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Stock Price Dynamics in Artificial Multi-Agent Stock Markets

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Introduction

- Does finance have a problem?
  - Real-life stock market dynamics are hard to explain using modern finance (MF) assumptions
- Can this problem be solved?
  - Behavioral finance (BF) uses psychology and sociology to explain what modern finance left unexplained
- Is the problem now solved?
  - BF relies too strongly on MF axiom and methods, risking to lose it's own identity (Frankfurter and McGoun, 2002: 376)
- What are we going to do about this?
  - Use theories, research techniques and methods from consumer behavior and social simulation research

Introduction

- What do we want?
  - A better understanding of micro level investor behavior
  - A better understanding of macro level stock market dynamics
  - A better understanding of the micro-macro link

- What methods will we use?
  - Consumer and Investment research theories
  - Survey research amongst individual investors
  - Use theoretical insights and the survey results in order to parameterize a multi-agent simulation model
  - Compare outcomes simulation with real market data

Theoretical Background

- Utility functions that only incorporate risk and return ignore:
  - The multiplicity of human needs
  - The heterogeneity in satisfying these needs
  - The possible utility of the investment process as such
- If investors also have more socially oriented needs, this implies that they do not make their decisions in social isolation
- Investors are susceptible to social influences from others and socially influence others in their social networks; this might help explain the background of hypes, crashes, and bubbles
- Can these assumptions be empirically confirmed?

Empirical Background

- We performed a survey amongst individual investors in The Netherlands

- We found that individual investors, among other things:

  – Rate financial needs as most important, a close second are more social needs like identification and participation

  – Are susceptible to social influences

  – With a higher ranking of social needs display more socially influenced behavior

Simulation

- Why should we use simulation? It can help:
  - In developing and exploring theories concerned with social processes (Gilbert and Troitsch, 2003)
  - With understanding the relation between the micro and macro level (Gilbert and Troitsch, 2003)

- We started with a very simple simulation model adapted from Day and Huang (1990) with two types of strategies:
  - Investors using an Alpha strategy trading in a fundamental way by comparing the current price with a long run investment value
  - Investors using a Beta strategy trading in a trend-following socially oriented way

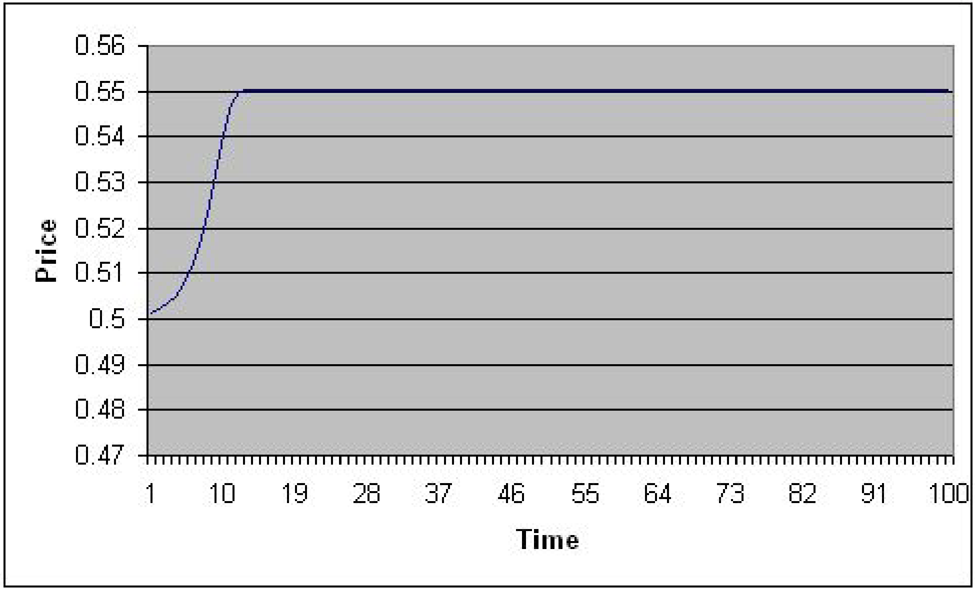
The Simulation Model

- Key parameters:
  - P: current price
  - U: long run investment value
  - S: proportion of Beta strategy of each investor
  - (1-S): proportion of Alpha strategy of each investor

- With this model, it is possible to investigate the influence of Alpha and Beta strategies on the stock market price dynamics
- Two series of experiments: simultaneous versus sequential market updating
- In all the presented experiments, P = 0.501, and U = 0.500

Simulation Experiments with Simultaneous Updating

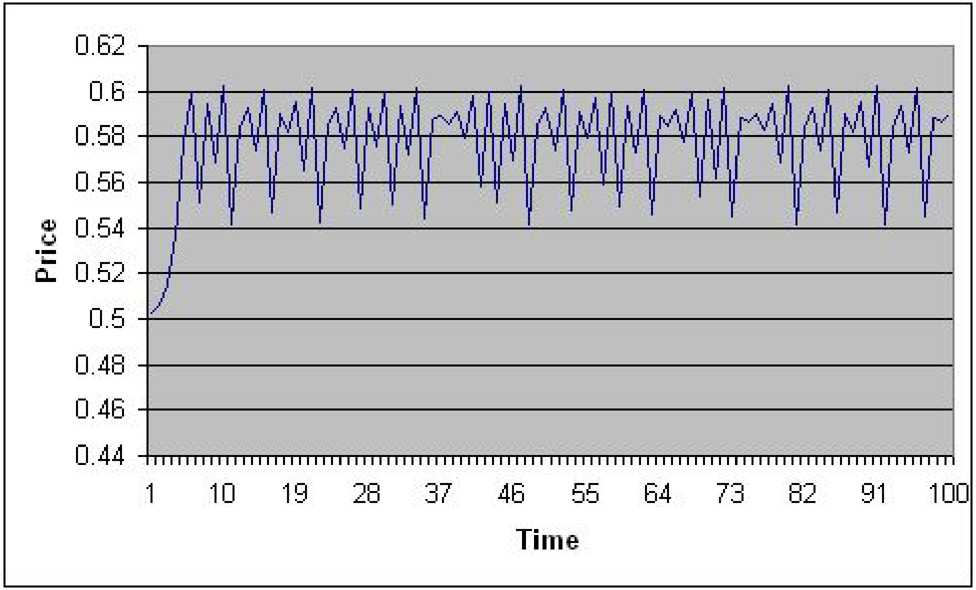
- Experiment 1.1: S = 0.01 and 100 agents



- A small proportion of Beta strategy already suffices to push the stock price away from the long run investment value

Simulation Experiments with Simultaneous Updating

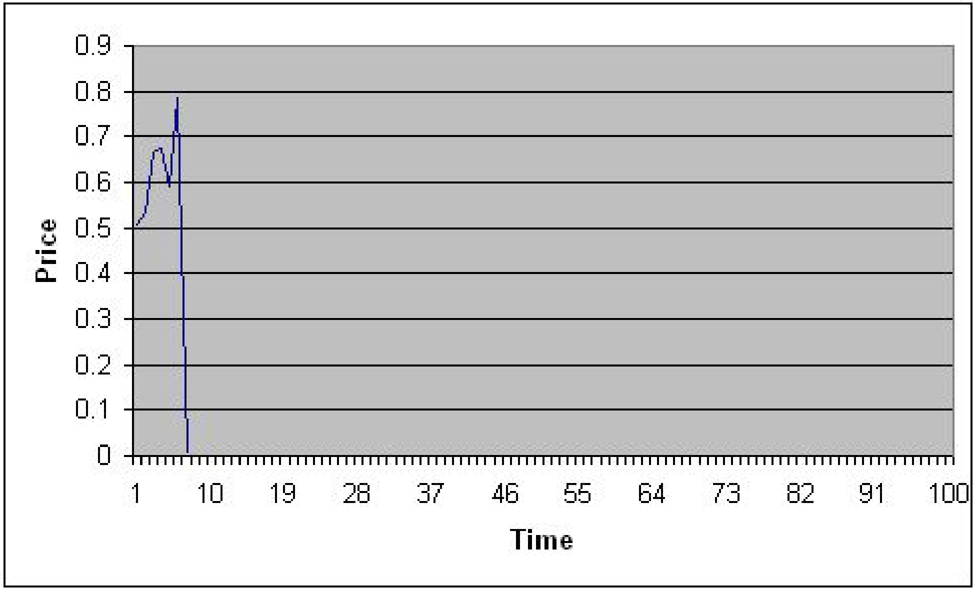
- Experiment 1.2: S = 0.03 and 100 agents



- Increasing the proportion of Beta strategy results in chaotic-like stock price dynamics

Simulation Experiments with Simultaneous Updating

- Experiment 1.3: S = 0.10 and 100 agents



- Increasing the proportion of Beta strategy even more results in stock price dynamics that easily get out of bounds

Simulation Experiments with Simultaneous Updating: Wrap Up

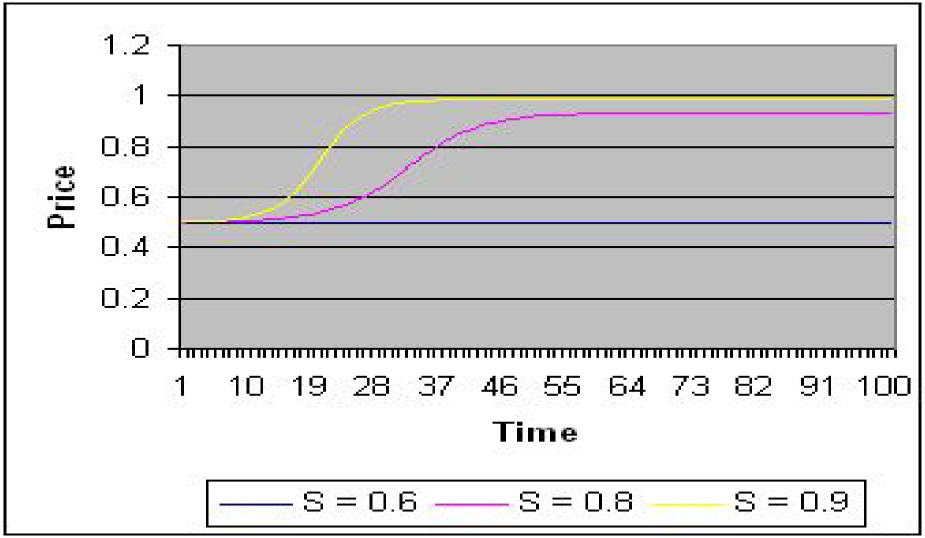
- With simultaneous updating, the parameter space for which we obtain useful price series is relatively small
- All agents make their decisions at exactly the same moment in time, this is empirically deviant and not realistic
- The very large aggregate demand or supply caused by the above easily causes overshooting of the stock price

Simulation Experiments with Sequential Updating

- To increase the parameter space which can be studied in a sensible way, sequential market updating was introduced
- Moreover, in reality investors differ to what extent they weigh an Alpha and a Beta strategy, i.e. investors can be heterogeneous with respect to the parameter S
- Therefore, in the following experiments, we compared:
  - Simultaneous versus sequential market updating
  - Homogeneity versus heterogeneity with respect to S
  - Impact of different levels of S on price volatility
  - Simulation-generated data with Dow Jones Index (DJI) data

Simulation Experiments with Sequential Updating

- Experiment 2.1: S = 0.6, 0.8, 0.9 and 100 agents



- With homogeneous investors (all the same value for S), markets eventually always reach equilibrium, no matter how high S is

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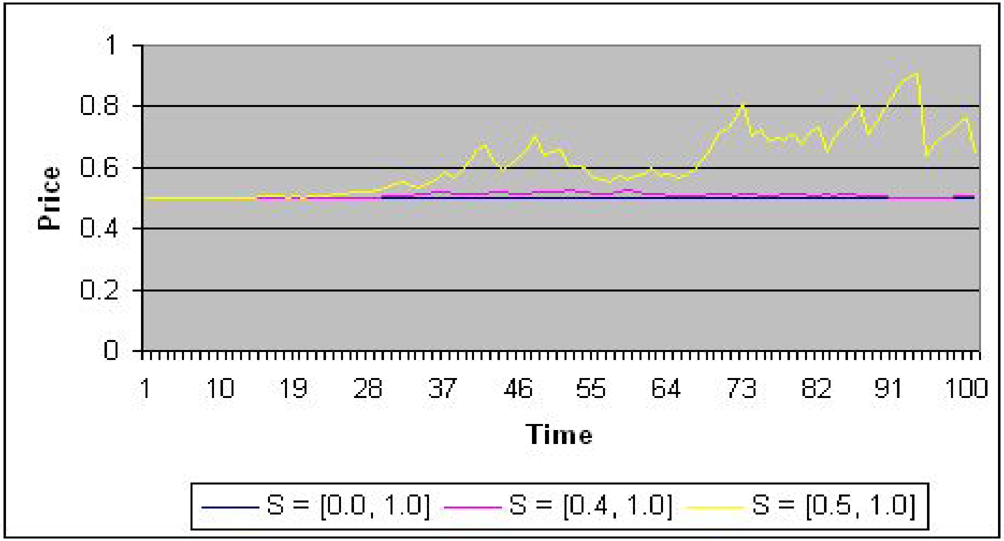
Simulation Experiments with Sequential Updating

- Experiment 2.2: S = heterogeneous and 100 agents



- When investors are heterogeneous, markets still reach equilibrium at relatively low levels of S, at higher levels of S, chaotic-like stock market price dynamics result

Simulation Experiments with Sequential Updating: Wrap Up

- Sequential instead of simultaneous market updating gives less susceptibility to overshooting

- Garch (1,1) analysis compared our outcomes with a recent period without special holidays of the DJI

- Simulation results were arbitrarily chosen, therefore no comparison of estimated coefficients, but the significances for DJI and our example (S [0.5, 1.0]) are quite similar

- Arch and Garch effects might be attributed to trend-following investors that randomly enter the stock market

Discussion: so what did we not do?

- Investors in this simple first simulation model did not get information from their social network, but derived it directly from stock prices
- New information arrival to the market was not incorporated
- Effect of different networks on information diffusion processes was not studied
- Market dynamics are generated by the actions of investors, but the cognition of investors is never affected by the evolution of the market; no feedback mechanism
- Investors could only trade the shares of one company
- Investors were not limited by a budget

Discussion: so what will we do?

- Build a new multi-agent simulation model with the following properties:

  - Implementation of different social network structures
  - Feed news into the market about the expectation of next period's stock price
  - An agent's success in the market feeds back into his choice between different investment strategies
  - Agents have a personal budget
  - Agents can choose between different shares and/or cash
  - All the above has been incorporated in our RUGAM model

Questions and Remarks

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Garch (1,1) Analysis

	Dow Jones percentage returns		S=[0.5,1.0]		S=[0.4,1.0]	
	Coefficient	Prob.	Coefficient	Prob.	Coefficient	Prob.
C	0.269	0.283	0.065	0.007	0.000	0.845
MONDAY	-0.190	0.642				
TUESDAY	-0.118	0.732				
WEDNESDAY	-0.091	0.756				
THURSDAY	-0.381	0.190				
Variance Equation						
C	0.057	*0.200*	0.001	*0.508*	0.000	*0.358*
RESID(-1)^2	-0.150	*0.066*	0.306	*0.059*	0.503	*0.000*
GARCH(-1)	1.025	*0.000*	0.803	*0.000*	0.610	*0.000*
Equation Statistics						
Adj. R-squared	-0.151		-0.034		-0.034	
DW statistic	1.716		1.923		1.601	