ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

DGESS
Departement Geistes-, Sozial- und Staatswissenschaften

Modeling Financial Markets, Bubbles and Cascades

Understanding and Solving Societal Problems with Modeling and Simulation

Exam: Reminder

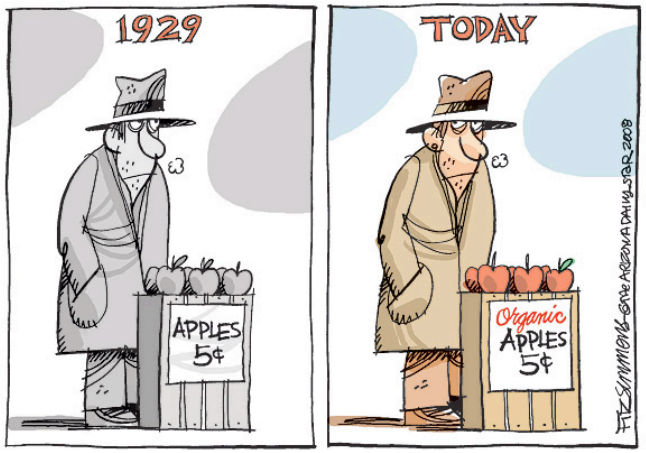
Where: IFW A 32.1

When: 27.05.2013 10-12 a.m.

How: Multiple choice test

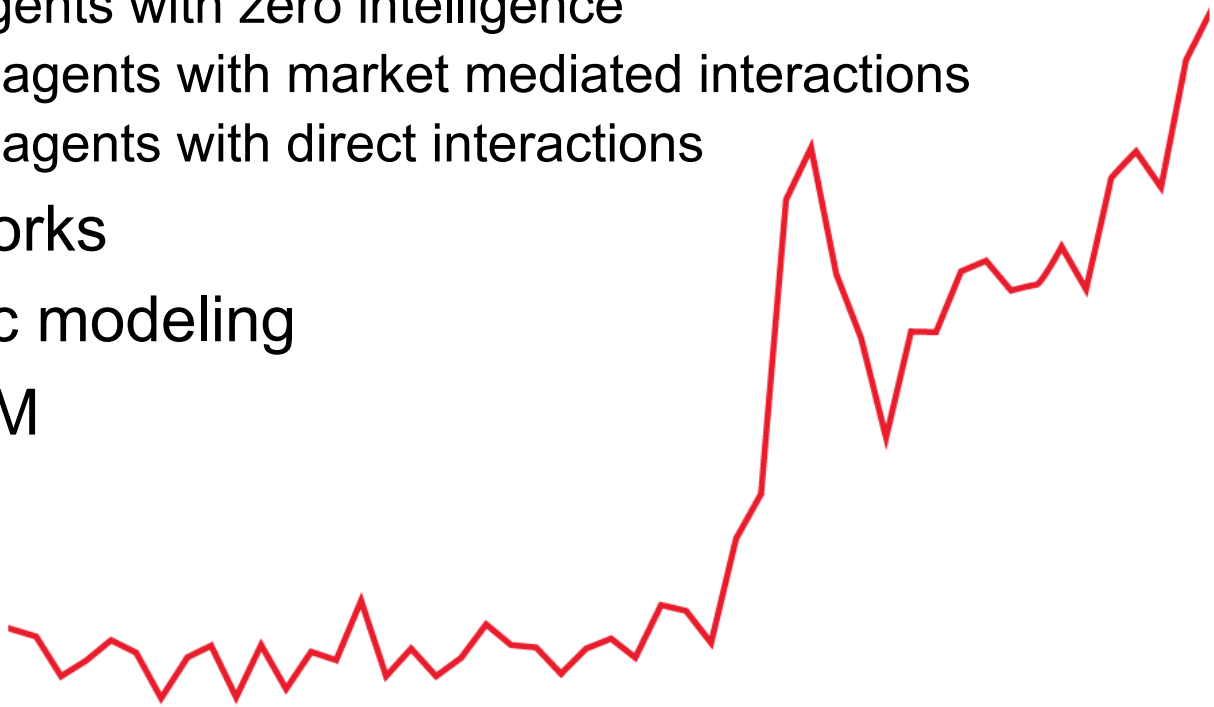
Outline

'Your card is fine. I'm just checking that your bank hasn't expired'



Outline

- Introduction
- ABM for financial markets
  - Homogenous agents with zero intelligence
  - Heterogeneous agents with market mediated interactions
  - Heterogeneous agents with direct interactions
- Interbank networks
- Macroeconomic modeling
- Criticism of ABM



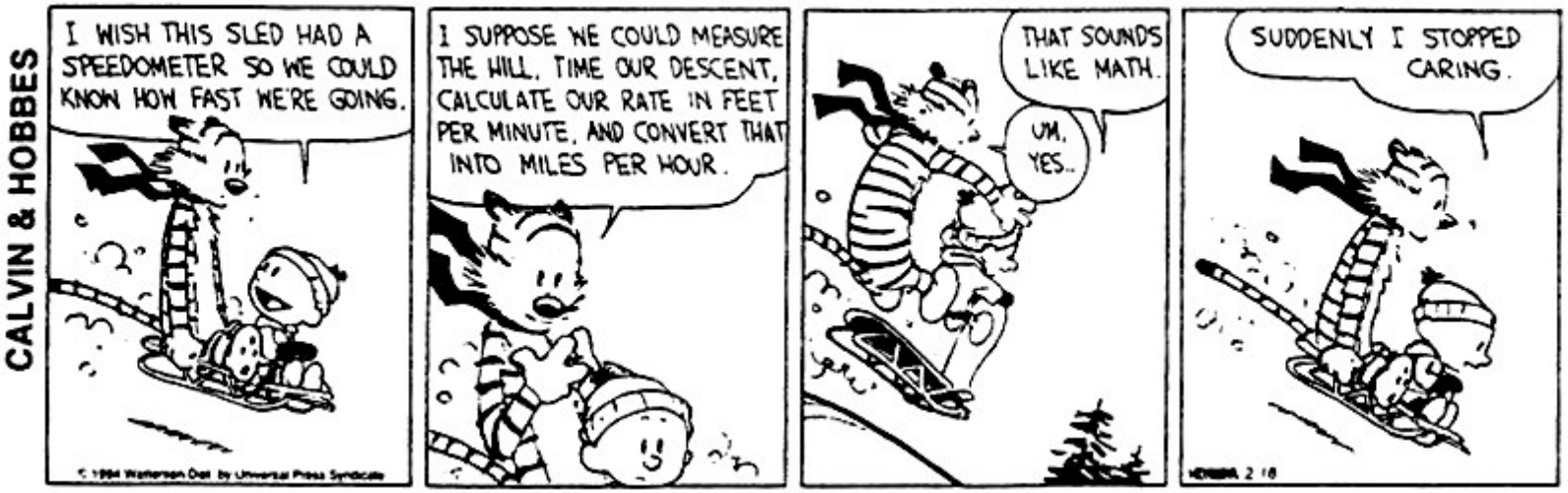
Outline

Goals of the course

- Understand market structures and their importance
- Understand the origin of basic financial market characteristics such as clustered volatility and fat tails
- Understand what leads to herding behavior and bubbles
- Understand how financial stress is cascading through an interbank lending market
- Understand different approaches for macroeconomic modeling

Introduction

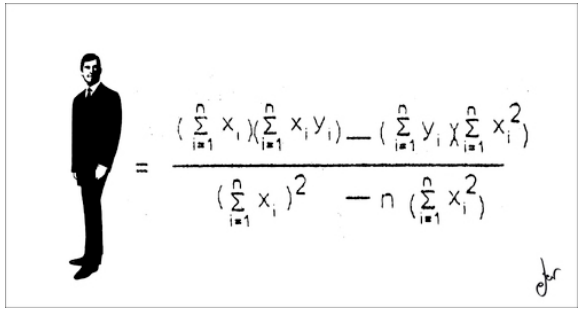
Do people think everything through?



Introduction

Neoclassical assumptions

- "Perfect information" and informationally efficient markets
- Agents with infinite computing capacities
- Rational expectations
- Representative agents
- Interactions through the market only



- What is the real structure of markets?
- What behavior do we really observe at markets?
- How do individuals really behave?

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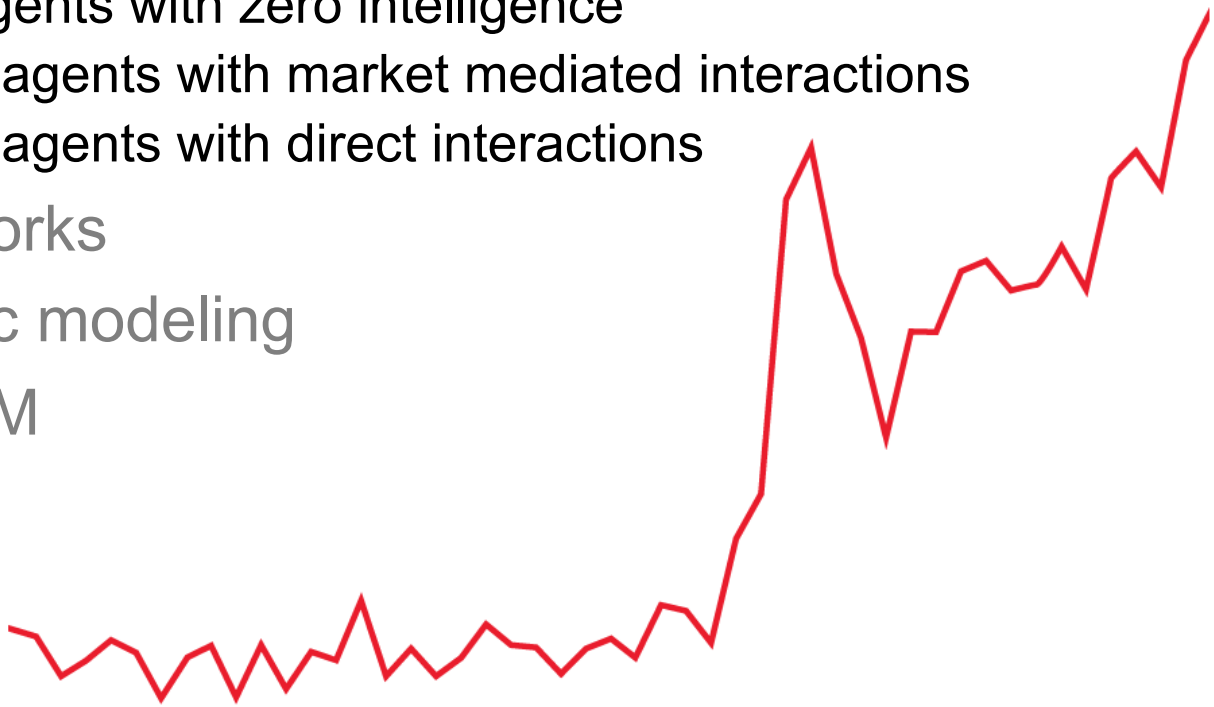


Financial markets: Zero intelligence

Zero intelligence agents

- Minimalistic behavioral approach
- Lack of learning

What economic features can be derived as market characteristics?

- Allocative efficiency
- Volatility
- Market depth
- Bid-ask spreads
- …

Financial markets: Zero intelligence

Is allocative efficiency a consequence of rational, utility maximizing and learning individuals?

Sunder and Gode (1993) compared the efficiency in a double auction of zero-intelligence traders with human traders

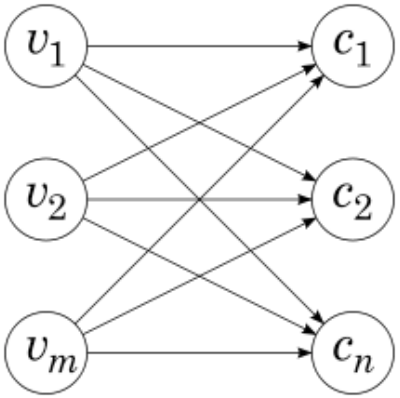


Image source: wikipedia

Financial markets: Zero intelligence

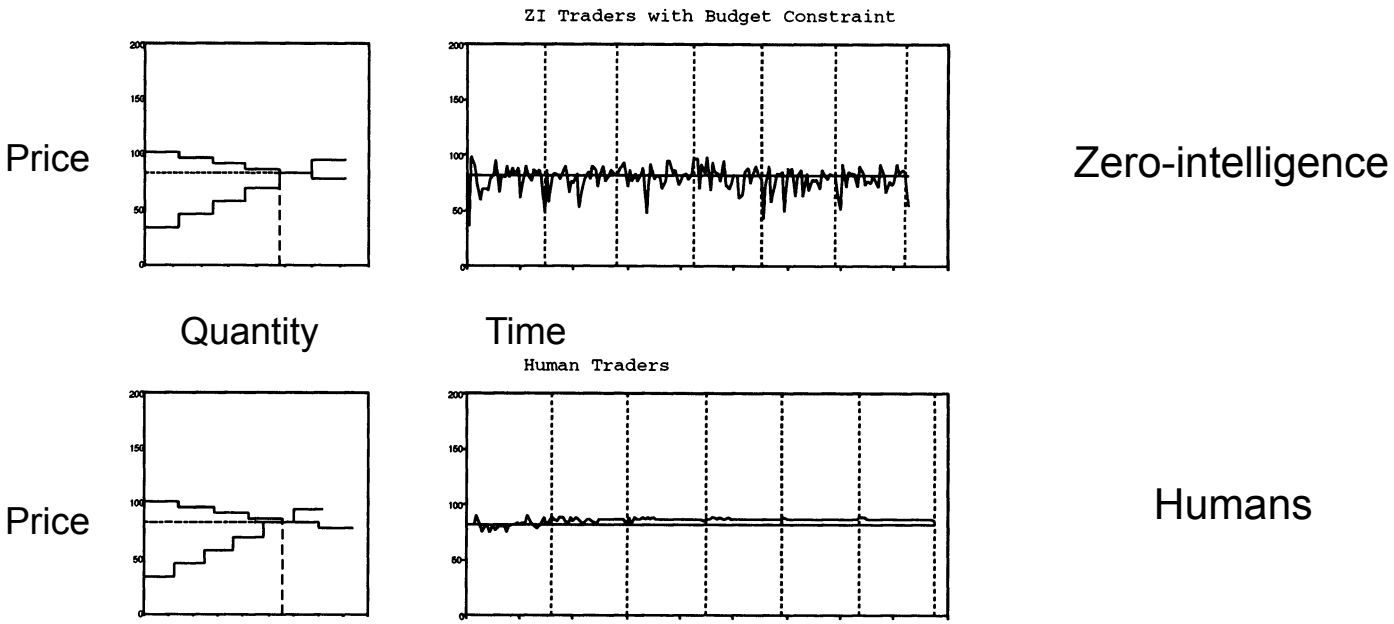
The Sunder Gode model (1993)

- Two groups: sellers endowed with units of a good and buyers with units of money
- Sellers have secret individual costs c_i per unit
- Buyers secretly value a unit v_i
- The surplus of a transaction at price p is $p - c_i$ for the seller and $v_i - p$ for the buyer
- Zero-intelligence agents place orders with uniform probabilities above c_i and below v_i, respectively

What would you be ready to pay?

Financial markets: Zero intelligence

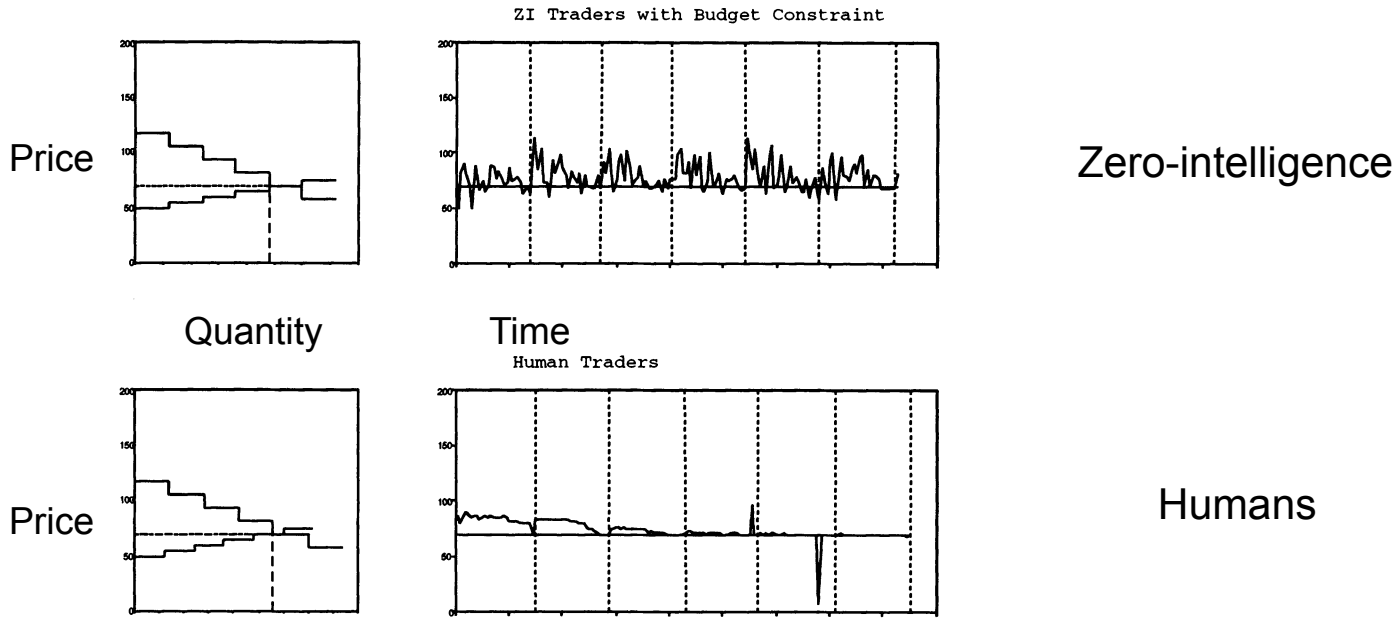
Sunder and Gode observe the following outcomes (1993)



Demand and supply functions and time series of the price for zero-intelligence traders and human traders

Financial markets: Zero intelligence

Sunder and Gode observe the following outcomes (1993)



Demand and supply functions and time series of the price for zero-intelligence traders and human traders

Financial markets: Zero intelligence

Sunder and Gode draw the following conclusions (1993)

- Allocative efficiency close to 100% can be reached without learning or rational agents and without central control
- Allocative efficiency seems to be a property of the market rather than of the agents
- “Irrational behavior” on the micro level may lead to rational outcomes on the macro level

Financial markets: Zero intelligence

Does a simple model also explain observations of real financial markets?

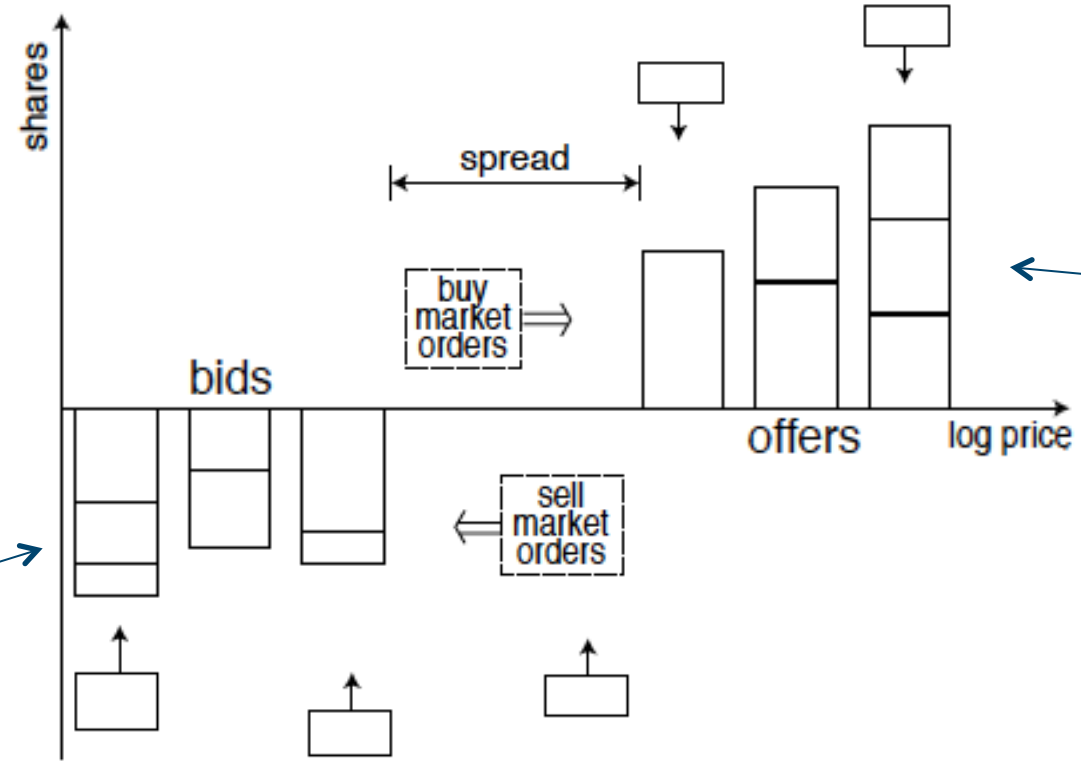
J.D. Farmer et al. (2005) analyze stock markets with zero intelligence traders. How does the market structure determine

- Bid-ask spread
- Price volatility
- Price impact function
- …

Image source: bigcharts.com

Financial markets: Zero intelligence

The order book for one stock by Farmer et al. (2005a)

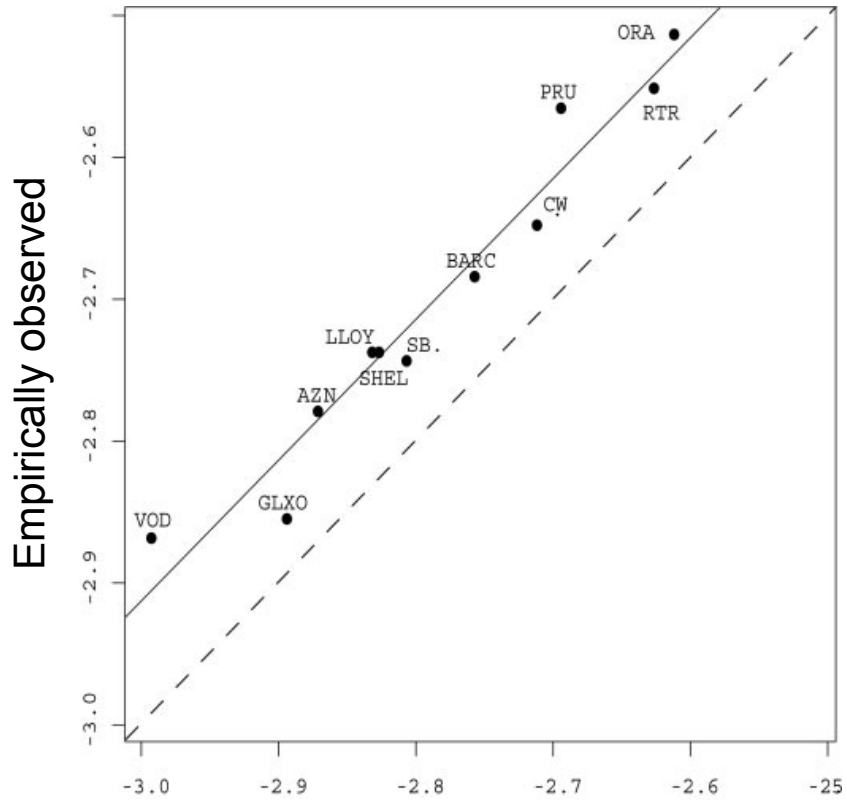


Limit orders stored in the order book

Limit orders stored in the order book

Financial markets: Zero intelligence

Spread as predicted by Farmer et al. 2005b



$$\hat{s} = (\mu/\alpha)\cdot f(\sigma\delta/\mu)$$

Financial markets: Zero intelligence

Price diffusion rate as predicted by Farmer et al. 2005b

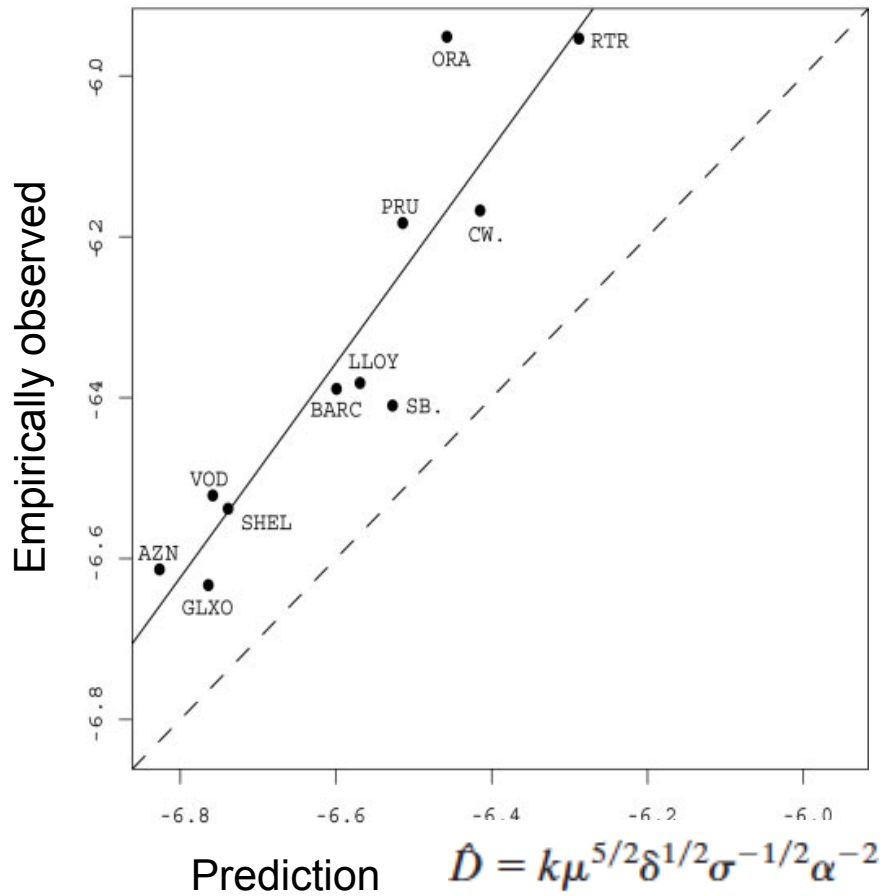
For a random walk:

V(t) = D t

V Variance

D diffusion rate

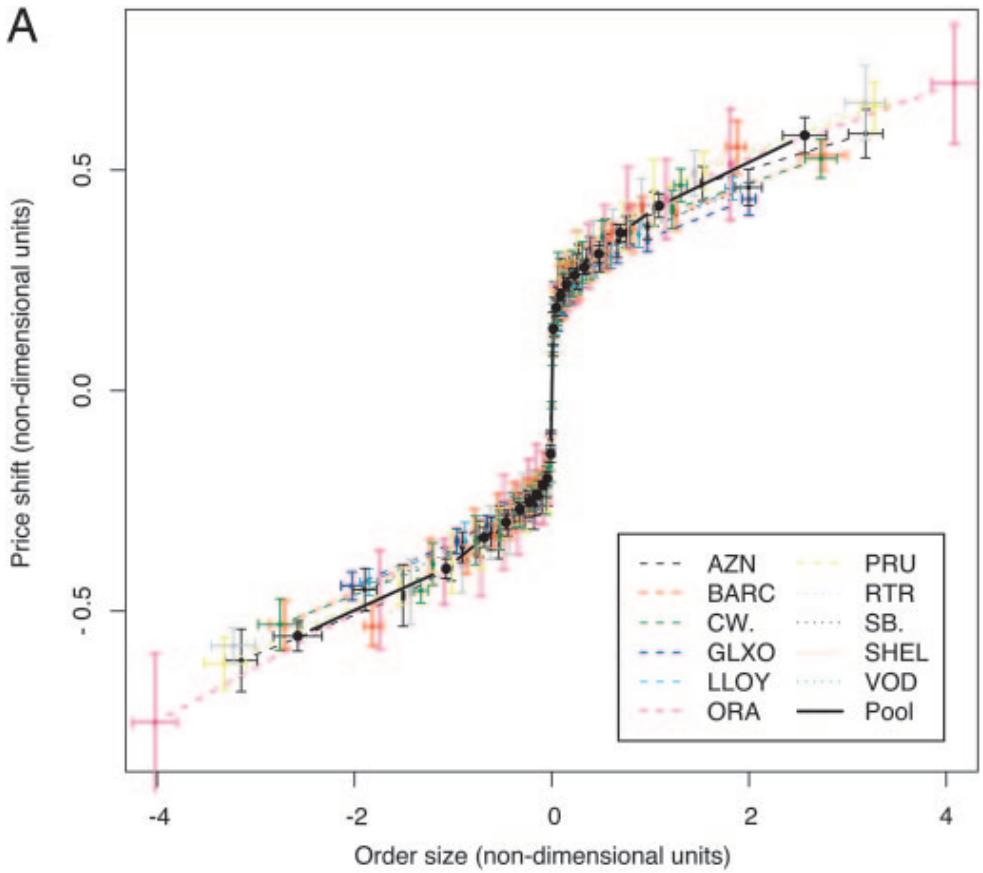
t time



$$\hat{D} = k\mu^{5/2}\delta^{1/2}\sigma^{-1/2}\alpha^{-2}$$

Financial markets: Zero intelligence

Price impact function (Farmer et al. 2005b)



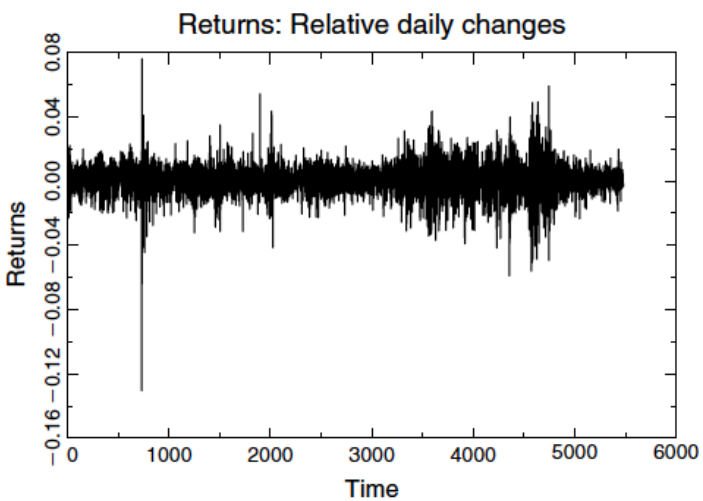
Financial markets: Heterogeneous agents with market mediated interactions

Some of the market characteristics cannot be explained by the market structure alone

Fat tails of returns

Power law distribution

Volatility clustering



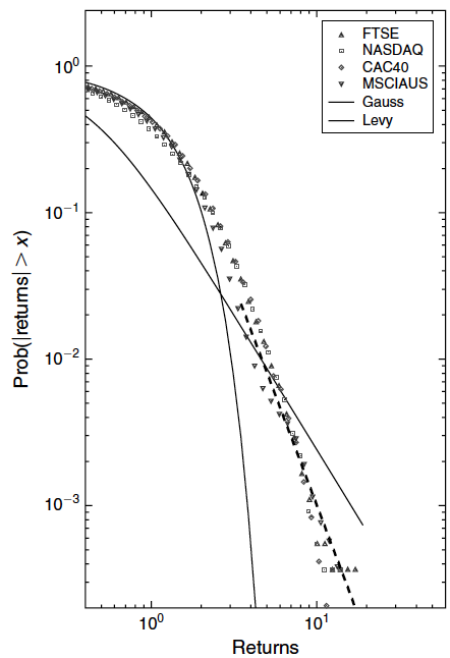


Image source: Handbook of Financial Markets

One solution: take interactions of agents into account!

Financial markets: Heterogeneous agents with market mediated interactions

ABM by Lux and Marchesi (2000)

- Fundamentalists
- Chartists

Apple Inc.
June 25, 2011, Consolidated Balance Sheet
(In millions)

	Assets	Liabilities	
Cash and cash equivalents	12,091	26,859	Current liabilities
Short-term marketable securities	16,304	10,556	Non-current liabilities
Long-term marketable securities	47,761		
Total liquid assets	76,156		
Curren assets, excl. cash+s.t. sec.	18,503		
PPE, net	6,749		
Goodwill	741		
Acquired intangible assets, net	1,169		
Other	3,440	69,343	Equity
Total	106,758	106,758	Total

Images: bettingthebusiness, Yahoo

Financial markets: Heterogeneous agents with market mediated interactions

Details of Lux and Marchesi (2000)

- $N = n_c + n_f$ number of traders constant
- Chartists are either optimistic or pessimistic
- There is an opinion index x leading to switching probabilities π

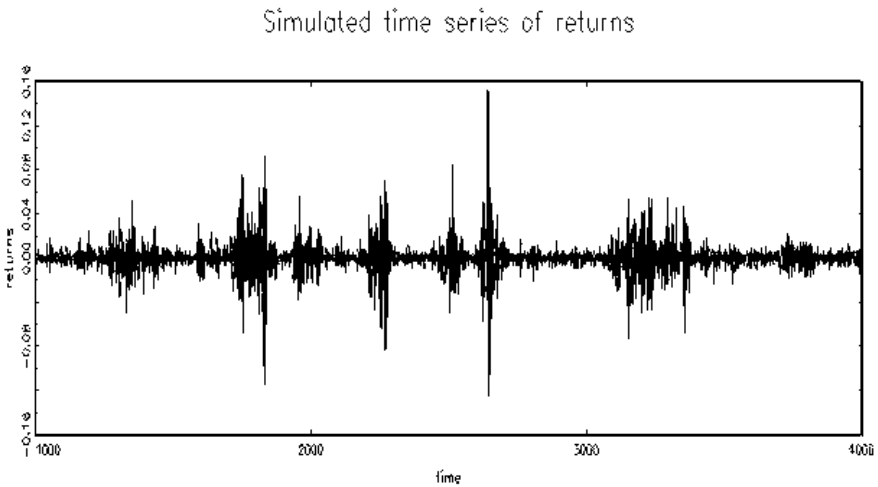
$$\pi_{+-} = \nu_1 \left(\frac{n_c}{N} \exp(U_1) \right)$$
$$\pi_{-+} = \nu_1 \left(\frac{n_c}{N} \exp(-U_1) \right) \quad , \qquad U_1 = \alpha_1 x + \alpha_2 \frac{\dot{p}}{\nu_1} \qquad x = \frac{n_+ - n_-}{n_c}, x \in [-1, 1]$$

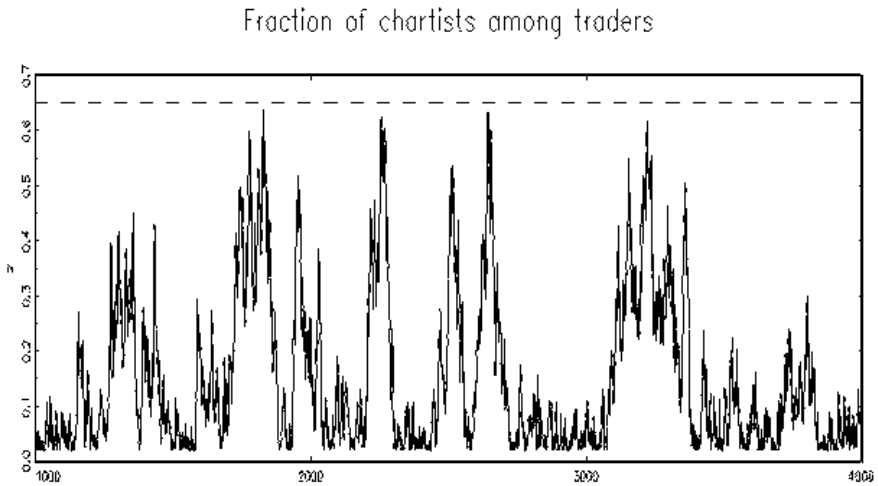
- Switching from fundamentalist to chartist behavior
- Prices are adjusted by a market maker

Financial markets: Heterogeneous agents with market mediated interactions

Results of Lux and Marchesi (2000) mainly by computer simulations

- Clustered volatility due to endogenous evolution of behavior composition
- Prices follow a random walk
- Fat tails in the return distribution (power law distribution)





Financial markets: Heterogeneous agents with direct interactions

ABM allow for more realistic behavior of agents and market structures

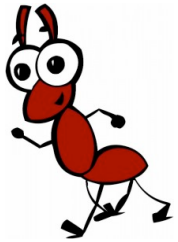
- Behavioral finance
- Sophisticated learning
- Communication networks
- Informational cascades
- Epidemic spreading

Image: Ivo Welch

Financial markets: Heterogeneous agents with direct interactions

Learning from ants – Kirman (1993)

- Empirical observation: in a symmetric configuration ants behave in an asymmetric way


- This can be explained as an outcome of direct interaction between identical, simple individuals

Financial markets: Heterogeneous agents with direct interactions

Kirman's model (1993)

- N ants choose between two sources "black" and "white"
- They are recruited individually with probability 1-δ by randomly encountering an ant of the other type
- With probability ε they switch the source without interaction
- This defines the following Markov process for the number of ants k choosing the black source

$$k \to k+1 \text{ with probability } p_1 = P(k,k+1) = \left(1-\frac{k}{N}\right)\left(\epsilon + (1-\delta)\frac{k}{N-1}\right)$$

$$k \to k-1 \text{ with probability } p_2 = P(k,k-1) = \frac{k}{N}\left(\epsilon + (1-\delta)\frac{N-k}{N-1}\right).$$

Financial markets: Heterogeneous agents with direct interactions

Kirman's model: results

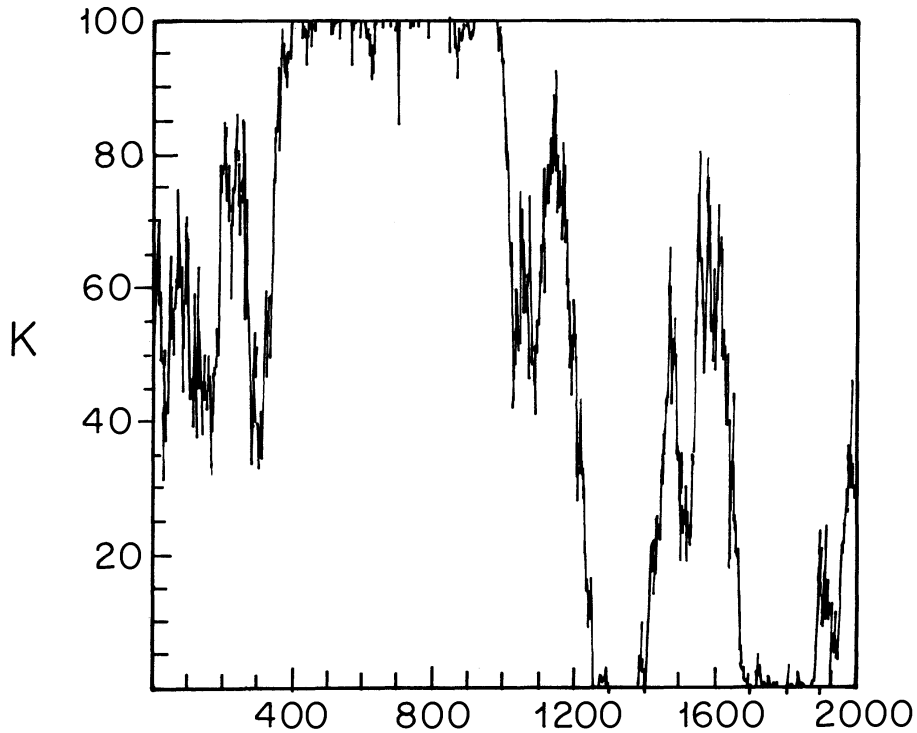


FIGURE IIb
100,000 meetings, every fiftieth plotted, $\epsilon = 0.002$, $\delta = 0.01$.

Financial markets: Heterogeneous agents with direct interactions

The “Black Monday” 1987

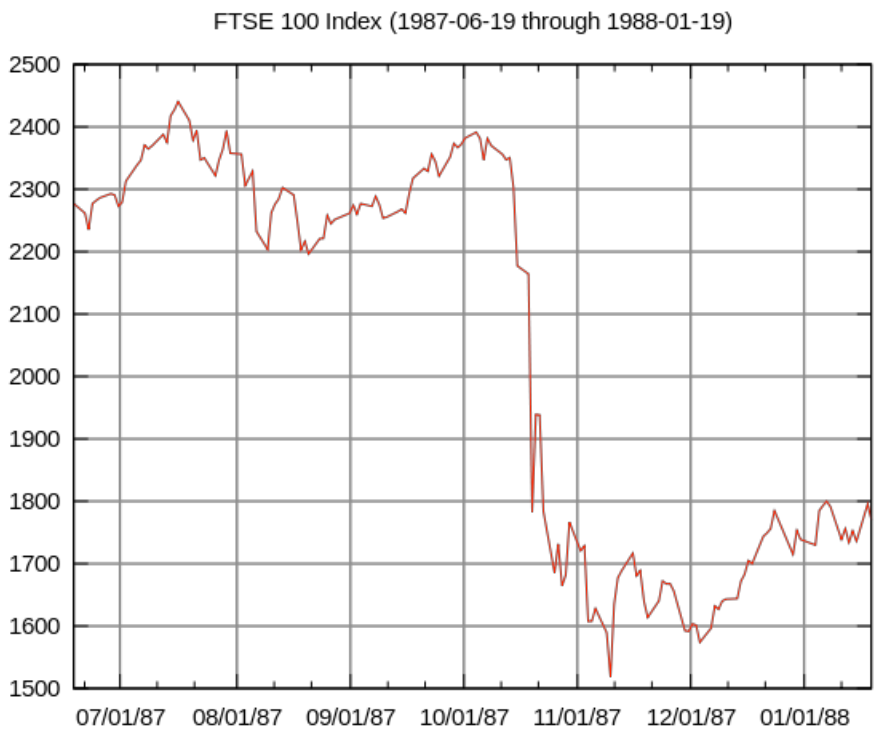


Image: wikipedia

Financial markets: Heterogeneous agents with direct interactions

Direct imitation is a strong force (cf. social influence chapters)

Fig. 1. Sample photographs from videotape recordings of 2- to 3-week-old infants imitating (a) tongue protrusion, (b) mouth opening, and (c) lip protrusion demonstrated by an adult experimenter.

Image: Andrew Meltzoff

Thy Neighbor's Portfolio: Word-of-Mouth Effects in the Holdings and Trades of Money Managers

HARRISON HONG, JEFFREY D. KUBIK, and JEREMY C. STEIN*

ABSTRACT

A mutual fund manager is more likely to buy (or sell) a particular stock in any quarter if other managers in the same city are buying (or selling) that same stock. This pattern shows up even when the fund manager and the stock in question are located far apart, so it is distinct from anything having to do with local preference. The evidence can be interpreted in terms of an epidemic model in which investors spread information about stocks to one another by word of mouth.

IN THIS PAPER, WE EXPLORE THE HYPOTHESIS that investors spread information and ideas about stocks to one another directly, through word-of-mouth communication. This hypothesis comes up frequently in informal accounts of the behavior of the stock market.[1] For example, in his bestseller *Irrational Exuberance*, Shiller (2000) devotes an entire chapter to the subject of "Herd Behavior and Epidemics," and writes

> A fundamental observation about human society is that people who communicate regularly with one another think similarly. There is at any place and in any time a *Zeitgeist*, a spirit of the times. . . . Word-of-mouth transmission of ideas appears to be an important contributor to day-to-day or hour-to-hour stock market fluctuations. (pp. 148, 155)

Financial markets: Heterogeneous agents with direct interactions

Iori (2002) builds a model of a financial market with

- Risky and riskfree assets
- Heterogeneous agents with idiosyncratic information, beliefs and behavior
- Simple learning
- Communication to nearest neighbors
- Imitation of agents
- Trading frictions
- Different time-scales
- A market maker clearing orders

Financial markets: Heterogeneous agents with direct interactions

In each time period agents "consult" with their neighbors

- Agent i receives an aggregate signal Y

$$Y_i(\tilde{t}) = \sum_{\langle i,j \rangle} J_{ij} S_j(\tilde{t}) + A\nu_i(t)$$

- Based on this signal they behave as

$$S_i(\tilde{t}) = \begin{cases} 1, & \text{if} \quad Y_i(\tilde{t}) \leq \xi_i(t) \\ 0, & \text{if} \quad \xi_i(t) < Y_i(\tilde{t}) < \xi_i(t) \\ -1, & \text{if} \quad \xi_i(\tilde{t}) \leq -\xi_i(t) \end{cases}$$

Financial markets: Heterogeneous agents with direct interactions

From one period to the next

- The market maker adjusts prices according to

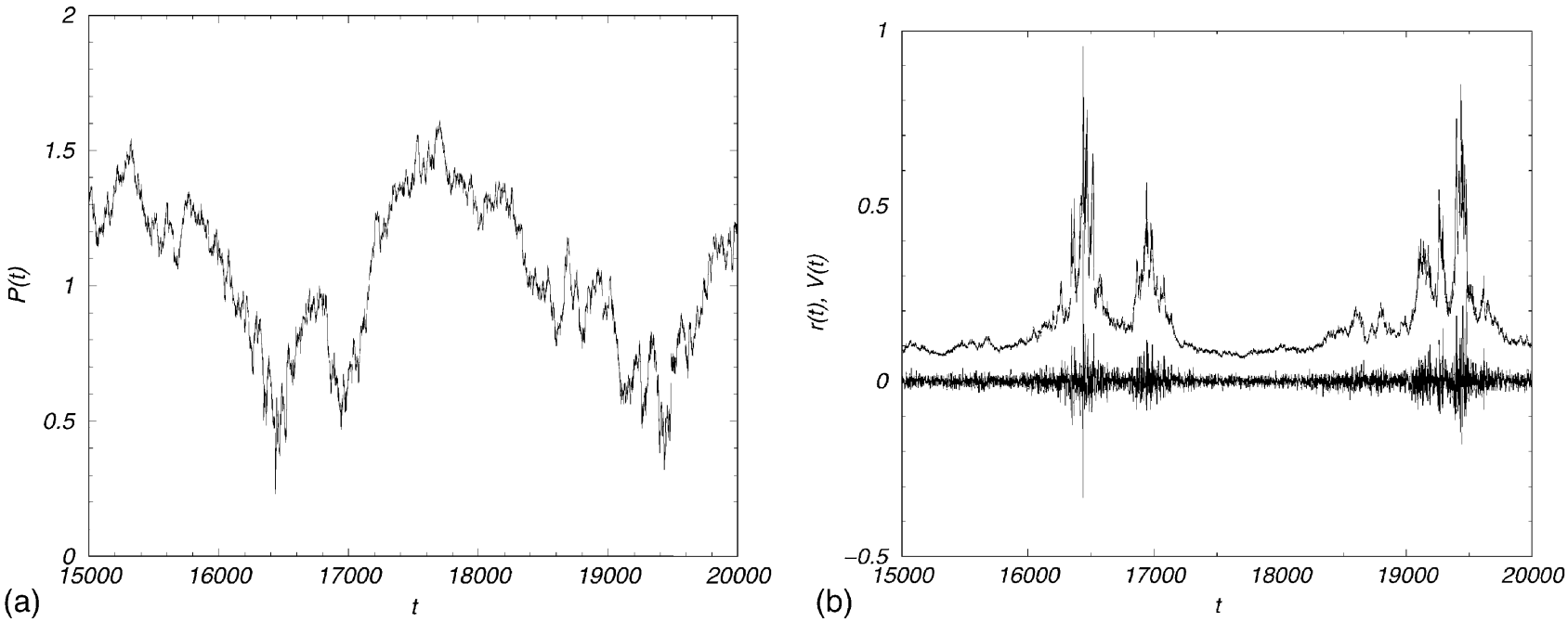
$$P(t+1) = P(t)\left(\frac{D(t)}{Z(t)}\right)^{\alpha}$$

- Agents adapt their behavior

$$\xi_i(t+1) = \xi_i(t)\frac{P(t)}{P(t-1)}$$

Financial markets: Heterogeneous agents with direct interactions

Results of Iori (2002)



Financial markets: Heterogeneous agents with direct interactions

Tedeschi et al. (2012) analyze the effects of endogenous dynamic network formation

- Risky and riskfree assets
- Order book
- Expectations as observable
- Dynamic and endogenous fitness-based imitation

Questions:

- Can we observe the emergence of a George Soros?
- Do “social traders” outperform chartists or fundamentalists?

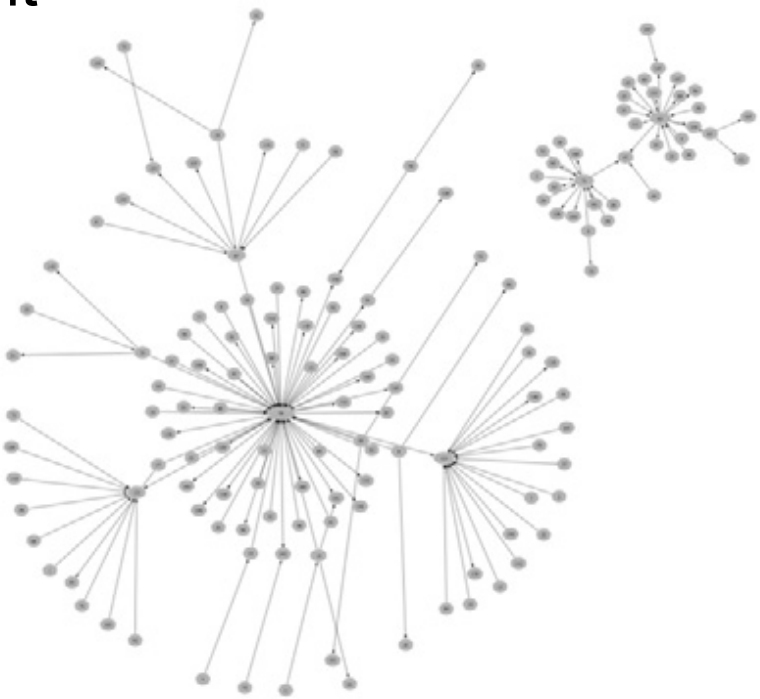
Financial markets: Heterogeneous agents with direct interactions

The communication network of Tedeschi et al. (2012)

- One outgoing directed link per agent
- Fitness-based rewiring

$$f_t^i = \frac{W_t^i}{W_t^{\max}} \qquad p_r^i = \frac{1}{1 + e^{-\beta^i (f_t^j - f_t^k)}}$$

- Agents know how many "followers" they have



Financial markets: Heterogeneous agents with direct interactions

Expectations in Tedeschi et al. (2012):

- Agents start with idiosyncratic expectations

$$\hat{r}^i_{t_k,t_k+\tau} = \sigma^i_{t_k}\epsilon^i_{t_k}$$

- Consultation round of expectations

$$r^i_{t_k,t_k+\tau} = w\hat{r}^i_{t_k,t_k+\tau} + (1-w)\hat{r}^j_{t_k,t_k+\tau}$$

- Popular agents become overconfident

Image: Greg Fisher

Financial markets: Heterogeneous agents with direct interactions

The rise of gurus in Tedeschi et al. (2012)

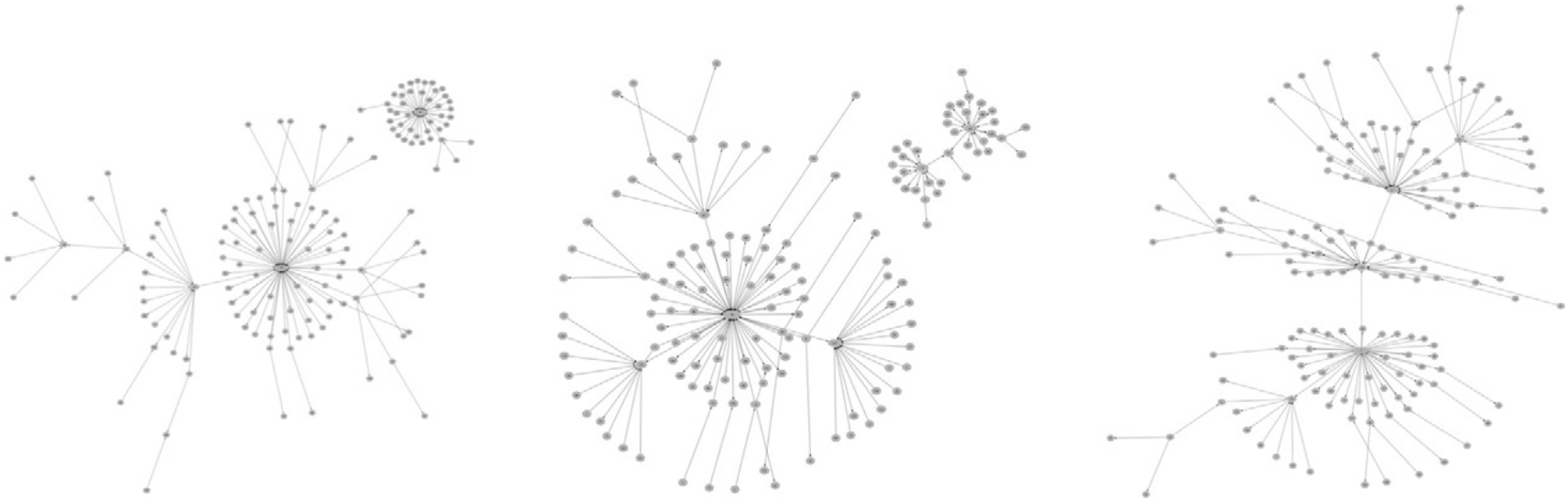
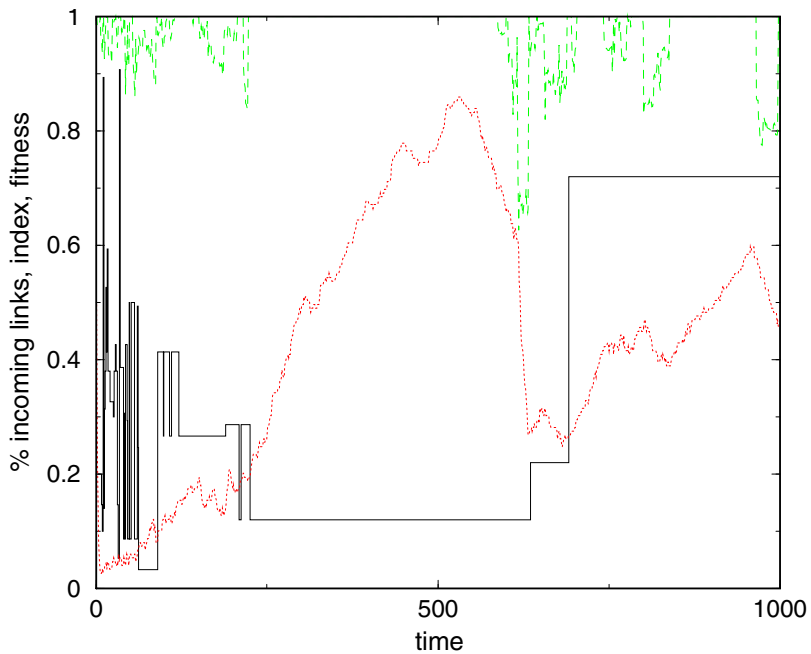
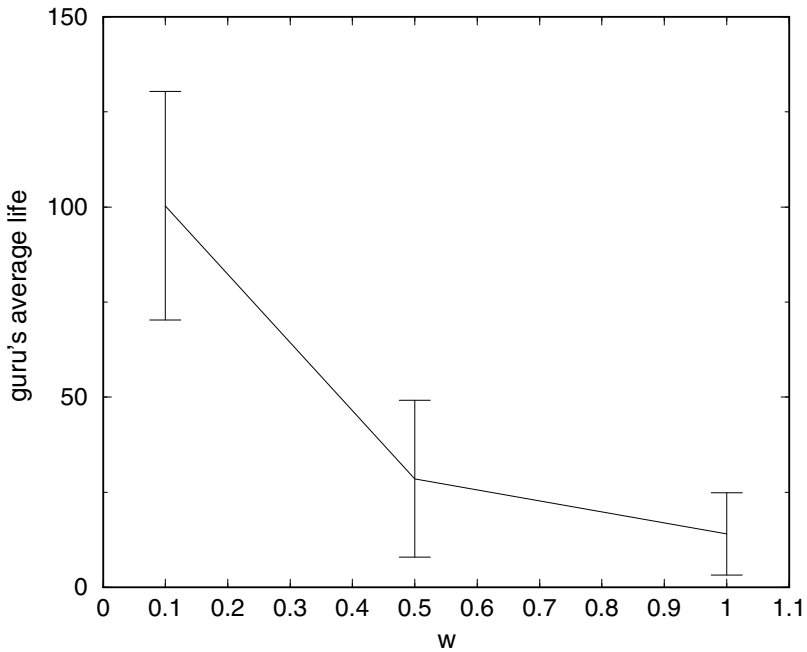


Fig. 1. Network configuration for $w = 0.1$ (the guru is agent 108) (left side), for $w = 0.5$ (the guru is agent 78) (centre) and for $w = 1$ (the guru is agent 6) (right side).

Financial markets: Heterogeneous agents with direct interactions

The fall of gurus in Tedeschi et al. (2012)





Financial markets: Heterogeneous agents with direct interactions

Competitive strategies in Tedeschi et al. (2012)

Average time ($\bar{t}$) at which the guru's wealth (W^g) dominates the two competitive strategies (chartists (W^c) & fundamentalists (W^f)) across 10 Monte Carlo simulations of $T = 10,000$ periods at different level of w.

Imitation level	$w = 0.1$	$w = 0.5$	$w = 1$
$W^c_{\bar{t}} < W^g_{\bar{t}}$	Ave $\bar{t}$: 400, st.dev: 230	Ave $\bar{t}$: 2507, st.dev: 1022	Never
$W^f_{\bar{t}} < W^g_{\bar{t}}$	Ave $\bar{t}$: 800, st.dev 122	Never	Never

- Chartists and fundamentalists are added to the population
- With strong imitation gurus can outperform both chartists and fundamentalists

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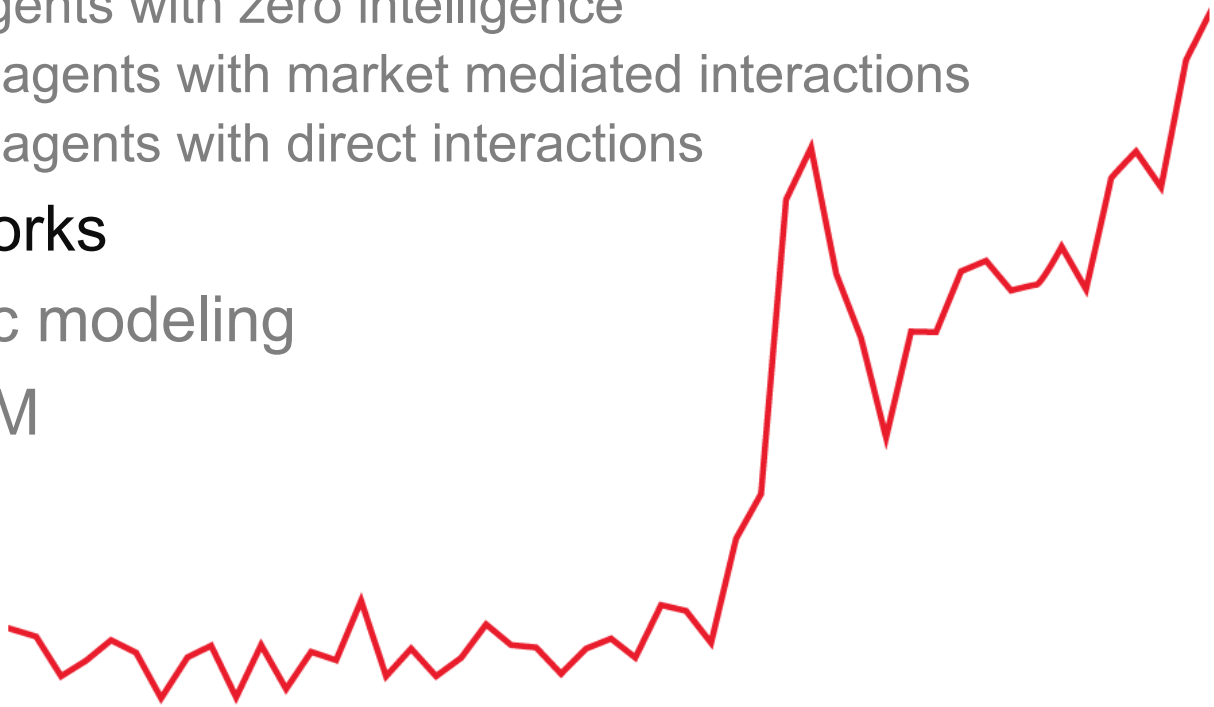


Interbank markets

Research questions

- How does systemic risk arise endogenously?
- What kind of financial architecture is more resilient to global crises?
- To what extent is risk diversification beneficial?

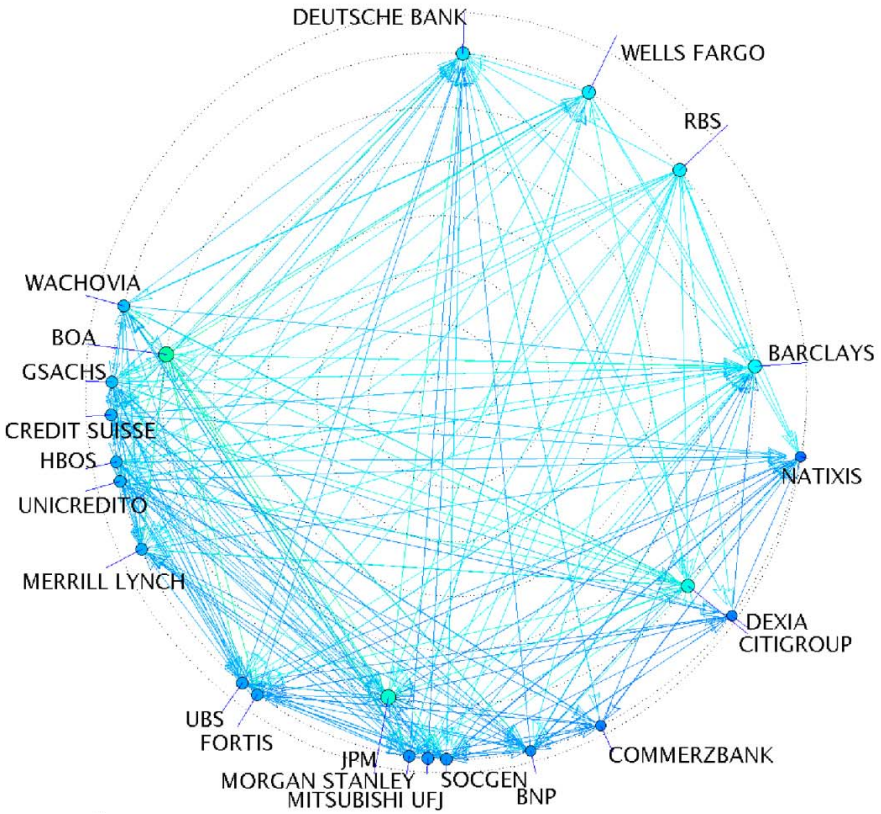


Image: Battiston et al. (2012)

Interbank markets

Battiston et al. (2012) study the effects of interdependence of financial institutes through interbank lending

- Diversification of risk

- Financial contagion

Interbank markets

The model of Battiston et al. (2012)

- Evolution of financial robustness of banks η_i with $\eta_i = 0$ indicating bankruptcy
- Financial acceleration as positive reinforcement of financial stress

$$d\eta_i = \sigma\, d\xi_i + h(t)\, dN \qquad dN = \sum_{t \in \mathcal{N}} \delta(t' - t)$$

$$h(t) = \begin{cases} -\alpha & \text{if } \eta_i(t-dt) - \eta_i(t-dt-\tau) < -\epsilon\sigma \\ 0 & \text{otherwise} \end{cases}$$

Interbank markets

Interdependence in Battiston et al. (2012)

- Interdependence of banks due to interbank lending

$$W_{ij} = L_{ji} / \sum_k L_{ki}$$

- Homogenous level of diversification
- Shocks on other banks are shared linearly to relative exposure

$$\eta_i(t+1) = \sum_j W_{ij}(\eta_j(t) + \sigma \xi_j(t))$$

- Risk diversification leads to $\sigma_z = \sigma / \sqrt{k}$.

Interbank markets

Single default probability in Battiston et al. (2012)

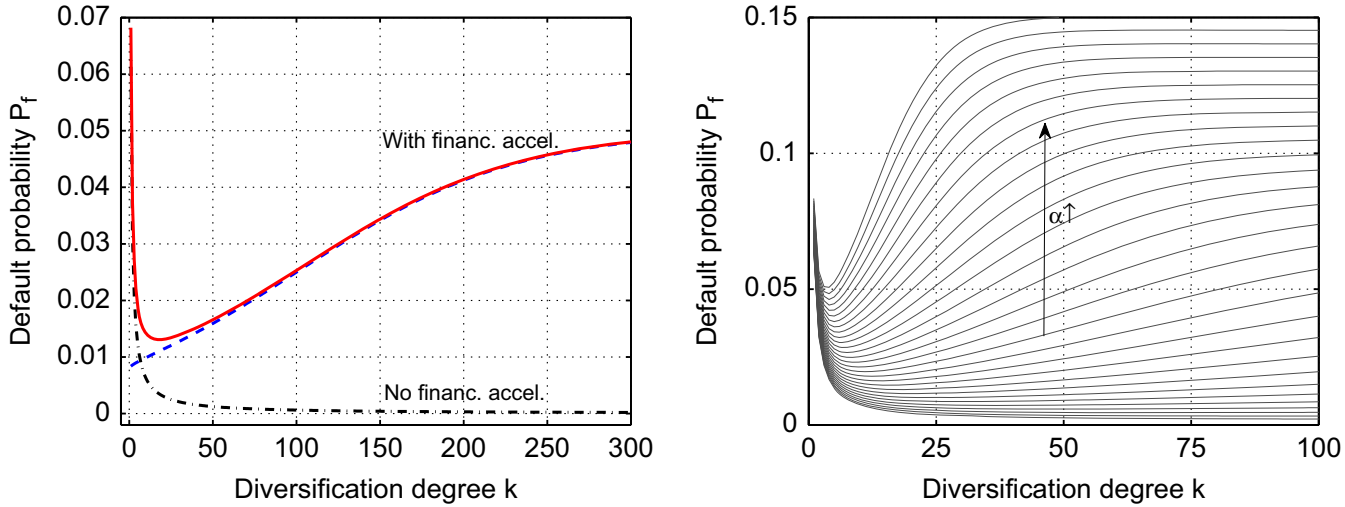


Fig. 1. Default probability P_f as a function of the diversification degree k. (Left) Comparison of presence (solid line) and absence (dotted line) of the financial acceleration. The dot-dashed line represents the values of the term $\alpha q(k)$ in Eq. (11). Parameters setting: $\epsilon = 1$, $\sigma = 0.25$, $\alpha = 0.055$. (Right) Illustration of dependence on α. Parameters: $\epsilon = 1$, $\sigma = 0.25$, α varies in [0.01 0.15] in steps of 0.005.

Interbank markets

Systemic default probability in Battiston et al. (2012)

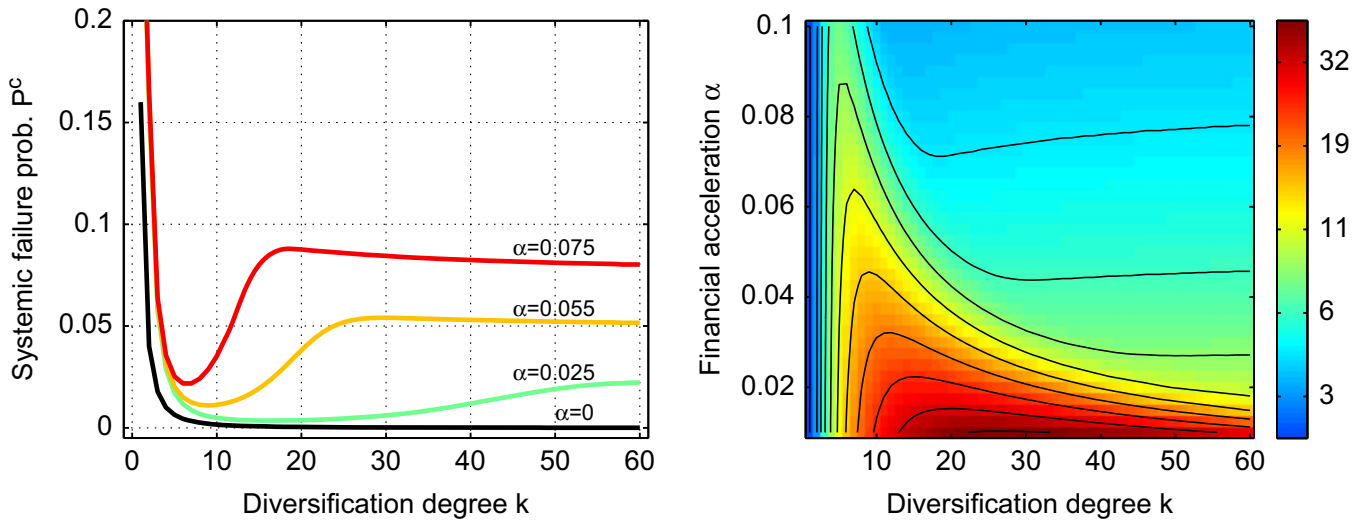


Fig. 3. (Left) Probability P^c of occurrence of large cascades as a function of risk diversification k for some values of the intensity α of financial acceleration. (Right) Expected time T^c to large default cascades plotted in color code (log scale) as a function of k and α. The scale on the color bar indicates the range of the expected time to default in the time units of Eq. (11). Values of the parameters: $\epsilon = 1$ and $\sigma = 0.25$. α varies in steps of 0.0001. The isoclines in black show that for any given α, by increasing k the expected time to default has an intermediate maximum. (For interpretation of the references to color in this figure caption, the reader is referred to the web version of this article.)

Interbank markets

Systemic importance measure in Battiston et al. (2012)

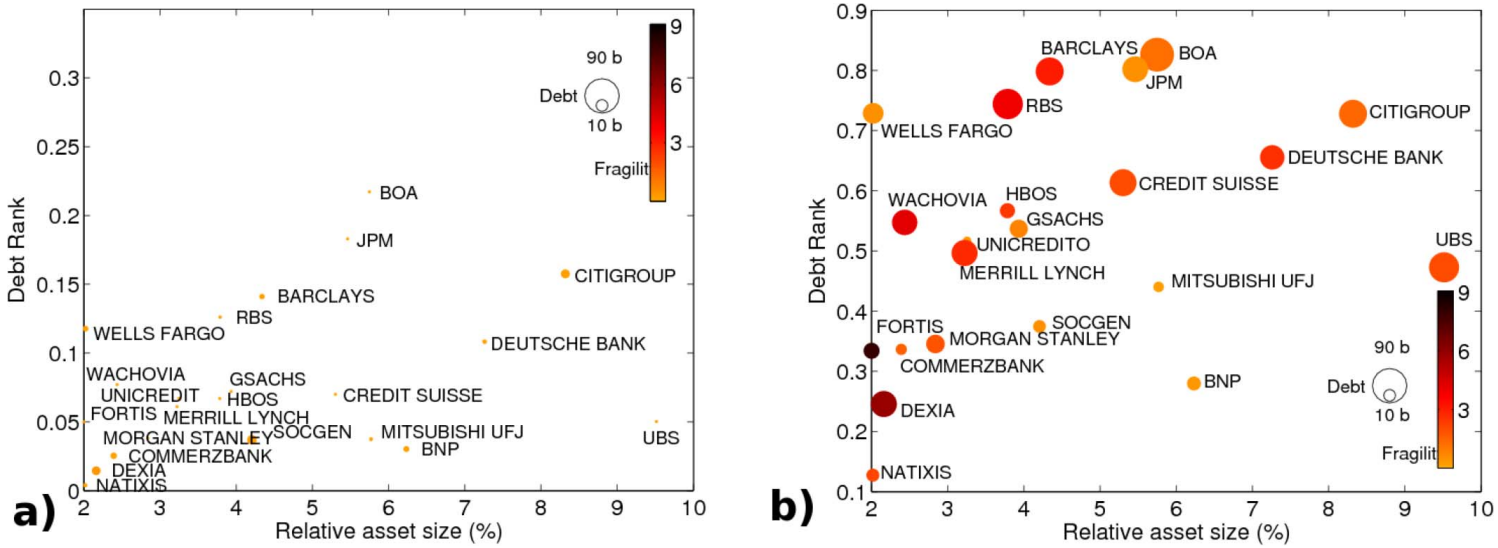
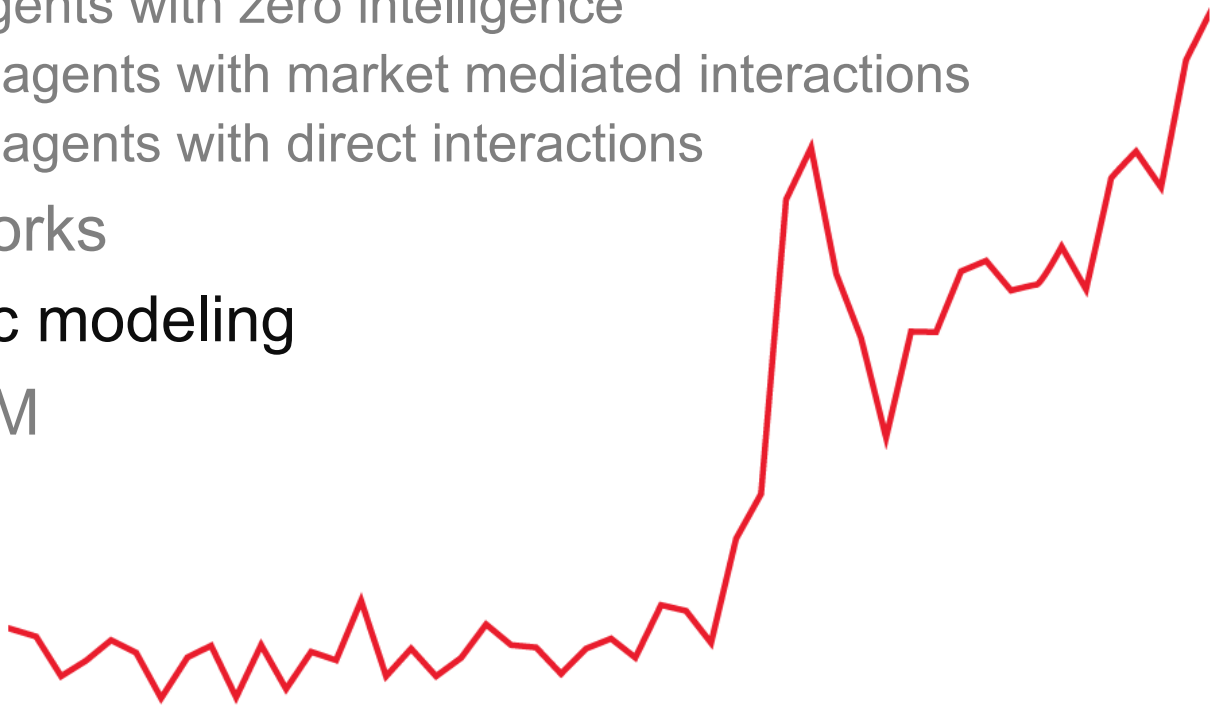


Figure 4 | Debt Rank, asset size and fragility. Scatter plot of DebtRank versus asset size, measured as a fraction (in %) of the total of the asset size in the network. For sake of simplicity, in the experiment, asset size was assumed constant during the time span of the data. Notice that institutions such as UBS, or CITIGROUP alone account for almost 10% of the total assets. The size of each bubble is proportional to the outstanding debt of the institution while the color reflects its fragility, defined as the ratio of debt over market capitalization in the given period, as in the previous section. (a) Period one. Since the outstanding debt was very low or zero, most nodes appear small and have levels of DebtRank below 0.3, but comparable among each other. (b) Period four. Many institutions have a Debt Rank larger then 0.5, i.e. each can impact, alone, the majority of the economic value in the network. The outstanding debt in this period is close to the peak for all the institutions, as reflected by the size of the bubbles. Notice, also a higher fragility, most bubbles are red, although with some heterogeneity.

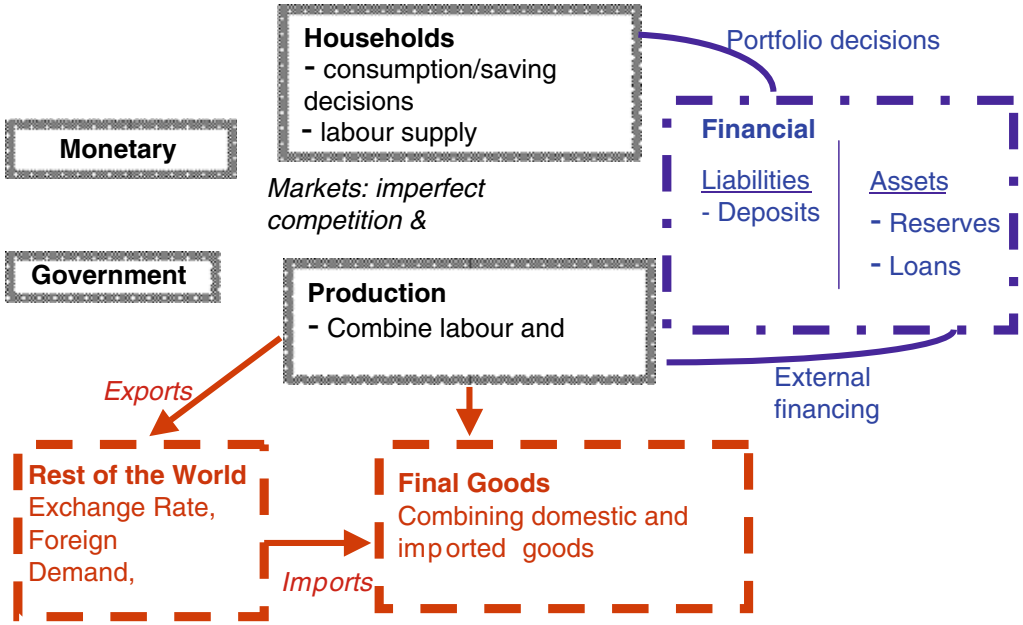
Outline

- Introduction
- ABM for financial markets
  - Homogenous agents with zero intelligence
  - Heterogeneous agents with market mediated interactions
  - Heterogeneous agents with direct interactions
- Interbank networks
- Macroeconomic modeling
- Criticism of ABM



Macroeconomic modeling

Dynamic stochastic general equilibrium models in Smets (2010)



Macroeconomic modeling

"**The standard macroeconomic models have failed, by all the most important tests of scientific theory. They did not predict that the financial crisis would happen;** and when it did, they understated its effects. Monetary authorities allowed bubbles to grow and focused on keeping inflation low, partly because the standard models suggested that low inflation was necessary and almost sufficient for efficiency and growth. After the crisis broke, policymakers relying on the models floundered. **Notwithstanding the diversity of macroeconomics, the sum of these failures points to the need for a fundamental re-examination of the models**—and **a reassertion of the lessons of modern general equilibrium theory** that were seemingly forgotten in the years leading up to the crisis. "

Joseph Stiglitz (2011)

Image source: wikipedia

Macroeconomic modeling

The Eurace project (Cincotti 2010)

- Complete agent-based model economy
- Bounded rationality
- Non-clearing markets
- Endogenous instabilities
- Quantitative easing
- Asynchronous actions on various time scales

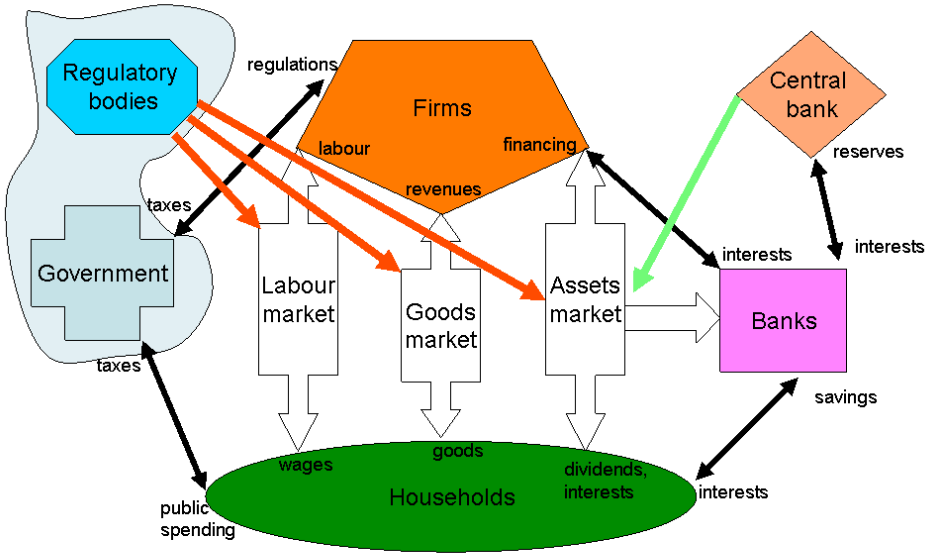


Image: ec.europe.eu

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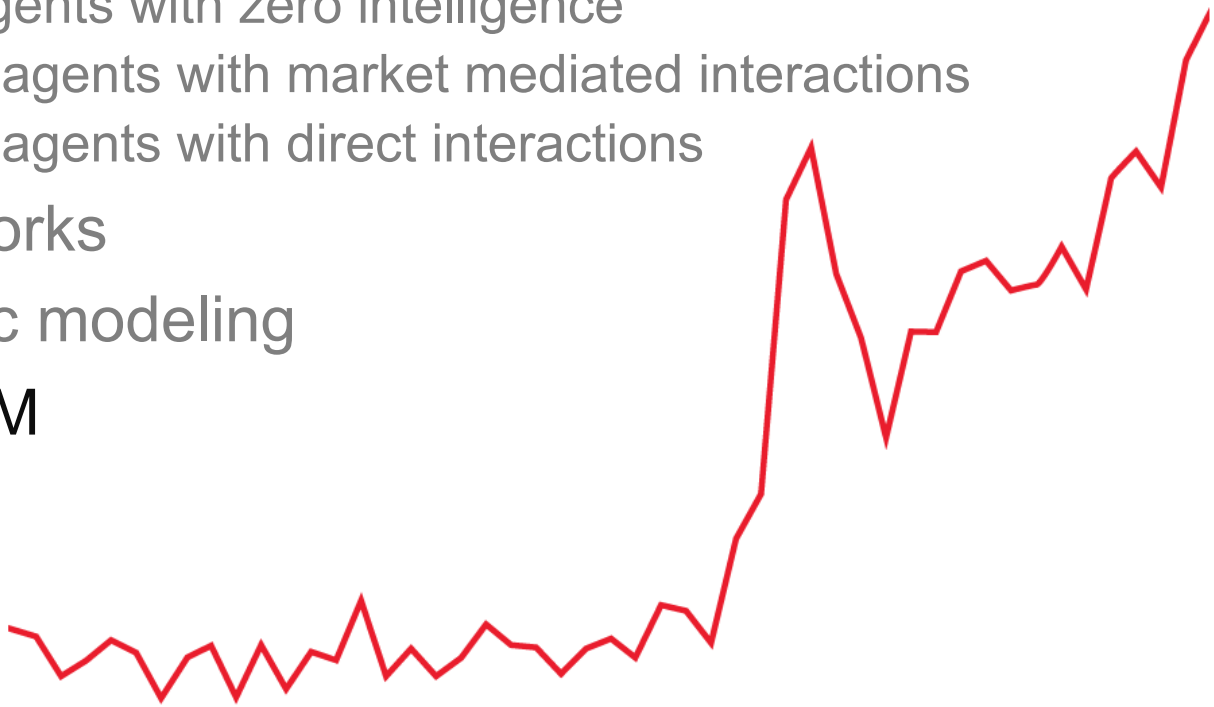

Criticism of the ABM approach

Agent-based modeling has been criticized for

- Number of parameters and calibration difficulties
- Loss of tractability and clarity
- Stability against the addition of new behavior
- Stability against changes in size
- Stability against changes in algorithm and timing

Summary

- The structure of a market is important
- Fat tails of returns and clustered volatility follow from market mediated interactions
- Direct communication and imitation results in herding and bubbles
- Centrality and interdependence dominate systemic risks and instability
- Agent-based modeling may help to overcome problems in macroeconomic modeling

Further reading

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