On the Naturally Allied Spiral of Agent-based Computational Economics and Experimental Economics

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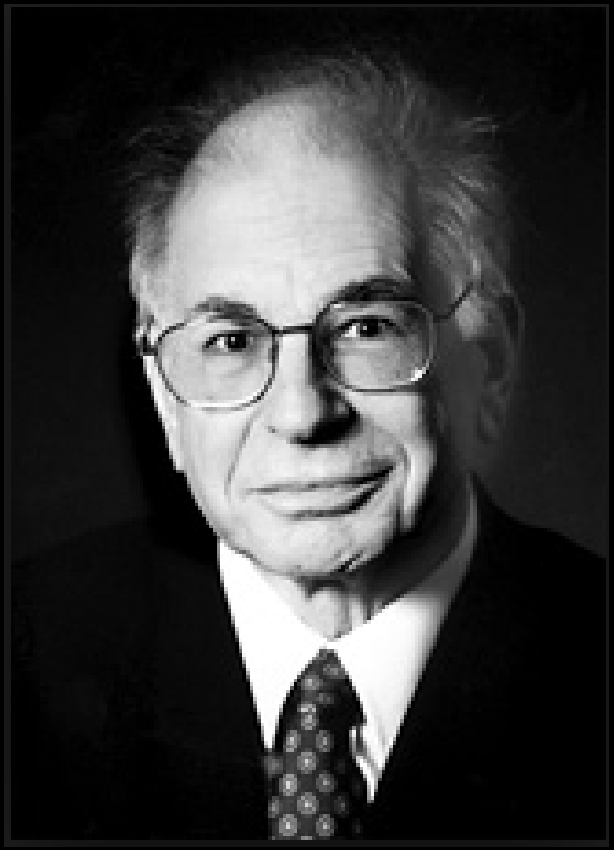
What is the relationship between ACE and EE as two research tools in Economics?

“Natural Allies” (Duffy, 2006)

Nobel Laureates in Economics, 2002

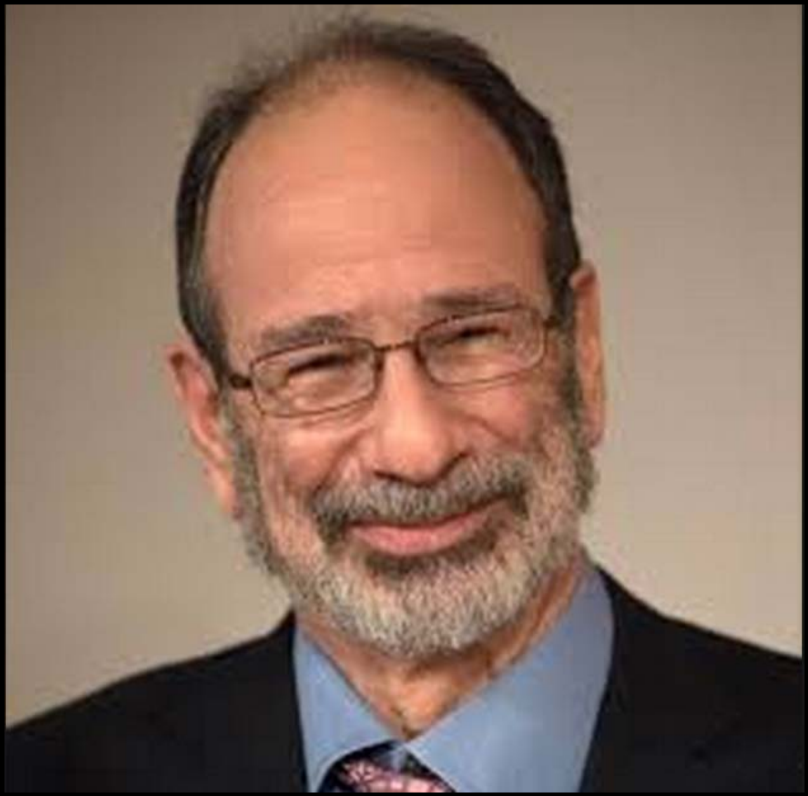
Vernon Smith



Daniel Kahneman

Nobel Laureate in Economics, 1994 and 2012

Reinhard Selten



Alvin Roth

Nobel Laureate in Economics, 1978

- Using experiments with human subjects to generate observations so as to examine economic theory, policy, and market designs has become a widely-accepted research paradigm in economics.
- This helps make economics be an experimental science.

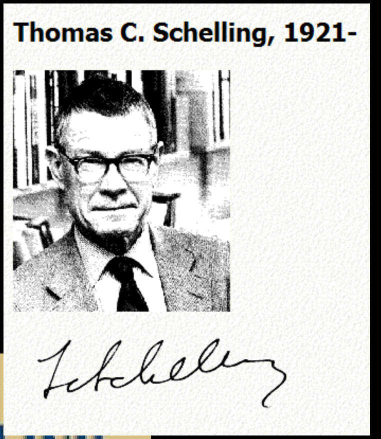
Scaling-Up Issues of EE

- Space Limit
- Budget Limit
- Attention Limit (Fatigue)

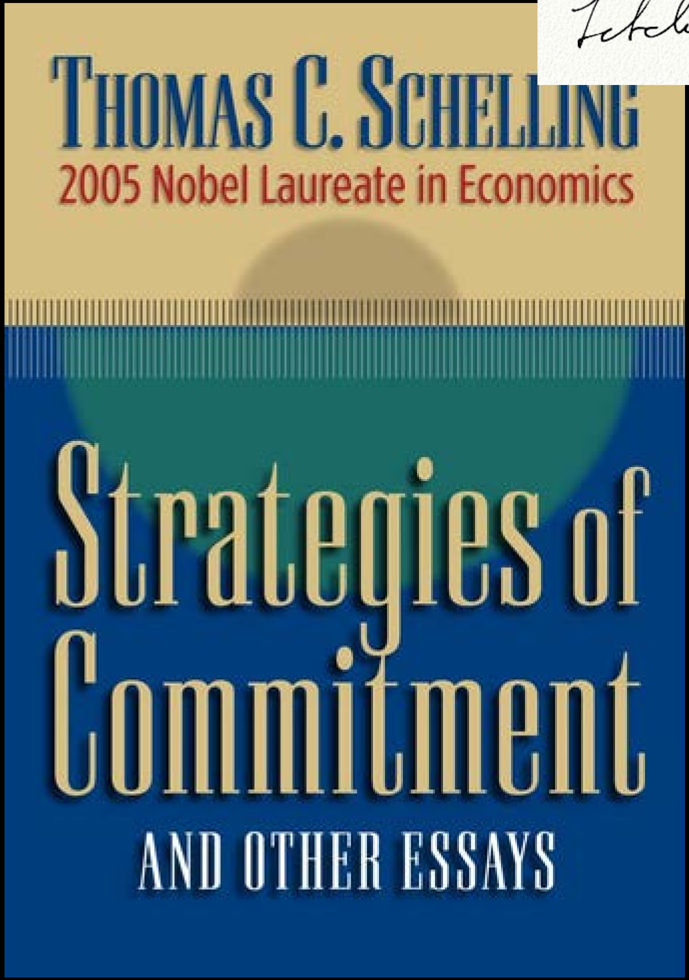
- Experimental economics at this point has not carefully reviewed to what extent their obtained results can be sensitive to the number of agents.
- One difficulty is that many experiments are not easy to be scaled-up.

Layout C (UCLA)

Schelling (2007)



- What I did not know when I did the experiments with my twelve-year-old son using copper and zinc pennies was that I was doing later became known as 'agent-based computational models,' or 'agent-based computational economics.' (Schelling (2007), p. xi.)
- Schelling T (2007) Strategies of Commitment and Other Essays. Harvard University Press.



Outline

- EE as an Origin of ACE
- Natural Allied Spiral
- Learning-to-Forecast Asset Market Experiments
- Cognitive Double Auction Experiments
- Concluding Remarks

Allocative Efficiency of Markets with Zero-Intelligence Traders: Market as a Partial Substitute for Individual Rationality

Dhananjay K. Gode and Shyam Sunder

Carnegie Mellon University

We report market experiments in which human traders are replaced by "zero-intelligence" programs that submit random bids and offers. Imposing a budget constraint (i.e., not permitting traders to sell below their costs or buy above their values) is sufficient to raise the allocative efficiency of these auctions close to 100 percent. Allocative efficiency of a double auction derives largely from its structure, independent of traders' motivation, intelligence, or learning. Adam Smith's invisible hand may be more powerful than some may have thought; it can generate aggregate rationality not only from individual rationality but also from individual irrationality.

Allocative Efficiency of Markets with Zero-Intelligence Traders: Market as a Partial Substitute for Individual Rationality

Dhananjay K. Gode and Shyam Sunder
Carnegie Mellon University

Zero Intelligence (Entropy Maximization)

J Evol Econ (1993) 3:1–22
Journal of Evolutionary Economics

On designing economic agents that behave like human agents

W. Brian Arthur

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Abstract. This paper explores the idea of constructing theoretical economic agents that behave like actual human agents and using them in neoclassical economic models. It does this in a repeated-choice setting by postulating "artificial agents" who use a learning algorithm calibrated against human learning data from psychological experiments. The resulting calibrated algorithm appears to replicate

Reinforcement Learning

Journal of Economic Dynamics and Control 18 (1994) 3–28. North-Holland

Genetic algorithm learning and the cobweb model*

Jasmina Arifovic
McGill University, Montréal, Qué. H3A 2T7, Canada

Evolutionary Computation

Chapter 19

AGENT-BASED MODELS AND HUMAN SUBJECT EXPERIMENTS

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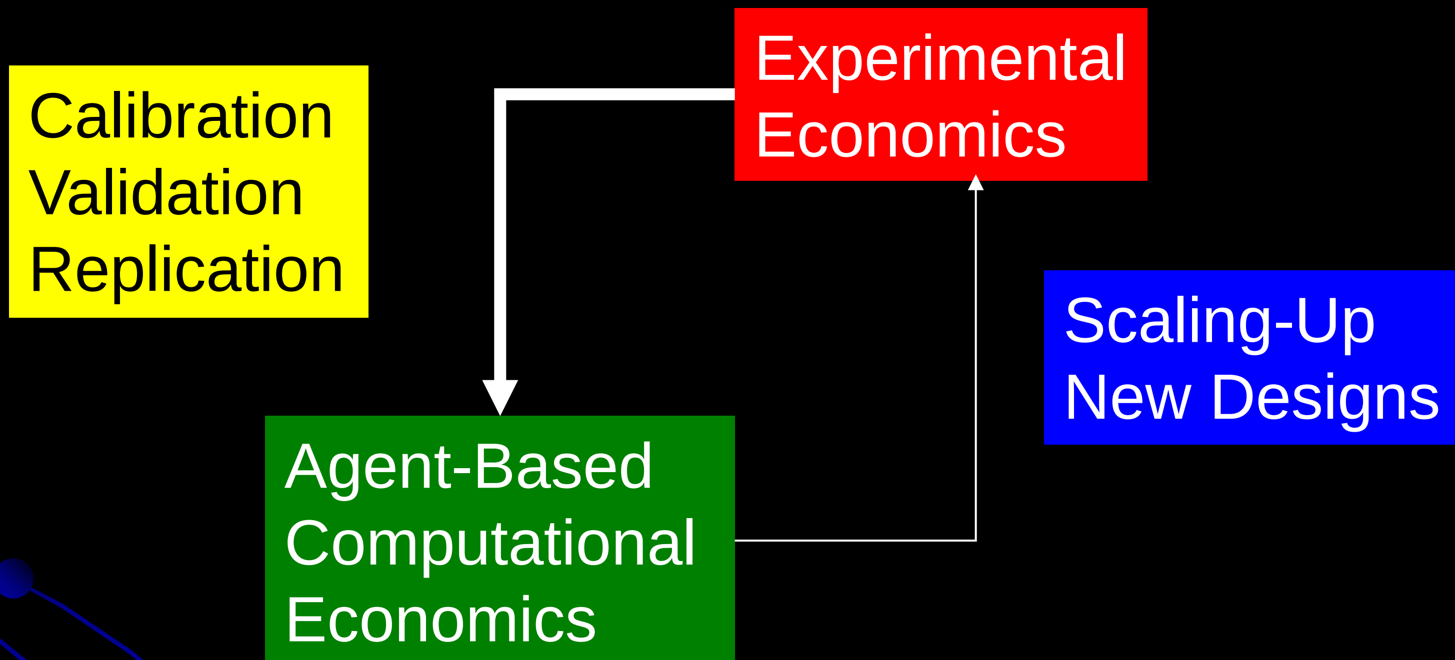
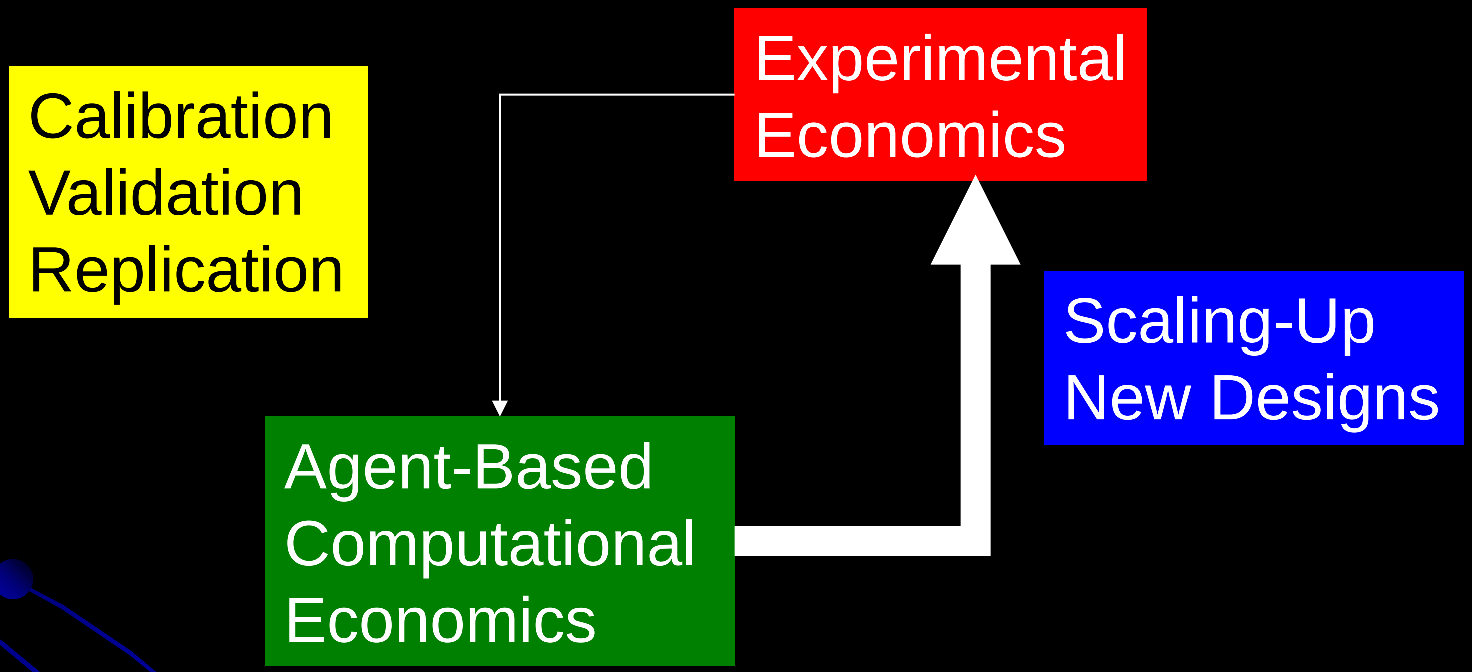
ACE and Experimental Economics

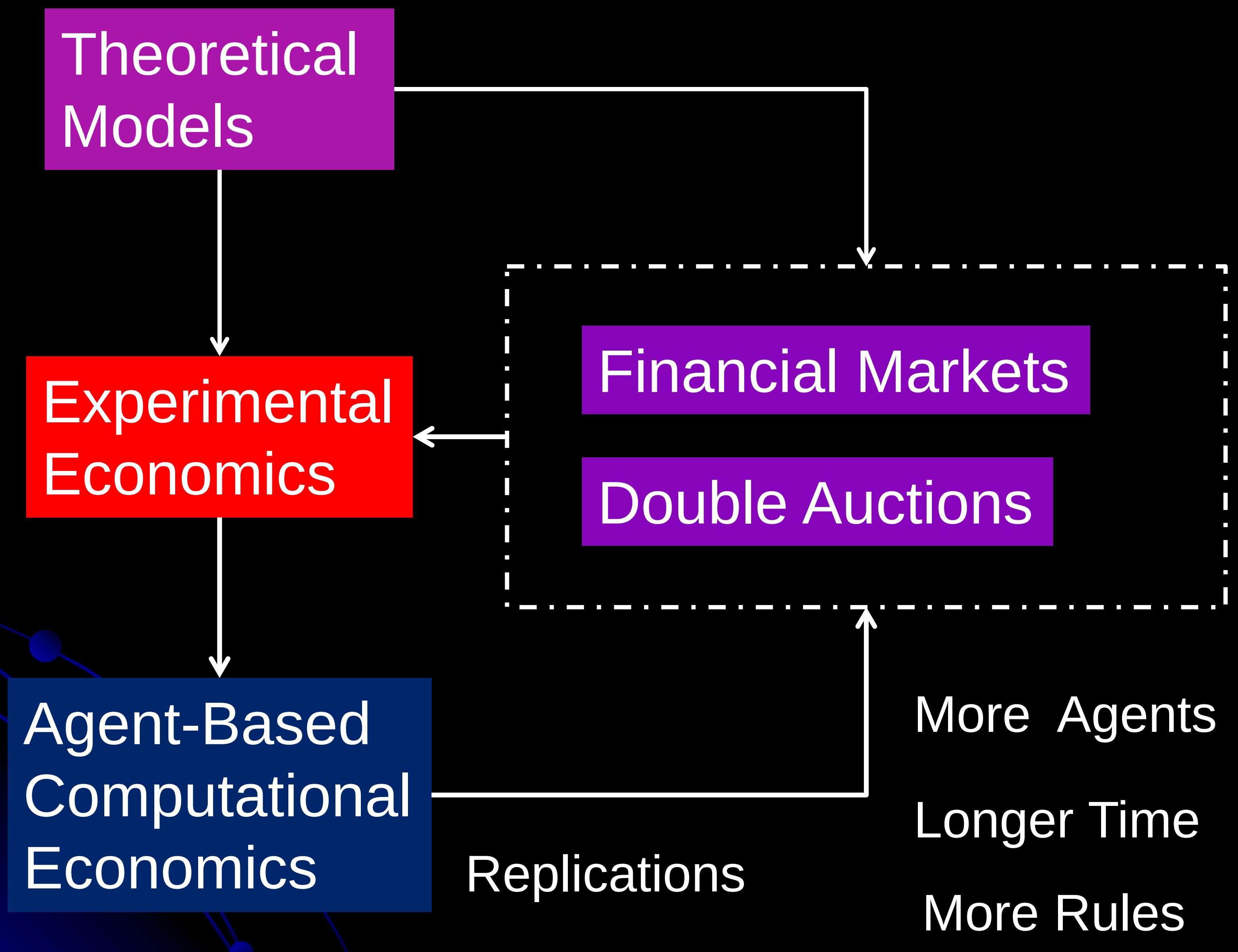


ACE and EE

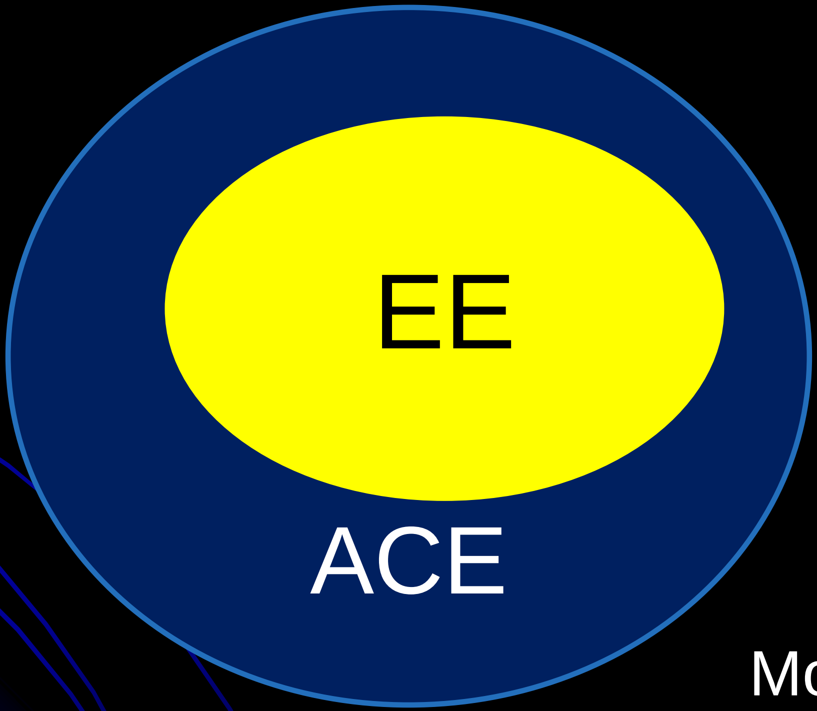
Most of the studies combining the two approaches have used agent-based methodology to understand results obtained from laboratory studies with human subjects; ***with a few notable exceptions, researchers have not sought to understand findings from agent-based simulations with follow-up experiments involving human subjects***. (Ibid, p. 951)

ACE and Experimental Economics




Theoretical Models
Experimental Economics
Financial Markets
Double Auctions
Agent-Based Computational Economics
Replications
More Agents
Longer Time
More Rules

Naturally Allied Sprial



More Agents

Longer Time

More Rules

LtFEs

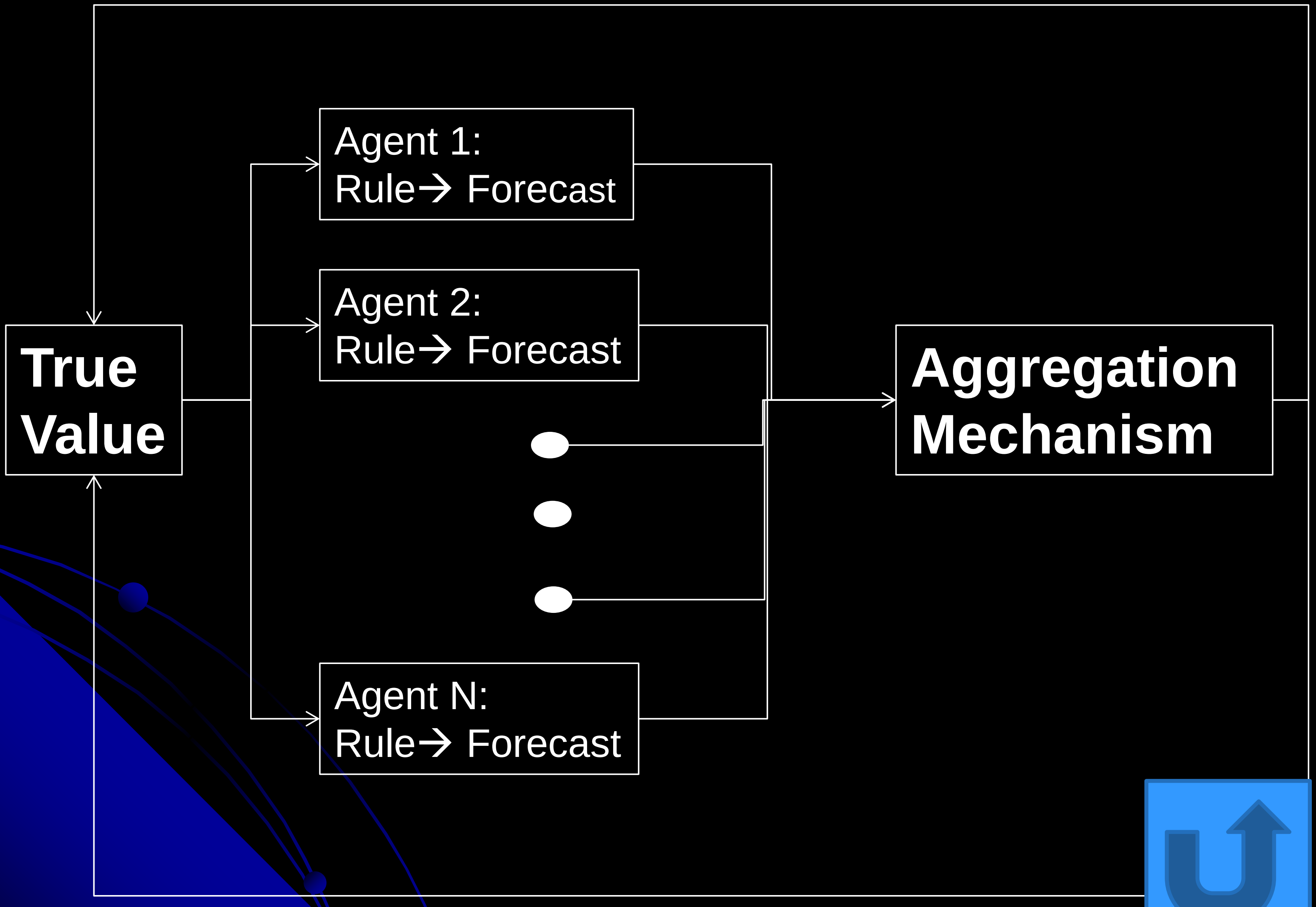
- Significance
- Learning-to-Forecast Experiments (LtFEs)
- Earliest LtFEs
- LtF Asset Market Experiments

Gerber, Hens, and Vogt (2002)

- **Ninety percent of what we do is based on perception. It doesn’t matter if that perception is right or wrong or real. It only matters that other people in the market believe it. I may know it’s crazy, I may think it’s wrong. But I lose my shirt by ignoring it.** (“Making Book on the Buck”Wall Street Journal, Sept. 23, 1988, p. 17)

Learning-to-Forecast Experiments (LtFEs)

- A concentrated task (no trading, no optimization, and so on)
- Market design (endogeneity)
- Repeated game (feedbacks)



True Value
Agent 1:
Rule→ Forecast
Agent 2:
Rule→ Forecast
Agent N:
Rule→ Forecast
Aggregation Mechanism

Heemeijer et al.(2009)

B.1.2. General information

You are an advisor of an importer who is active on a market for a certain product. In each time period the importer needs a good prediction of the price of the product. Furthermore, the price should be predicted one period ahead, since importing the good takes some time. As the advisor of the importer you will predict the price $P(t)$ of the product during 50 successive time periods. Your earnings during the experiment will depend on the accuracy of your predictions. The smaller your prediction errors, the greater your earnings.

B.1.3. About the market

The price of the product will be determined by the law of supply and demand. The size of demand is dependent on the price. If the price goes up, demand will go down. The supply on the market is determined by the importers of the product. Higher price predictions make an importer import a higher quantity, increasing supply. There are several large importers active on this market and each of them is advised by a participant of this experiment. Total supply is largely determined by the sum of the individual supplies of these importers. Besides the large importers, a number of small importers is active on the market, creating small fluctuations in total supply.

LetFEs: From EE to ACE

LtFES Overlapping Generation Experiments
(Marimon and Sunder, 1993, 1994, 1995; Marimon, Spear and Sunder, 1993)

Agent-based Macroeocnomic (Overlapping Generation Model)
(Arifovic, 1995, Bullard and Duffy, 19988a, b, 1999; Chen and Yeh, 1999)

Earliest LtFEs

- Marimon R, Sunder S (1993) Indeterminacy of equilibria in a hyperinflationary world: Experimental evidence. Econometrica 61:1073-1107.
- Marimon R, Spear S, Sunder S (1993) Exceptionally driven market volatility: An experimental study. Journal of Economic Theory 61(1):74-103.
- Marimon R, Sunder S (1994) Expectations and learning under alternative monetary regimes: An experimental approach. Economic Theory 4:131-62.
- Marimon R, Sunder S (1995) Does a constant money growth rule help stabilize inflation? Carnegie-Rochester Conference Series on Public Policy 43:111--156.

Complex Dynamics: Grandmont (1985)

As relative risk aversion parameter is increased,
the period of cycle also increased

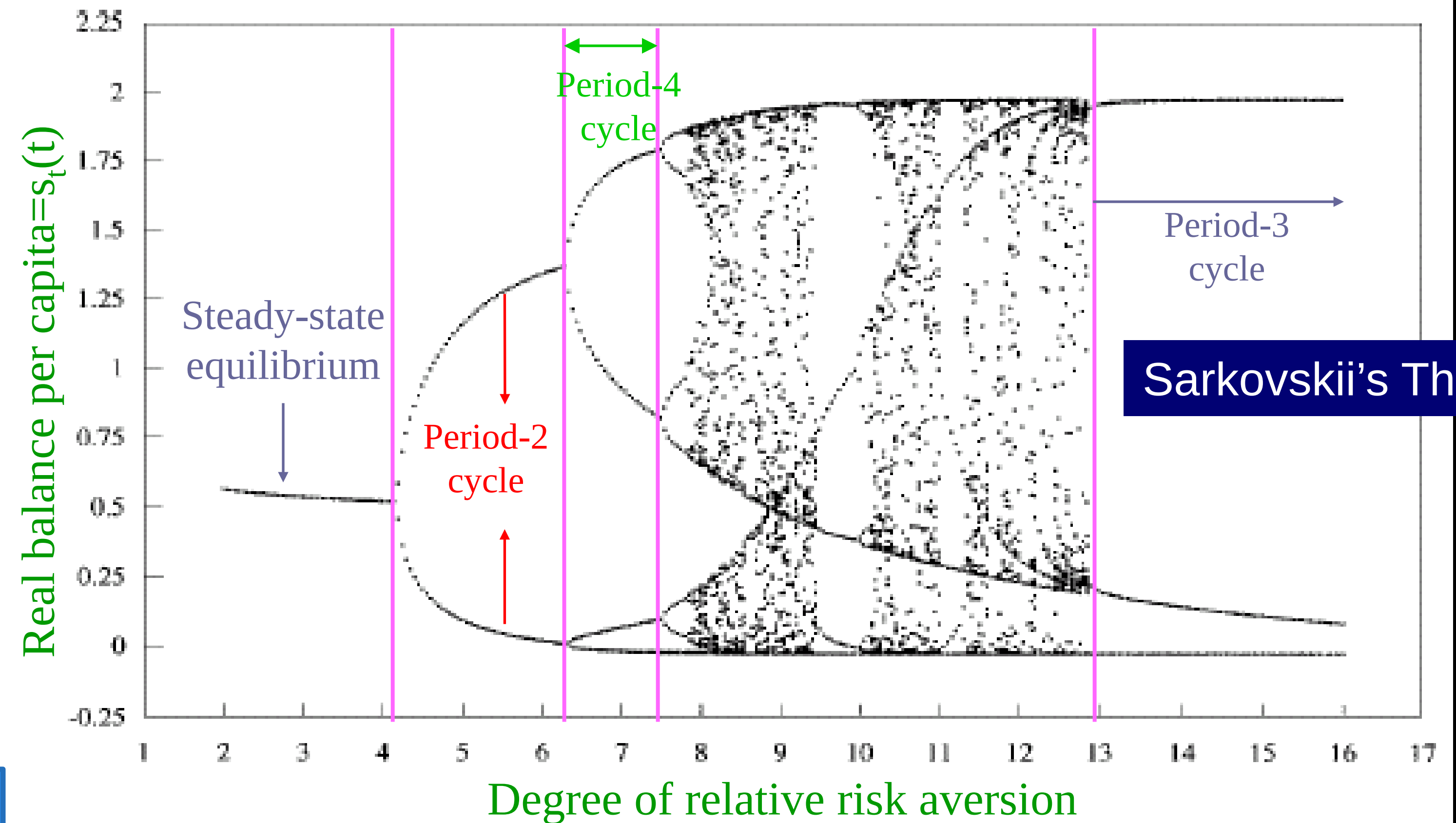


Figure1. Bifurcation diagram, backward perfect-foresight dynamic (last 50 of 1,000 iterations).

Sarkovskii's Theorem

Replicates the figure 4 of Grandmont (1985)

LtFEs and Agent-Based Macroeconomic Model

- Arifovic J (1995) Genetic algorithms and inflationary economies. Journal of Monetary Economics 36(1): 219--43.
- Bullard J, Duffy J (1998a) A model of learning and emulation with artificial adaptive agents. Journal of Economic Dynamics and Control 22: 179--207.
- Bullard J., Duffy J. (1998b) Learning and the stability of cycles. Macroeconomic Dynamics 2(1): 22--48.
- Bullard J, Duffy J (1999) Using genetic algorithms to model the evolution of heterogeneous beliefs. Computational Economics 13(1): 41—60.
- Chen S.-H, Yeh C.-H (1999) Modeling the expectations of inflation in the OLG model with genetic programming. Soft Computing 3(2): 53--62.

Inflation Bottom Up

$$\pi^e_{i,t} = f_{i,t}(\pi_{i,t-1}, \pi_{i,t-2}, \ldots)$$

$$\begin{bmatrix} \pi^e_{1,t+1} \\ \pi^e_{2,t+1} \\ \vdots \\ \pi^e_{N,t+1} \end{bmatrix} \rightarrow \begin{bmatrix} s_{1,t} \\ s_{2,t} \\ \vdots \\ s_{N,t} \end{bmatrix} \rightarrow \begin{bmatrix} P_t \\ \pi_t \end{bmatrix} \rightarrow \begin{bmatrix} \pi^e_{1,t+2} \\ \pi^e_{2,t+2} \\ \vdots \\ \pi^e_{N,t+2} \end{bmatrix} \rightarrow \begin{bmatrix} s_{1,t+1} \\ s_{2,t+1} \\ \vdots \\ s_{N,t+1} \end{bmatrix} \rightarrow \begin{bmatrix} P_{t+1} \\ \pi_{t+1} \end{bmatrix} \cdots$$

Forecasting errors as feedbacks to trigger further review and revision

Bullard and Duffy (1998), Figure 2

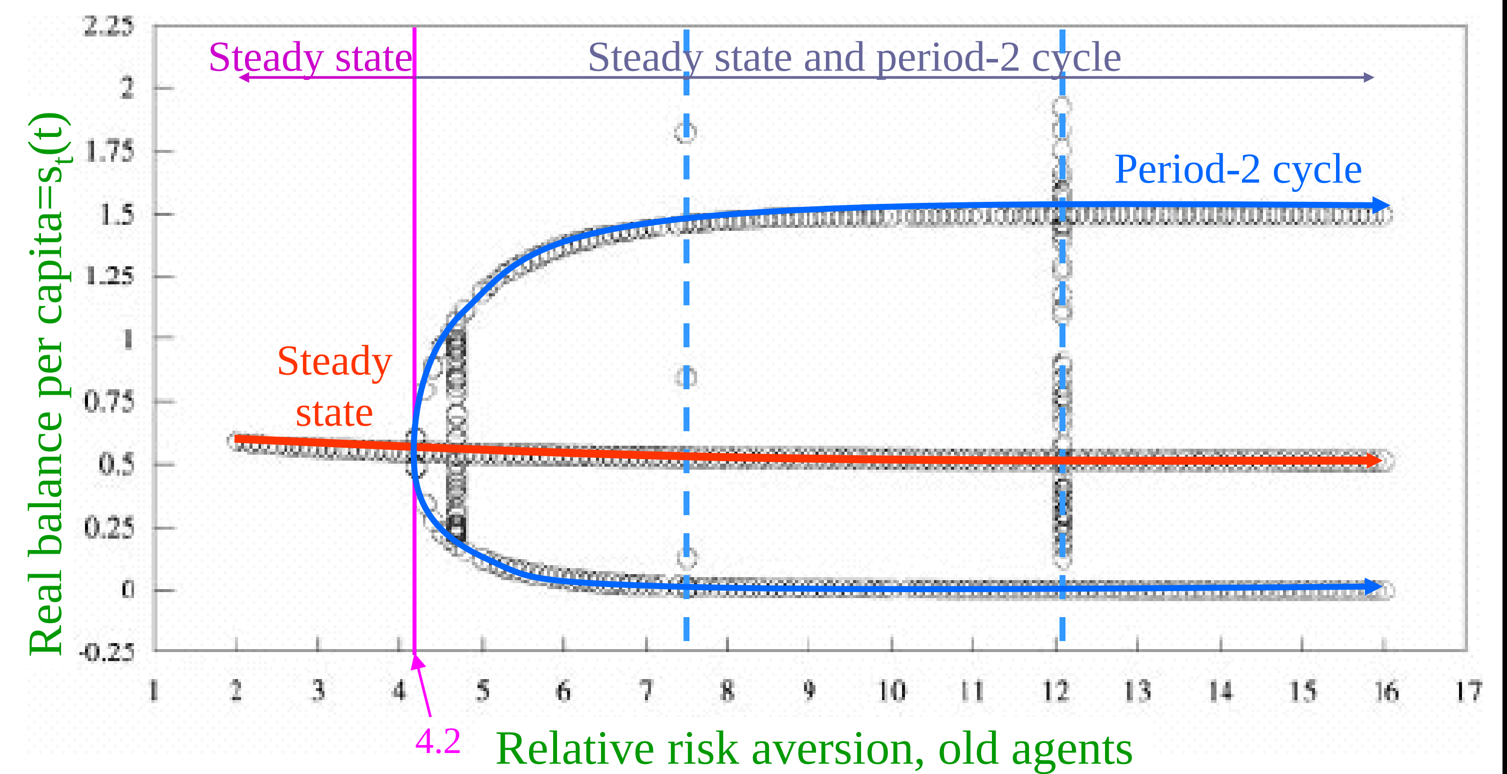
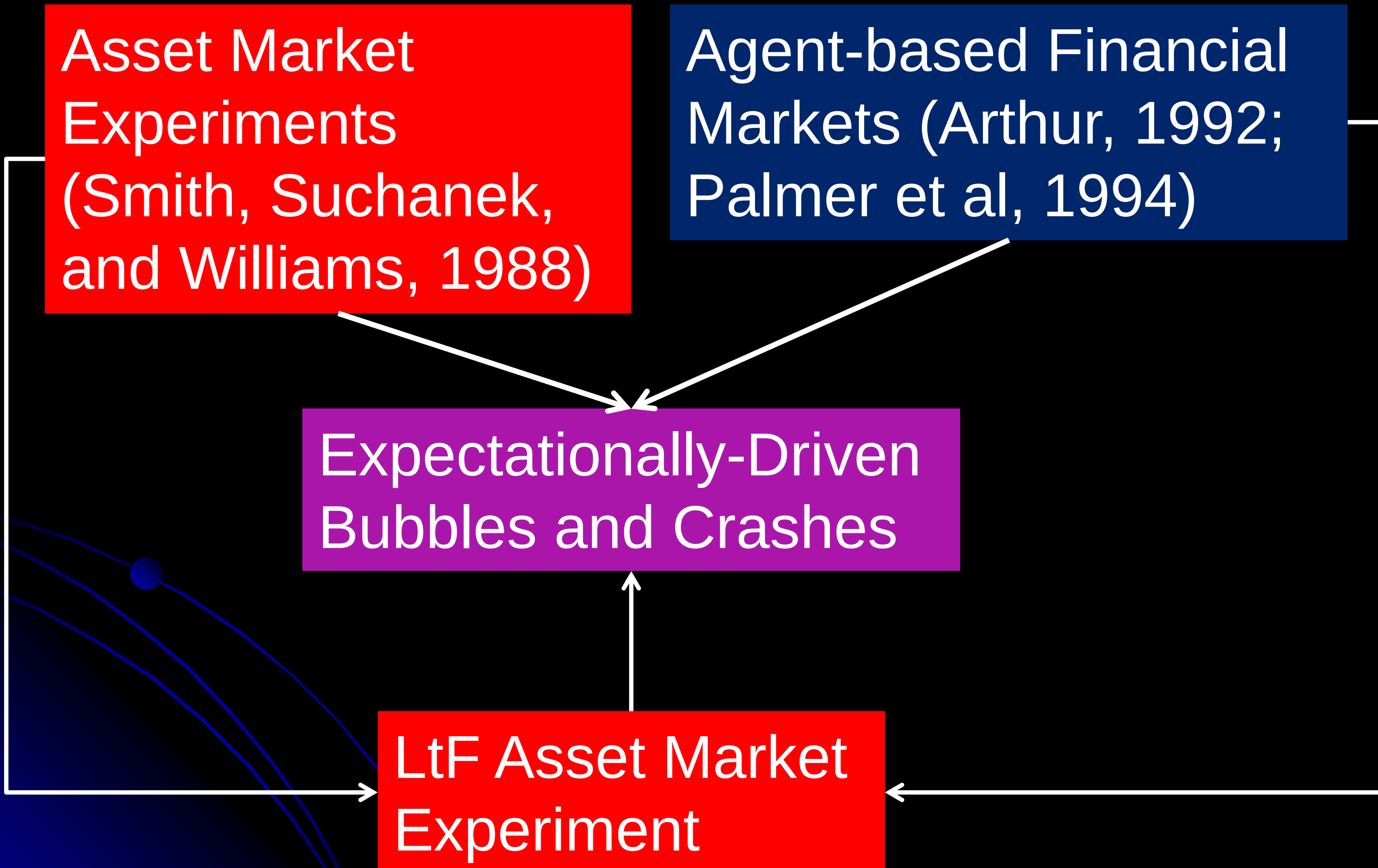
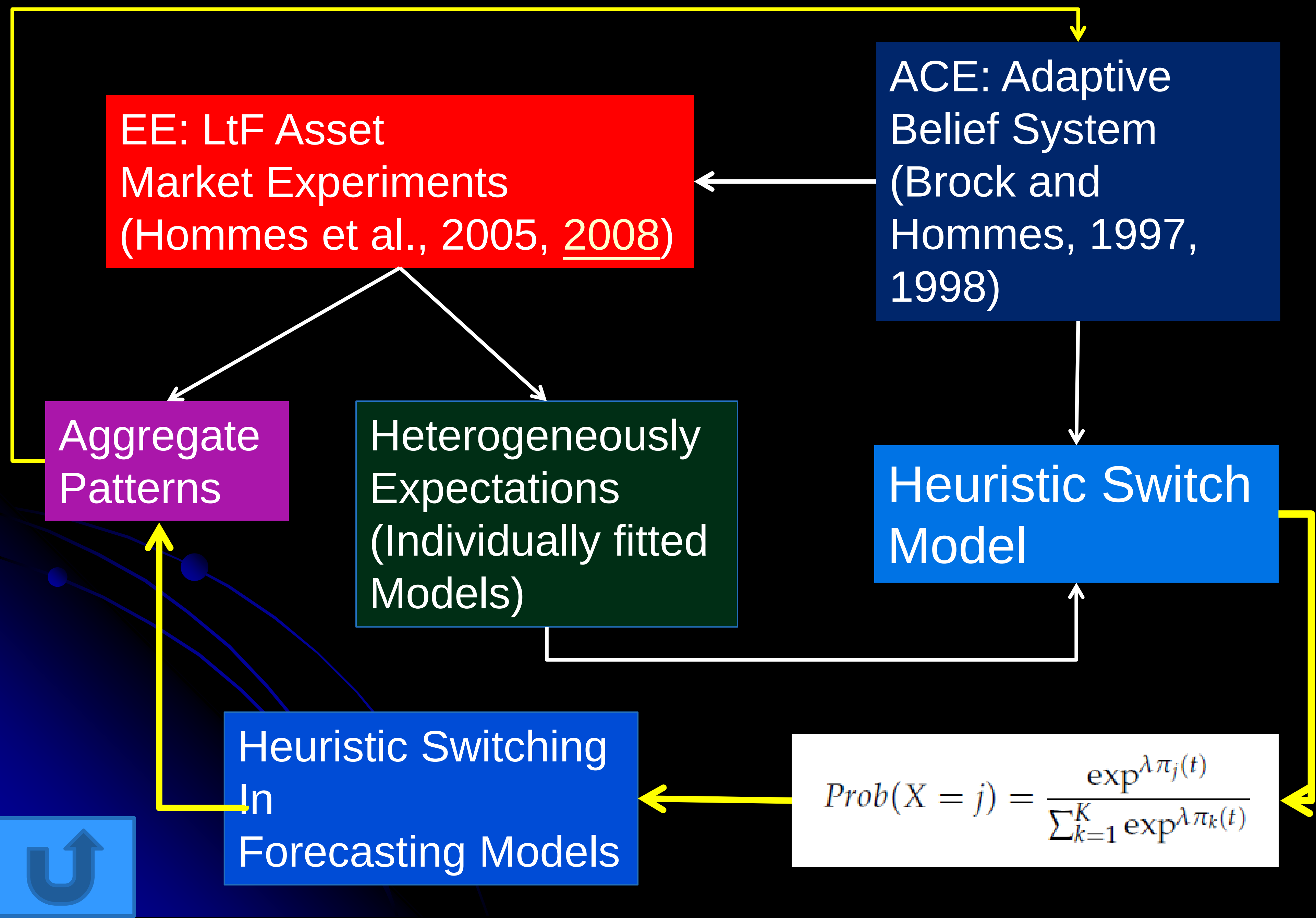


Figure2. Limiting learning dynamics: 10 replications at each old-agent relative risk aversion; convergence values or last 50 iterations of each replication plotted. ◯ Observed after convergence or 2,000 iterations.


Asset Market Experiments (Smith, Suchanek, and Williams, 1988)
Agent-based Financial Markets (Arthur, 1992; Palmer et al, 1994)
Expectationally-Driven Bubbles and Crashes
LtF Asset Market Experiment


EE: LtF Asset Market Experiments (Hommes et al., 2005, 2008)
ACE: Adaptive Belief System (Brock and Hommes, 1997, 1998)
Aggregate Patterns
Heterogeneously Expectations (Individually fitted Models)
Heuristic Switch Model
Heuristic Switching In Forecasting Models
$Prob(X=j)=\frac{\exp^{\lambda\pi_j(t)}}{\sum_{k=1}^{K}\exp^{\lambda\pi_k(t)}}$

Asset Market Experiments

- In late 1980, the laboratory approach has been extended to the study of financial markets, called the asset market experiments (Smith, Suchanek, and Williams, 1988).
  - Smith V, Suchanek G, Williams A (1988) Bubbles, crashes, and endogenous expectations in experimental spot asset markets. Econometrica 56(5): 1119-1151.

A REVIEW OF BUBBLES AND CRASHES IN EXPERIMENTAL ASSET MARKETS

Stefan Palan

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Abstract. This paper discusses the literature on bubbles and crashes in the most commonly used experimental asset market design, introduced by Smith *et al*. It documents the main findings based on the results from 41 published papers, 3 book chapters and 20 working papers.

Keywords. Experimental asset markets; Market design; Bubbles

In 1988, Vernon Smith, Gerry Suchanek and Arlington Williams published the results of experiments which would spawn a new twig on the young tree of experimental economic research. Earlier studies had used the double auction design (Smith, 1962), studied intertemporal markets (Forsythe *et al*., 1982) or investigated securities with homogeneous value to all market participants (Smith, 1965). Yet it was the pioneering work of Smith *et al*. (1988) (hereafter SSW) to combine all of the above. To their surprise, the design they expected to yield informationally efficient prices exhibited large bubbles and crashes. Since then, hundreds of SSW markets have been run, yielding valuable insights into the behavior of economic actors and the factors governing bubbles.

In this paper we collect and aggregate the results from 41 published and 20 working papers.[1] We thereby hope to give readers unfamiliar with this literature a convenient introduction and provide researchers with a reference resource. The study is structured as follows: Section 1 describes the baseline design. Section 2 discusses the results from 25 years of research under this paradigm. Section 3 concludes the paper.

- In the early 1990s, in addition to macroeconomics, another development of agent-based models to economics is the domain of financial markets.
- The literature is known as artificial stock markets.

Agent-Based Artificial Stock Markets: Origin

- Origin: Brain Arthur at Santa Fe Institute (SFI)
- Arthur, B. (1992), "On Learning and Adaptation in the Economy," 92-07-038.
- Palmer, R. G., W. B. Arthur, J. H. Holland, B. LeBaron, and P. Tayler (1994), "**Artificial Economic Life: A Simple Model of a Stockmarket**," ***Physica D***, 75, pp. 264-274.
- Tayler, P. (1995), "Modelling Artificial Stocks Markets Using Genetic Algorithms," in S. Goonatilake and P. Treleaven (eds.), *Intelligent Systems for Finance and Business*, pp.271-288.

Artificial Stock Markets: Further Development

- Arthur, W. B., J. Holland, B. LeBaron, R. Palmer and P. Tayler (1997), ``**Asset Pricing under Endogenous Expectations in an Artificial Stock Market**," in W. B. Arthur, S. Durlauf & D. Lane (eds.), ***The Economy as an Evolving Complex System II***, Addison-Wesley, pp. 15-44.
- LeBaron, B., W. B. Arthur and R. Palmer (2000), ``**Time Series Properties of an Artificial Stock Markets,**'' ***Journal of Economic Dynamics and Control***.
- LeBaron, B. (1999), ``**Building Financial Markets with Artificial Agents: Desired goals and present techniques** ,'' in G. Karakoulas (ed.), ***Computational Markets***, MIT Press.
- LeBaron, B. (1999), ``**Evolution and Time Horizons in an Agent Based Stock Market,''**

Agent-Based Modelling for Financial Markets

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ABSTRACT

1.1 Introduction

An agent-based model (ABM)[1] is a computational model which can simulate the actions and interactions of individuals and organisations, in complex and realistic ways. Even simple ABMs can exhibit complex behavioural patterns and provide valuable information about the dynamics of the real-world system which they emulate. ABMs are not limited by the numerous restrictive and empirically problematic assumptions underlying most mainstream economic models. They can create emergent properties arising from complex spatial interaction and subtle interdependencies between prices and actions, driven by learning and feedback mechanisms. They replace the theoretical assumption of mathematical optimisation by agents in equilibrium by explicit agents with bounded rationality adapting to market forces.

Many approaches have been adopted in modelling agent behaviour for financial ABMs. Agents can range from passive automatons with no cognitive function to active data-gathering decision makers with sophisticated learning capabilities. Indeed, agents

[1] From now on we use the abbreviation ABM for both agent-based model and agent-based modelling; it should be clear from the context which is intended.

Forthcoming in Chen S-H, Kaboudan M, and Du Y-R (eds), *Handbook on Computational Economics and Finance*, Oxford University Press.

- Brock W. Hommes C (1997) A rational route to randomness, Econometrica 65:1059–1095.
- Brock W. Hommes C (1998) Heterogeneous beliefs and routes to chaos in a simple asset pricing model. Journal of Economic Dynamics and Control, 22: 1235-1274.
- Hommes C (2002) Modeling the stylized facts in finance through simple nonlinear adaptive systems. Proceedings of the National Academy of Sciences of the United States of America 99:7221-28.

Adaptive Belief System
(Brock and Hommes, 1997, 1998; Hommes, 2002)

Risk Attitude: CARA

Objective Function: Myopic Expected Utility Maximization

Portfolio Optimization (Subjective Forecasts)

Expected Utility Maximization

$$Max\ E_{h,t}(U(W_{h,t+1}))$$

$$\Leftrightarrow Max\ E_{h,t}(W_{h,t+1}) - \frac{\lambda}{2} Var_{h,t}(W_{h,t+1})$$

$$F.O.C \Rightarrow$$

$$E_{h,t}(p_{t+1} + y_{t+1}) - (1+r)p_t - \lambda d_{h,t} Var_{h,t}(p_{t+1} + y_{t+1}) = 0$$

$$\Rightarrow d^*_{h,t} = \frac{E_{h,t}(p_{t+1} + y_{t+1}) - (1+r)p_t}{\lambda Var_{h,t}(p_{t+1} + y_{t+1})}$$

Optimal Portfolio and Asset Demand

$$d_{h,t}^{*} = \frac{E_{h,t}(p_{t+1} + y_{t+1}) - (1+r)p_t}{\lambda Var_{h,t}(p_{t+1} + y_{t+1})}$$

$Model:$

$(1)\ Perceived\ Return: E_{h,t}(p_{t+1} + y_{t+1})$

$(2)\ Perceived\ Risk: Var_{h,t}(p_{t+1} + y_{t+1})$

Market Equilibrium

Aggregate Demand

$$= \sum_{h=1}^{H} n_{h,t} d_{h,t}^{*} = \sum_{h=1}^{H} n_{h,t} \frac{E_{h,t}(p_{t+1} + y_{t+1}) - (1+r)p_t}{\lambda Var_{h,t}(p_{t+1} + y_{t+1})}$$

Walrasian Makret Clearing Price :

$$\sum_{h=1}^{H} n_{h,t} \frac{E_{h,t}(p_{t+1} + y_{t+1}) - (1+r)p_t}{\lambda Var_{h,t}(p_{t+1} + y_{t+1})} = Z_t$$

4-Type Design

Brock and Hommes (1998)

simple linear forecasting rules :

$$E_{h,t}(x_{t+1}) = f(x_{t-1}, \ldots, x_{t-L}) = \alpha_h x_{t-1} + \beta_h$$

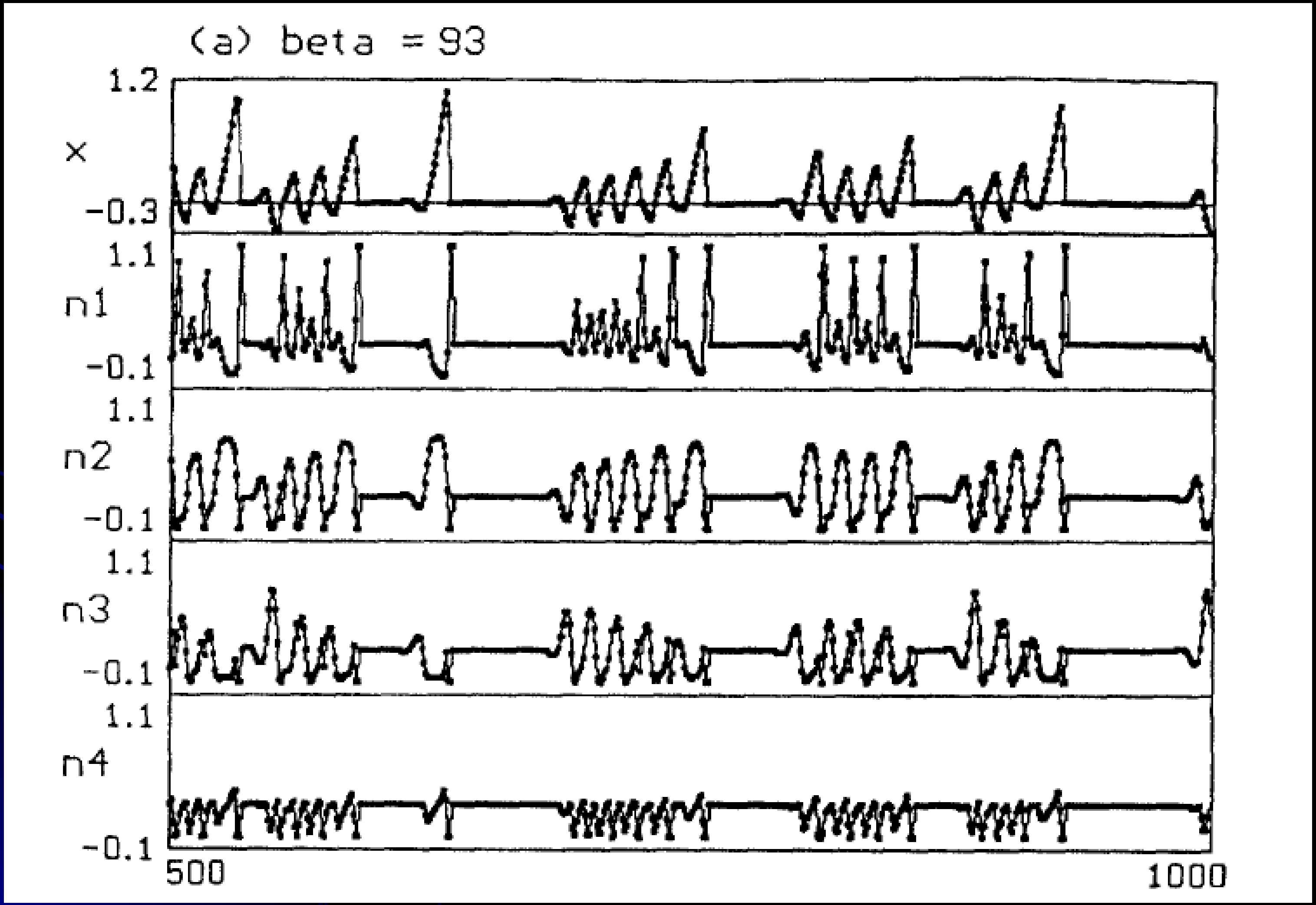
$$E_{f,t}(x_{t+1}) = 0 \ \textit{(fundamentalists)}$$

$$E_{2,t}(x_{t+1}) = 0.9 x_{t-1} + 0.2$$

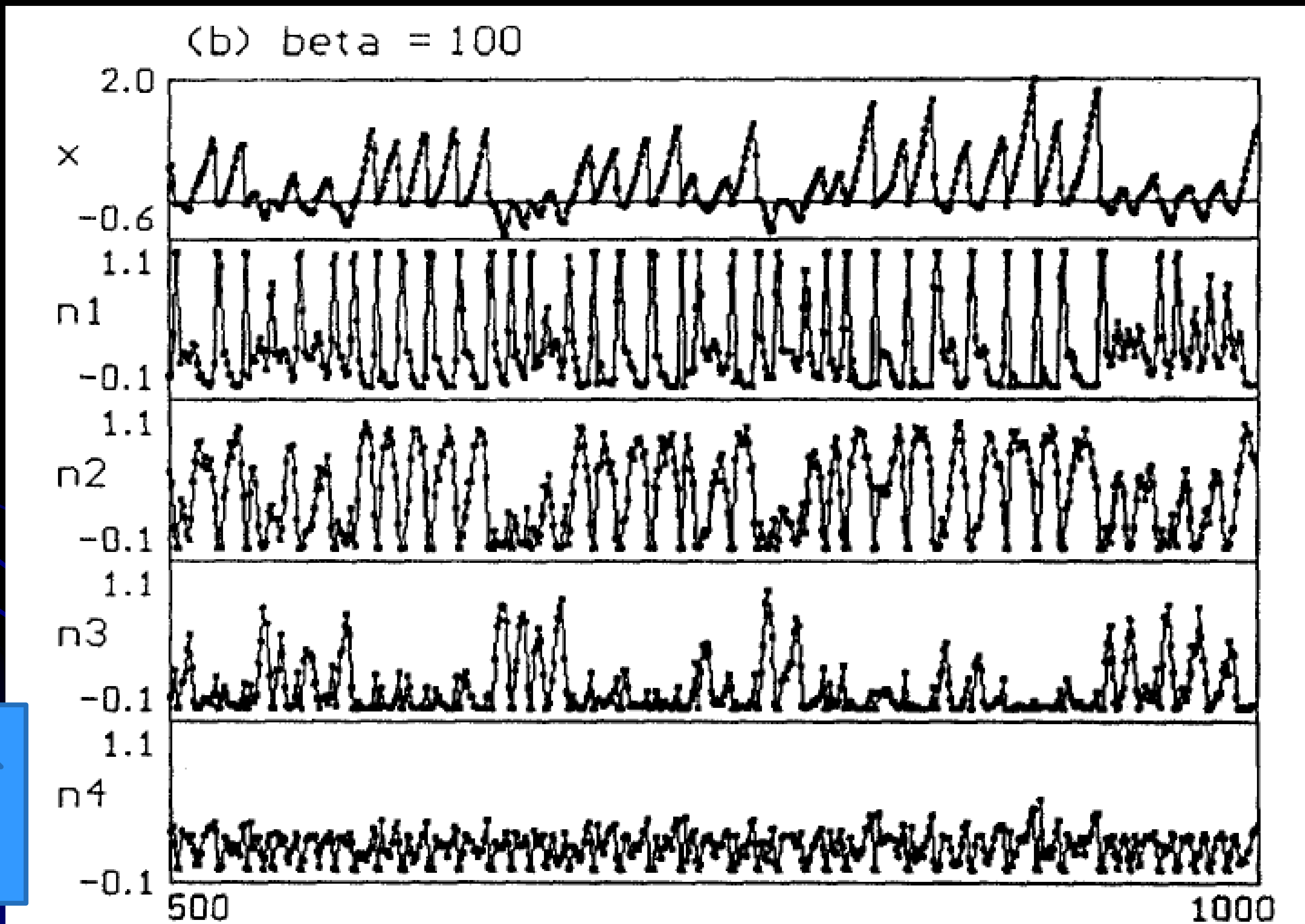
$$E_{3,t}(x_{t+1}) = 0.9 x_{t-1} - 0.2$$

$$E_{3,t}(x_{t+1}) = 1.01 x_{t-1}$$

Brock and Hommes (1998), p. 1264, Figure 11(a)



Brock and Hommes (1998), p. 1264, Figure 11(b)



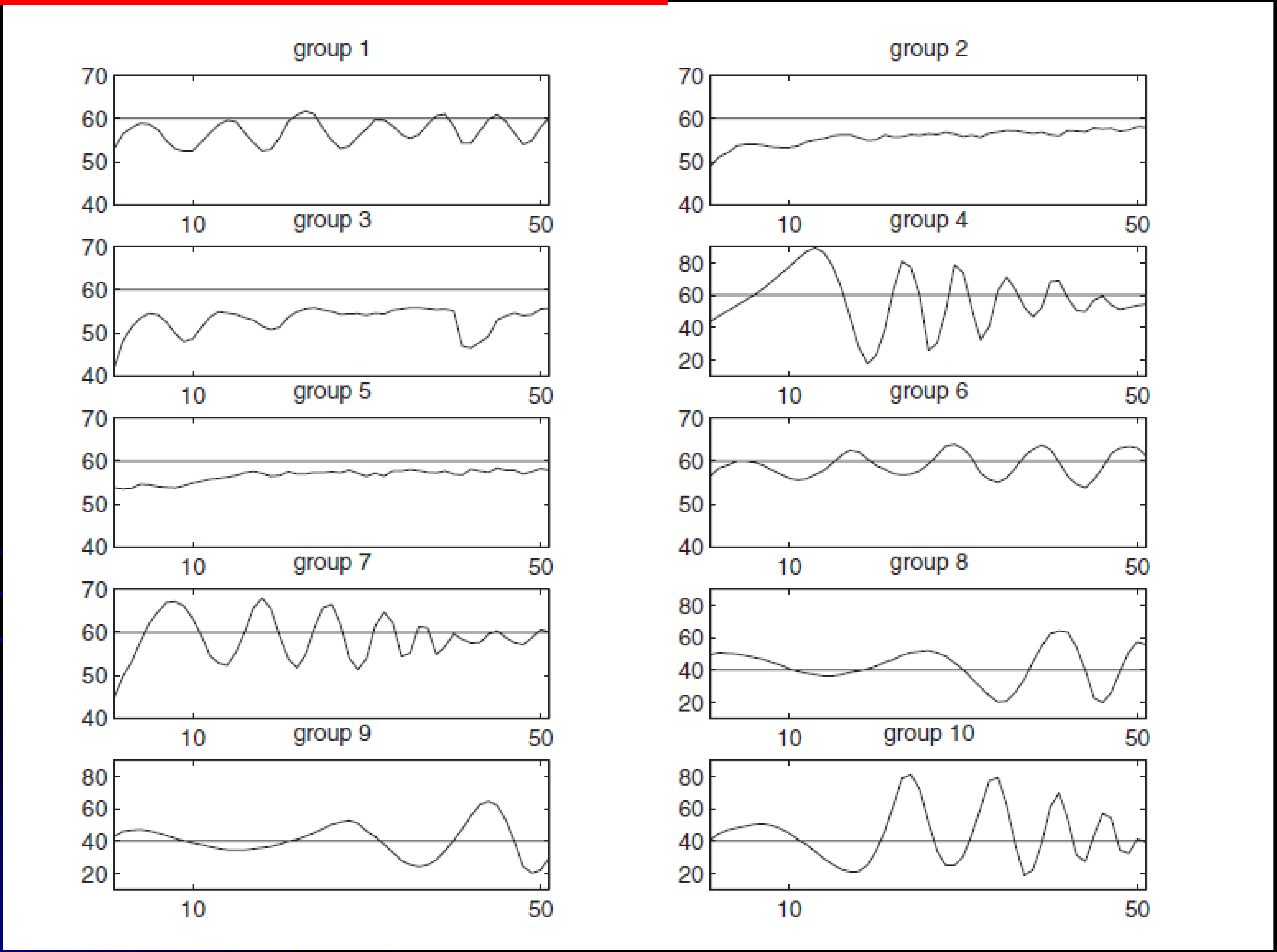
- Hommes C, Sonnemans J, Tuinstra J, van de Velden H (2005) Coordination of expectations in asset pricing experiments. Review of Financial Studies 18(3): 955-980.
- Hommes C, Sonnemans J, Tuinstra J, van de Velden H (2008) Expectations and bubbles in asset pricing experiments. Journal of Economic Behavior and Organization 67(1):116-133.

Adaptive Belief System
(Brock and Hommes, 1997, 1998; Hommes, 2002)

$$P(t) = f(\{P^e_{i,t-1}(t+1)\}_{i=1}^N)$$

$$P(t) = \frac{1}{1+r}((1-n_t)\bar{P}^e(t+1) + n_t P^f + \bar{y} + \varepsilon_t)$$

LtFES Asset Market Experiments (Hommes, et al. 2005)



LtFES Asset Market Experiments (Hommes, et al., 2008)

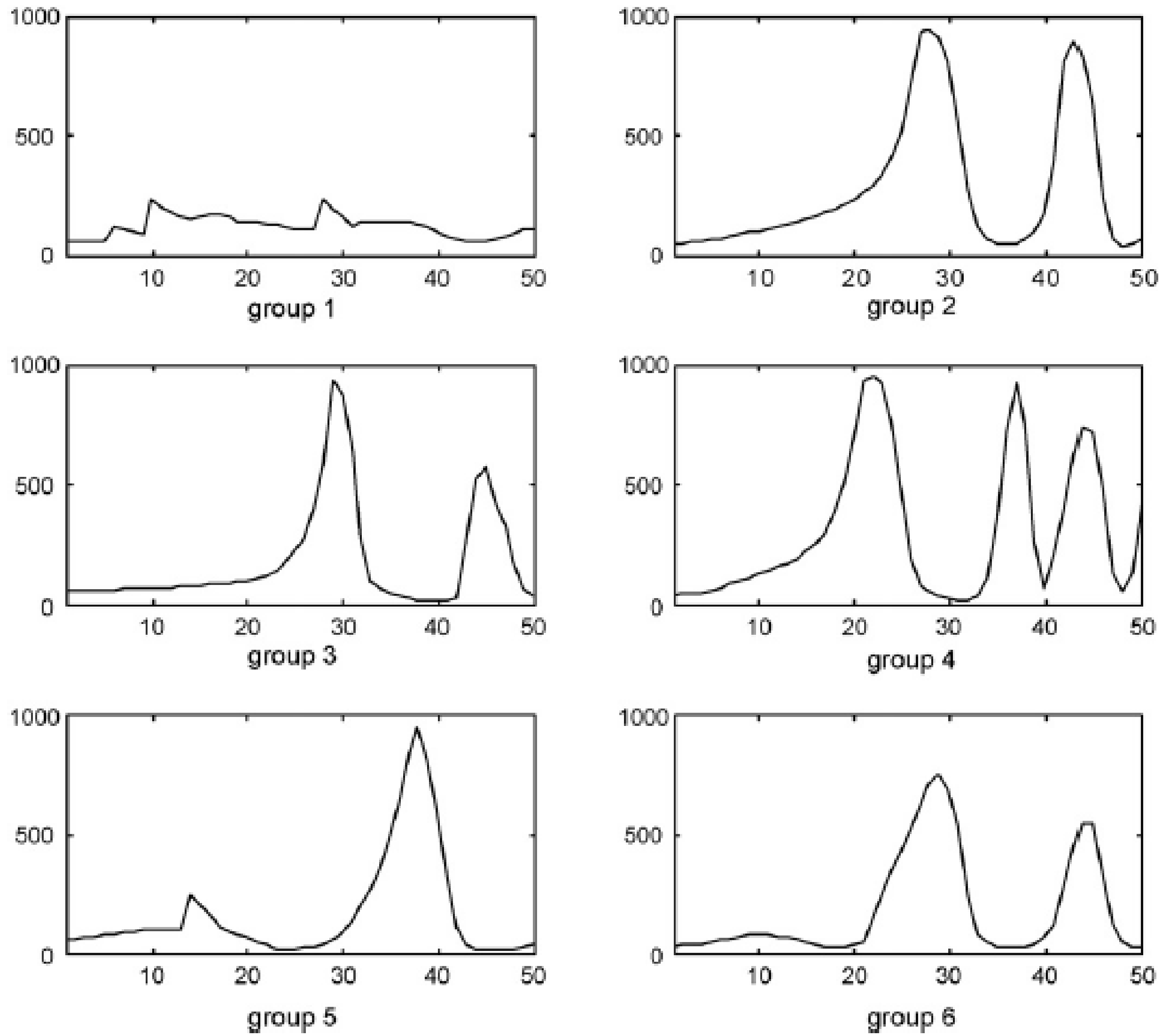


Fig. 3. Realized prices in the experiment for the different groups.

$$\boxed{P_i^e(t+1) = \alpha_i + \sum_{j=1}^{4} \beta_{i,j} P(t-i) + \sum_{j=0}^{3} \gamma_{i,j} P_i^e(t-j) + \epsilon_t}$$

$$P_i^e(t+1) = \beta_{i,1} P(t-1) + \epsilon_t$$

$$P_i^e(t+1) = \beta_{i,1} P(t-1) + \gamma_{i,0} P_i^e(t) + \epsilon_t, \ \ \beta_{i,1} + \gamma_{i,0} = 1$$

$$P_i^e(t+1) = \alpha_i + \sum_{j=1}^{4} \beta_{i,j} P(t-i) + \epsilon_t$$

Table C2
Estimation individual forecasting rules (positive feedback).

Participant	c	p_{-1}	p_{-2}	p_{-3}	p^e_{-1}	p^e_{-2}	p^e_{-3}	R^2	*AC*	*Eq.*	*MSE*
1	−0.790*	1.675	0	−0.4329	−0.2324	0	0	0.9965	No	81.44	0.622
2	−0.682*	1.340	−0.5007	0	0.4642	−0.2914	0	0.9980	No	56.36	0.708
3	−1.176*	1.724	0	−0.3995	−0.3069	0	0	0.9932	No	66.82	0.738
4	−1.121	1.893	−0.8748	0	0	0	0	0.9971	No	61.59	0.518
5	0.417*	1.443	−0.8745	0	0.4264	0	0	0.9975	No	81.76	0.529
6	−0.817*	1.787	−0.7724	0	0	0	0	0.9982	No	55.96	0.538
7	0.742*	1.184	0	−0.1698	0	0	0	0.9964	Yes	–	0.550
8	−0.179*	1.463	−0.4552	0	0	0	0	0.9938	No	22.95	0.536
9	0.657*	1.220	−0.7315	0	0.5006	0	0	0.9969	No	60.28	0.477
10	0.339*	1.285	0	0	0	−0.2887	0	0.9969	No	91.62	0.381
11	0.693*	1.368	−0.8523	0	0.4743	0	0	0.9948	No	69.30	0.472
12	0.223*	1.851	0	0	−0.3270	−0.3533	−0.1723	0.9926	No	139.4	0.521
13	0.040*	1.450	−0.4504	0	0	0	0	0.9870	No	100.0	0.545
14	0.164*	1.069	−0.4708	0	0.4000	0	0	0.9943	No	91.11	0.460
15	−0.251*	1.275	−0.2989	−0.2706	0	0.2984	0	0.9981	No	64.36	0.649
16	2.170*	1.232	0	0	0	−0.2662	0	0.9780	No	63.45	1.136
17	−0.985*	1.251	0	−0.2345	0	0	0	0.9900	No	59.70	0.452
18	−0.1026	1.219	−0.5430	0	0.4372	0	0	0.9942	No	−0.07	0.417
19	2.411	1.084	0	0	0.2635	0	−0.3910	0.9940	No	55.43	0.880
20	1.956*	−0.9115	0	0	0	0	0	0.8975	No	1.02	0.875
21	1.382	1.641	−0.9729	0	0.3084	0	0	0.9978	No	58.81	0.515
22	2.687	1.6274	−0.4900	0	0	0	−0.1816	0.9934	No	60.79	0.683
23	1.475	1.441	0	−0.4659	0	0	0	0.9948	No	59.24	0.858
24	0.062*	1.943	−0.9439	0	0	0	0	0.9953	No	68.89	0.977
25	34.27	0	0.1203	0	0.3421	0.2670	−0.3179	0.9892	Yes	–	1.578
26	173.7*	0	0	0	0	0	0	0.0000	No	173.7	0.780
27	2.601	1.000	0	−0.1972	−0.0384	0.1215	0.0682	1.0000	Yes	–	1.000
28	4.160	1.005	0	0	0	−0.1025	0	0.9981	No	42.67	0.705
29	15.71	1.004	0	0.5544	−0.2446	−0.4973	−0.1217	0.9981	Yes	–	1.385
30	13.52	1.062	−0.5319	0.3410	0.2280	−0.0978	−0.2084	0.9995	No	65.28	0.860
31	2.295*	0.8857	0	−0.4284	0.5064	0	0	0.9866	No	63.22	1.336
32	0.7813*	1.117	−0.7796	0	0.6513	0	0	0.9927	No	69.14	0.823

Table 2
Qualitative estimation results for individual prediction strategies

	AR(1) (Naive)	AR(2)	AR(3)	Adaptive	Other
Group 1	0	5	0	0	B (4,2)
Group 2	4(3)	0	0	1	B (1,2)
Group 3	2	3	0	1	—
Group 4	0	3	1	0	B (3,1), B (4,3)
Group 5	3	1	0	1	B (2,1)
Group 6	0	5	0	0	B (2,2)
Group 7	0	4	1	0	B (1,2)
Group 8	0	4	0	0	B (1,1), B (4,3)
Group 9	0	2	0	0	B (1,1), B (2,2), B (2,3), B (4,1)
Group 10	0	2	1	0	2×B (1,1), B (3,0)
Total	9	29	3	3	16

For each participant we estimated a linear forecasting rule $p^e_{h,t+1} = \alpha_h + \sum_{i=1}^{4} \beta_{hi} p_{t-i} + \sum_{j=0}^{3} \gamma_{hj} p^e_{h,t-j} + v_t$, from $t = 11$ to $t = 51$. AR(1) means that only α and β_1 are significant at the 5% level. Naive for three of the participants in group 2 refers to the fact that the null hypothesis $\beta_1 = 1$ and all other coefficients equal to 0 cannot be rejected at the 5% significance level. For AR(2) only α, β_1, and β_2 are significant and for AR(3) only α, β_1, β_2, and β_3 are significant. Adaptive refers to the fact that the null hypothesis $\beta_1 + \gamma_0 = 1$, and all other coefficients equal to 0 cannot be rejected at the 5% significance level. $B(k, l)$ refers to a prediction strategy where k is the highest significant lag of the price and l is the highest significant lag of the prediction (which does not necessarily mean that all smaller lags are also significant) in the regression.

Marimon, Spear, and Sunder (1993)

TABLE III

Estimated Forecast Equations for Individual Subjects[a] for Economy 5 (See Figs. 6 and 7 for Forecast Data)

Subject no.	$P^e_{t+1} = \alpha_0 +$	$\alpha_1 P_{t-1} +$	$\alpha_2 P^e_{t-1} +$	$\alpha_3 P^e_t$	N	R^2
	Pre-Generation-Shock		Periods (1–14)			
1		0.87 (0.37)		0.43 (0.25)	13	0.62
2		−0.38 (0.89)		1.44 (0.83)	13	0.16
3		0.05 (0.01)		0.98 (0.00)	13	1.00
4		−1.62 (1.48)		2.56 (1.46)	13	0.44
5		−5.76 (3.74)		6.77 (3.75)	13	0.96
6	No significant variables				13	
7		−0.04 (0.16)		1.02 (0.17)	13	0.96
8		−0.37 (0.55)		1.42 (0.51)	13	0.86
9		−2.41 (0.35)		3.33 (0.32)	13	0.87
10		1.14 (0.06)		−0.01 (0.01)	13	0.62
11		1.07 (0.03)		−0.03 (0.01)	13	0.92
12		0.62 (0.31)		0.47 (0.25)	13	0.68
13		0.03 (0.23)		1.04 (0.20)	13	0.69
14		−0.71 (0.26)		1.75 (0.24)	13	0.85
15		−0.13 (0.13)		1.02 (0.11)	13	0.06
	Post-Generation-Shock		Periods (37–67)			
1		0.94 (0.23)	0.24 (0.20)		31	0.60
2		0.77 (0.05)	0.23 (0.05)		31	0.93
3		1.10 (0.07)	0.09 (0.03)		31	0.42
4		0.86 (0.19)	0.22 (0.17)		31	0.57
5		1.07 (0.06)	−0.05 (0.06)		31	0.86
6			−0.08 (0.02)	0.41 (0.02)	31	0.85
7		0.92 (0.16)	0.16 (0.09)		31	0.17
8		0.97 (0.13)	−0.01 (0.12)		31	0.74
9		0.59 (0.06)	0.35 (0.08)		31	0.85
10		0.62 (0.09)	0.40 (0.08)		31	0.85
11		0.73 (0.08)	0.28 (0.08)		31	0.85
12		0.56 (0.09)	0.41 (0.09)		31	0.72
13		0.87 (0.13)	0.14 (0.11)		31	0.58
14		1.09 (0.16)	0.01 (0.15)		31	0.71
15		1.05 (0.07)	−0.05 (0.09)		31	0.85

[a] Standard errors of estimates are given in parentheses.

Four Bases (Heuristics)

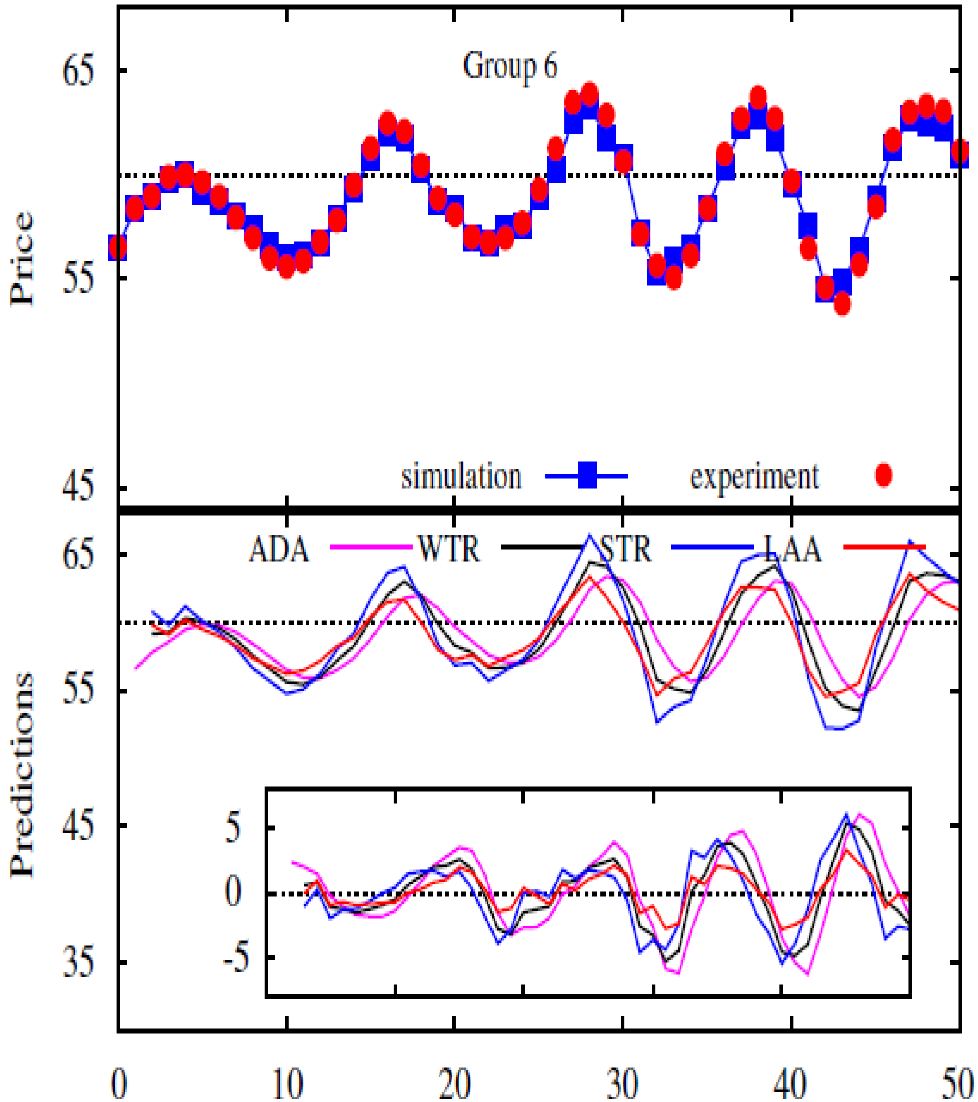
$$P^e_{ada}(t+1) = 0.65P(t-1) + 0.35P^e_{ada}(t)$$

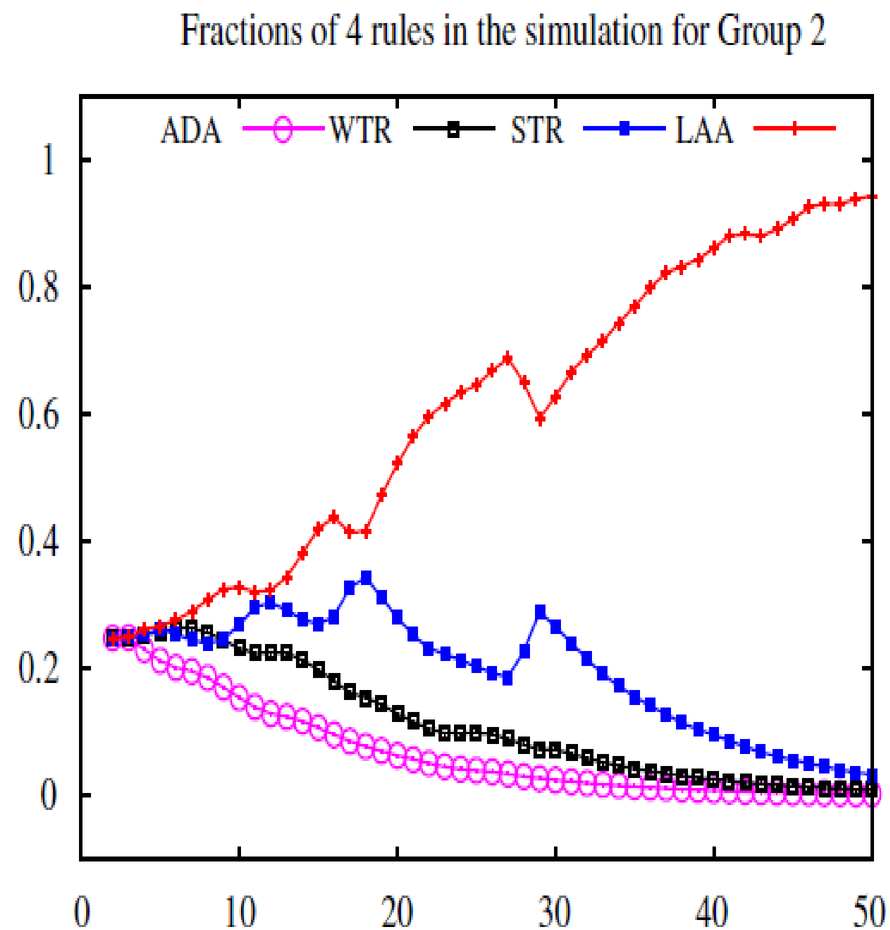
$$P^e_{WTR}(t+1) = P(t-1) + 0.4(P(t-1) - P(t-2))$$

$$P^e_{STR}(t+1) = P(t-1) + 1.3(P(t-1) - P(t-2))$$

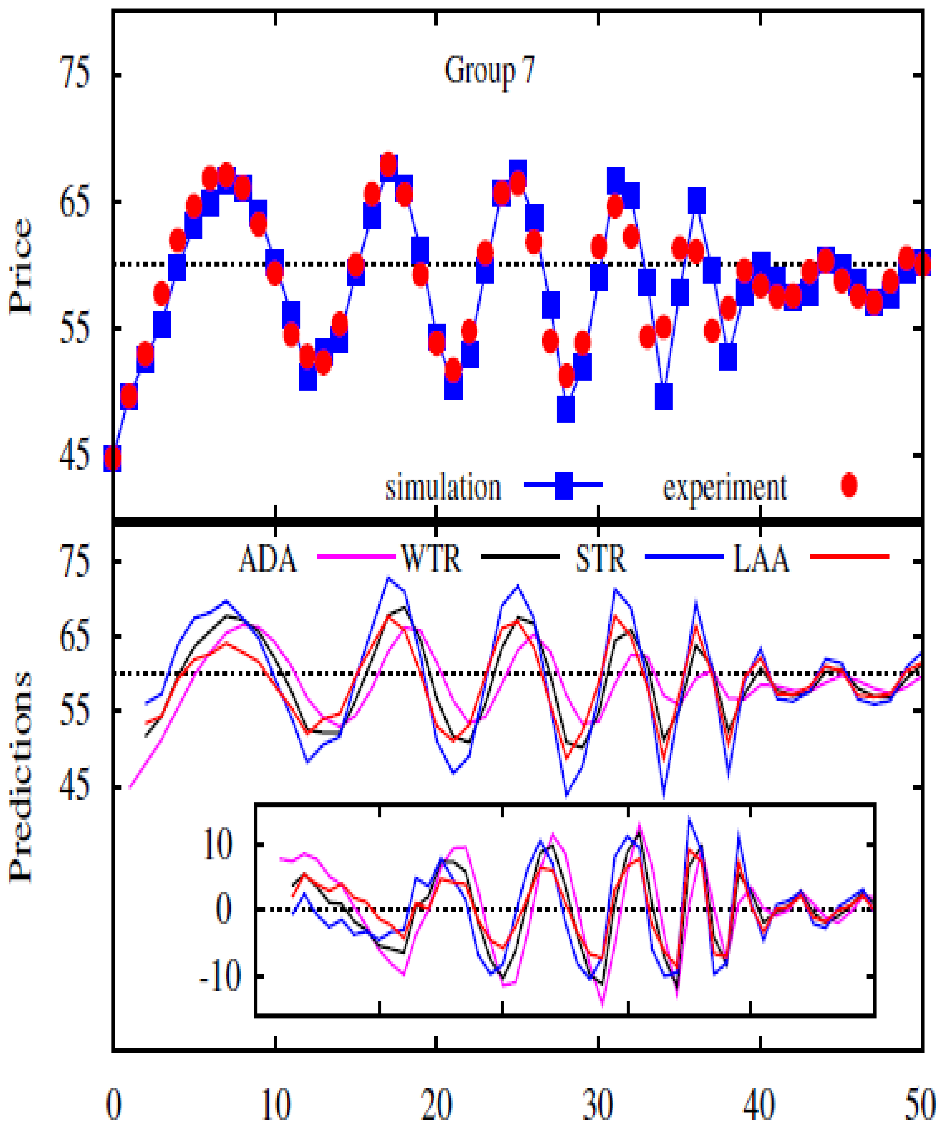
$$P^e_{LAA}(t+1) = 0.5\bar{P}(t-1) + 0.5P(t-1) + (P(t-1) - P(t-2))$$

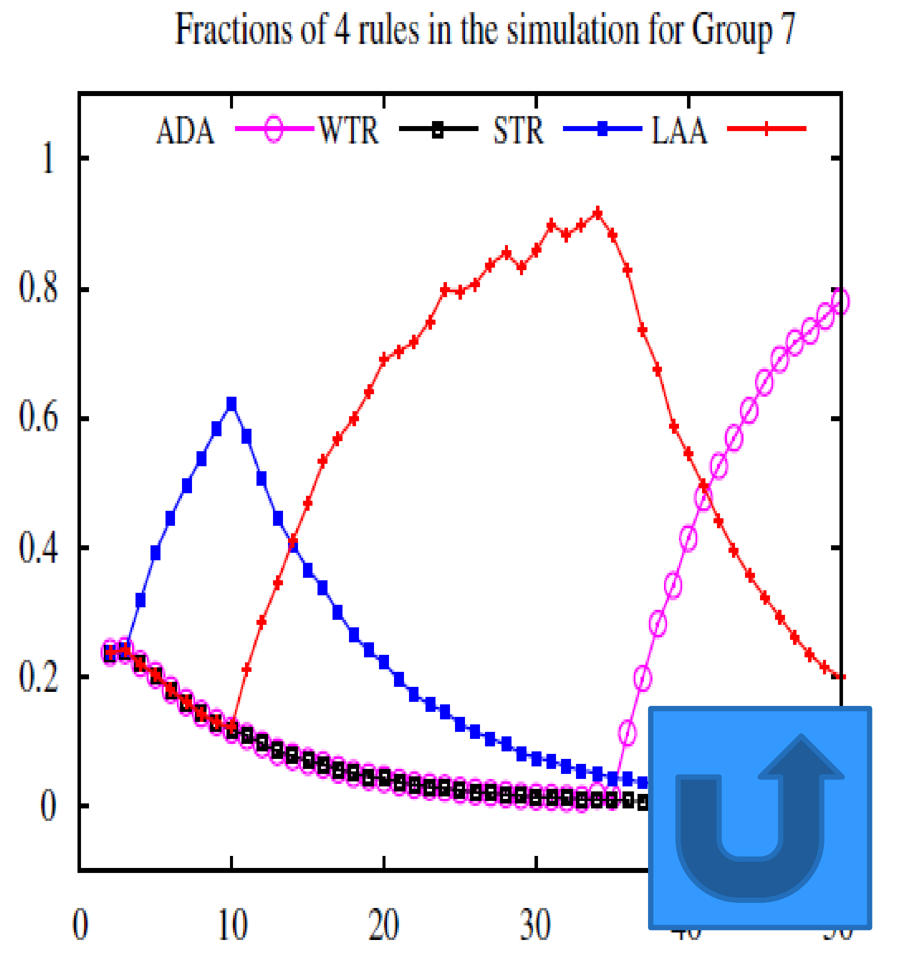
EE and ACE (Hommes, 2011)





EE and ACE (Hommes, 2011)





Hommes and Lux (2013)

- Using the GAs for individual learning, our paper makes another contribution that goes beyond the limitations of laboratory experiments. Laboratory experiments are costly, because subjects must be paid according to their performance, and typically experimental markets are small because of capacity limitations. After fitting our GA model to individual learning, we can easily investigate price behavior in alternative, more realistic market scenarios through numerical simulations. In particular, we investigate the occurrence of excess volatility when the number of subjects in the market becomes large and/or when the number of rules per individual becomes large. (Hommes and Lux (2013), p.375; Italics added.)

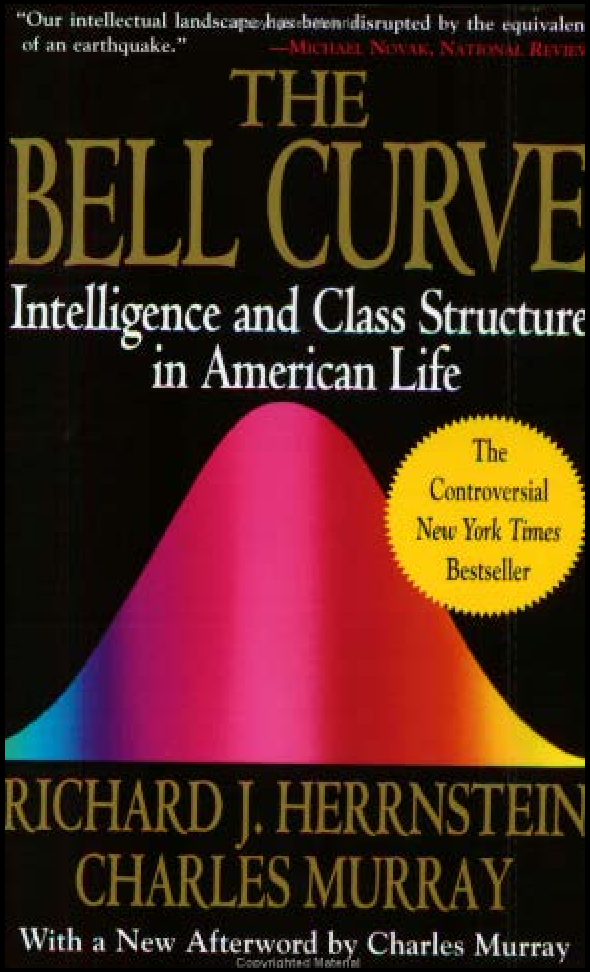
- Lager number of subjects (> > 6)
- Heterogeneous pools of heuristics

Cognitive Market Experiments

- Significance
- Backgrounds
- Cognitive Capacity in ACE: DA Markets
- Cognitive Capacity in EE: DA Markets

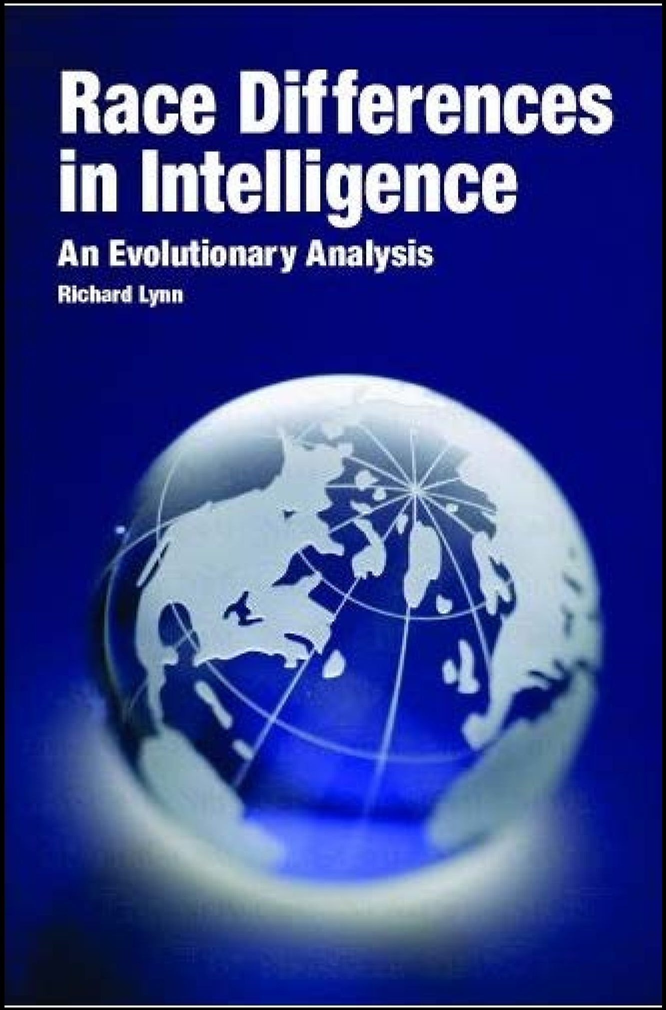
Economic Significance of Intelligence

- Some empirical studies support a positive correlation between Intelligence Quotient (IQ) and income.
- While the correlation coefficient is often found to be less than 0.5, it may increase with age to some extent (Herrnstein and Murray, 1996; Jensen, 1998).



Economic Significance of Intelligence

- Lynn and Vanhanen (2002, 2006) and Lynn (2006) further provided rich resources on the comparative studies of IQ among different countries and races, and indicated that IQ's significance can even come to the social or country level.
- Other similar findings regarding the effect of intelligence on growth (Weede and Kampf, 2002; Jones and Schneider, 2006; Ram, 2007)
- Human capital is approximated by national IQ.



Cognitive Capacity and Income

- **Individual ability and income**:
  Ammon (1895), Moore (1911), Staehle (1943)

- **Cognitive ability and wages**:
  Murnane, Willett, & Levy (1995),
  Cawley, Conneely, Heckman, & Vytlacil (1997),
  Cawley, Heckman, & Vytlacil (2001),
  Zax & Rees (2002), Gould (2005),
  Heckman, Stixrud, & Urzua (2006)

Cognitive Capacity and Financial Portolios

- **Cognitive ability and financial portfolios**: Christelis, Jappelli, & Padula (2010), Grinblatt, Keloharju, & Linnainmaa (2011)

Cognitive Capacity in Experimental Economics

- **Cooperation and Coordination**:
  Segal & Hershberger (1999), Devetag & Warglien (2003), Jones (2008), Burks, Carpenter, Göette, & Rustichini (2009)

- **Representation and Depth of Reasoning**:
  Devetag and Warglien (2008)

- **Winner's Curse**:
  Casari, Ham and Kagel (2007).

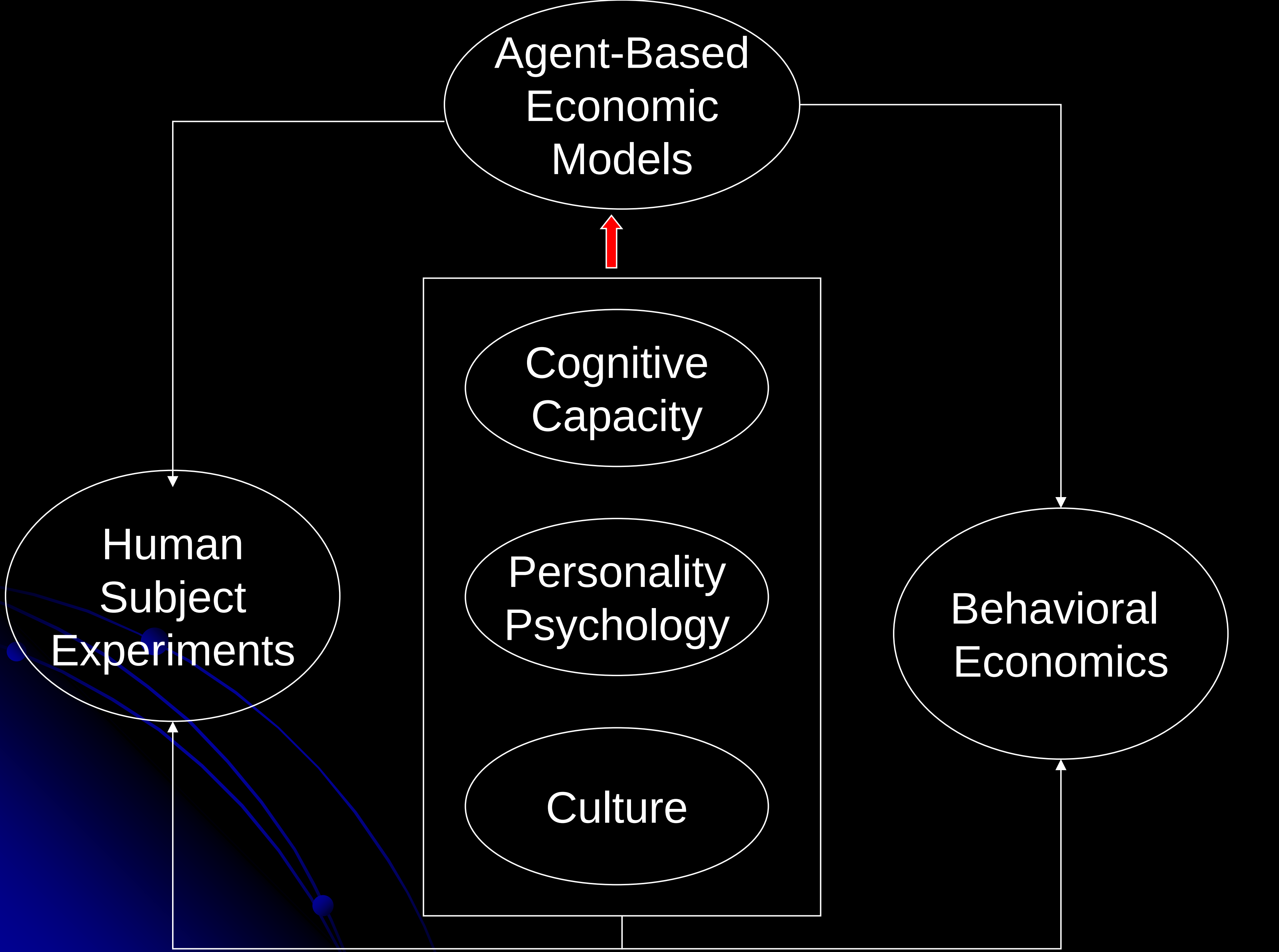
Question

- We know intellectual quality plays an important role in various aspects of people's economic life.

- We do not have much knowledge about the influence of intellectual quality on human traders' market performance.

Cognitive Capacity in Experimental Economics

- Segal and Hershberger(1999): prisoners’ dilemma game
- Devetag and Warglien (2003): dominance-solvable game
- Ohtsubo and Rapoport (2006): beauty contest game
- Casari, Ham and Kagel (2007): common-value auction
- Cornelissen, Dewitte and Warlop (2007): dictator game
- Cappelletti, Guth and Ploner (2008): ultimatum game
- Devetag and Warglien (2008)
- Jones (2008): prisoners’ dilemma game
- Burks, Carpenter, Goette, and Rustichini (2009)


Agent-Based Economic Models
Human Subject Experiments
Cognitive Capacity
Personality Psychology
Culture
Behavioral Economics

Research Frontier

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Software-Agent Designs in Economics: An Interdisciplinary Framework

Introduction and Background

One of the most fascinating and promising research areas in economics is the recent integration of the following three fields of economics: *experimental economics, computational economics* and *neuroeconomics* (Figure 1). Due to their methodologically interdisciplinary nature, the development of each of the three should interest computer scientists and engineering people [1]. The relationship among experimental economics, agent-based computational economics and neuroeconomics is, in essence, a relationship between *human agents* and *software agents*. Software agents can be regarded as the effective abstraction or model of human agents which we learn from experimental economics or neural economics.

Experimental Economics and Agent-Based Computational Economics

Experiments with Human Subjects

Among the three, experimental economics is the oldest one and has a sixty-year history. The first paper was published in 1948 by Edward Chamberlin [2], and his student Vernon Smith, a Nobel Laureate in 2002, continued the laboratory studies with human subjects in the 1960s. The advantage of experimental economics is that it allows us to observe human behavior in a highly controlled environment so that we can give the economic theory a sharper test, i.e., a test based on less-polluted or less noisy data.

However, the disadvantage is that using human agents can be quite costly, considering the pecuniary incentive paid to the human agents and the physical space required to accommodate their bodies. Therefore, *scaling-up* becomes a severe constraint to experimental economics, and it is hard to conduct experiments with a large number of agents for many iterations. In other words, size is not really a control variable in experiments. Hence, one may question to what extent the results obtained from small experiments can be extended or generalized.

Simulations with Software Agents

Given the constraint above, it is preferable if the experiments with human subjects can be replaced by simulations with *software agents*, which is the essence of *agent-based computational economics* (ACE). The idea of agent-based modeling in economics also has a long history. Thomas Schelling, a Nobel Laureate in 2005, is well known for his work on the segregation model (or spatial proximity model), which appeared in the late 1960s [3], [4]. However, the term "agent-based computational economics" (ACE) did not exist in economics until Leigh

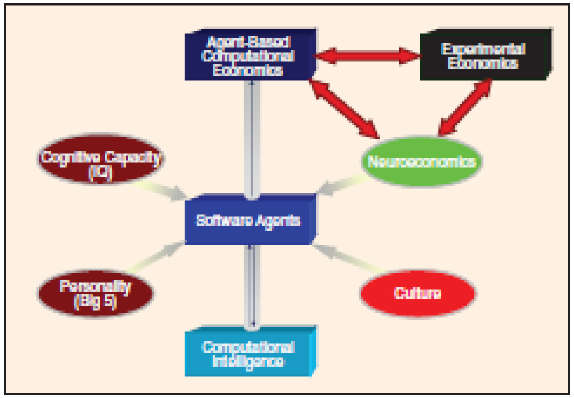

FIGURE 1 Economic software agents in an interdisciplinary framework.

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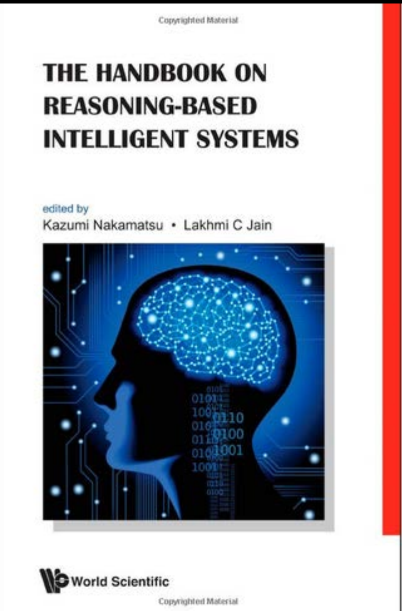

Chapter 21

REASONING-BASED ARTIFICIAL AGENTS IN AGENT-BASED COMPUTATIONAL ECONOMICS

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In this chapter, we compare the development of the artificial agents in two popular kinds of agent-based computational economic models. One is the agent-based models guided by game experiments. The other is the agent-based financial markets. While the conversation between these two classes of agent-based models is rare, the two can be connected through the idea of the generalized reinforcement learning. This is because that the artificial agents in game experiments have been well developed into a hierarchical framework such that the cognitive capacity can be incrementally added to the artificial agents from a low-level one, such as zero-intelligence agents, to a high-level one, such as belief learning agents or level-k reasoning agents. However, this hierarchy has not been found in agent-based financial markets. Therefore, bridging the two classes of agent-based models through artificial agents can help build financial agents with different level of cognitive capacity. This step is crucial for the cognitive foundation of agent-based financial markets and is related to the recent piling-up empirical studies of cognitive finance.

Game Experiments

Agent-Based Financial Markets

Zero-Intelligence Agents

Reinforcement Learning Agents

Belief Learning Agents

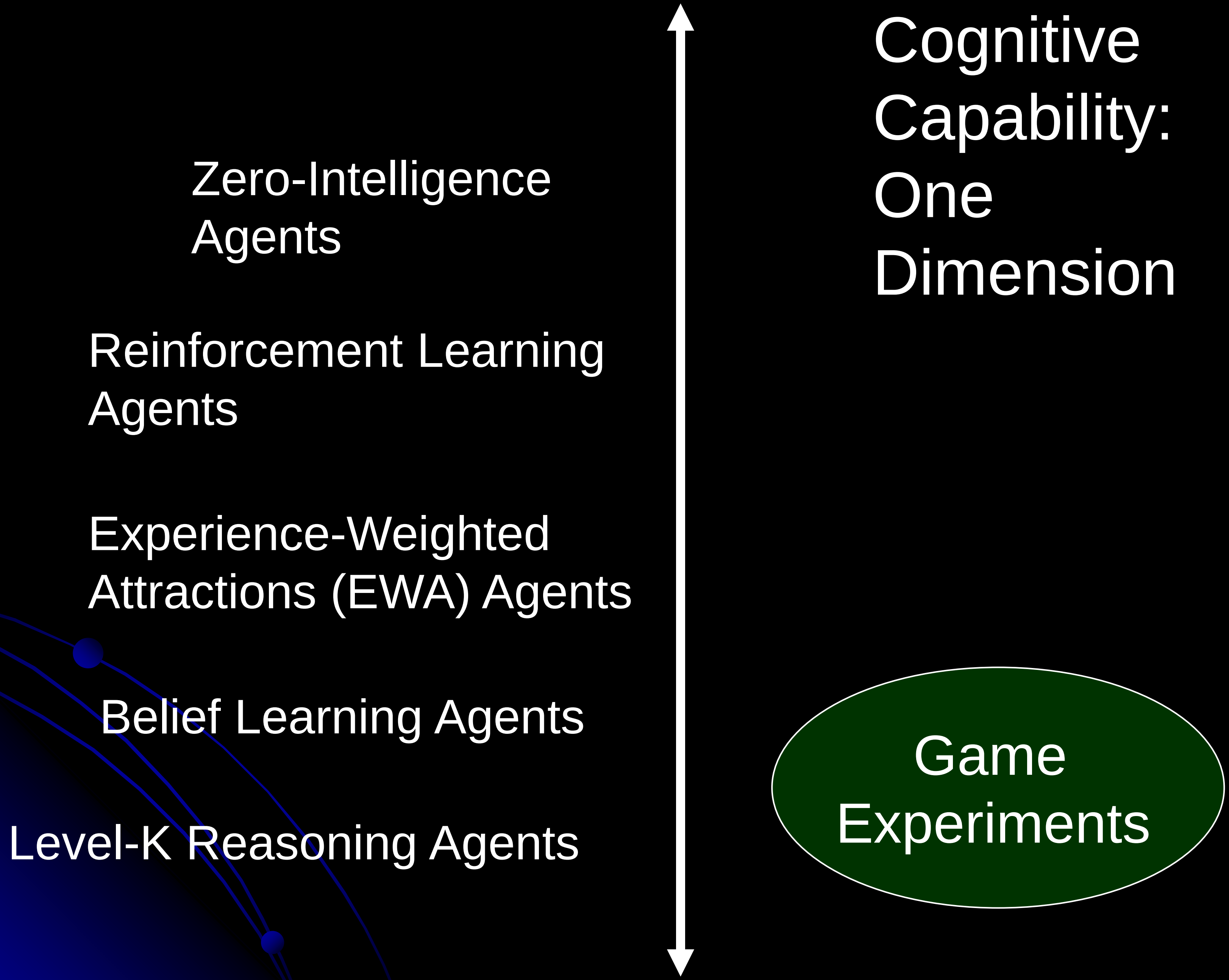
Experience-Weighted Attraction (EWA) Agents

Sophisticated (EWA) Agents

Regime-Switching Agents

Level-K Reasoning

Novelty-Discovering Agents


Zero-Intelligence Agents
Reinforcement Learning Agents
Experience-Weighted Attractions (EWA) Agents
Belief Learning Agents
Level-K Reasoning Agents
Cognitive Capability: One Dimension
Game Experiments

Artificial Agents with Incremental Cognitive Capability

Table 21.1. Artificial Agents with Incremental Cognitive Capacity.

Models	Memory	Consciousness	Reasoning
Zero-Intelligence	None	None	None
Reinforcement Learning	Short to Long	None	None
Belief Learning	Short to Long	Strong	Weak
EWA Learning	Short to Long	Weak to Strong	Weak
Sophisticated EWA	Short to Long	Weak to Strong	Weak to Strong
Regime Switching	Short to Long	Weak	None
Novelties-Discovering Agents (Autonomous Agents)	Short to Long	Weak to Strong	Weak to Strong

Does Cognitive Capacity Matter When Learning Using Genetic Programming in Double Auction Markets?

Shu-Heng Chen[1], Chung-Ching Tai[2], and Shu G. Wang[1]

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Abstract. The relationship between human subjects' cognitive capacity and their economic performances has been noticed in recent years due to the evidence found in a series of cognitive economic experiments. However, there are few agent-based models aiming to characterize such relationship. This paper attempts to bridge this gap and serve as an agent-based model with a focus on agents' cognitive capacity. To capture the heterogeneity of human cognitive capacity, this paper employs genetic programming as the algorithm of the learning agents, and then uses population size as a proxy parameter of individual cognitive capacity. By modeling agents in this way, we demonstrate a nearly positive relationship between cognitive abilities and economic performance.

1 Introduction

Information and cognitive capacity are the two sources of bounded rationality of human decision makers. While economists, either theorists or experimentalists, have mainly emphasized the importance of information, the significance of cognitive capacity has been lost but started to regain its position in economic experiments in recent years. We term experimental studies which discuss the implications of the heterogeneous cognitive capacity of human decision makers as ***cognitive economic experiments*** to highlight their emphasis on *human decision makers'* cognitive capability.

Some of the earliest experimental ideas concerning cognitive capacity came from Herbert Simon, who was the initiator of bounded rationality and was awarded the Nobel Memorial Prize in Economics. In problems such as the "concept formation" experiment and the arithmetic problem, Simon pointed out that the problem was strenuous or even difficult to solve, not because human subjects did not know how to solve the problem, but mainly because such tasks could easily overload human subjects' "working memory capacity" and influence their performance when decision supports such as paper and pencil were lacking [1].

More concrete evidence comes from the economic laboratories. Devetag and Warglien (2003) found a significant and positive correlation between subjects'

G. Di Tosto and H. Van Dyke Parunak (Eds.): MABS 2009, LNAI 5683, pp. 37–48, 2010.

The Agent-Based Double Auction Markets: 15 Years On

Shu-Heng Chen and Chung-Ching Tai

Abstract Novelties discovering as a source of constant change is the essence of economics. However, most economic models do not have the kind of novelties-discovering agents required for constant changes. This silence was broken by Andrews and Prager 15 years ago when they placed GP (genetic programming)-driven agents in the double auction market. The work was, however, neither economically well interpreted nor complete; hence the silence remains in economics. In this article, we revisit their model and systematically conduct a series of simulations to better document the results. Our simulations show that human-written programs, including some reputable ones, are eventually outperformed by GP. The significance of this finding is not that GP is alchemy. Instead, it shows that novelties-discovering agents can be introduced into economic models, and their appearance inevitably presents threats to other agents who then have to react accordingly. Hence, a potentially indefinite cycle of change is triggered.

Keywords Novelties discovering • Economic changes • Double auctions • Genetic programming • Autonomous agents

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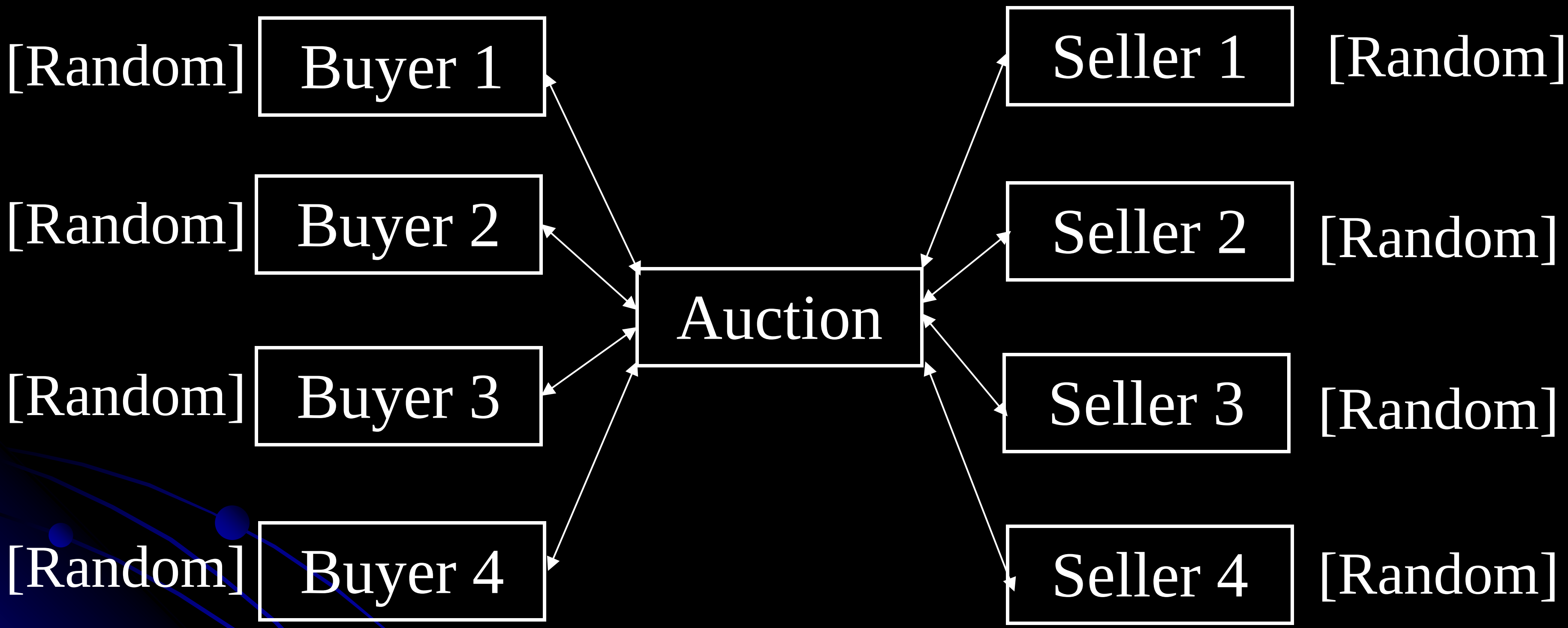
Population Size and WMC

- The idea of using population size as a proxy variable for working memory is first proposed in Casari (2004), who literally treated the population size used in the genetic algorithm equivalent to the number of chunks that human can process at a time.
- Genetic programming is a population-based algorithm, which can implement parallel processing. Hence, on the one hand, the size of the population will directly determine the capability of parallel processing.
- On the other hand, the human's working memory capacity is frequently tested based on the number of the cognitive tasks which humans can simultaneously process (Cappelletti, Guth and Ploner, 2008)
- Dual tasks have been used in hundreds of psychological experiments to measure the attentional demands of different mental activities (Pashler, 1998).
- Hence, the population size seems to be an appropriate choice with regard to mimicking the working memory capacity of human agents.

Experiment Setups

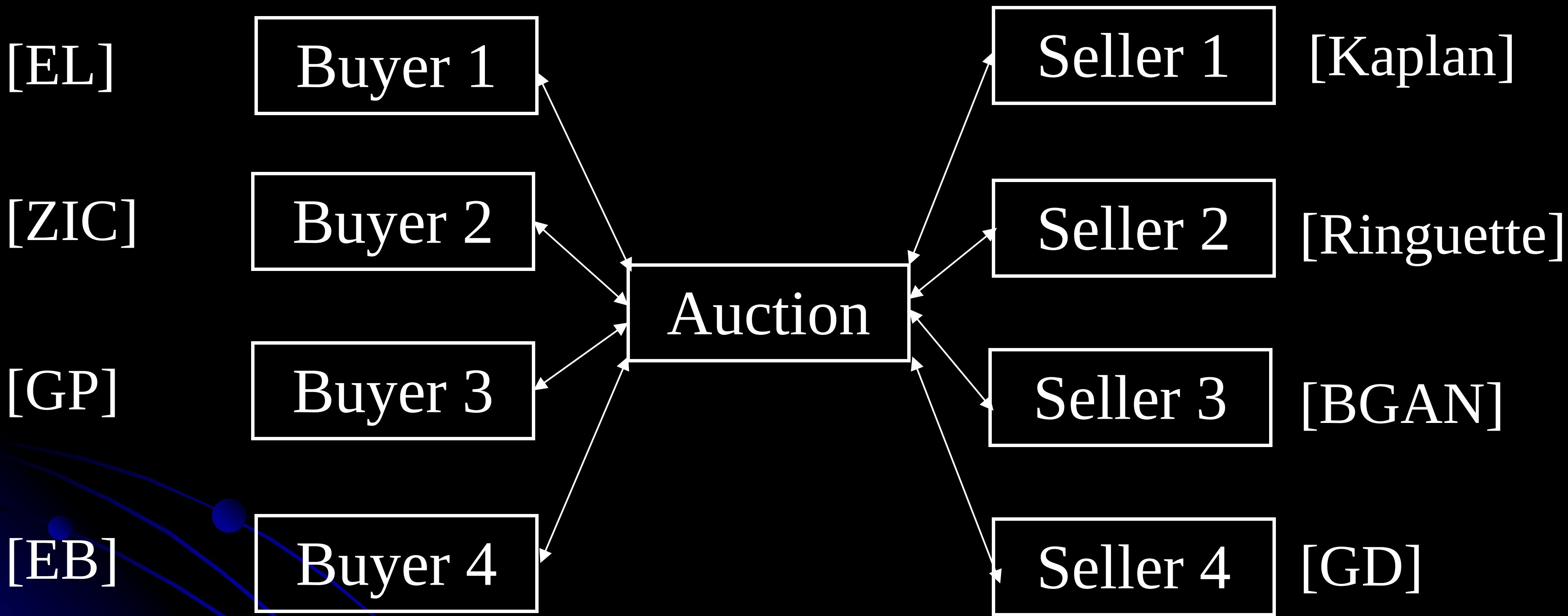
- 300 Runs for each Pop
  - Each run starts with a renew sample of the eight software traders and with a renew demand and supply schedule
- Each Run last for 7,000 trading days
- Each trading day consists of 25 steps
- Each generation of a GP cycle is composed of (2 times Pop) trading days.

Market Architecture



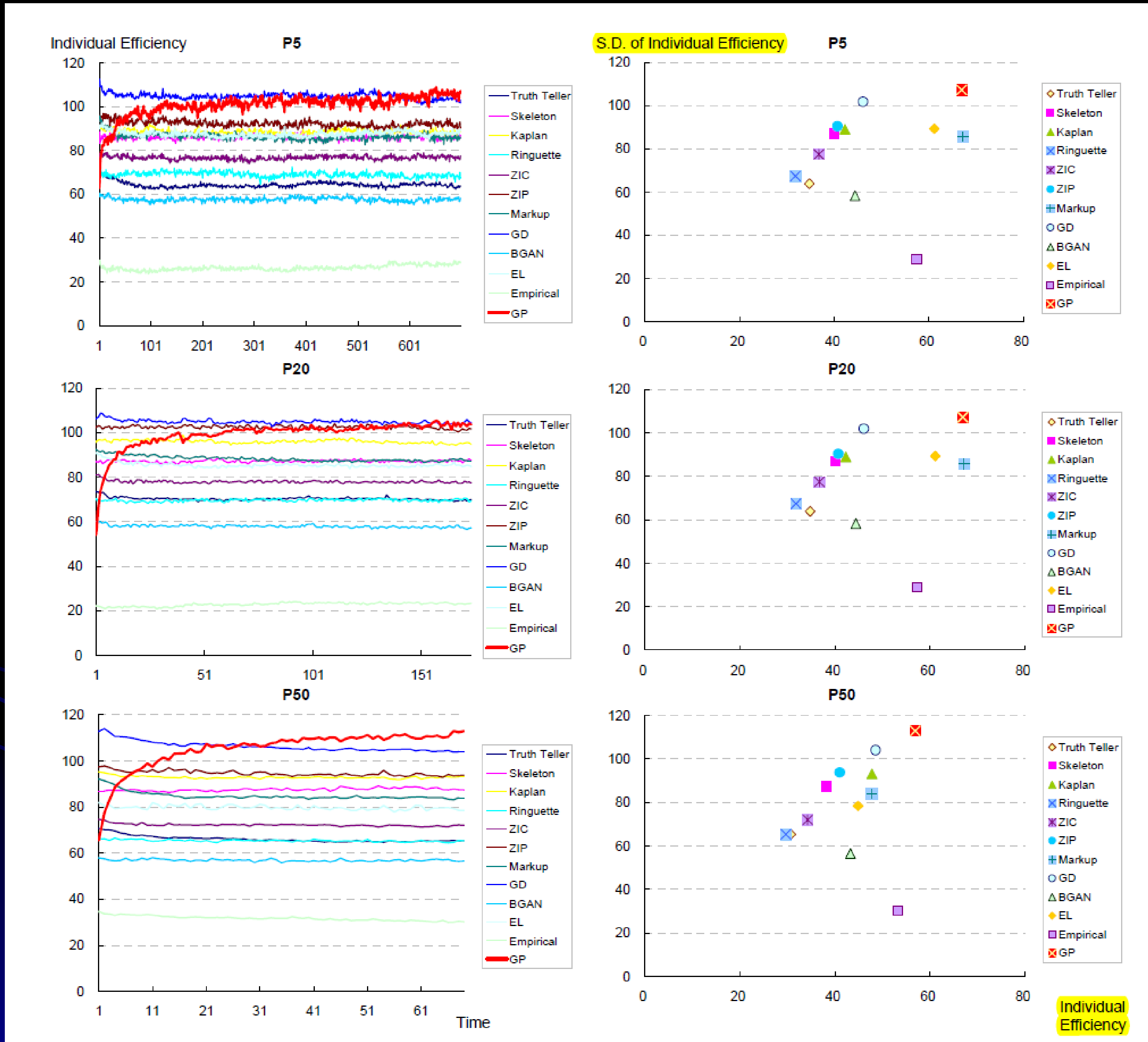
Traders = Sampling without Replacement(10, 7){Kaplan, Ringuette, Skeleton, ZIC, ZIP, Markup, Gjerstad-Dickhaut (GD), BGAN, Easley-Ledyard, Empirical Bayesian} + GP

Market Architecture: One Realization, One Run



Result I

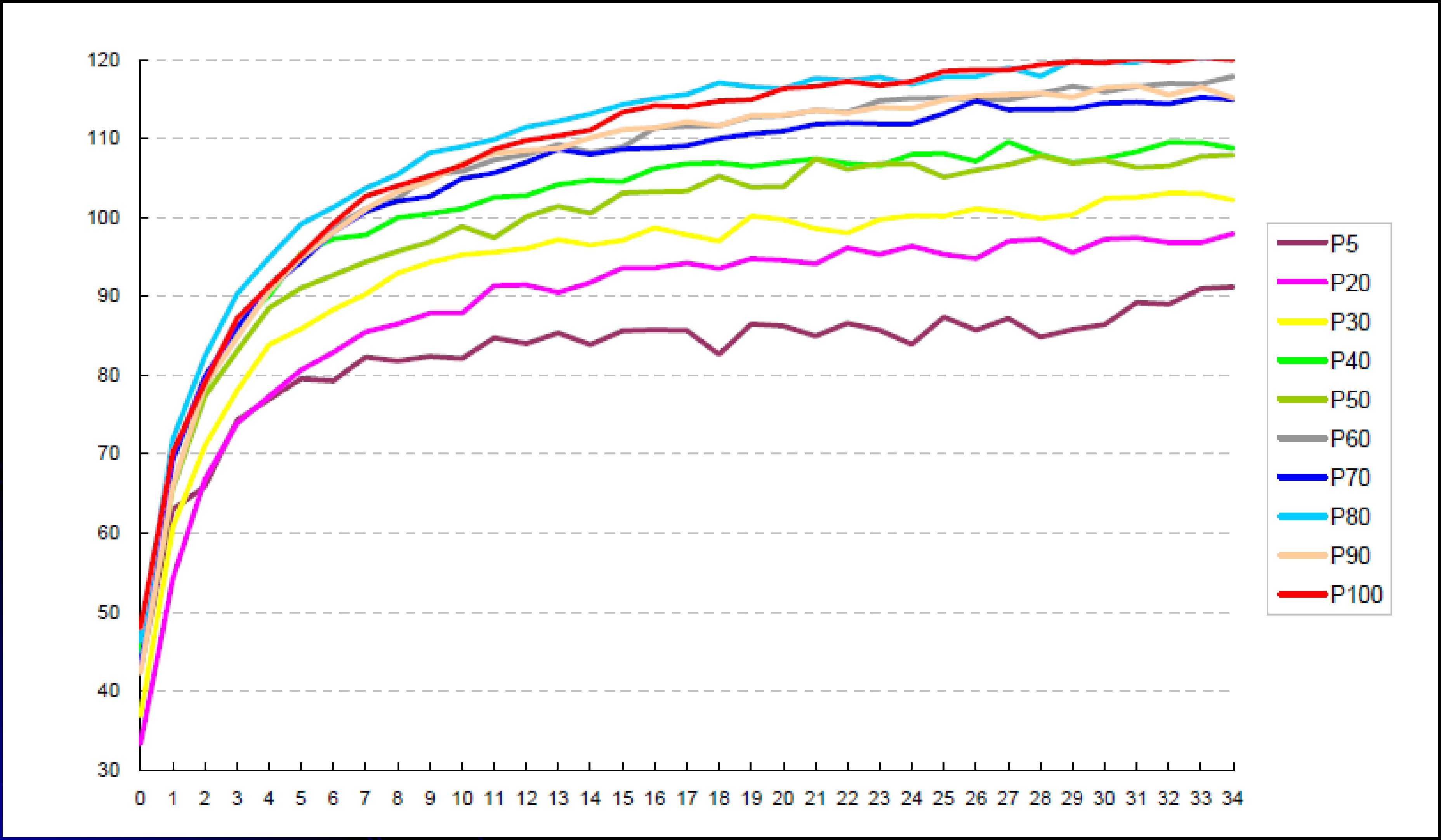
- There are three major findings from these simulations with software agents.
- First, GP traders with different cognitive capacities, from Pop=5 to Pop=100, can all outperform the human-supplied programmed agents, while with different speed in terms.
- GP traders with higher cognitive capacity tend to learn faster and consequently accumulate more wealth.



Individual Efficiency
P5
S.D. of Individual Efficiency
P5
P20
P20
P50
P50
Time
Individual Efficiency
Truth Teller
Skeleton
Kaplan
Ringuette
ZIC
ZIP
Markup
GD
BGAN
EL
Empirical
GP

Result II

- Second, however, GP traders with larger cognitive capacity perform better than GP traders with smaller cognitive capacity; however, this dominance become less significant when cognitive capacity increases further.
  - *Remark:* Again, double auction market is a rather easy environment that income inequality can be significant only if the gap in cognitive capacity is large enough.



120
110
100
90
80
70
60
50
40
30
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34
P5
P20
P30
P40
P50
P60
P70
P80
P90
P100

Result III

- Third, if we allow GP traders with lower cognitive capacity more time to learn, the above income gap can disappear if the difference in cognitive capacity among traders is limited; otherwise, the gap can be only narrowed but not disappear.
  - Remark: Therefore, even though the double auction market is an easy environment, it can still generate persistent income inequality if the heterogeneity in cognitive capacity of traders is significant enough. In this sense, Gode-Sunder intelligence irrelevancy hypothesis is invalid.

		P5	P20	P30	P40	P50	P60	P70	P80	P90	P100
A	P5	X									
	P20	0.099*	X								
	P30	0.010**	0.328	X							
	P40	0.002**	0.103	0.488	X						
	P50	0.000**	0.009**	0.129	0.506	X					
	P60	0.000**	0.000**	0.003**	0.034**	0.130	X				
	P70	0.000**	0.000**	0.015**	0.121	0.355	0.536	X			
	P80	0.000**	0.000**	0.003**	0.036**	0.131	1.000	0.558	X		
	P90	0.000**	0.000**	0.011**	0.079*	0.250	0.723	0.778	0.663	X	
	P100	0.000**	0.000**	0.000**	0.002**	0.009**	0.284	0.093*	0.326	0.150	X
B	P5	X									
	P20	0.571	X								
	P30	0.589	0.288	X							
	P40	0.170	0.060*	0.442	X						
	P50	0.090*	0.020**	0.236	0.834	X					
	P60	0.004**	0.001**	0.019**	0.159	0.207	X				
	P70	0.066*	0.015**	0.191	0.671	0.848	0.280	X			
	P80	0.016**	0.003**	0.062*	0.333	0.422	0.656	0.577	X		
	P90	0.043**	0.010**	0.144	0.552	0.714	0.384	0.845	0.658	X	
	P100	0.001**	0.000**	0.008**	0.062*	0.091*	0.736	0.150	0.444	0.201	X

Intelligence Irrelevance Hypothesis

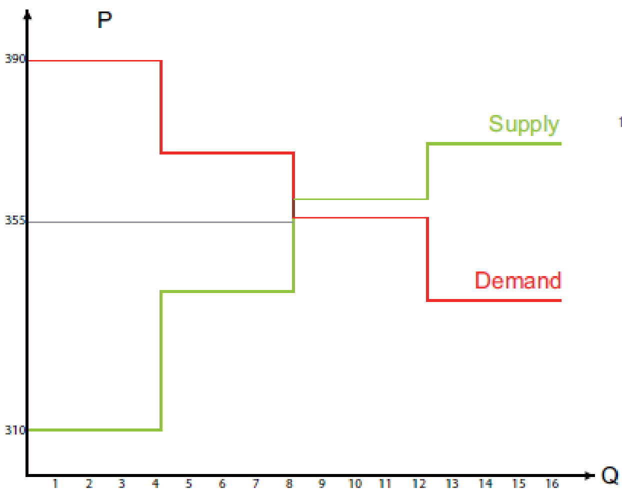
- The intelligence irrelevance hypothesis basically states that competitive market can help determine the price and facilitate trading opportunities, and the gain that one can have from the competitive market is independent of his/her cognitive ability.
- Is that real?

Alignment from ACE to EE

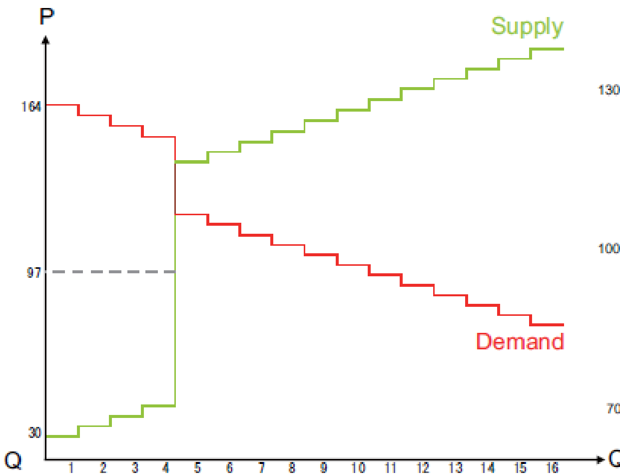
- Markets: 300 → 3
- Opponents: 10 → 7
  - Sophisticated Traders (the seven)
  - Simple Traders (truth tellers)
- Cognitive Capacity → Working Memory Test (Lewandowsky et al., 2010)
- Subjects: 173 subjects for each series

The Three Markets

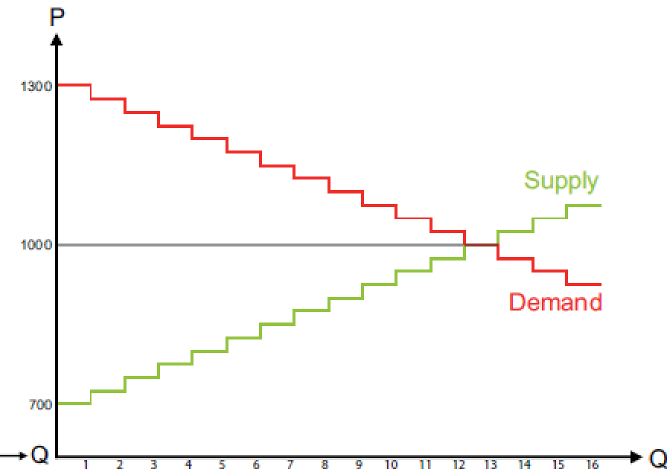
M1



M2



M3



- First, cognitive capacity matters. Subjects with higher cognitive capacity perform better than subject with lower cognitive capacity.

Multiple Regression in Simple Environment

Variable	Profit (M1)	Profit (M2)	Profit (M3)
Constant	446.17****	546.1192****	593.62****
	(39.27)	(73.3441)	(16.63)
WMC	145.92****	159.3392***	43.72****
	(29.22)	(54.5807)	(12.38)
X_1	74.70**	151.5478**	7.64
	(37.67)	(70.3491)	(15.95)
X_2	107.25***	−229.4911***	−18.65
	(37.87)	(70.7335)	(16.04)
X_3	−47.95	−47.9077	−21.54
	(38.89)	(72.6339)	(16.47)
X_4	63.68	55.6353	−43.92*
	(53.56)	(100.0330)	(22.68)
X_5	28.27	0.4086	34.01
	(63.85)	(119.2451)	(27.04)
X_6	85.71**	128.6838*	21.43
	(39.95)	(74.6106)	(16.92)

Buyer or not

Note: Standard errors are in parentheses.
Significant at the 0.1% level: ****
Significant at the 1% level: ***
Significant at the 5% level: **
Significant at the 10% level: *

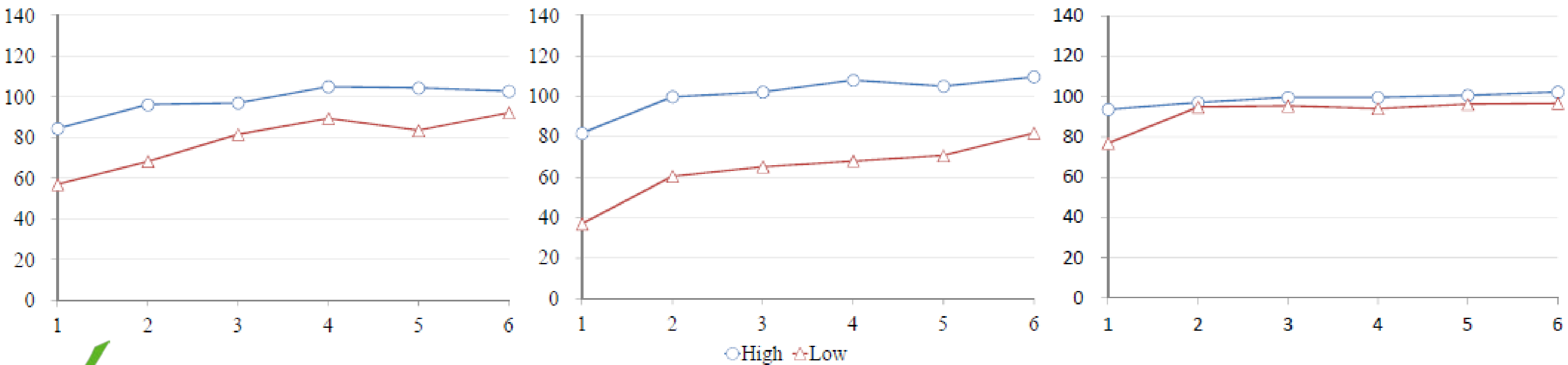
Multiple Regression in Sophisticated Environment

Variable	Profit (M1) Model 1	Profit (M1) Model 2	Profit (M2) Model 1	Profit (M2) Model 2	Profit (M3) Model 1	Profit (M3) Model 2
Constant	614.79****	487.75****	627.57****	763.711****	744.5****	567.07****
	(29.28)	(63.9)	(26.89)	(54.24)	(26.39)	(57.7)
WMC	136.52***	143.53***	112.62**	99.176**	62.4	52.78
	(47.93)	(46.93)	(44.02)	(39.838)	(43.19)	(42.38)
Male		60.58		60.289		79.25
		(57.35)		(48.678)		(51.78)
Buyer		184.53***		−333.892****		166.13***
		(56.62)		(48.058)		(51.12)
Online		−23.86		−3.898		58.82
		(56.33)		(47.813)		(50.86)
Financial		206.1**		126.764*		130.46*
		(83.51)		(70.879)		(75.4)
Other		−144.09		29.725		31.29
		(100.61)		(85.398)		(90.85)
Tool		−42.26		−88.715		−52.04
		(75.73)		(64.281)		(68.38)

Note: Standard errors are in parentheses.
Significant at the 0.1% level: ****
Significant at the 1% level: ***
Significant at the 5% level: **
Significant at the 10% level: *

- Second, cognitive capacity still matters even after learning has been taken into account.

Simple Environment



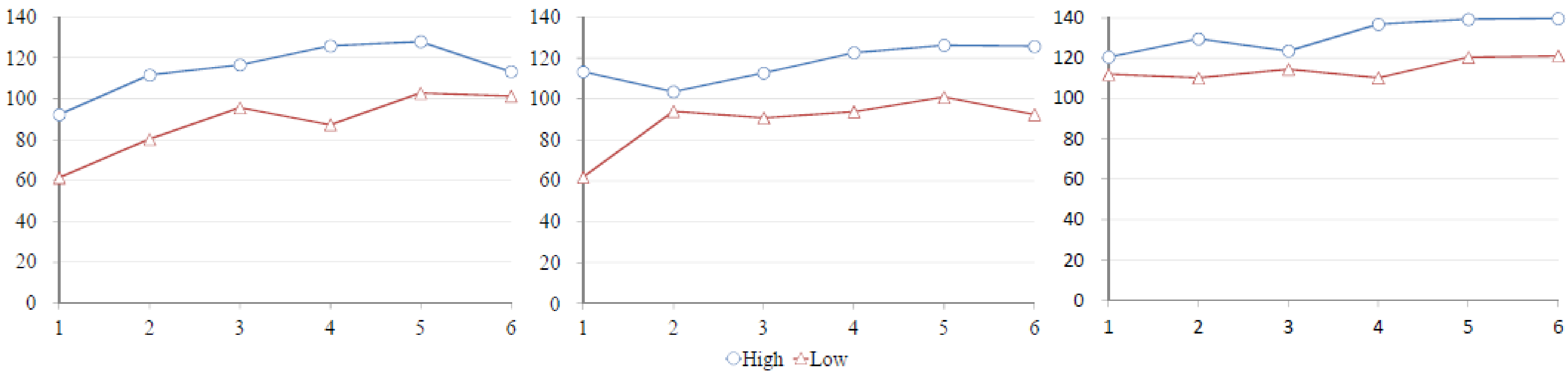
- Observations:
  - The High Group outperformed the Low Group in every period of every market.
  - There is obvious learning for both High and Low Groups.
  - The gap between High and Low Groups shrinks overtime.
  - Subjects' performance drops when the demand-supply schedule changes.

Wilcoxon Rank Sum Test

	M1			M2			M3		
Period	High	Low	p-value	High	Low	p-value	High	Low	p-value
1	84 (39.93)	57 (97.47)	0.0434	82 (60.83)	37 (116.73)	0.0021	94 (19.85)	77 (122.14)	0.1328
2	96 (33.21)	68 (89.87)	0.0015	100 (53.82)	61 (92.83)	0.0004	97 (11.40)	95 (11.66)	0.1279
3	97 (41.91)	82 (66.50)	0.0386	102 (67.41)	65 (118.54)	0.0037	100 (8.47)	95 (12.18)	0.0113
4	105 (30.75)	89 (50.14)	0.0504	108 (56.08)	68 (123.24)	0.0048	100 (11.89)	94 (16.00)	0.0023
5	104 (37.29)	83 (76.24)	0.0945	105 (61.38)	71 (120.53)	0.0171	101 (11.24)	96 (12.86)	0.0017
6	103 (45.65)	92 (54.12)	0.2100	110 (57.15)	82 (93.46)	0.0065	102 (9.05)	97 (11.94)	0.0001

Note: Standard deviations are in parentheses.

Complex Environment



Concluding Remarks

- Data under the lab is under control and clean?
  - Not entirely, because human is complex.
- Agent-based model can assure how the data is socially generated.
  - However, have to show that the artificial agents under control are `human'.

Let the naturally allied spiral to constantly spiral!

Thank for your Attention!

Slides are available on

www.aiecon.org

Questions?