Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

Entrepreneurial Risks

Reverse Engineering Financial Markets with Mixed Agent-Based Games

Regime shifts and market inefficiency

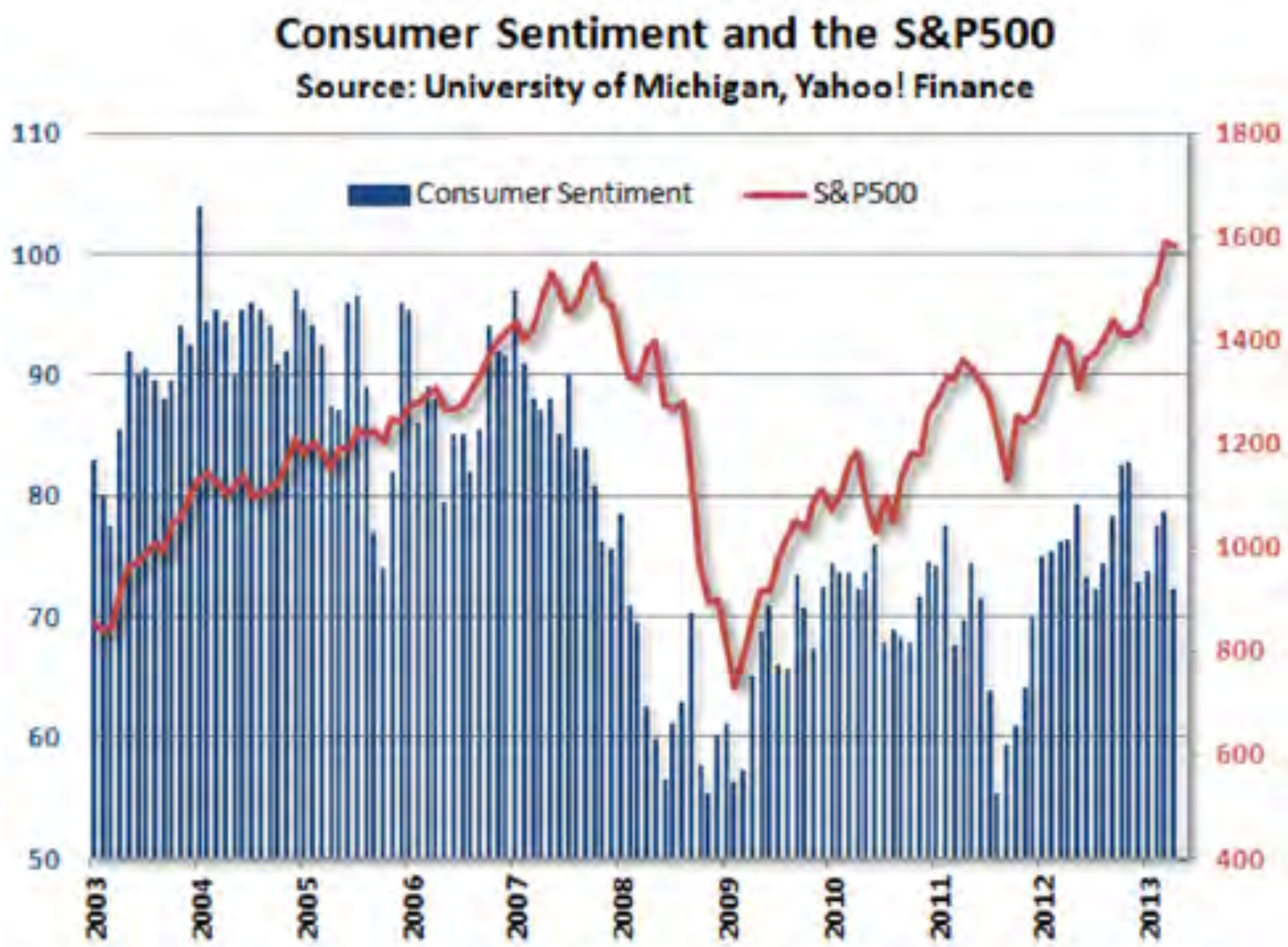
Qunzhi Zhang, **Didier Sornette**, Jeffrey Satinover

www.er.ethz.ch

Reverse-engineering of financial markets by agent-based models: regime shifts and breakdown of market efficiency

Key Propositions

- The assumption of stationarity in financial time series is fundamentally wrong and misleading!
- Regime shifts and change of regimes are the “norm” rather than the exception.
- Financial markets exhibit transitions between phases of growth, exuberance and crises.



Consumer Sentiment and the S&P500
Source: University of Michigan, Yahoo! Finance
Consumer Sentiment
S&P500
110
100
90
80
70
60
50
1800
1600
1400
1200
1000
800
600
400
2003
2004
2005
2006
2007
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2009
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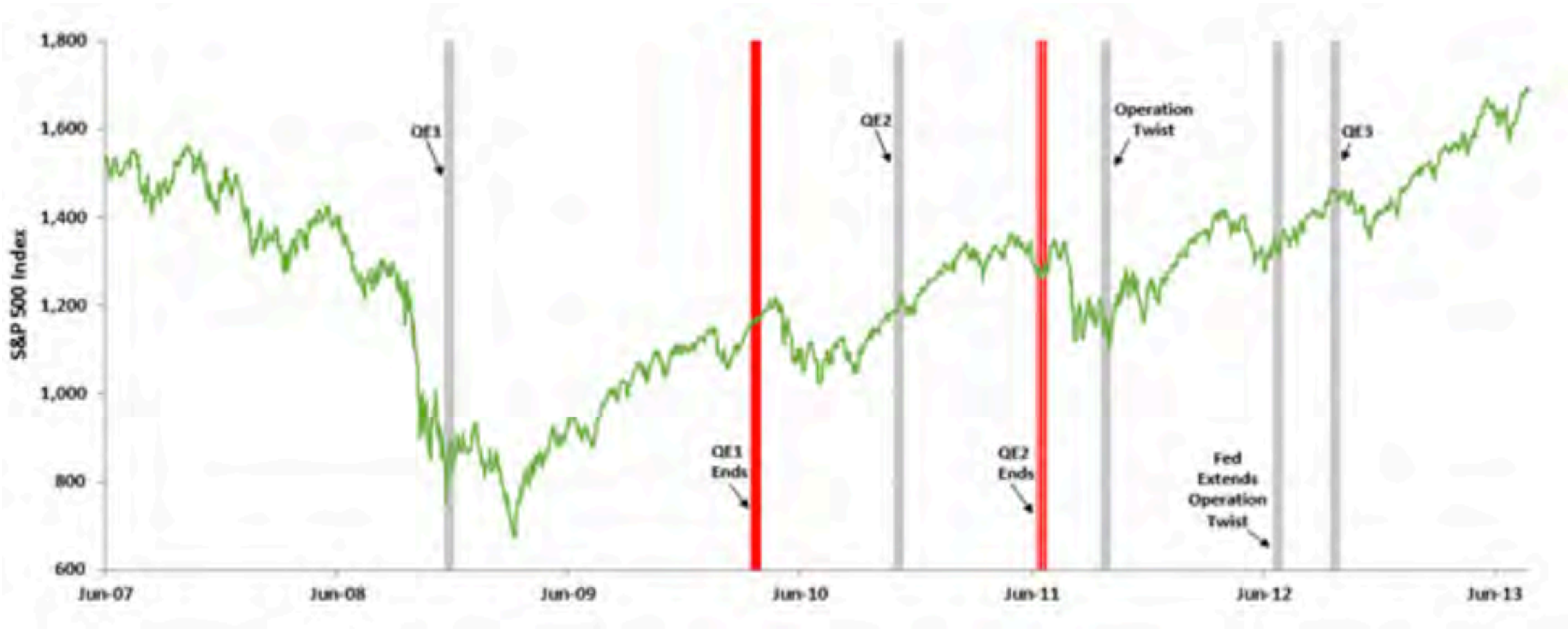
2012
2013



(source: www.JohnMaulding.com)

Bond Bubble, Or Rational Expectations? Visualizing 220 Years Of Treasury Yields

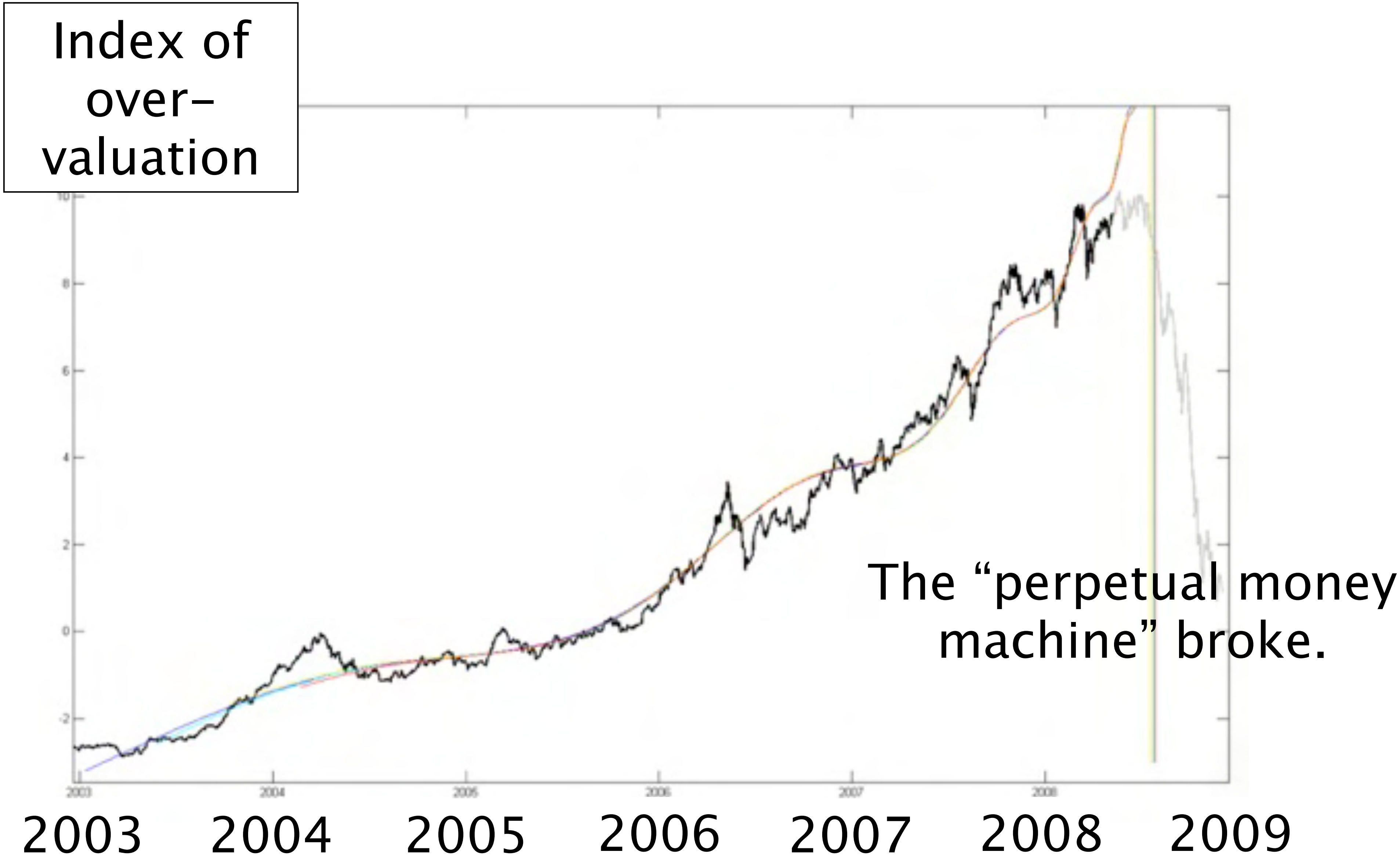
Source: Global Financial Database, Goldman Sachs Global ECS Research. Special thanks to Jose Ursua.

Near multi-generational low bond yields, driven at least in part (and some think in full) by the undeniably large asset purchase program (Quantitative Easing (QE)) that the US Federal Reserve has been implementing in one form or another since the 2008 Global Financial Crisis (GFC), have pushed the question of whether or not the bond market is a bubble to the front of many people's minds. However, while the chart below of over **220 years of 10-year treasury yields** shows the extraordinarily low bonds yields, they have resulted from many fundamental and rational drivers (expectations of weak economic growth and safe haven flows amid the European sovereign debt crisis) in addition to Fed purchases. **So while bond prices look expensive, there is nothing particularly bubbly about the bond market today.** http://www.zerohedge.com/news/2013-04-23/bond-bubble-or-rational-expectations-visualizing-220-years-treasury-yields

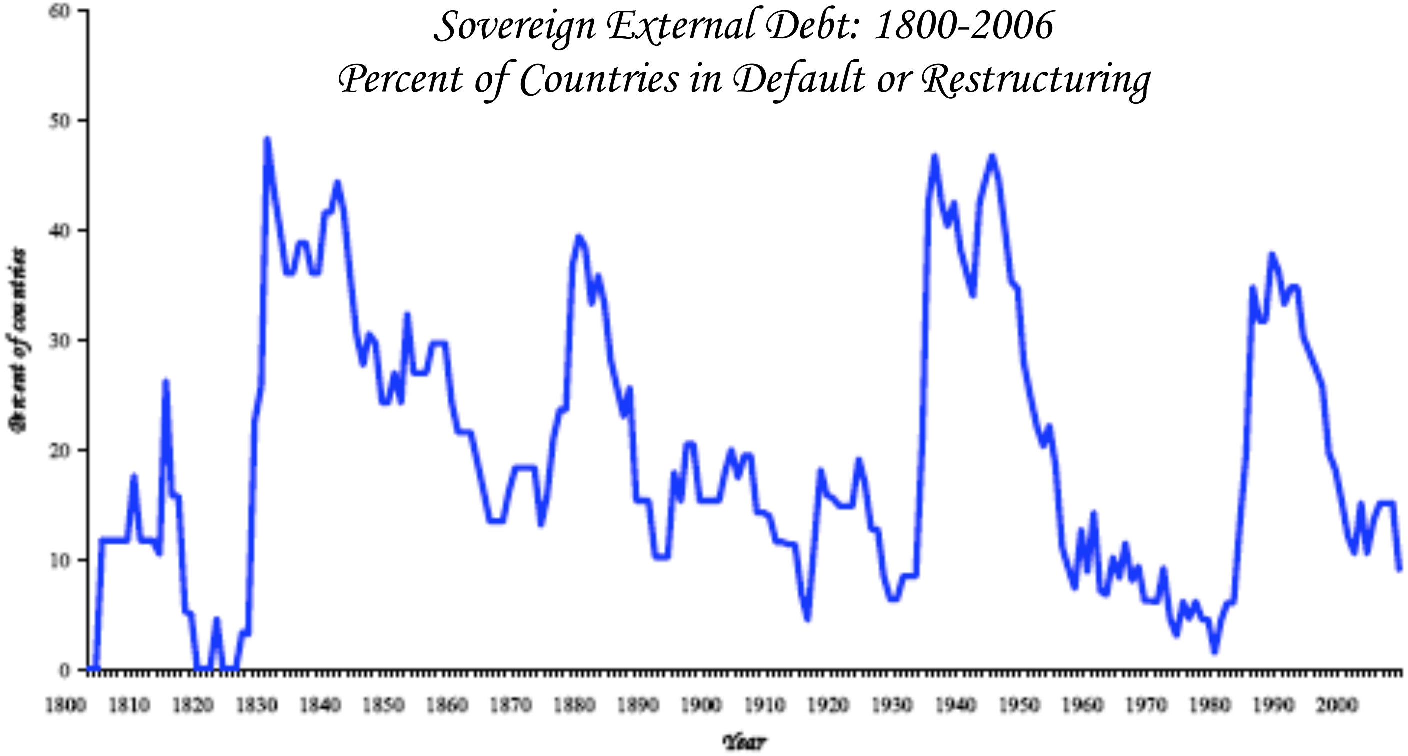
Key Propositions

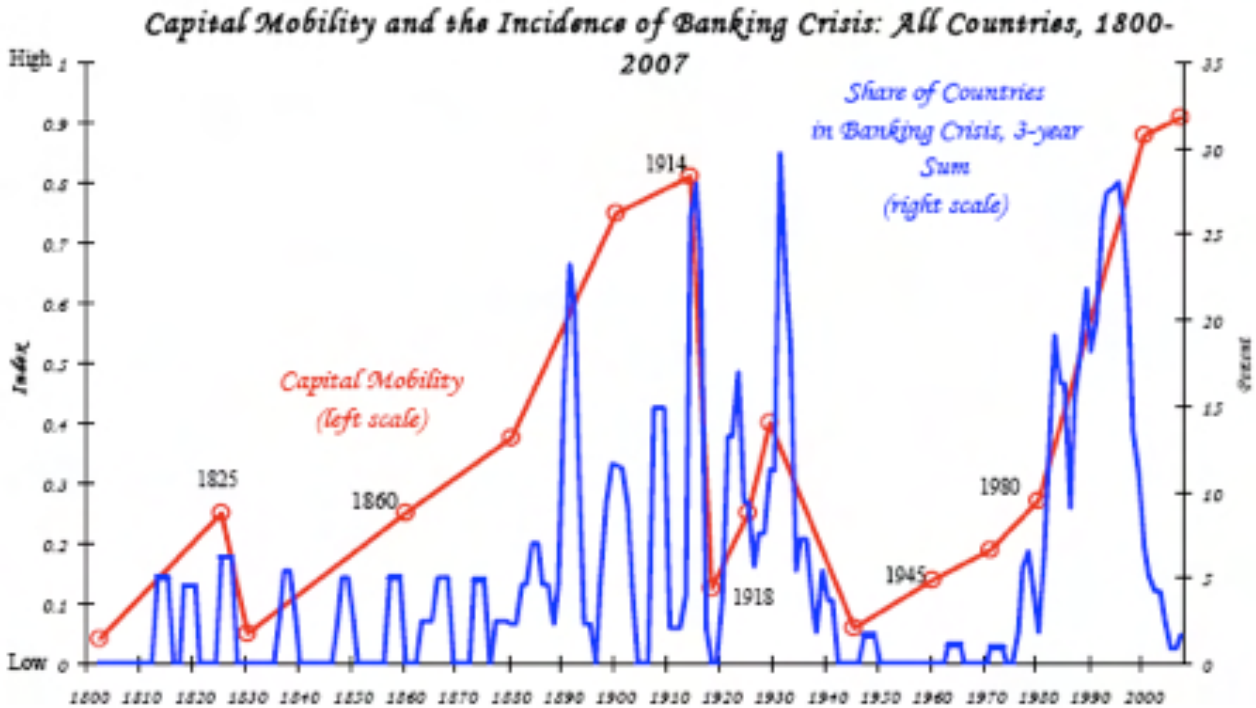
- The assumption of stationarity in financial time series is fundamentally wrong and misleading!
- Regime shifts and change of regimes are the “norm” rather than the exception.
- Financial markets exhibit transitions between phases of growth, exuberance and crises.
- Most crises are endogenous and are the consequence of procyclical positive feedbacks that burst.
- Possibility of developing probabilistic warning and forecast of change of regime

The Global Bubble



D. Sornette and P. Cauwels, The Illusion of the Perpetual Money Machine,
Notenstein Academy White Paper Series (Dec. 2012) (http://arxiv.org/abs/1212.2833)





Crises frequently emanate from the financial centers with transmission through interest rate shocks and commodity price collapses. Thus, the recent US sub-prime financial crisis is hardly unique.

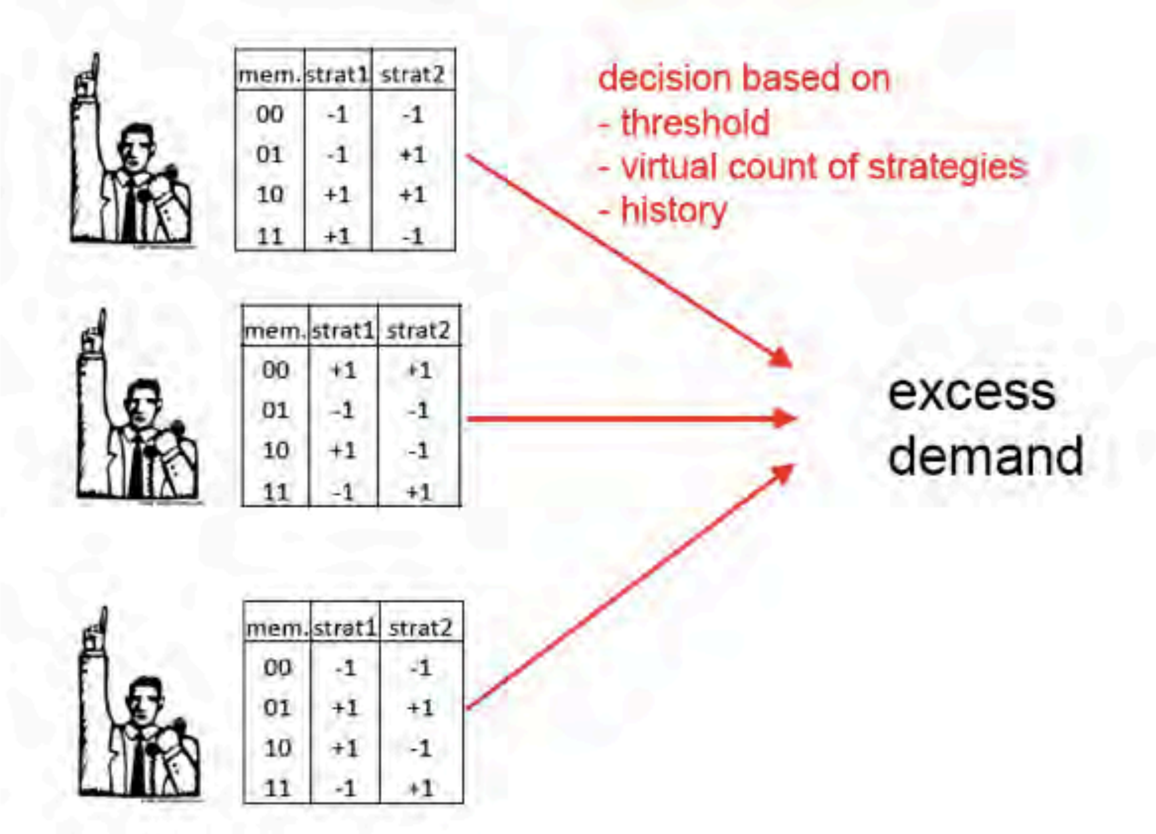
This Time is Different: A Panoramic View of Eight Centuries of Financial Crises
Carmen M. Reinhart and Kenneth S. Rogoff, NBER Working Paper No. 13882, March 2008

Goals

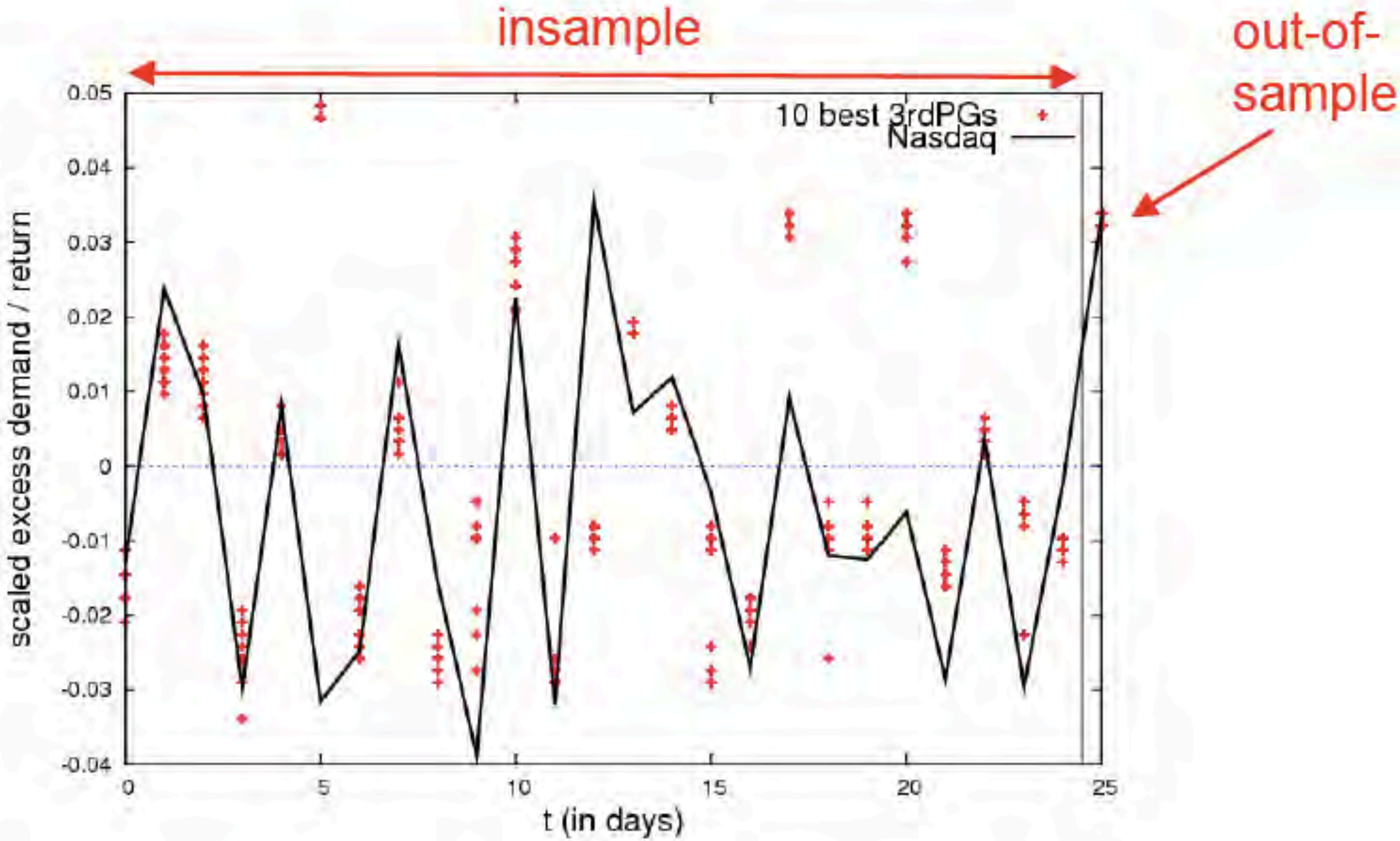
Get a scientific understanding of the generating process of a time series by finding 3rd Party Games (3rdPG) which produce similar time series to the one which is fed (insample)

→*Reverse Engineering*

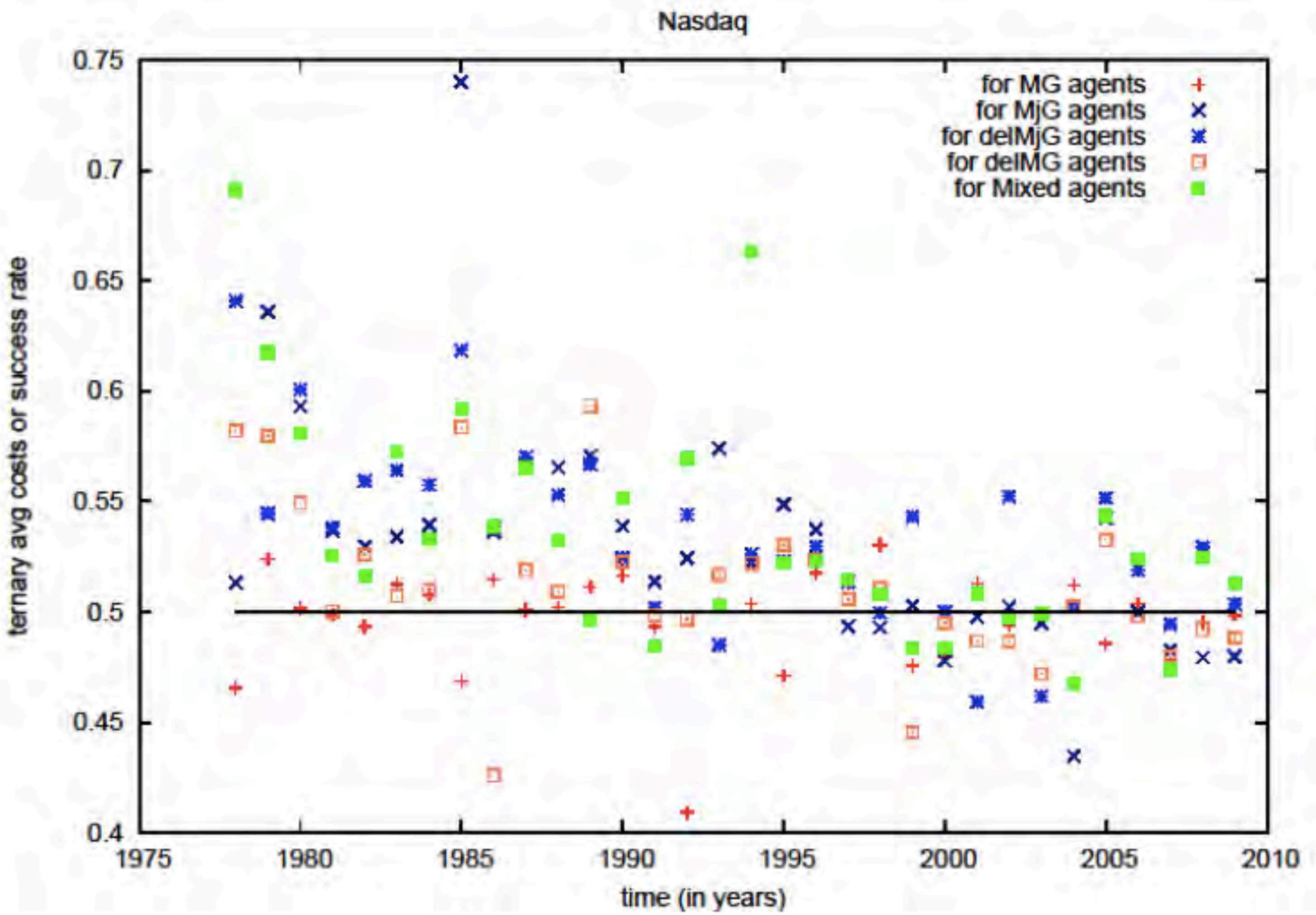
Grand Canonical Minority Game (GCMG)



Genetic Algorithm Optimization



Result of Academic Interest:
Markets become more and more efficient



J. Wiesinger, D. Sornette, J. Satinover, Reverse Engineering Financial Markets with Majority and Minority Games using Genetic Algorithms, Computational Economics DOI 10.1007/s10614-011-9312-9 (2012) (http://arxiv.org/abs/1002.2171)

Reverse engineering stock markets with mixed games and alpha generation

- Mixed games
- Dynamics of the games
- Stylized facts generated by the mixed games
- Calibrate the mixed games
- Predict the future return signs with the mixed games
- Trading strategies based on the mixed games
- Structures of ABM's and market regimes
- Conclusions

Mixed games

- General definitions
  - **N** agents in a virtual market
  - they trade from time **t = 1** to **Z**
  - they generate a return time series $\{r_t\}$
- Agent decision making rules
  - bounded rationality
  - limited knowledge
    - memory length **m**
    - history price change directions $\{0,1\}^m$
  - limited computation capacity
    - **s** trading strategies
    - **f**: $\{0,1\}^m \rightarrow \{+1,-1\}$
  - Preference of an agent over her trading strategies
    - backward-looking and myopic
    - choose the trading strategy that maximized the score
    - the score is based on her belief
  - An agent will not trade if she is not confident enough
    - check the success rate of last **T** times, if the success rate is lower than τ, she will not trade
- A virtual market is defined by parameters **N,m,s,τ,T** and $\{f_i\}$

Mixed games

- Price formation

$$A_t = \sum_{i=1}^{N} a_i^t(\mu_t) .$$

$$r_t = \frac{A_t}{\lambda} ,$$

  - **μ_t** – the history information
  - **a_i^t** – the action of agent **i** at time **t**
  - **A_t** – the collective actions of all agents
  - λ – liquidity, a normalization factor
  - **r_t** – the return of the virtual market at time **t**

Mixed games

- Beliefs of agents
  - minority game

$$\pi^{\mathrm{mg}}(f_i^j(\mu_t)) = -\kappa f_i^j(\mu_t) A_t \,,$$

  - delayed minority game

$$\pi^{\mathrm{dmg}}(f_i^j(\mu_t)) = -\kappa f_i^j(\mu_t) A_{t+1} \,.$$

  - majority game

$$\pi^{\mathrm{majg}}(f_i^j(\mu_t)) = \kappa f_i^j(\mu_t) A_t \,,$$

  - \$-game

$$\pi^{\mathrm{dg}}(f_i^j(\mu_t)) = \kappa f_i^j(\mu_t) A_{t+1} \,.$$

- Symbols
  - **μ_t** – the history information
  - **f_i^j** – **j**-th strategy of agent **i**
  - **A_t** – the collective actions of all agents
  - κ – a positive normalization factor
  - π – the payoff functions of strategies

Dynamics of the games – minority game

- Consider an ideal minority game virtual stock market
  - A virtual stock market defined as in the preceding slides
  - $\tau=0$
  - The input information $\{\mu_t\}$ is i.i.d and exogenous as given. The trading strategies f of agents are thus random variables
  - agents pick trading strategies randomly from their trading strategy sets according to performance of the trading strategies, with probability defined by the following equation:

$$\mathrm{P}(f_i^* = f_i^j) := \frac{e^{\kappa U(f_i^j, t)}}{\sum_{k=1}^{s} e^{\kappa U(f_i^k, t)}}$$

$$U(f_i^j, t) = \sum_{\varsigma=1}^{t-1} \pi(f_i^j(\mu_\varsigma))$$

Dynamics of the games – minority game

- **Proposition**: for an ideal minority game virtual stock market, if there is a stationary state, then the agents' decisions are the solution of the following optimization problem:

$$\textit{minimize:} \quad \mathrm{E}_0[(\sum_{i=1}^{N}\sum_{j=1}^{s}\beta_i^j f_i^j(\mu_t))^2]$$

$$\textit{subject to:} \quad \sum_{j=1}^{s}\beta_i^j = 1, \forall i = 1, \ldots, N$$

$$\beta_i^j \geq 0, \forall i = 1, \ldots, N, j = 1, \ldots, s$$

The minimization is respect to the parameters β_i^j, which is the probability that the i-th agent picks the j-th strategy.

β_i^j are constants when the game is stationary.

Because every agent wants to pick the strategy that maximizes $\sum f_i^j(\mu_t)A(t)$, where A(t) is the collective action of all agents, and on average $A(t) = \sum_i \sum_j \beta_i^j f_i^j(\mu_t)$ so the decisions of the agents are to minimize $E\left[A(t)^2\right]$

- **Remark**: In most cases, ideal minority game virtual stock markets will converge to a stationary state. In some rare cases, there will be periodic Markov chains.

Dynamics of the games – majority game

- In the same way we can define ideal virtual stock markets for majority game, $-game and delayed minority game
- Ideal majority game virtual stock market:

$$\textit{maximize:} \quad \mathrm{E}_0[(\sum_{i=1}^{N}\sum_{j=1}^{s}\beta_i^j f_i^j(\mu_t))^2]$$

$$\textit{subject to:} \quad \sum_{j=1}^{s}\beta_i^j = 1, \forall i = 1,\ldots,N$$

$$\beta_i^j \geq 0, \forall i = 1,\ldots,N, j = 1,\ldots,s$$

Dynamics of the games – $game

- In the same way we can define ideal virtual stock markets for majority game, $-game and delayed minority game
- Ideal $-game virtual stock market. When the market is stationary, the decisions of the agents are a local maximum of the following optimization problem

$$\textit{maximize:} \quad E_0^2\left[\sum_{i=1}^{N}\sum_{j=1}^{s} \beta_i^j f_i^j(\mu_t)\right]$$

$$\textit{subject to:} \quad \sum_{j=1}^{s} \beta_i^j = 1, \forall i = 1, \ldots, N$$

$$\beta_i^j \geq 0, \forall i = 1, \ldots, N, j = 1, \ldots, s$$

Dynamics of the games – delayed minority game

- In the same way we can define ideal virtual stock markets for majority game, \$-game and delayed minority game
- Ideal delayed minority game virtual stock market. When the market is stationary, the decisions of the agents are a local minimum of the following optimization problem

$$\textit{minimize:} \quad \mathrm{E}_0^2\left[\sum_{i=1}^{N}\sum_{j=1}^{s}\beta_i^j f_i^j(\mu_t)\right]$$

$$\textit{subject to:} \quad \sum_{j=1}^{s}\beta_i^j = 1, \forall i = 1,\ldots,N$$

$$\beta_i^j \geq 0, \forall i = 1,\ldots,N, j = 1,\ldots,s$$

Dynamics of the games

- In the same way we can define ideal virtual stock markets for majority game, \$-game and delayed minority game
- Ideal mixed game virtual stock market. When the market is stationary, the decisions of the different kinds of game players are local optimum of the following different optimization problems:

  - Minority game players:

$$\begin{aligned}
\textit{minimize:}\quad & \mathrm{E}_0[\sum_{i_{\mathrm{mg}}=1}^{N_{\mathrm{mg}}}\sum_{j=1}^{s}\beta^j_{i_{\mathrm{mg}}} f^j_{i_{\mathrm{mg}}}(\mu_t)\sum_{i=1}^{N}\sum_{j=1}^{s}\beta^j_i f^j_i(\mu_t)] \\
\textit{subject to:}\quad & \sum_{j=1}^{s}\beta^j_i = 1, \forall i = 1,\ldots,N \\
& \beta^j_i \geq 0, \forall i = 1,\ldots,N, j = 1,\ldots,s
\end{aligned}$$

  - \$-game players:

$$\begin{aligned}
\textit{maximize:}\quad & \mathrm{E}_0[\sum_{i_{\mathrm{dg}}=1}^{N_{\mathrm{dg}}}\sum_{j=1}^{s}\beta^j_{i_{\mathrm{dg}}} f^j_{i_{\mathrm{dg}}}(\mu_t)]\mathrm{E}_0[\sum_{i=1}^{N}\sum_{j=1}^{s}\beta^j_i f^j_i(\mu_t)] \\
\textit{subject to:}\quad & \sum_{j=1}^{s}\beta^j_i = 1, \forall i = 1,\ldots,N \\
& \beta^j_i \geq 0, \forall i = 1,\ldots,N, j = 1,\ldots,s
\end{aligned}$$

  - Majority game players:

$$\begin{aligned}
\textit{maximize:}\quad & \mathrm{E}_0[\sum_{i_{\mathrm{majg}}=1}^{N_{\mathrm{majg}}}\sum_{j=1}^{s}\beta^j_{i_{\mathrm{majg}}} f^j_{i_{\mathrm{majg}}}(\mu_t)\sum_{i=1}^{N}\sum_{j=1}^{s}\beta^j_i f^j_i(\mu_t)] \\
\textit{subject to:}\quad & \sum_{j=1}^{s}\beta^j_i = 1, \forall i = 1,\ldots,N \\
& \beta^j_i \geq 0, \forall i = 1,\ldots,N, j = 1,\ldots,s
\end{aligned}$$

  - Delayed minority game players:

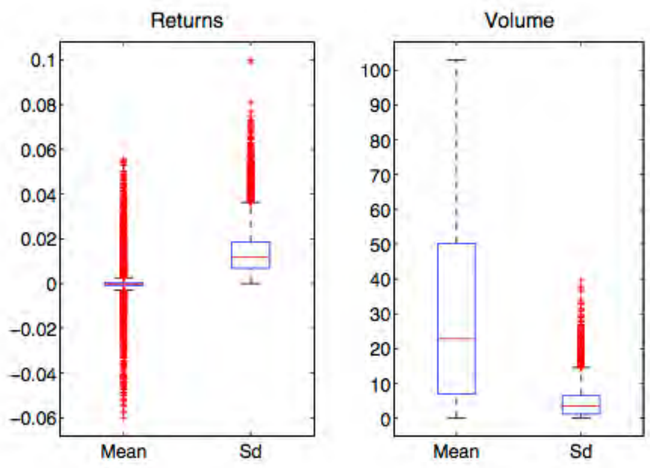
$$\begin{aligned}
\textit{minimize:}\quad & \mathrm{E}_0[\sum_{i_{\mathrm{dmg}}=1}^{N_{\mathrm{dmg}}}\sum_{j=1}^{s}\beta^j_{i_{\mathrm{dmg}}} f^j_{i_{\mathrm{dmg}}}(\mu_t)]\mathrm{E}_0[\sum_{i=1}^{N}\sum_{j=1}^{s}\beta^j_i f^j_i(\mu_t)] \\
\textit{subject to:}\quad & \sum_{j=1}^{s}\beta^j_i = 1, \forall i = 1,\ldots,N \\
& \beta^j_i \geq 0, \forall i = 1,\ldots,N, j = 1,\ldots,s
\end{aligned}$$

Dynamics of the games

- We use minority game and delayed minority game players to model the behavior of fundamentalists. The actions of the delayed minority game players are cleverer than the minority game players. Moreover, the delayed minority game will generate negative lag 1 autocorrelations.
- We use majority game and $-game players to model the behavior of trend followers. The $-game players are more radical, and they generate positive lag 1 autocorrelations.
- We expect that the mixed game virtual markets will generate many stylized facts of the real stock markets.

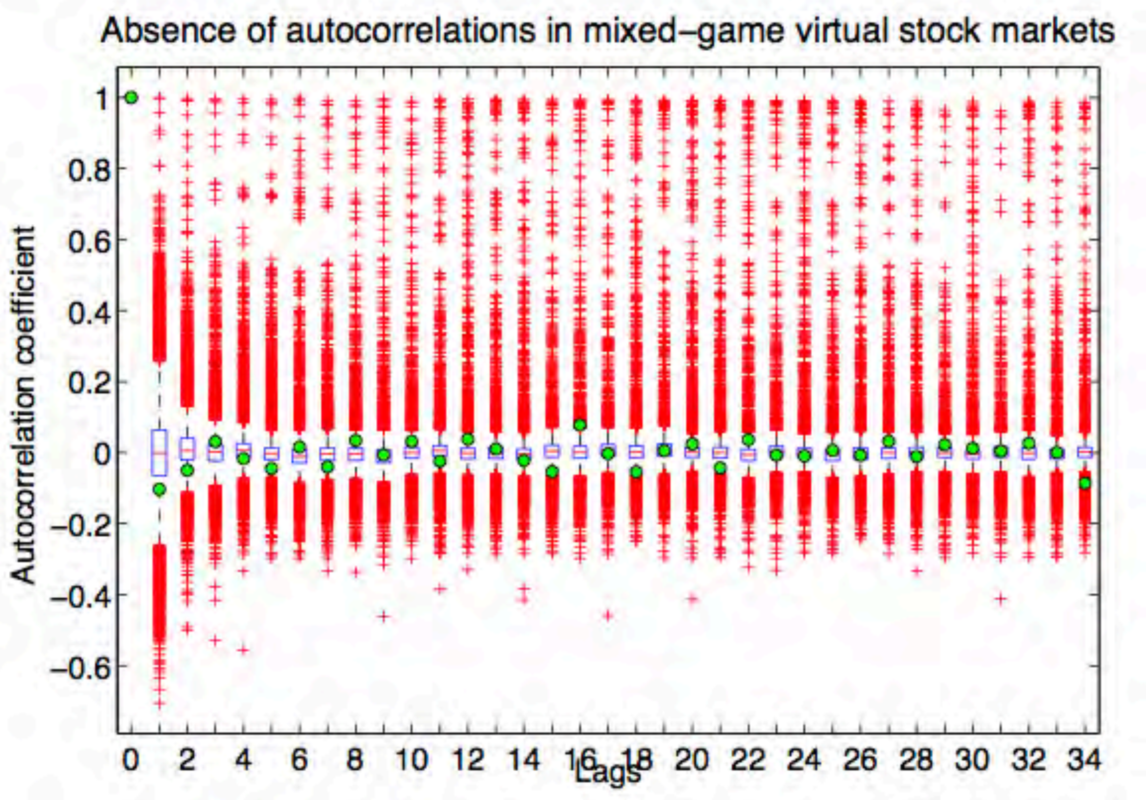
Stylized facts generated by the mixed games

- We generate randomly 10000 mixed-game virtual stock markets, which run for 12500 time steps
  - N from 3-103
  - m from 2-8
  - s from 1-16
  - τ from 0-1
  - T from 1-25
  - all trading strategies of the agents are randomly picked
- Distribution of returns and volumes of the 10000 mixed-game virtual stock markets



Stylized facts generated by the mixed games

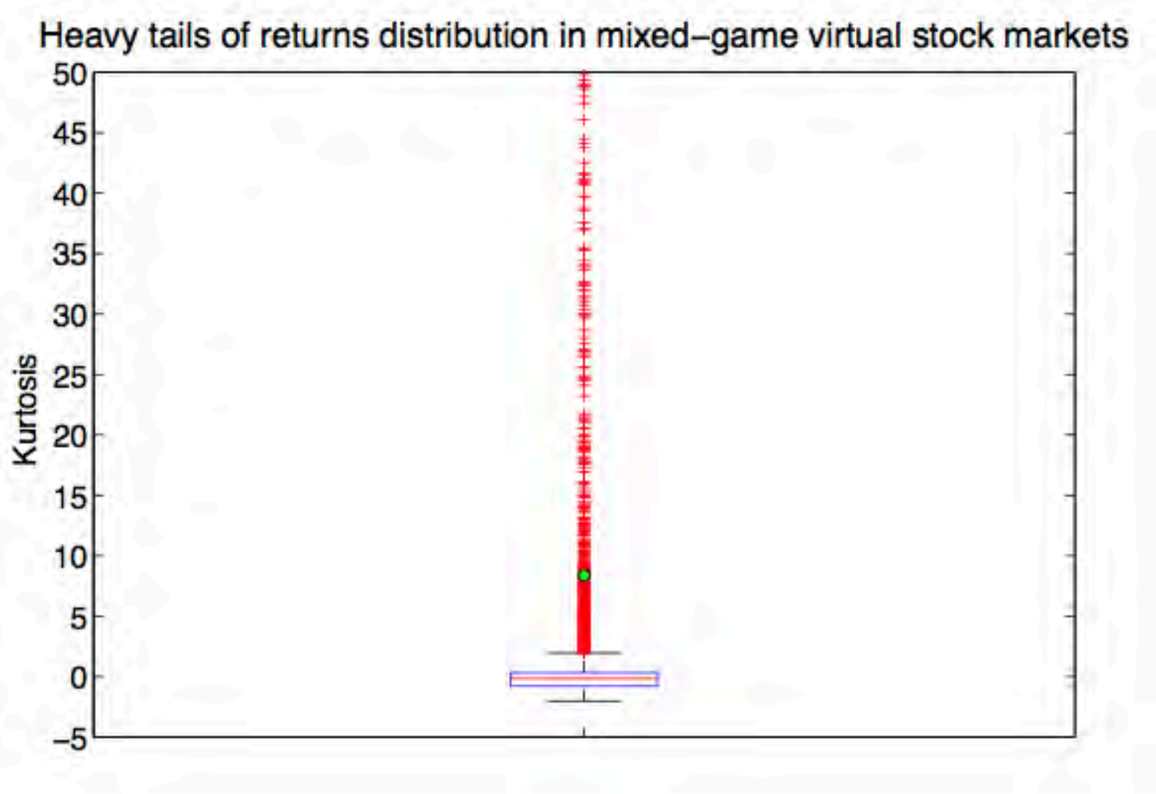
- Absence of autocorrelations



Boxplots of autocorrelation coefficients from lag 0 to lag 34 of returns in the 10000 mixed-game virtual stock markets. The green dot in each boxplot is the corresponding autocorrelation coefficient of the S&P500 returns from Jan 2, 2002 to Sep 12, 2012.

Stylized facts generated by the mixed games

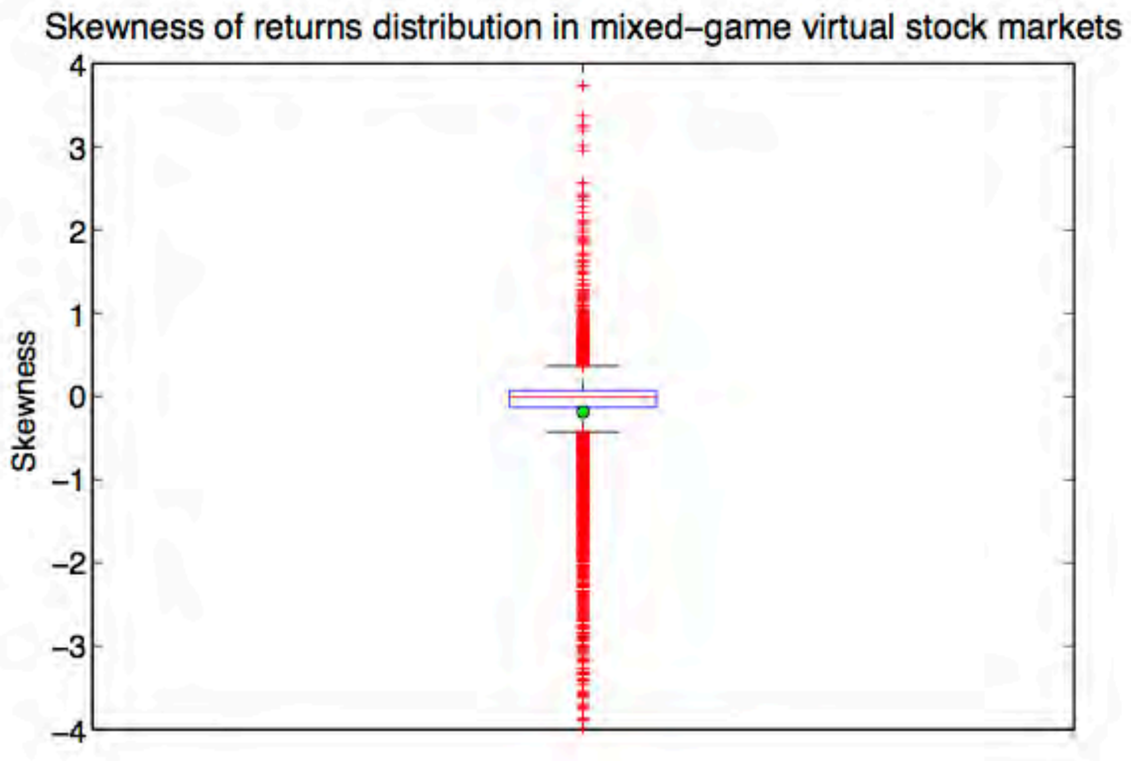
- Heavy tails of returns distribution



Boxplot of kurtosis of returns in the 10000 mixed-game virtual stock markets. The green dot is the kurtosis of the S&P500 returns from Jan 2, 2002 to Sep 12, 2012.

Stylized facts generated by the mixed games

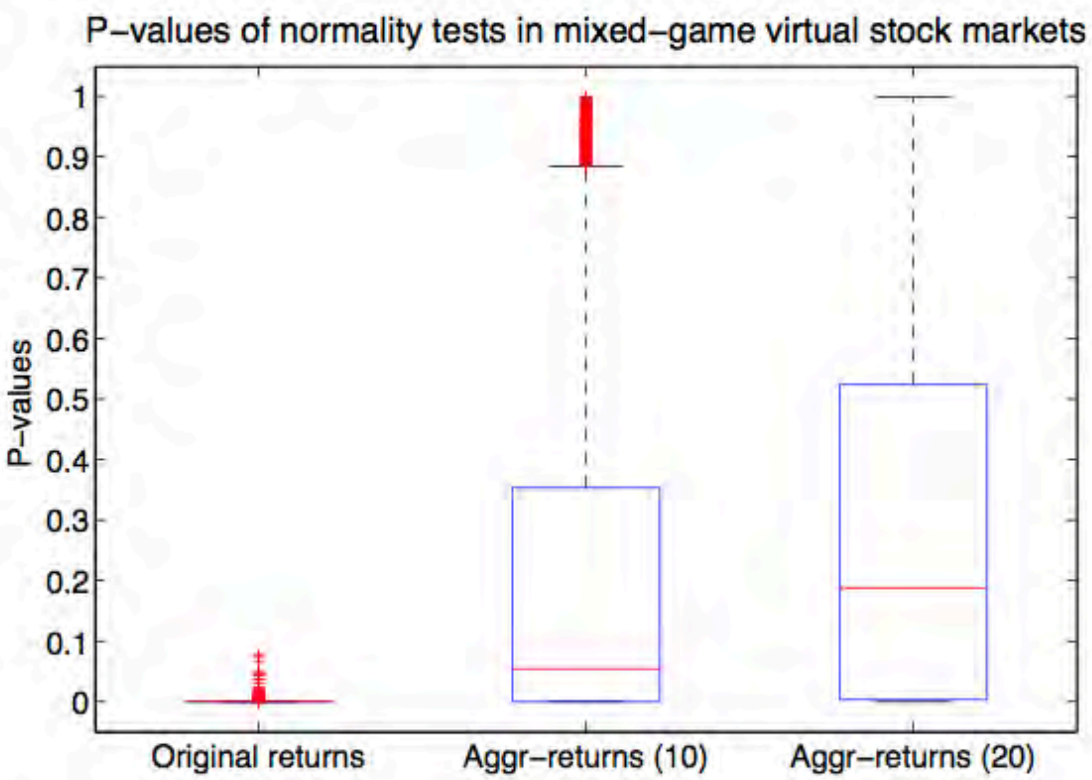
- Gain/loss asymmetry



Boxplot of skewness of returns in the 10000 mixed-game virtual stock markets. The green dot is the skewness of the S&P500 returns from Jan 2, 2002 to Sep 12, 2012.

Stylized facts generated by the mixed games

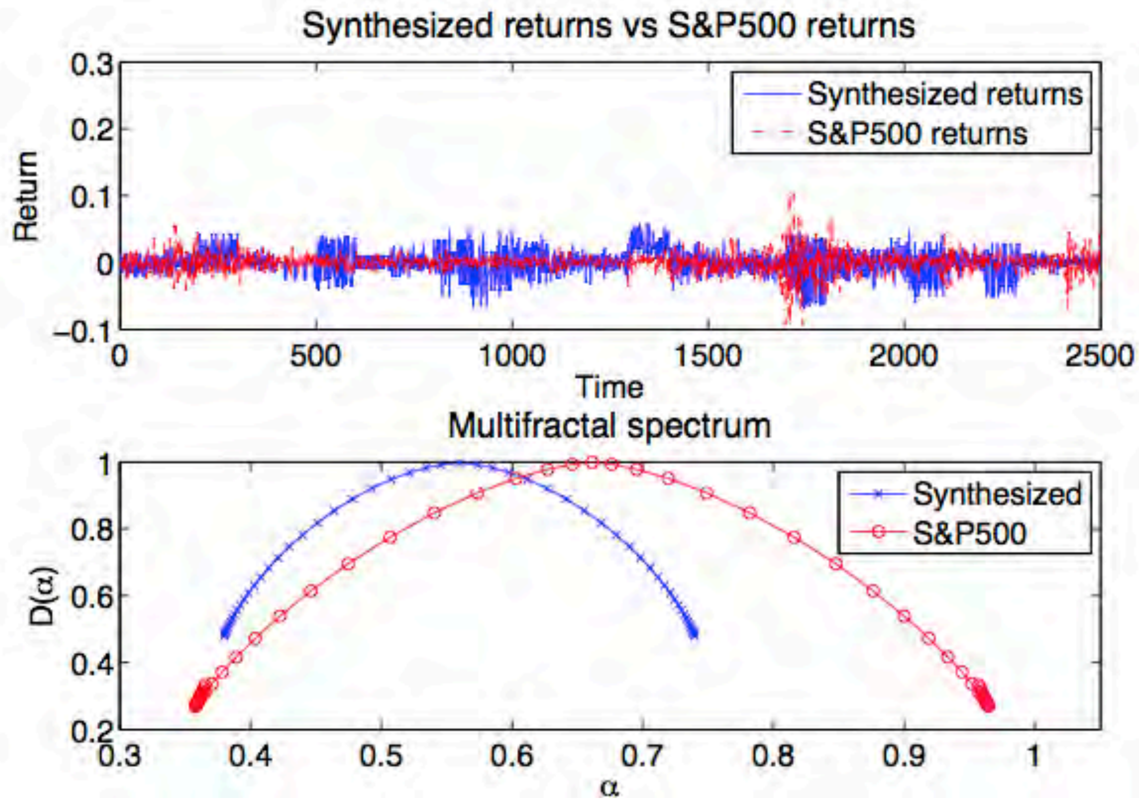
- Aggregational Gaussianity



Boxplots of p-values of normality tests of both the aggregated returns and the original returns of the 10000 mixed-game virtual stock markets. The “original returns” are the non-aggregational returns, the “aggr-returns (10)” are the aggregational returns over 10 time steps, and the “aggr-returns (20)” are the aggregational returns over 20 time steps.

Stylized facts generated by the mixed games

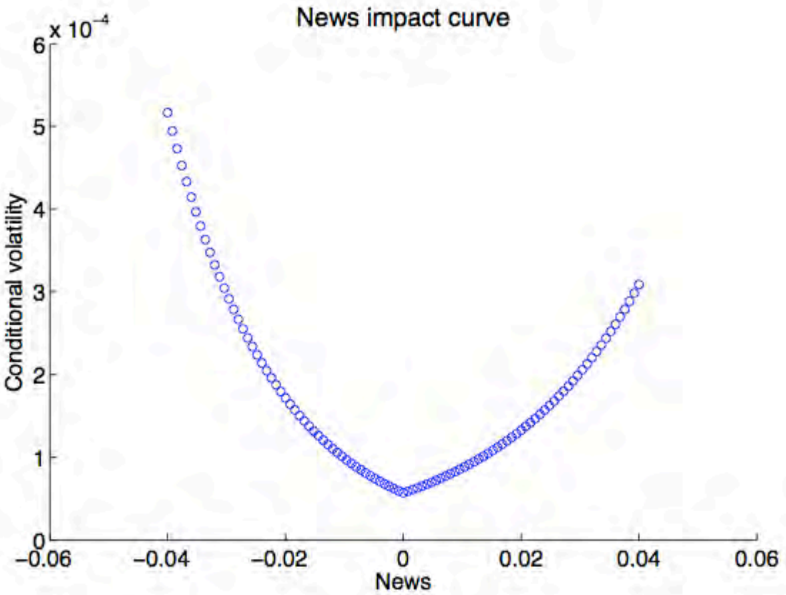
- Intermittency



Intermittency of a synthesized time series and the returns time series of the S&P500 index from Jan 2, 2002 to Sep 12, 2012. The synthesized time series are generated by combing 25 pieces extracted from the returns time series of 25 different virtual stock markets randomly picked from the 10000 mixed-game virtual stock markets, each of the 25 virtual stock markets providing 100 continuous data points. The upper sub-plot compares the synthesized time series and the S&P500 returns, and the lower sub-plot shows the multi-fractal spectra of the time series.

Stylized facts generated by the mixed games

- Volatility clustering and leverage effect
  - ARCH LM test (Engle 1982) with 10 lags
    - 7353 out of 10000 virtual stock markets' returns time series have p-value >= 0.05
  - 594 out of 10000 results generate the leverage effect



News impact curve of a time series reproducing the leverage effect.

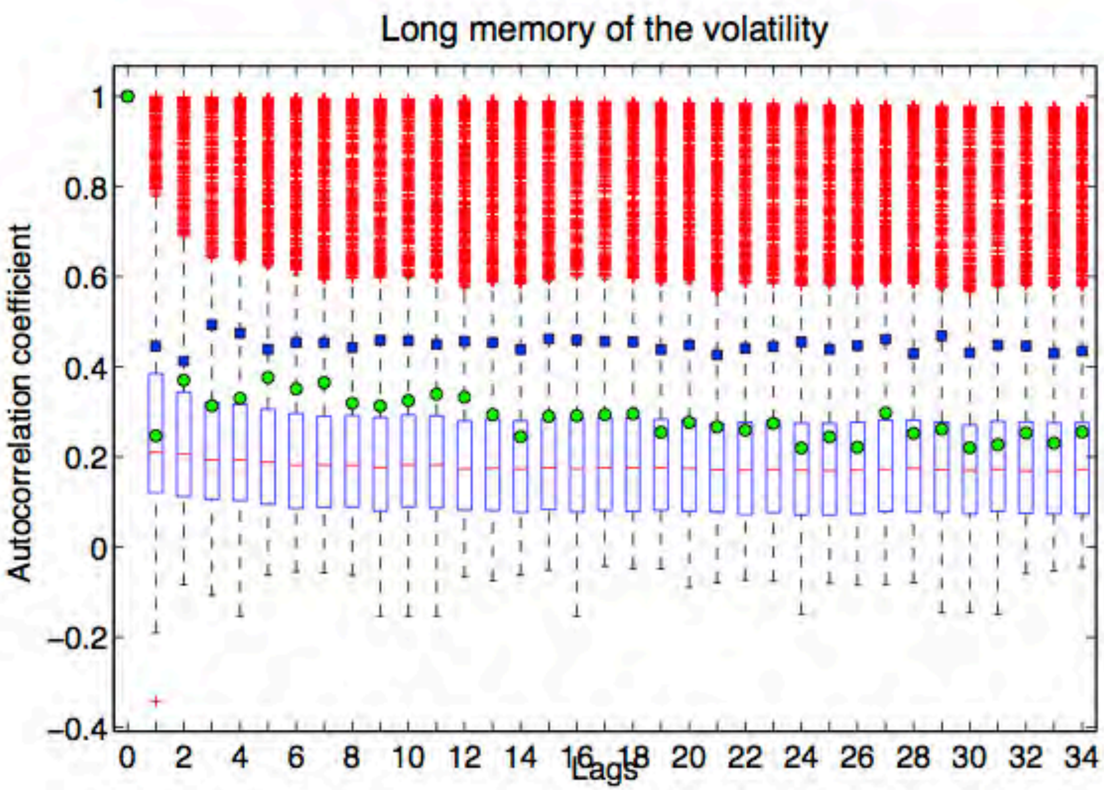
The news impact curve is a way to visualise the leverage effect in Pagan and Schwert (1990), Engle and Ng (1991).

The news is actually the history return, not the news in, e.g., newspapers.

The curve shows that a mixed-game reproduces a nice leverage effect - the negative returns have higher impact onto the volatility than the positive returns.

Stylized facts generated by the mixed games

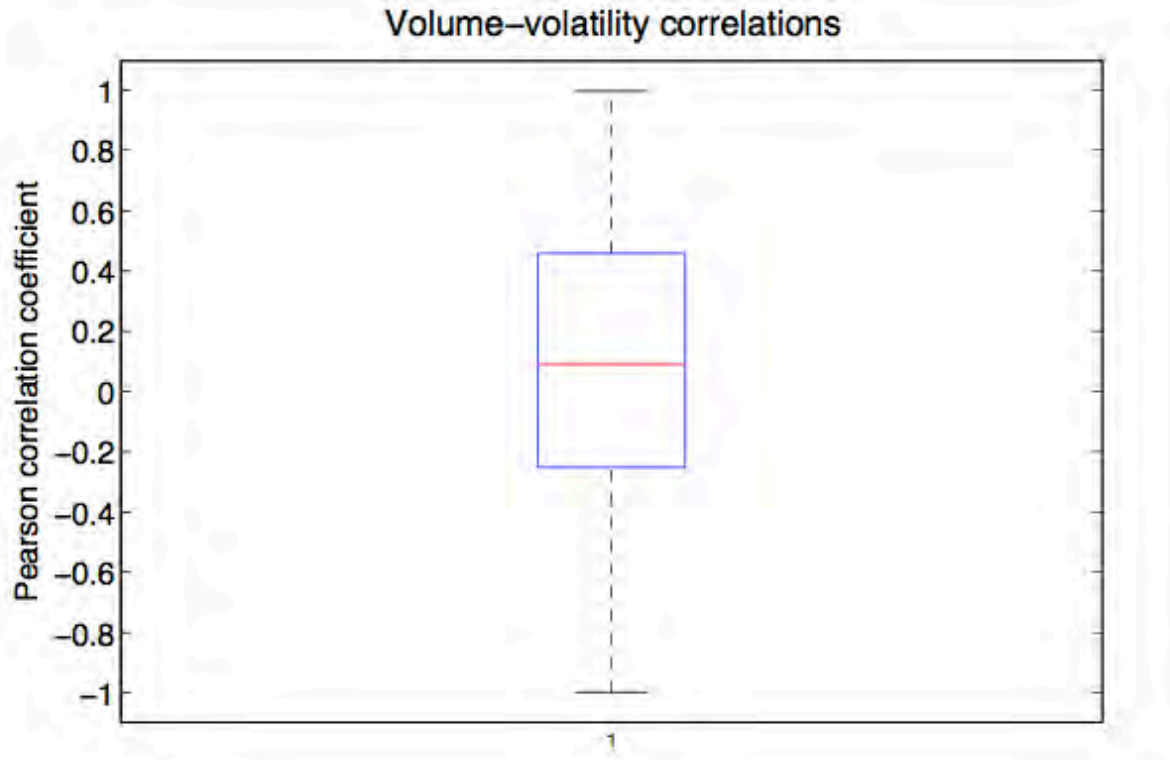
- Long memory of volatility



Boxplots of autocorrelation coefficients of lags 1 to 34 of the 3000 synthesized time series. The blue rectangles are autocorrelation coefficients of one sample among the synthesized time series, and the green circles are autocorrelation coefficients of the S&P500 returns, from Jan 2, 2002 to Sep 12, 2012.

Stylized facts generated by the mixed games

- Volume-volatility correlations



Boxplot of correlation coefficients between volume and volatility (represented by the absolute returns) of the 3000 synthesized time series.

Calibration of the mixed games

- Use the Genetic Algorithm to solve the following optimization problem

$$\text{minimize: } \sum_{t=0}^{W_{is}} (r_t^{\mathrm{r}} - r_t^{\mathrm{abm}})^2 ,$$

- 700 experiments with different in-sample window lengths
  - S&P500: 1992-2002, 2002-2012
  - Dow Jones: 1982-1992, 1992-2002, 2002-2012
  - Nasdaq: 1992-2002, 2002-2012

Success rates in predicting the future return signs

- Compare with random trading strategies
  - 1000 random trading samples for each experiment
  - random trading betting a positive future return with probability $\mathbf{f}_+$
- 654 out of 700 experiments are better than random trading with p-value=0.1
- 109 experiments have success rates higher than $\mathbf{f}_+$, the fraction of positive returns in the real data (which is not known ex-ante)

Success rates in predicting the future return signs

Index	Start year	End year	Data Points	Positive ratio	W_{is}	Success rate
S&P500	2002	2011	2080	0.550	380	0.556
Nasdaq	1992	2001	2352	0.546	120	0.556
Nasdaq	1992	2001	2144	0.549	320	0.555
S&P500	2002	2011	2224	0.552	240	0.554
S&P500	2002	2011	2256	0.550	200	0.553
Nasdaq	1992	2001	2304	0.545	160	0.553
S&P500	2002	2011	2288	0.548	180	0.552
S&P500	2002	2011	2144	0.551	320	0.552
S&P500	2002	2011	2128	0.553	340	0.552
S&P500	2002	2011	2240	0.550	220	0.552
S&P500	2002	2011	2176	0.551	280	0.551
S&P500	2002	2011	2336	0.547	120	0.551
S&P500	2002	2011	2160	0.552	300	0.550
Nasdaq	1992	2001	2064	0.548	400	0.550

Positive ratio – fraction of positive returns in the real return time series

W_{is} – in-sample window length

Trading strategies based on the mixed games

- Long when ABM predicts a positive return; otherwise short
- Compare with random trading strategies
- 15% of experiments generate results above 90% of random trading results
- 21 (21/654 =3.2%) experiments have statistically significantly positive α's, while less than 1% random trading strategies can generate the same results

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Trading strategies based on the mixed games

Index	Start year	End year	Data points	W_{is}	Total return	Sharpe ratio	PV_r	PV_{shr}	Annual return	α
S&P500	1992	2001	2128	340	5.117	1.287	0.00	0.00	0.601	0.045(0.018)**
S&P500	1992	2001	2112	360	4.869	1.254	0.00	0.00	0.576	0.043(0.018)**
S&P500	1992	2001	2112	360	4.159	1.178	0.00	0.00	0.492	0.047(0.021)**
S&P500	1992	2001	2192	280	4.284	1.151	0.00	0.01	0.489	0.028(0.013)**
S&P500	1992	2001	2192	280	4.027	1.132	0.00	0.01	0.459	0.040(0.017)**
Dow Jones	1982	1991	2416	60	5.726	1.064	0.00	0.02	0.592	0.043(0.022)**
S&P500	1992	2001	2144	320	3.431	1.056	0.00	0.01	0.400	0.023(0.014)*
Dow Jones	1982	1991	2384	80	5.227	1.027	0.00	0.02	0.548	0.048(0.023)**
Nasdaq	1992	2001	2352	120	44.041	0.999	0.00	0.00	4.681	0.137(0.051)***
Dow Jones	1982	1991	2256	220	4.192	0.998	0.00	0.02	0.465	0.040(0.022)*
Nasdaq	1992	2001	2400	60	39.265	0.953	0.00	0.00	4.090	0.126(0.051)**
Nasdaq	1992	2001	2128	340	23.586	0.884	0.00	0.01	2.771	0.116(0.057)**
Nasdaq	2002	2011	2176	280	4.482	0.818	0.00	0.02	0.515	0.054(0.027)**
S&P500	2002	2011	2160	300	3.491	0.813	0.00	0.01	0.404	0.049(0.024)**
Nasdaq	1992	2001	2304	160	18.265	0.783	0.00	0.02	1.982	0.103(0.053)*
S&P500	2002	2011	2288	180	3.212	0.739	0.00	0.02	0.351	0.040(0.024)*
S&P500	2002	2011	2288	180	2.819	0.689	0.00	0.03	0.308	0.038(0.022)*
Nasdaq	2002	2011	2416	40	4.226	0.664	0.00	0.04	0.437	0.053(0.032)*

PV_r – The p-value of the null hypothesis that returns of ABM based strategy is the same as random ones

PV_{shr} – The p-value of the null hypothesis that Sharpe ratios of ABM based strategy is the same as random ones

Fama-French 3 -factor model; 4-factor model gives even more significant results

Structures of ABM's and market regimes

- Consider six major regimes from 1982 to 2012
  - 1982-Oct. 1987 (bubble regime. Overall decreasing Fed rates. A crash on black Monday 19 Oct 1987)
  - Oct. 1987-1993 (post bubble regime)
  - 1993-2000 (the growth of the dot-com bubble)
  - 2000-2003 (post bubble, decreasing Fed rate to fight recession (burst of dot-com and biotech bubble))
  - 2003-Oct. 2007 (flat followed by slow-increase Fed rate, jointly with the global leverage bubble)
  - End 2007 - Present (the great recession)
- Study the relationships between returns and the ABM parameters with linear regression models
  - highly significant linear relationships between the real returns and the calibrated ABM parameters
  - **τ** is significant during the bubble regimes while insignificant after crashes; $\mathbf{fr_{act}}$ is usually significant and positively related to real returns during bubble regimes, and is on the contrary after crashes
  - fractions of majority game and $-game players are more strongly related to the real returns than that of minority game players. Fraction of delayed minority game players is insignificant

Trading strategies based on the mixed games

$$\hat{r} = a_0 + a_1 \hat{fr}_{act} + \epsilon\,,$$

$$\ldots\,,$$

$$\hat{r} = a_0 + a_6 \hat{fr}^{dmg} + \epsilon\,,$$

$$\hat{r} = a_0 + a_1 \hat{fr}_{act} + a_2 \hat{\tau} + \epsilon\,,$$

$$\hat{r} = a_0 + a_1 \hat{fr}_{act} + a_3 \hat{fr}^{mg} + \epsilon\,,$$

$$\ldots\,,$$

$$\hat{r} = a_0 + a_1 \hat{fr}_{act} + a_6 \hat{fr}^{dmg} + \epsilon\,,$$

$$\ldots\,,$$

$$\ldots\,,$$

$$\hat{r} = a_0 + a_1 \hat{fr}_{act} + a_2 \hat{\tau} + a_3 \hat{fr}^{mg} + a_4 \hat{fr}^{majg} + a_5 \hat{fr}^{dg} + \epsilon\,,$$

$$\ldots\,,$$

$$\hat{r} = a_0 + a_1 \hat{fr}_{act} + a_2 \hat{\tau} + a_4 \hat{fr}^{majg} + a_5 \hat{fr}^{dg} + a_6 \hat{fr}^{dmg} + \epsilon\,,$$

- Symbols
  - **r** – the real returns
  - **fr_{act}** – fraction of active agents
  - **fr^{mg}** – fraction of minority game players
  - **fr^{majg}** – fraction of majority game players
  - **fr^{dg}** – fraction of \$-game players
  - **fr^{dmg}** – fraction of delayed minority game players
  - τ – success rate threshold
  - **a_0 – a_6** – parameters to estimate
  - ε – white noise

Trading strategies based on the mixed games

Index	Start time	End time	Data points	Intercept	$\hat{fr}_{act}$	t	$\hat{fr}^{mg}$	$\hat{fr}^{majg}$	$\hat{fr}^{dg}$	$\hat{fr}^{dmg}$	F-test	R^2
Dow Jones	1982-01	1987-10	500	-0.00767*** (0.00185)	0.00102 (0.00116)	0.00304* (0.00166)	0.00090 (0.00196)	0.00860*** (0.00198)	0.01404*** (0.00185)		0.00000	0.18026
Dow Jones	1987-12	1993-01	245	-0.00142 (0.00175)	-0.00095 (0.00110)	-0.00091 (0.00157)	-0.00159 (0.00172)	0.00408** (0.00185)	0.00909*** (0.00156)		0.00000	0.21214
S&P500	1993-01	2000-01	600	-0.00242*** (0.00094)	0.00141** (0.00061)	0.00134 (0.00087)	-0.00131 (0.00107)	0.00274*** (0.00106)	0.00649*** (0.00097)		0.00000	0.15835
Dow Jones	1993-01	2000-01	600	-0.00345*** (0.00102)	0.00211*** (0.00071)	0.00311*** (0.00101)	-0.00238** (0.00106)	0.00330*** (0.00118)	0.00531*** (0.00098)		0.00000	0.15619
Nasdaq	1993-01	2000-01	600	-0.02115*** (0.00260)	0.01444*** (0.00144)	0.02091*** (0.00215)	-0.00267 (0.00306)	0.00425 (0.00323)	0.01311*** (0.00309)		0.00000	0.20023
Dow Jones	2000-01	2003-01	36	0.00055 (0.00047)	0.00068** (0.00029)			-0.00480* (0.00242)			0.06792	0.15040
Nasdaq	2000-01	2003-01	36	-0.00021 (0.00137)	-0.00346** (0.00167)						0.04612	0.11192
S&P500	2003-01	2007-10	400	-0.00317** (0.00140)	0.00279*** (0.00088)	0.00400*** (0.00121)	0.00012 (0.00114)	-0.00255* (0.00137)	0.00090 (0.00136)		0.00017	0.06019
Nasdaq	2003-01	2007-10	400	-0.00239** (0.00118)	0.00232*** (0.00076)	0.00274** (0.00113)	0.00095 (0.00111)	-0.00055 (0.00120)	-0.00000 (0.00117)		0.00880	0.03818
Dow Jones	2003-01	2007-10	400	-0.00549*** (0.00124)	0.00486*** (0.00080)	0.00563*** (0.00110)	0.00156 (0.00118)	-0.00195 (0.00129)	0.00177 (0.00127)		0.00000	0.11857
S&P500	2007-12	2012-01	236	-0.00253 (0.00201)	0.00020 (0.00125)	0.00291 (0.00182)	0.00047 (0.00232)	0.00400* (0.00233)	-0.00034 (0.00254)		0.00000	0.21695
Nasdaq	2007-12	2012-01	236	0.00137 (0.00275)	-0.00280 (0.00169)	-0.00198 (0.00244)	-0.00186 (0.00255)	0.00538* (0.00293)	0.00394 (0.00285)		0.00008	0.10771
Dow Jones	2007-12	2012-01	236	-0.00158 (0.00215)	-0.00239* (0.00143)	-0.00042 (0.00203)	0.00443** (0.00218)	0.00605** (0.00245)	0.00172 (0.00252)		0.00000	0.31871

Conclusions

- Use mixed games to model both fundamentalists and trend followers
- The mixed games can reproduce many stylized facts of the real stock markets
- 654 experiments generate statistically significant success rate of predicting the future return signs
- 15% experiments can generate statistically and economically significant returns
- Calibrated parameters of ABM's can help us diagnose market regimes
- Challenge the weak form of the efficient market hypothesis. Transient deviations from efficiency are mostly due to the role of trend followers