Agent-based artificial markets: a comparison of different architectures

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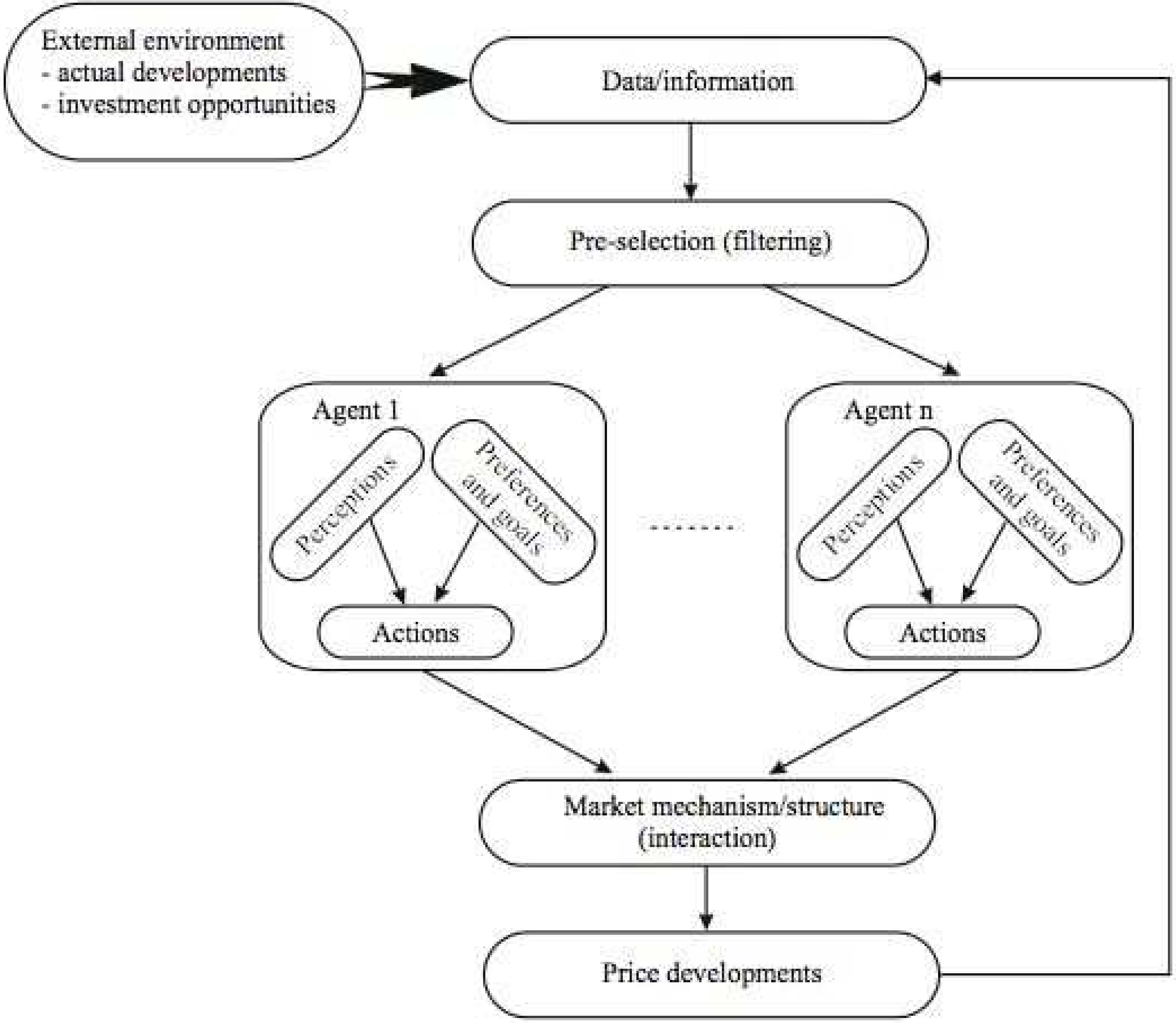
Introduction

- Markets are simple devices to coordinate agents
- Yet they are complex objects where the interaction of thousands of traders with different knowledge, skill, budget, horizon, target. . . takes place
- Analytical solutions are (almost) impossible to get if some realism is modelled
- Moreover, some features of financial markets are very difficult to obtain with simple, “representative” and classic models

Introduction (2)



Summary

- Agent based models and artificial markets
- A survey of themes and results (stylized facts)
  - Molecular
  - Organizational
  - Environmental
- Markets and institutional frameworks
- Some artificial markets models

Agent based models

- An Agent Based Model (ABM) is a specific individual based computational model for computer simulation extensively related to complex systems, emergence, Monte Carlo Method, computational sociology, multi agent systems, and evolutionary programming (Wikipedia, “Agent-based model”)
- (Agent based) Artificial markets are models of markets as evolving systems of autonomous agents that correspond to the trading parties
- Typically: hundreds of agents, realistic features, emergence of macro-properties from micro-motives
- Synonym: *Microsimulated* financial market, computational test bed

Agent based models (2)

- Classic models are often using the “representative agent” fiction and the market system is analyzed at equilibrium conditions
- This has huge advantages: analytical tractability, closed-form solution, powerful and clean implications. . .
- . . . but this come with a price.
  - How is this equilibrium reached, if it is reachable at all?
  - Do agents have (almost) infinite resources or analytical abilities?
  - What about stylized facts?

Artificial markets

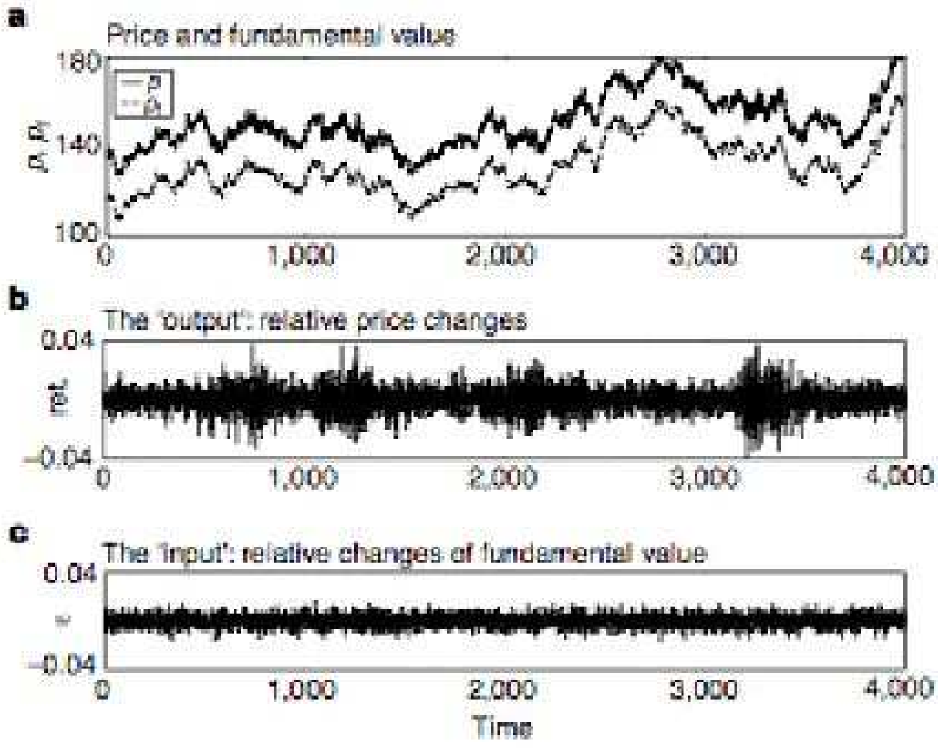
- AM are used to understand at the micro level what is going on in real financial markets
- AM are used to point to operational (i.e. computational) mechanisms that can generate phenomena of interest, dubbed stylized facts
- *Be aware!* Sufficient conditions are not necessary. Hence AM are not used (yet) for forecasting purposes or for optimization tasks. AM stress that something could be caused by some micro-features
- The term AM has also different meanings: HP prediction market, Iowa election market. . . but this is another long story

Stylized facts

- Prices/returns are normal/log-normal in main stream classic finance, but real prices:
- are not normal
  1. fat tails [α-stable distribution]
  2. are dependent [long memory, private informations]
  3. have volatility clusters [ARCH-GARCH]
- Return distribution is peaked, volume is intermittent (activity bursts), there are bubbles and crashes for no clear reasons
- Standard models have problems in dealing with the previous “oddities”, virtually all ABM can reproduce some effect. . . [Cont “model”]

Themes and results

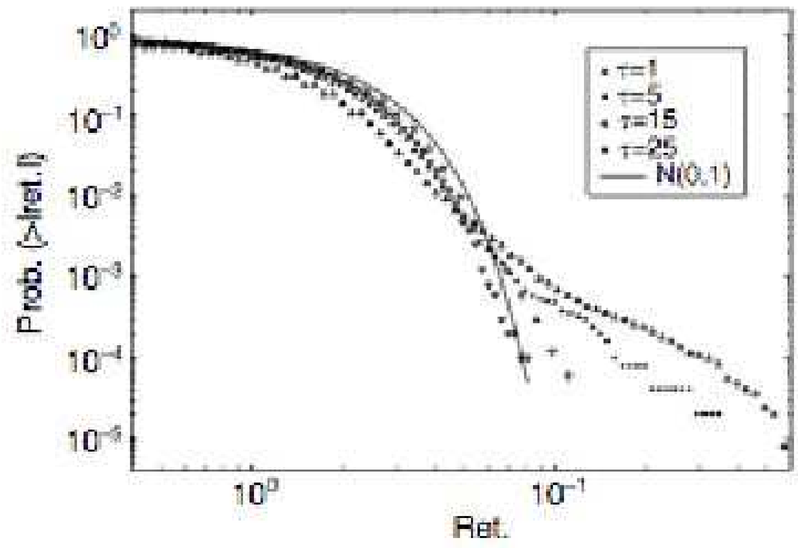
- Lux-Marchesi (1999): optimistic, pessimistic chartist and fundamental traders switch among strategies. Fundamental value changes are *normally* distributed.
- The returns are fat tailed and heteroskedastic



Themes and results

- Lux-Marchesi (1999): price adjustment is done by

$$p_{t+1} = p_t + cE[D_t]$$



- Hence, chartist/fundamental switching suffices to get some stylized facts

Themes and results (2)

- Santa Fe Artificial Stock Market (SFASM) by Arthur *at alii* (1997): learning and prices
- Agents are myopic wealth maximizers. They have a set of strategies that are continuously monitored in the quest for the best one
- Strategies are based on fundamental (price/earning ratios) and chartist (moving averages) indicators
- Every k steps a genetic algorithm, mimicking the learning effort by agents, is run in order to copy and improve the best strategies so far in the market
- Observe that the best strategy cannot be the best too long…

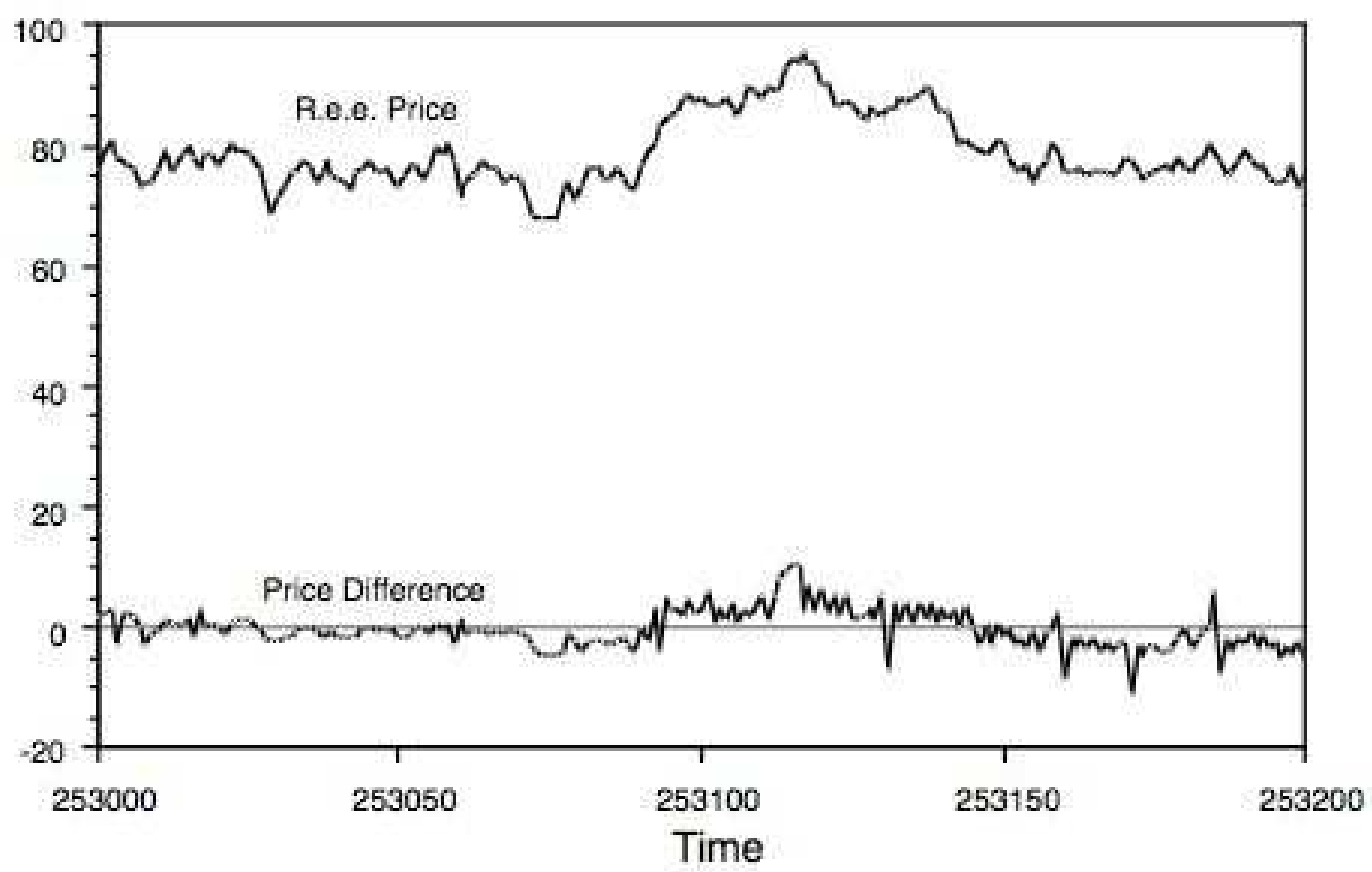
Themes and results (2)

- SFASM: if k is high, prices are nicely close to the fair value. However if k is low, meaning that agents learn (and react) too quickly then

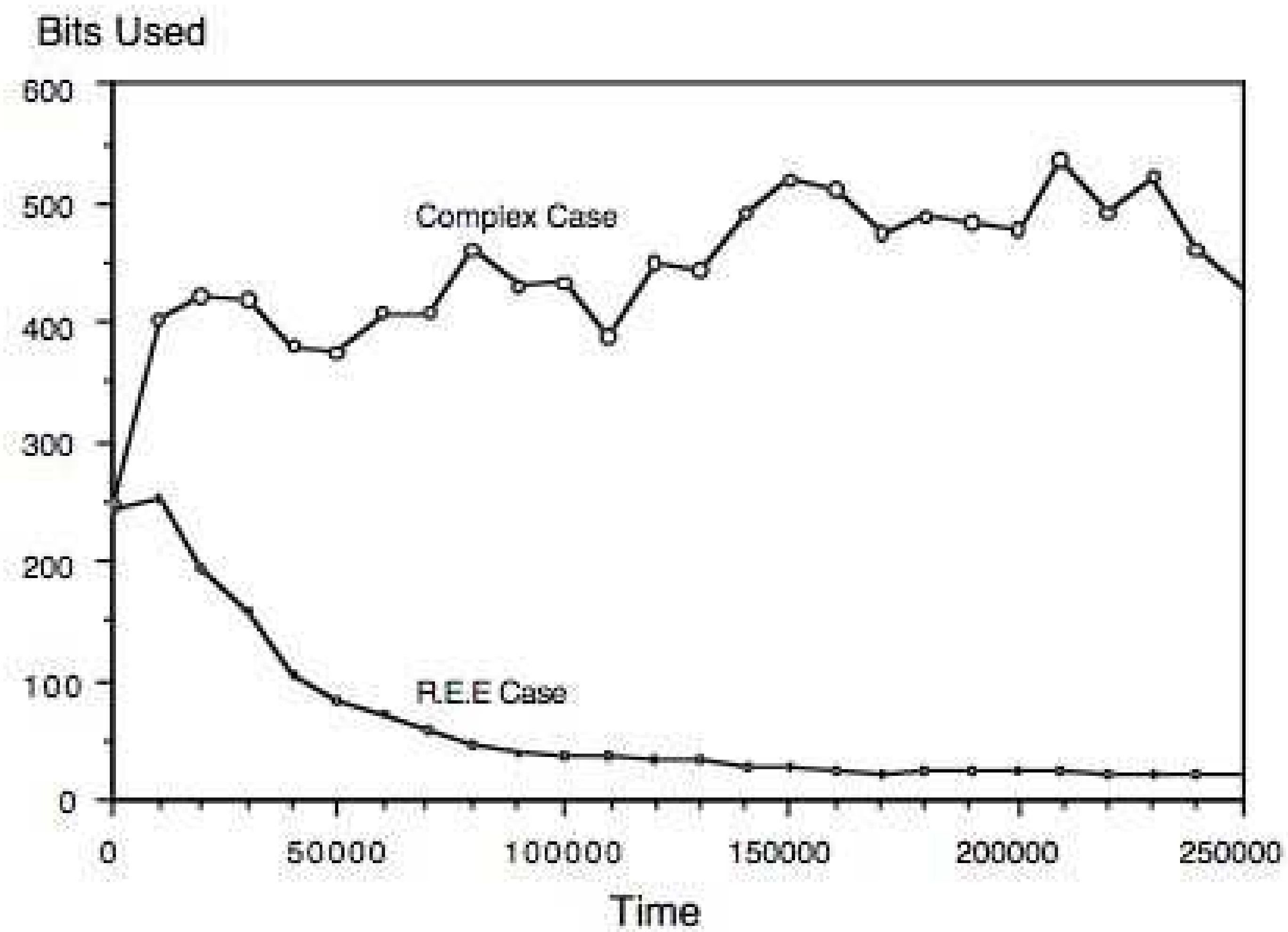
  > “Within a regime where the rate of exploration of alternative expectations is higher, the market self-organizes into a complex pattern. It acquires a rich psychology, technical trading emerges, temporary bubbles and crashes occur, and asset prices and trading volume show statistical features—in particular, GARCH behavior—characteristic of actual market data”

- (Too) fast learning is responsible for stylized facts (!?, recall Lux-Marchesi)

Themes and results (2)

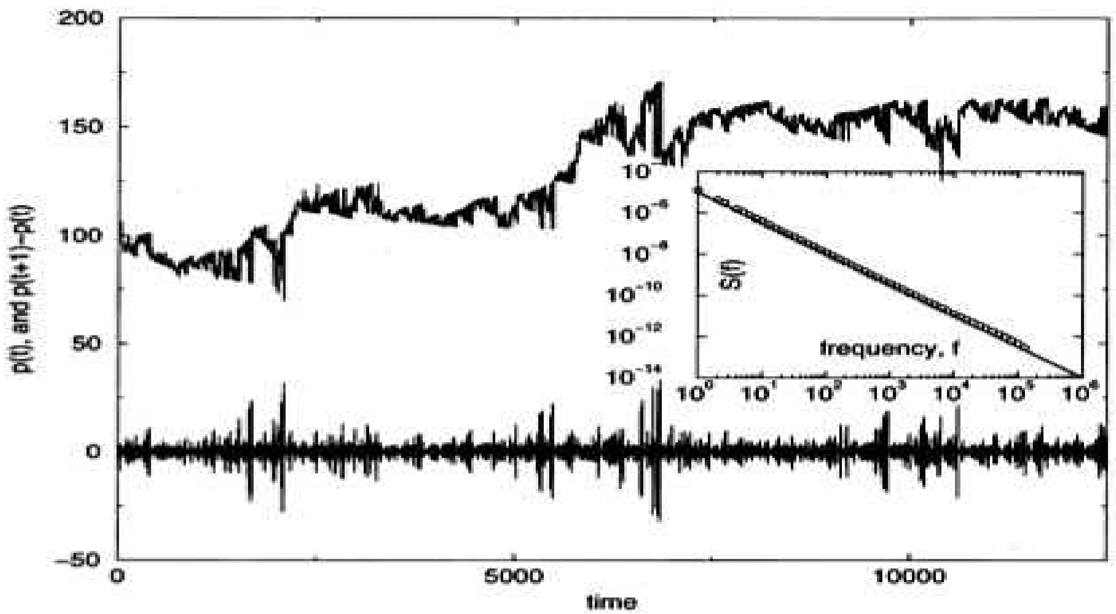


Themes and results (2)



Themes and results (3)

- Maslov (2000): random traders submit limit and market orders in a book market (very similar to nowadays exchages)
  The limit price is obtained offsetting the current price: $p(t) \pm \Delta$
- Fat tails and volatility clusters are obtained



Themes and results (3)

- Maslov (2000): the results *do not* depend on traders features (they just buy/sell randomly using a very primitive limit price adjustment rule)
- The (only) other ingredient is the market, the way prices are computed
- The conclusion is

  > The properties of the returns depend on the institutional details

- This a new research avenue in artificial markets: comparison of market architectures

Complexities

- Molecular: refers to the inherent complexity of the agent [Lux-Marchesi]
- Organizational: refers to the way agents perceive other agents, interact, learn and/or use information [SFASM]
- Environmental: traders are embedded in a market environment, they must use some rules dictating what they can and can not do [Maslov]
- ABM should try to disentangle different effects, hoping to answer to the question “What is causing what?”

Institutional framework

- We take the stance of a regulatory agency, that is trying to decide the rules of the game
- The regulator can not force agents to act “wisely” (too wild and heterogeneous)
- But it can shape the market in different ways and set some rules for trading
- Example: traffic congestion markets. Batch Auction (BA), Continuous Double Auction (CDA), Dealership?
- Some possible targets for the regulator are: low volatility, low volume, low risk, high liquidity, high allocative efficiency, high information discovery, investors protection and so on

Institutional framework (2)

- There are ovious tradeoffs and it is unlikely that all these objectives can be obtained at the same time
- In this approach, we look for the best market architecture along the following agenda
  - Set up different markets;
  - Set up (simple) agents;
  - Let them act, trade, coevolve, learn. . . recording some important statistics;
  - Select the market framework that best suits some predefined targets
- Hence, AMs are computational experiments to guide policy choices

References

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Comparison of different architectures

- Price stability and execution quality
- Price stability
  - financial fragility
  - capital protection
- Execution quality
  - liquidity
  - profits
- We are not interested in allocative or informational efficiency (but these are important topics)
- We run terse computerized experiments to evaluate the effect of the market alone

An artificial market

- The environment: there are two asset, a bond paying an interest r and a risky stock. Trading is organized in sessions called *days*
- Behavioral assumptions: an agent is initially endowed with cash c_i and s_i units of stock. Agents spend entirely the interest payments. Agents have heterogeneous parameters, namely
  - investment horizon h_i
  - risk premia $\pi_i^B > \pi_i^S > 0$ to buy and sell
  - estimate of fundamental value v_i

  Agents buy stocks if the price is sufficiently low on a *risk-adjusted* basis
  Conversely, agents sell stocks if the price raises enough on a *risk-adjusted* basis

Behavioral assumptions

- Agents set buy limit prices using

$$\frac{v_i}{p} \geq \left(1 + r + \pi_i^B\right)^{(h_i - t)},$$

i.e. the gross return rate must exceed r by π_i

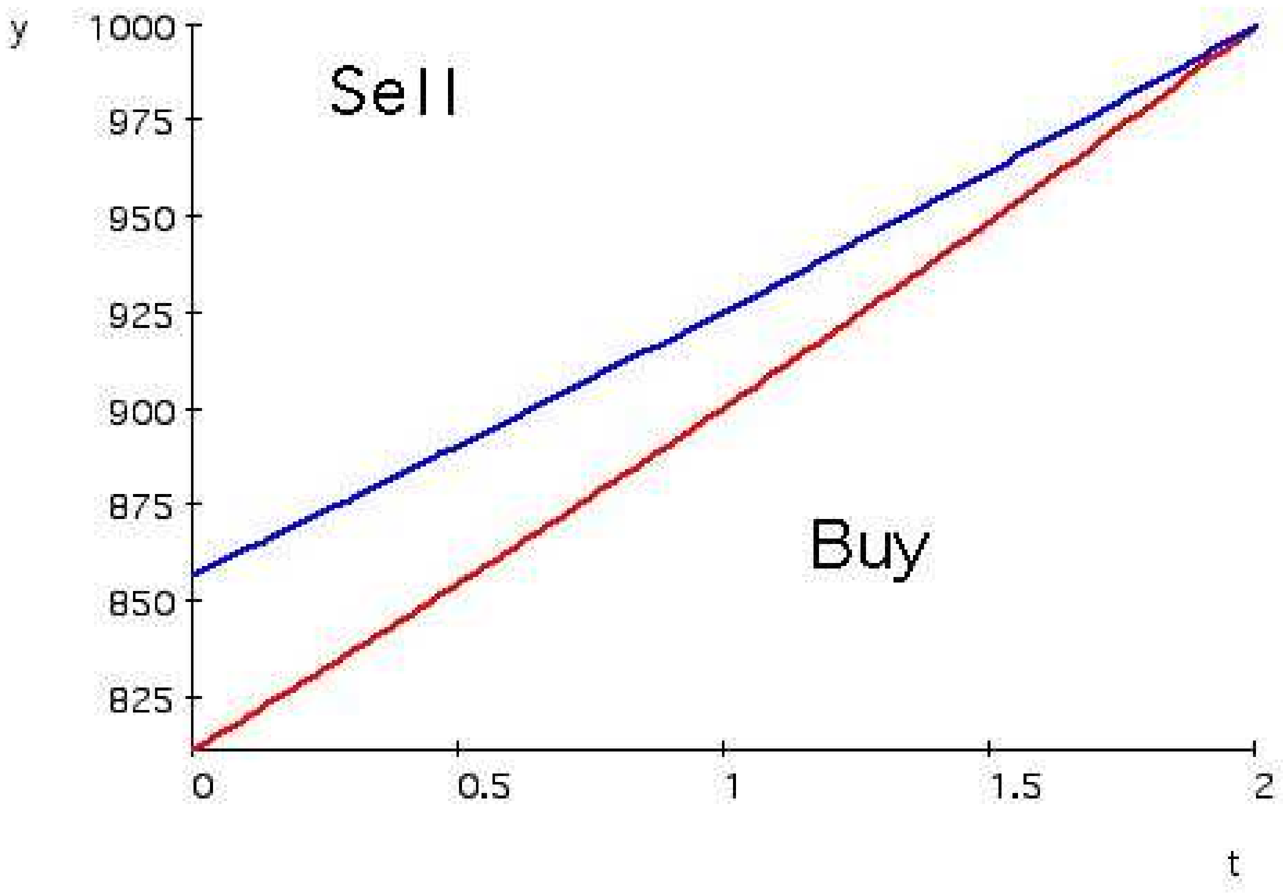
- The bid price is

$$\beta_i(t) = \frac{v_i}{\left(1 + r + \pi_i^B\right)^{(h_i - t)}}$$

- Similarly, the ask price is

$$\alpha_i(t) = \frac{v_i}{\left(1 + r + \pi_i^S\right)^{(h_i - t)}}$$

Behavioral assumptions (2)



Market protocols

- Batch Auction (BA): demand and supply curves are computed and crossed at the end of the session. There is a unique price per day
- Continuous Double Auction (CDA): orders not finding an immediate counterpart are stored in two books

	Price	Qty
	...	...
	999	2
(best) Ask ->	997	1
(best) Bid ->	993	2
	990	3
	...	...

- Buy 3 @ 995

Price	Qty
...	...
999	2
997	1
993	2
990	3
...	...

Price	Qty
...	...
999	2
997	1
995	3
993	2
990	3
...	...

- The order is stored for future use, the best bid increases

- Sell 4 @ 990

Price	Qty
...	...
999	2
997	1
993	2
990	3
...	...

Price	Qty
...	...
999	2
997	1
990	1
...	...

- The order is completely executed (2 units sold @ 993, 2 unit sold @ 990). Observe that the seller gained 6 cash units more that what he would have accepted (perceived gain)

Market protocols

- Dealership: an automated specialist posts at any time quotes (bid and ask)
- An agent willing to trade is checking the quotes and takes action if the proposed price is acceptable
-
Price	Qty
994	∞
990	∞

- After each successfull trade, the dealer moves its quotes, keeping the bid-ask spread constant

Dealership

- (Agent) buys 2 @ 996

Price	Qty
994	∞
990	∞

Price	Qty
995	∞
991	∞

  The agent gets 2 units @ 994, the dealer is increasing the quotes to foster sellers

- (Agent) sells 2 @ 992

Price	Qty
994	∞
990	∞

  Nothing happens

- This simple mechanic rule is intended to keep the inventory under control [we just scratched dealer surface. . .]

The parameters

- Parameters used in the simulations

	Parameters	Initialization
Global	N	1500
	r	0.02
	p_0	1000
Dealer	Γ	4
Trader	c_i	2000 (first activation only)
	s_i	1 (first activation only)
	v_i	$\sim U[950, 1050]$
	π_i^B	$\sim U[0, 0.06]$
	π_i^S	$\pi_i^B/2$
	h_i	$\sim t + \lceil \exp(1/250) \rceil$ days
	τ_i	$\sim h_i + \lceil \exp(1/250) \rceil$ days

-

The statistics

Volatility: standard deviation of the returns

Excess kurtosis: it describes the peakedness and fatness of tails

Tail exponent α: the cumulative distribution functions of returns is $F(x) \sim x^{\alpha}$ for large $|x|$

Volume: the cumulated number of transactions

Perceived gain: for each trading day, it is the cumulated excess gain, computed with the absolute difference of the limit price order P_j and the price p_j actually payed/received

Bid-ask spread: the difference between the best ask and the best bid (measure of liquidity)

To sum up

- We set up a market with fundamental *risk-adjusted* traders
- We have BA, CDA and dealership as market platforms (the markets are otherwiese identical)
- We assess the quality of the market using 6 statistic indicators

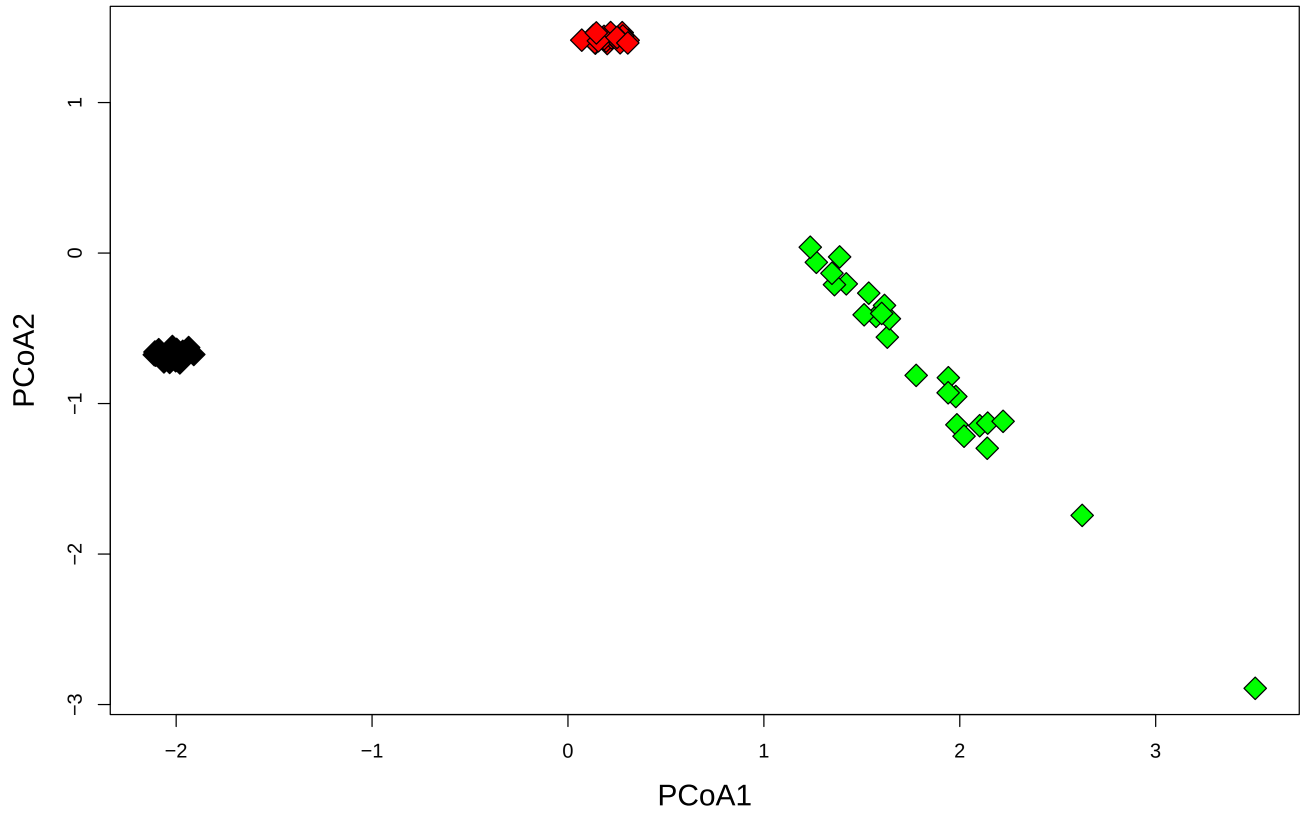
- Are you ready?

Results (25 runs, 2000d)

Vol	EKurt	TExp	Volume	PercG	Spread
			BA		
3.00%	1.00	-7.62	5.51	174.34	-
(0.063%)	(0.39)	(1.96)	(0.07)	(2.87)	-
			CDA		
0.53%	39.36	-2.60	8.19	372.38	3.49
(0.054%)	(26.94)	(0.54)	(0.12)	(5.82)	(0.08)
			Dealership		
0.24%	0.067	-	5.28	376.43	[4.00]
(0.005%)	(0.10)	-	(0.08)	(6.86)	-

Vectors in $\mathbf{R}^6$ are difficult to visualize, so we use a multidimensional scaling to have a planar graph

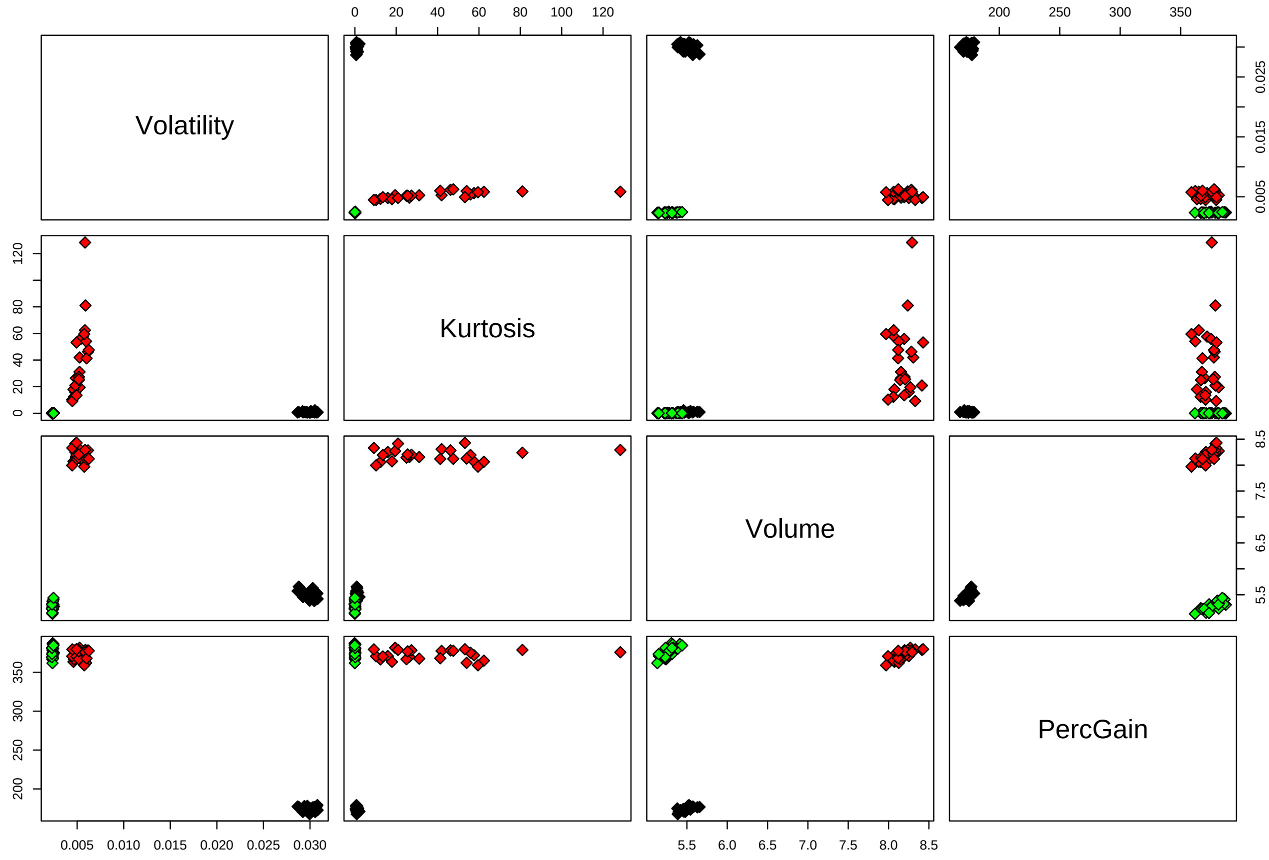
Results (planar)



Regulator be aware! Markets are (very) different

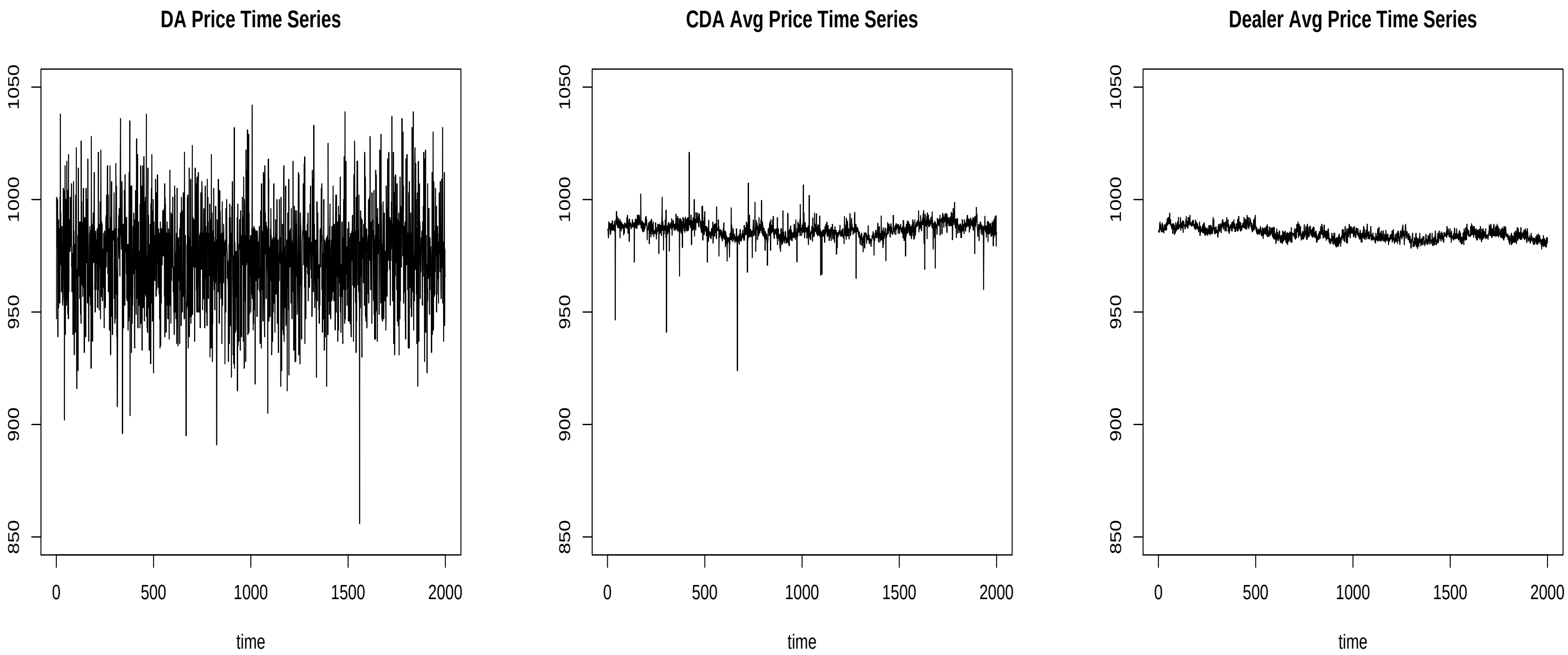
[Black=BA, Red=CDA, Green=Dealership]

Results (pairwise)

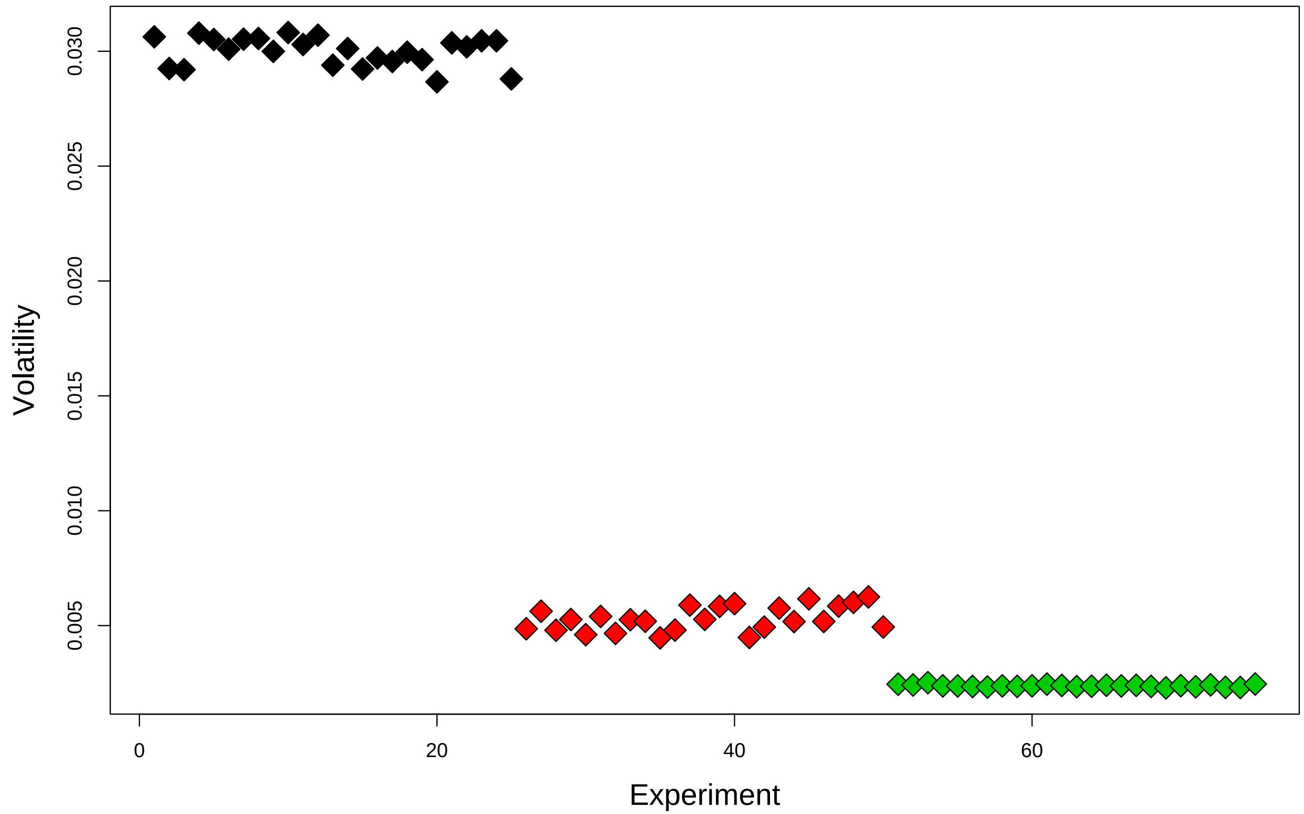


[Black=BA, Red=CDA, Green=Dealership]

Results (time series)

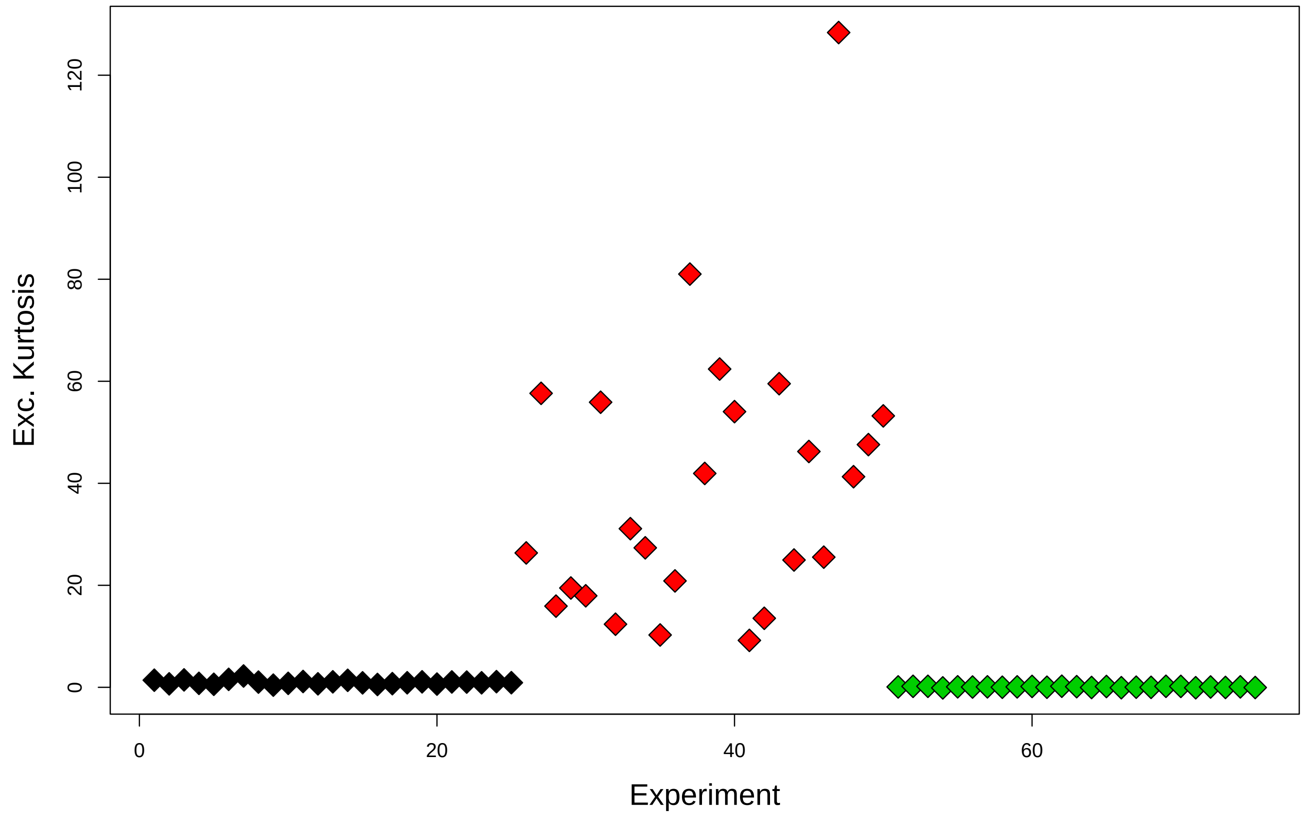


Results (volatility)



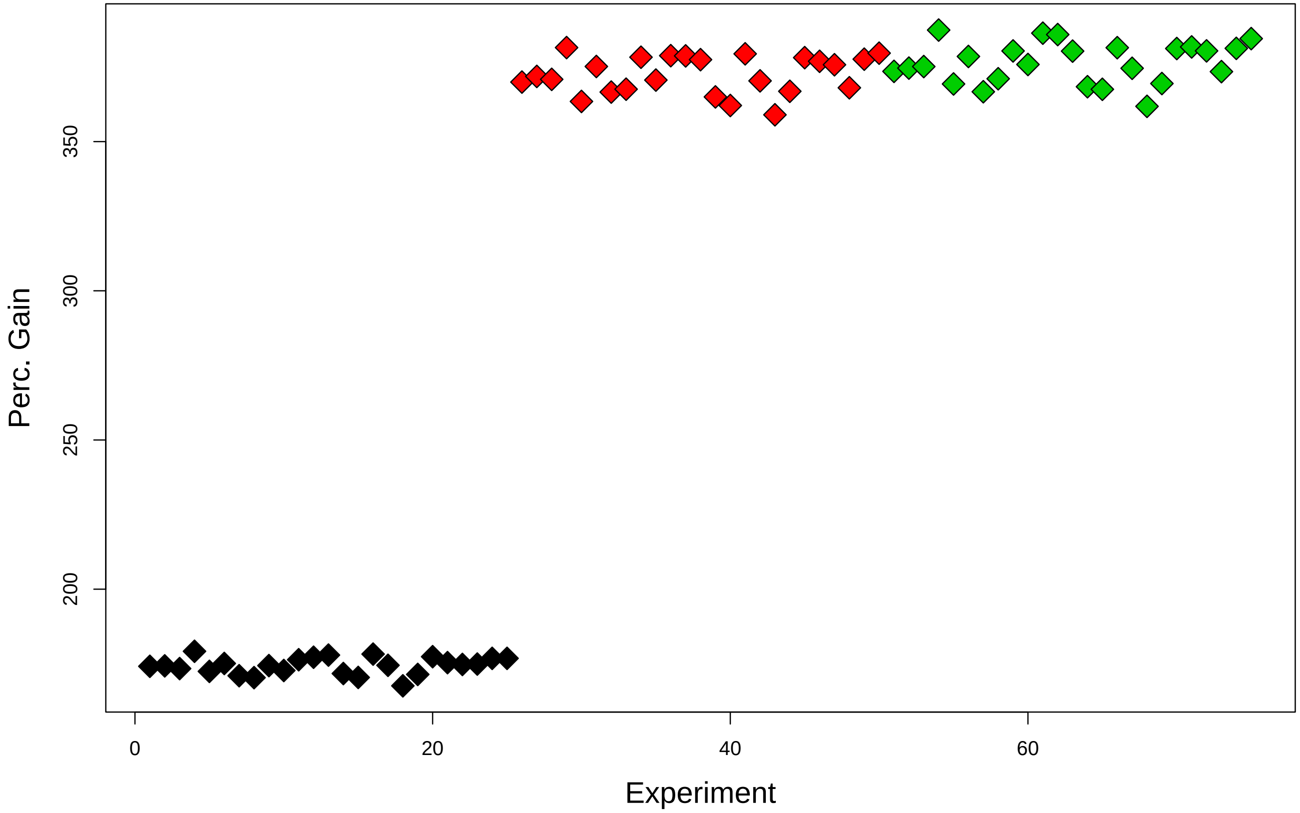
[Black=BA, Red=CDA, Green=Dealership]

Results (excess kurtosis)



[Black=BA, Red=CDA, Green=Dealership]

Results (perceived gain)



[Black=BA, Red=CDA, Green=Dealership]

In a nutshell

1. The BA produces **very volatile returns** coupled with **low kurtosis** and **fast tail** decay (i.e. extreme returns are rare). The volume ranks in between the CDA and the dealership and the **agents perceive a low gain** from BA markets
2. The CDA market has **low volatility** but **frequent extreme events**. Moreover, very slow tail decay makes it a **risky environment**. The market generates **the biggest amount** of trades and is liquid due to the low bid-ask spread. **Agents perceive high gain** when trading
3. The dealership return dynamics is **the least volatile**, no extreme events and ultra-fast tail decay. The **volume is low** but the **overall perceived gain is high**

Final remarks

- The dealership should be a good candidate (low volatility, no extreme events, high perceived gain)...
- ...but why do we see more CDAs than dealerships? Is it just randomness or a historical accident?
- This model is not considering allocative (!) and informational (?) issues so further research is in order to understand how robust are our findings.
  What about dividend announcements or terrorist attacks?

Conclusion

- Comments and remark are welcome:

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- Download papers at

  `http://www.dma.unive.it/∼paolop`

- Thanks for your attention!