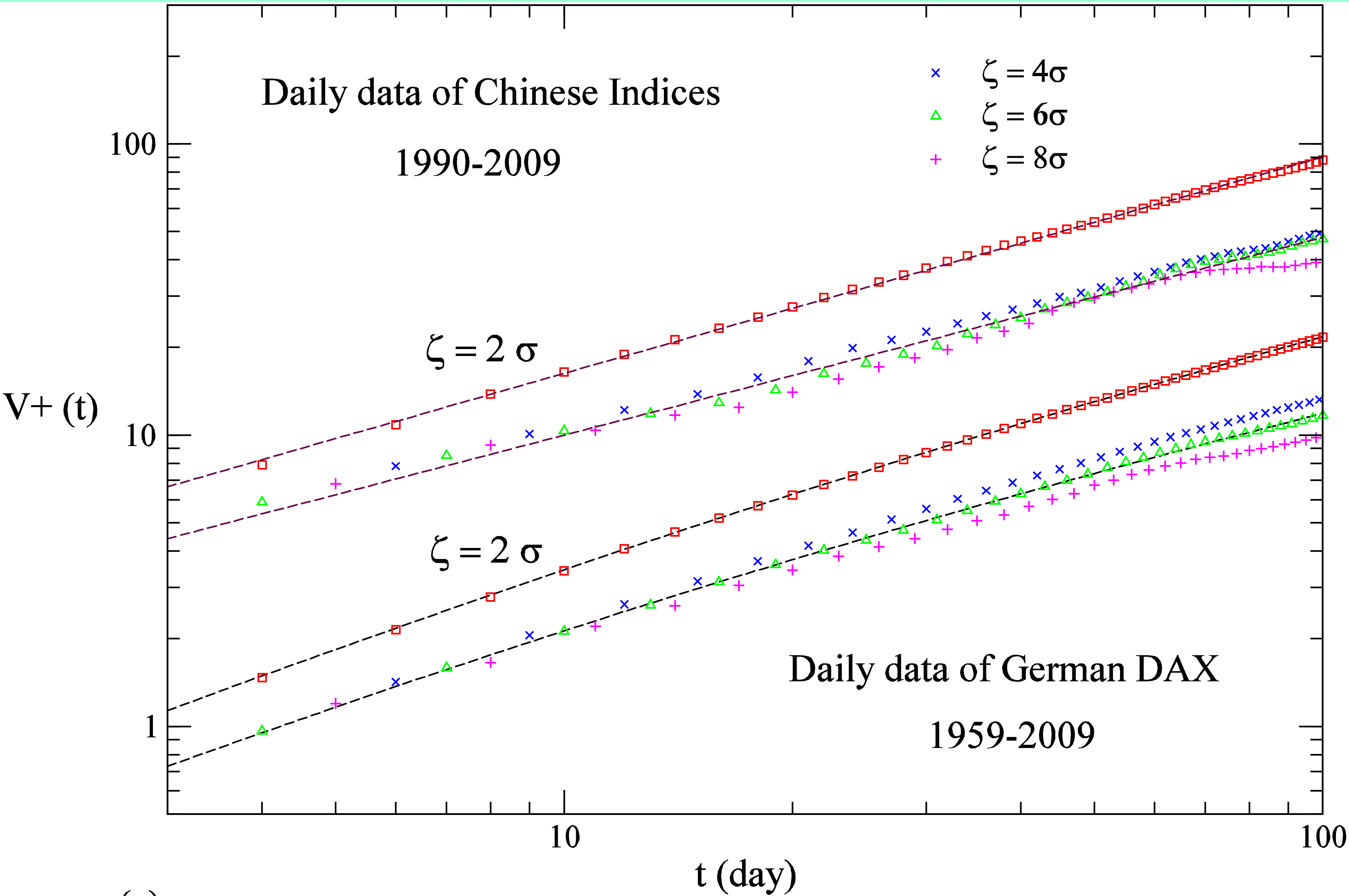
ζ	2σ	4σ	6σ	8σ
	CHN(min)			
p_-	0.11(1)	0.15(1)	0.17(1)	0.20(1)
p_+	0.11(1)	0.15(1)	0.18(1)	0.22(1)
	DAX(min)			
p_-	0.16(1)	0.23(1)	0.27(1)	0.29(1)
p_+	0.16(1)	0.22(1)	0.26(1)	0.29(1)
	CHN(day)			
p_-	0.27(3)	0.31(4)	0.36(4)	0.51(6)
p_+	0.26(2)	0.32(3)	0.33(4)	0.36(5)
	DAX(day)			
τ_-	13.11	9.06	4.07	3.78
p_-	0.41(3)	0.47(4)	0.60(5)	0.77(7)
τ_+	10.66	9.23	7.28	3.98
p_+	0.40(2)	0.42(3)	0.45(5)	0.46(5)
p_-	0.28(3)	0.30(3)	0.50(5)	0.61(5)
p_+	0.25(2)	0.28(2)	0.31(3)	0.35(4)



Minutely data of Chinese Indices
exclude intraday pattern
1998-2006
ζ = 2 σ
8 σ
2 σ
ζ = 8 σ
V- (t)
V+ (t)
100
10
1
0.1
10
100
t (min.)



Daily data of Chinese Indices
1990-2009
ζ = 2 σ
8 σ
2 σ
ζ = 8 σ
Daily data of German DAX
1959-2009
V- (t)
t (day)
100
10
1
10
100
(b)



Daily data of Chinese Indices
1990-2009
ζ = 4σ
ζ = 6σ
ζ = 8σ
ζ = 2 σ
ζ = 2 σ
Daily data of German DAX
1959-2009
V+ (t)
t (day)
100
10
1
10
100

(a)

Why is it time-reversal asymmetric in the daily time scale?

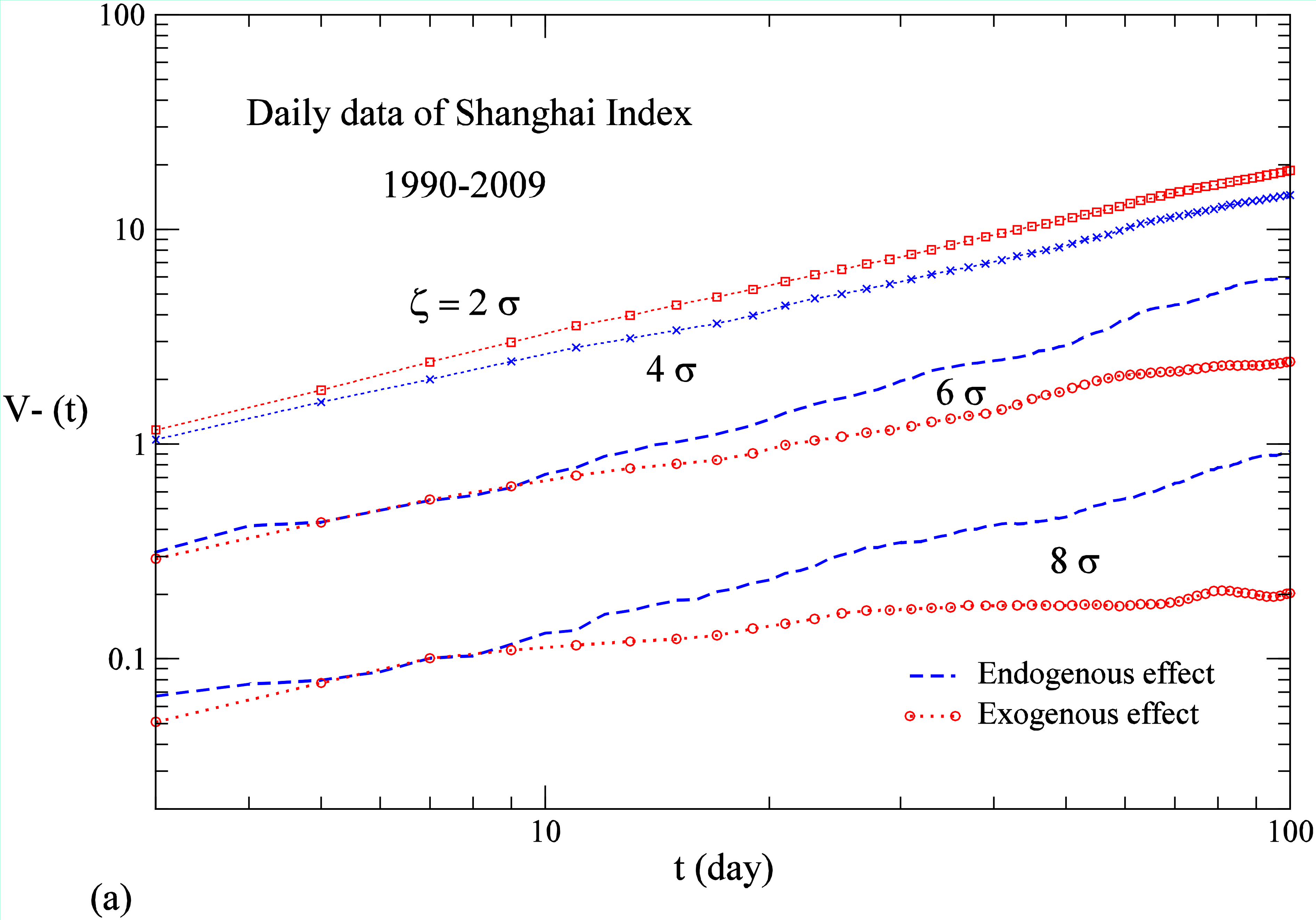
We classify the large volatilities into Exogenous and endogenous events.

Date	Event	
92.05.21	Rally	Chinese stock markets allowed free bidding transactions.
94.03.14	Rally	The State Council announced that income from stock transfer was exempt from tax this year, and banned the arbitrary right issue of listed companies.
94.08.01	Rally	CSRC decided to suspend new coming IPOs, to control the scale of right issues, and to develop mutual fund and fostered institution investors.
95.05.18	Rally	CSRC suspended the pilot program of the national debt and future trading.
95.05.23	Crash	CSRC declared large amount of deposits of IPOs in 1995.
96.12.16	Crash	CSRC set a limitation for the price change in a trading day in stock markets.
97.05.22	Crash	CSRC and Central Bank controlled the fund investing in stock markets.
01.10.23	Rally	CSRC declared stopping reduction of state-owned shares.
08.09.19	Rally	MFSAT declared reduction of the stamp tax rate in stock transactions; SASAC announced support for central enterprises and for holdings of listed companies to buy shares back.

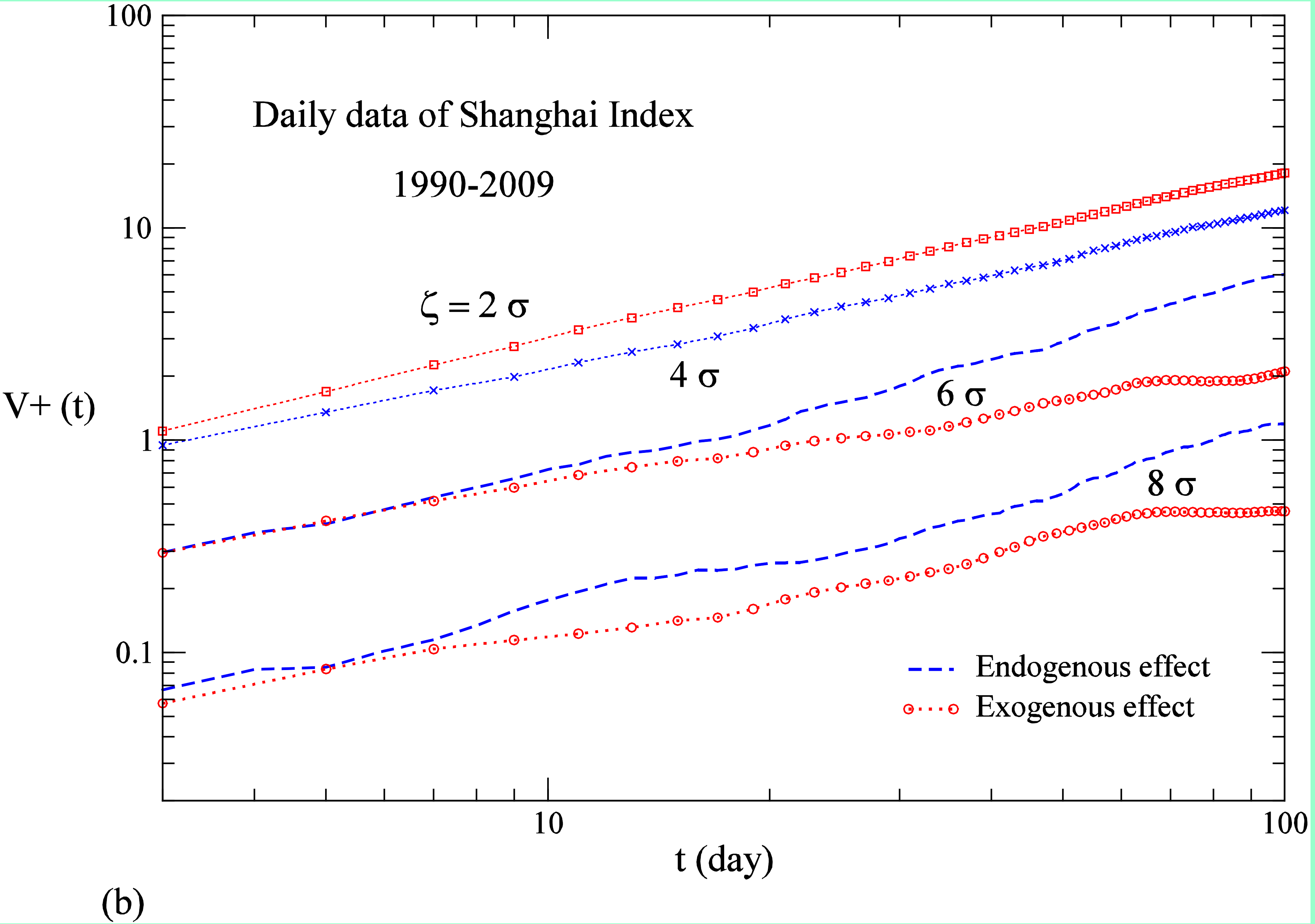
Table 2: The 9 exogenous events corresponding to $\zeta = 8\sigma$ for the daily data of the Shanghai Index. The total number of the large volatilities for $\zeta = 8\sigma$ is 16. IPOs: Initial Public Offerings; CSRC: China Security Regulatory Commission; MFSAT: Ministry of Finance and State Administration of Taxation; SASAC: State-owned Asset Supervision and Administration Commission.

Date	Event	
62.05.29	Crash	The big crash in NYSE in 05.28.
87.10.19	Crash	Black Monday all over the world.
87.10.22	Crash	
87.10.26	Crash	
87.10.28	Crash	
87.11.10	Crash	
89.10.16	Crash	Honecker in East Germany was forced to resign.
91.01.17	Rally	Gulf War started.
91.08.19	Crash	The coup against Gorbachev in Soviet Union.
97.10.28	Crash	Asian Financial Crisis.
01.09.12	Crash	Sep. 11 attack in US.
08.01.21	Crash	Subprime mortgage crisis.
08.10.06	Crash	
08.10.10	Crash	
08.10.13	Crash	
08.11.06	Crash	

Table 3: The 16 exogenous events corresponding to $\zeta = 8\sigma$ for the daily data of the German DAX. The total number of the large volatilities for $\zeta = 8\sigma$ is 27.



Daily data of Shanghai Index
1990-2009
ζ = 2 σ
4 σ
6 σ
8 σ
V- (t)
t (day)
100
10
1
0.1
10
100
Endogenous effect
Exogenous effect
(a)



Daily data of Shanghai Index
1990-2009
ζ = 2 σ
4 σ
6 σ
8 σ
V+ (t)
t (day)
Endogenous effect
Exogenous effect
100
10
1
0.1
10
100
(b)

ζ	2σ	4σ	6σ	8σ	
	SHI(day)				
p_-	0.22(2)	0.24(2)	0.18(3)	0.20(6)	En.
			0.54(4)	0.80(7)	Ex.
p_+	0.23(2)	0.25(3)	0.16(4)	0.21(6)	En.
			0.52(4)	0.51(5)	Ex.
	DAX(day)				
p_-	0.28(3)	0.30(3)	0.37(3)	0.31(4)	En.
			0.50(4)	0.76(6)	Ex.
p_+	0.25(2)	0.28(2)	0.31(3)	0.34(5)	En.
			0.32(4)	0.35(4)	Ex.

Table 4: $p_\pm$ of the endogenous (EN.) and exogenous (EX.) events for the daily data of the Shanghai Index (SHI) and DAX.

Contents

Conclusion

Chinese and western stock markets

share common basic features,

such as probability distribution of returns,
auto-correlations of returns and volatility

but not all characteristics, e.g.,
higher-order time correlations,
cross-correlations of returns
Non-stationary dynamic behavior

股票价格运动粗略分解为：

* 股票整体运动 – market mode

* 股票局域运动 – group modes

* 准随机运动 – quasi-random modes

大盘指数和个体股票价格可以按模式展开

模式之间可以相干，如中国
也可以不相干，如美国

展 望

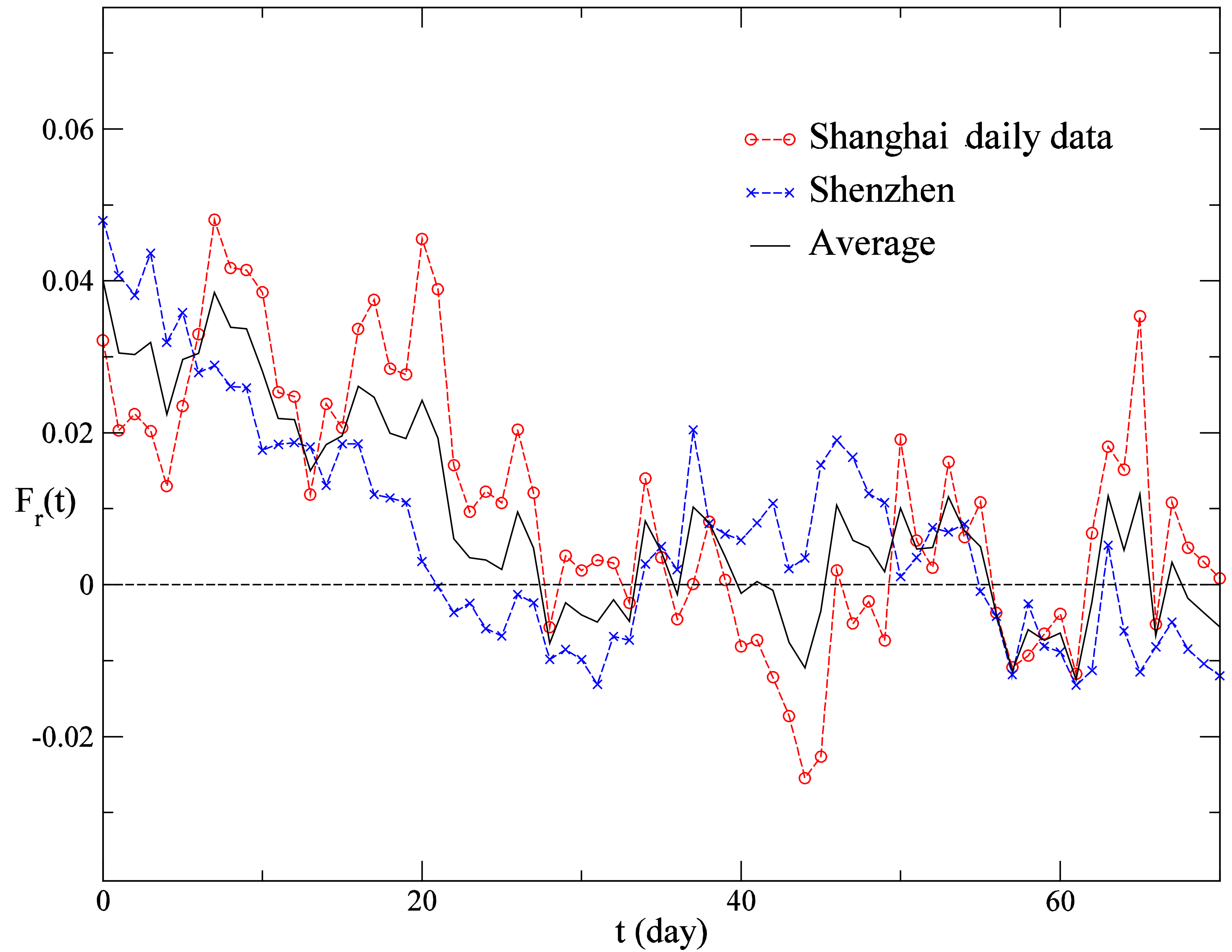
* 在经济金融研究中，统计物理学的研究思路和研究方法，具有重要科学价值
* 关联矩阵理论中的模式展开，经验模式展开以及价格预测等，是今后重要研究手段
* 时间非局域关联函数和相互作用，是今后探索的重点之一
* 真人实验和赚钱计划是极大的挑战

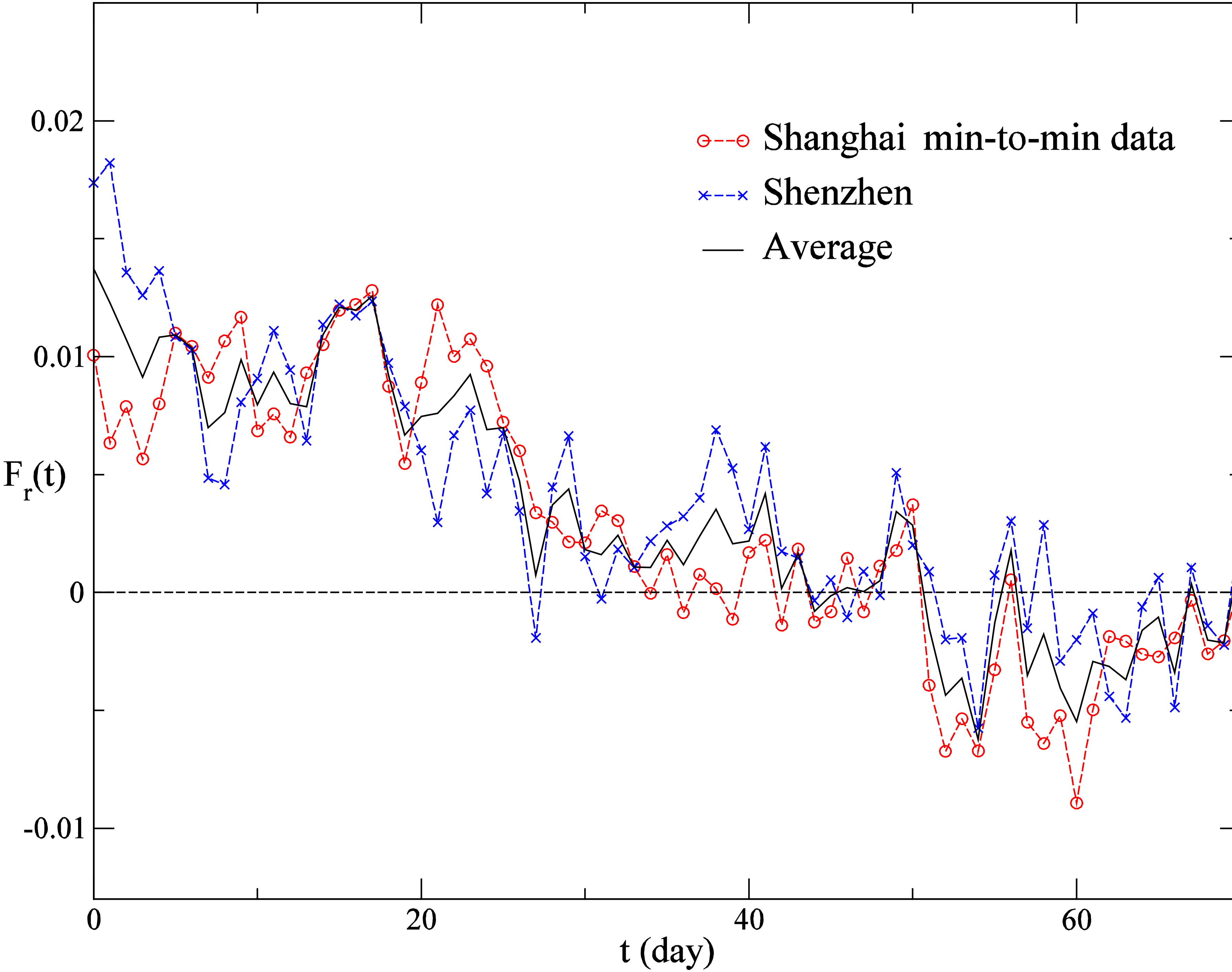
How do volatilities affect the movement of price returns?

* We need to compute volatility-return correlation non-local in time, and one detects 2-3% bias in Chinese markets, e.g.,

$$L(t) = < O(|R(t')|)R(t'+t) >$$

* Highly non-universal


Shanghai daily data
Shenzhen
Average
0.06
0.04
0.02
0
-0.02
F_r(t)
0
20
40
60
t (day)



Shanghai min-to-min data
Shenzhen
Average
0.02
0.01
0
-0.01
$F_r(t)$
0
20
40
60
t (day)

Thank you!

http://zimp.zju.edu.cn