Master's Thesis

Modelling and analysis of a financial market with slow and fast trading agents acting on time-delayed market information

Halfdan Rump

Waseda GRS-FSE

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1. Introduction
2. Model
3. Experiments
4. Results
   - Evolution of fitness and parameters
   - Typical markets
   - Fitness/parameter correlations
   - Parameter ratios
5. Conclusion

Background and motivation

A few fact about modern financial markets:

- Humans trade against software algorithms (the machines)
- Humans are slow but complex, whereas algorithms are fast, but (relatively) simple
- Fast crashes (flash crashes) has become a problem in recent years

Related work

Models for human/machine system must be developed. Previous work:

Analysis of market data: Works analyzing real market data for flash crashes and

Models of markets: Works that divide agents into two groups: **slow** and **fast** traders

All discovered works in the field are recent (published 2013, or yet unpublished).

Key points of proposed model

Delayed market information All information exchanged between agents and the market is delayed

Agents with arbitrary time delays Agents are not just *fast* or *slow*, but have **arbitrary** delays

Full-fledged MAS model Agents with various strategies and different delays.

Research goal

Market stability and agent speed

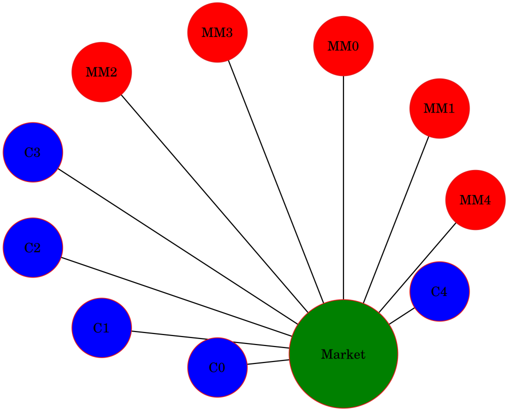
Investigate how the behavior (e.g. stable, crash, etc.) of a simulated financial market changes when the latency of the traders change

Very open research, but the first steps in a new field must necessarily be somewhat exploratory.

Model components

- Market and order book
- Stock
- Agents
- Messages

Market model



Market

Auction type

The market uses a continuous double auction. Prices are always executed at the prices of the best standing market orders.

Order book

Sell orders	Price	Buy orders
22	9994	
26	9993	
13	9992	
10	9991	
	9988	12
	9987	10
	9986	16
	9985	25

Messages

- Market information
- Orders
- Receipts
- Cancellations

All messages have a non-zero travel time

Stock

A single stock is traded at the market.

Fundamental price The "*true*" value of the stock

Traded price The price at which the stock is currently traded

Agents

- Slow traders (ST)
- Fast traders (AKA High Frequency Traders, HFT)
    - Market makers (MM)
    - Simple chartists (SC)

Slow traders

Slow traders model human traders

They know the **true** value of the fundamental, *but with a large delay*

The slow traders submit orders in order to *move the trade price towards the true price*.

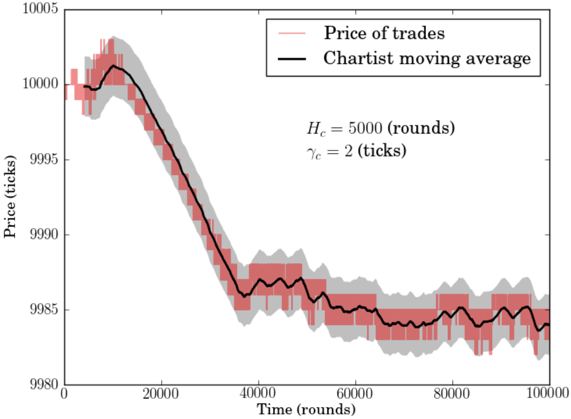
Simple chartists

The chartists use a simple moving average strategy

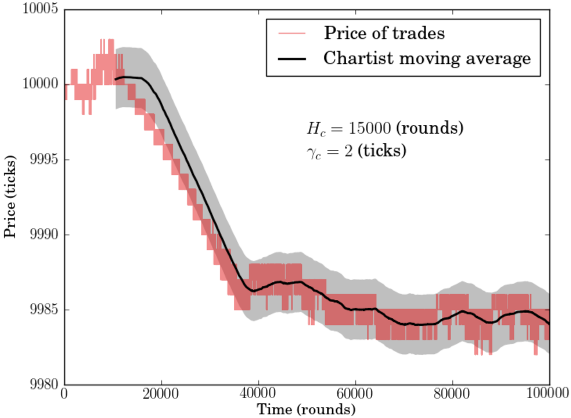
They calculate the moving from the delayed best buy and sell prices.

The chartist detects a trend if the moving average calculated over H_c rounds differs more than γ_c ticks from the currently traded price.

Chartist example 1



Chartist example 2



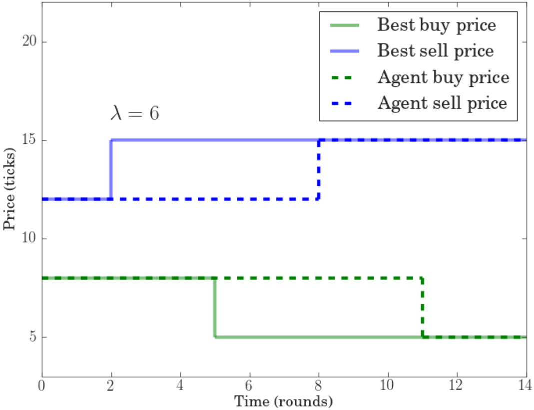
Market makers

Market makers keep constant buy and sell orders

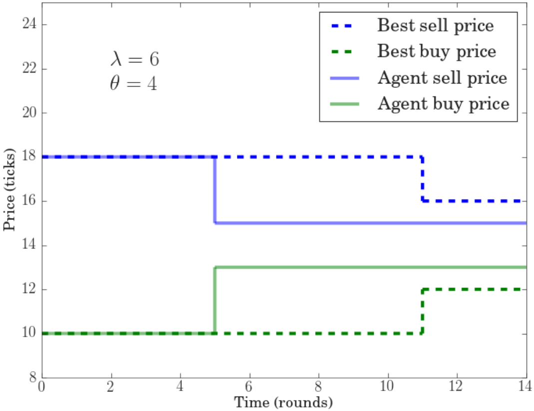
The market maker tried to follow the best buy/sell prices to stay competitive.

The market maker has a minimum-spread parameter, θ.

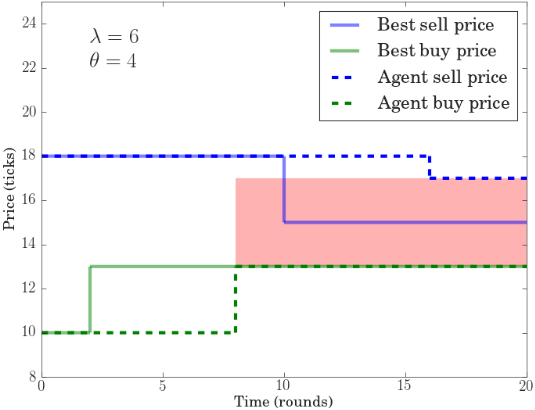
Market maker case 1



Market maker case 2



Market maker case 3



Important model parameters

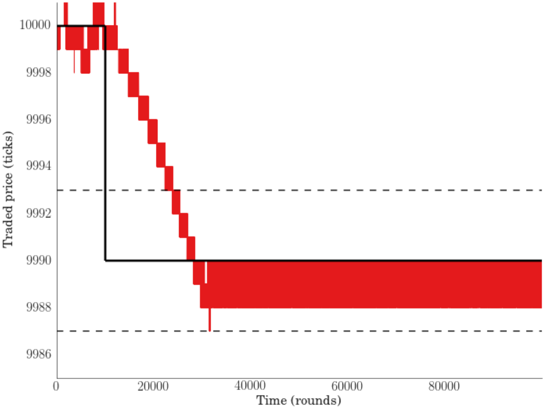
The model has many parameters. The most important ones are:

- The average latency of chartists and of market makers, λ
- The number of fast traders

Simulating bad news

Shock to the fundamental

How does the market react when the true price of the stock suddenly drops?


10000
9998
9996
9994
9992
9990
9988
9986
Traded price (ticks)
0
20000
40000
60000
80000
Time (rounds)

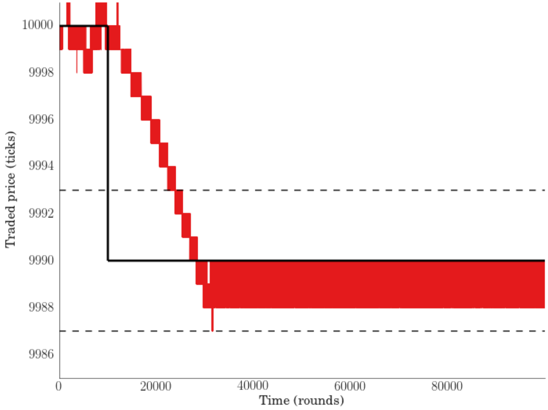
Exploring model behavior

We want to determine how the model behavior changes with the parameters

A genetic algorithm was used to search the parameter space. Four fitness measures were defined in order to quantify the model behavior.

Model fitness

- Overshoot
- Price flickering (standard deviation of trade prices)
- Response time (time to reach fundamental price after shock)
- Time to become stable (the traded price must stay within a certain range of the true price)


10000
9998
9996
9994
9992
9990
9988
9986
Traded price (ticks)
0
20000
40000
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80000
Time (rounds)

Search for stable markets

We want to see what the speed of the agents does to the market stability

The genetic algorithm was instructed to minimize overshoot, price flickering, response time and time to become stable.

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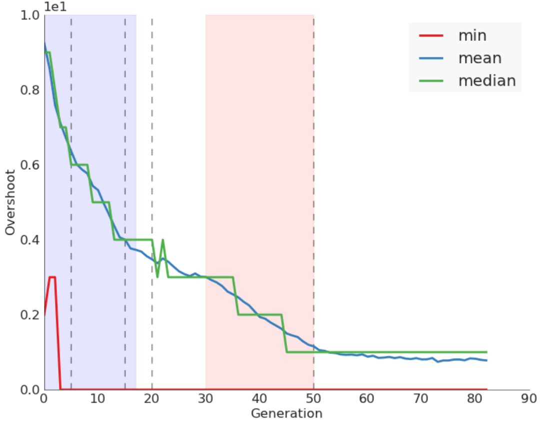
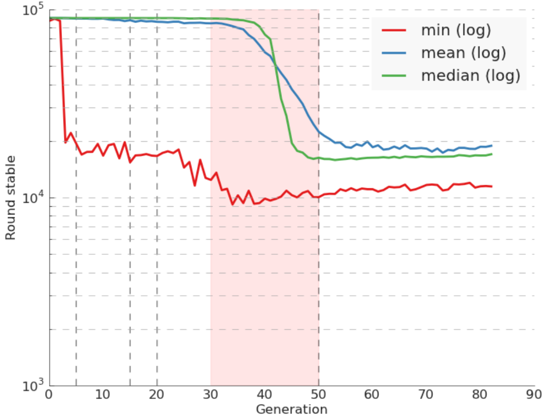
Overshoot

The genetic algorithm found markets with a small overshoot:



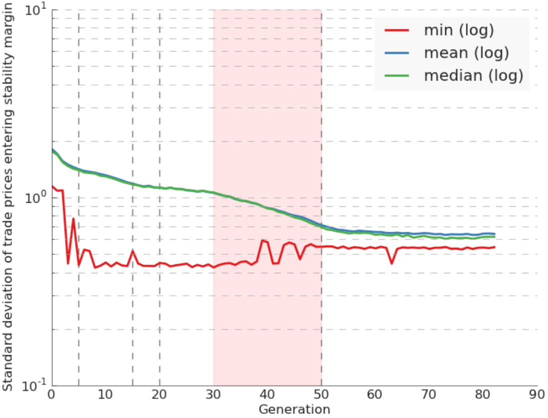
Time to become stable

..it found markets that quickly staying within the stability margin:



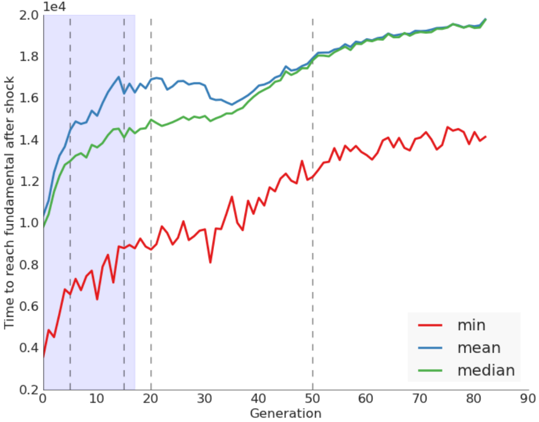
Price flickering

...it found markets with little price flickering:



Response time

...but it was not able to find markets that were fast at the same time



Interpretation of evolution results

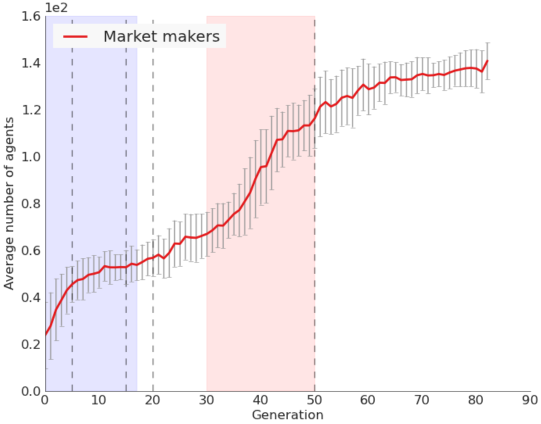
Speed/stability trade-off

The evolution of the fitness and parameters illustrates a trade-off between maket stability and the response time of the market: Stable market are also slower.

What parameters cause this behavior?

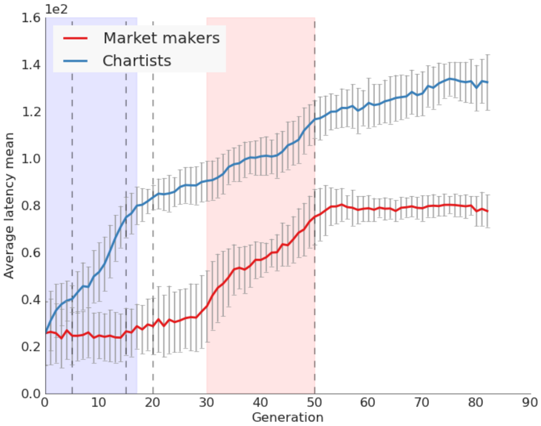
Number of market makers

The GA selects towards more market makers:



Latency of agents

...and towards slower agents.



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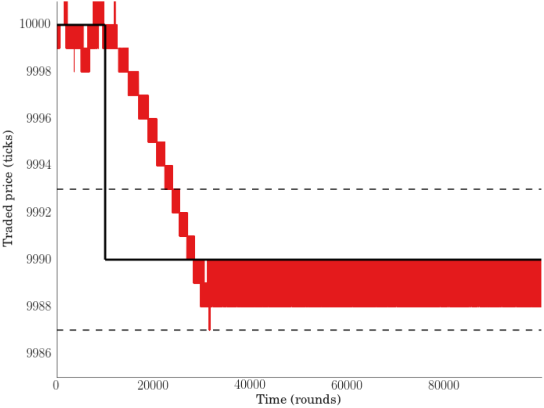
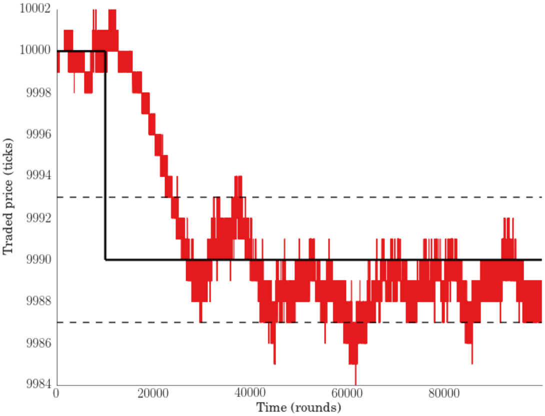
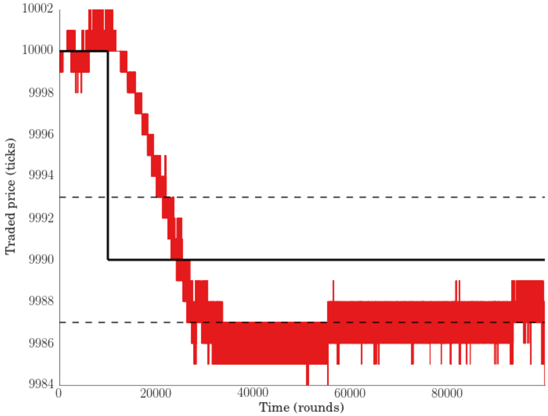
Market with nice behavior



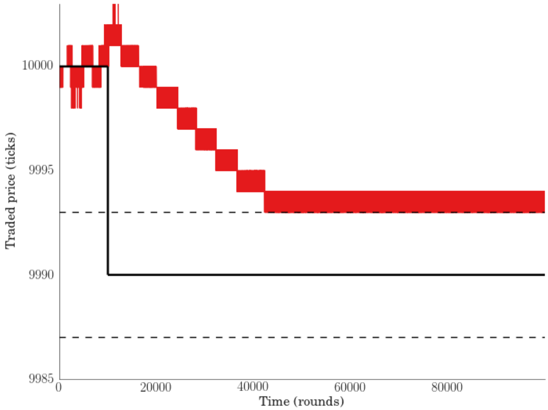
Large price flickers



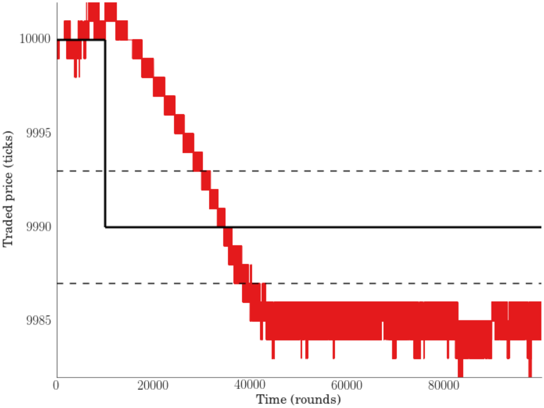
Never stable



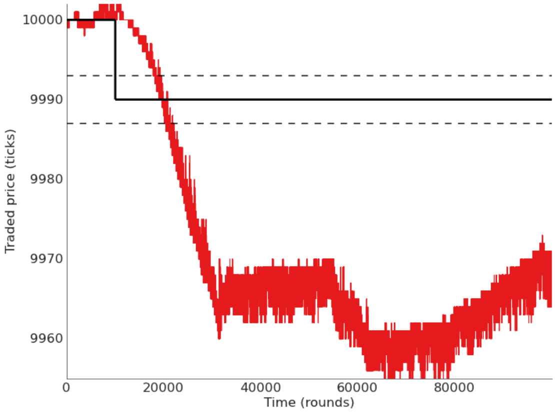
Overvaluation



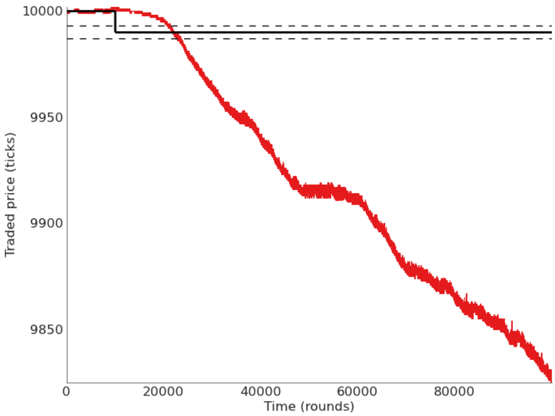
Undervaluation



Market crash



Supercrash


10000
9950
9900
9850
Traded price (ticks)
0
20000
40000
60000
80000
Time (rounds)

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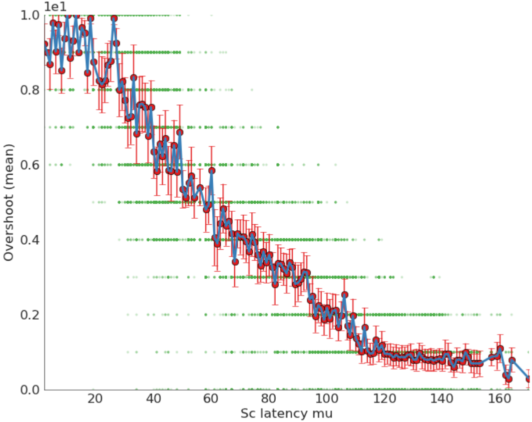
Parameters and model behavior

How does the speed of the agents affect the market behavior?

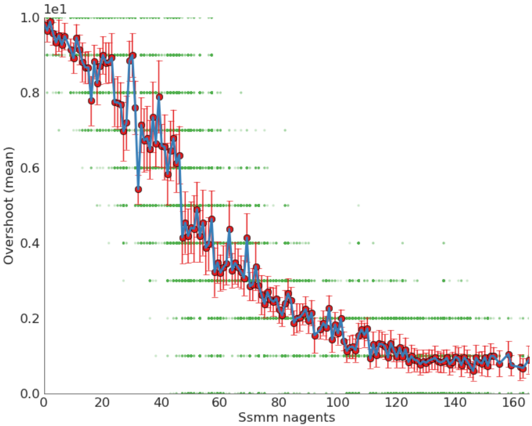
Chartist latency

Faster chartists cause the market to have a larger overshoot:



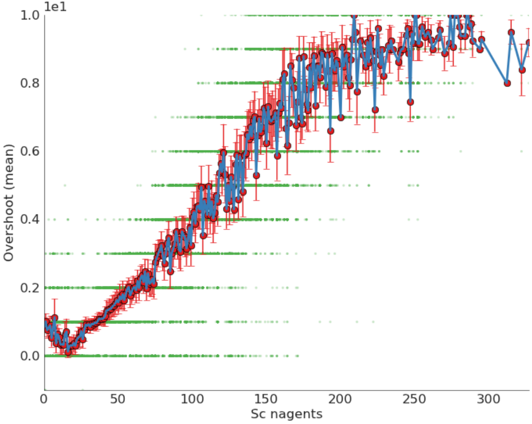
Number of market makers

The number of market makers has a great deal to say:



Number of chartists

...as has the number of chartists:



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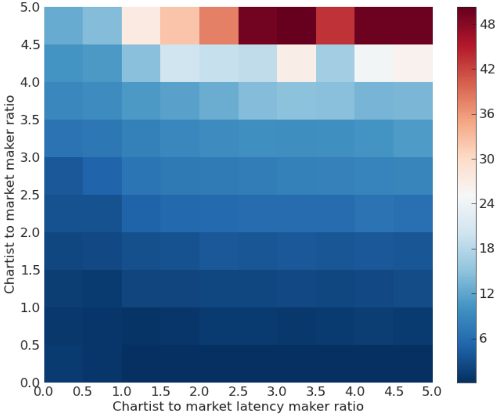
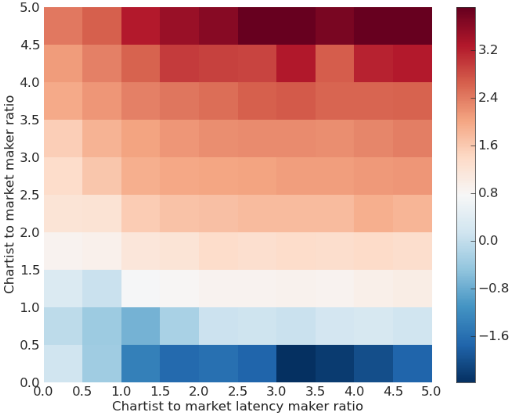
Latency ratio

What happens when the chartists are faster than the market makers, or the other way around?

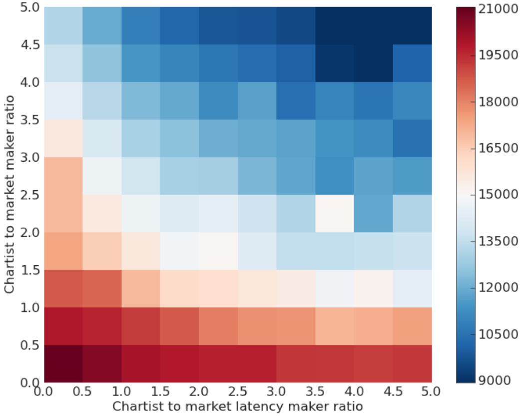
Overshoot


Chartist to market maker ratio
Chartist to market latency maker ratio
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
6
12
18
24
30
36
42
48

Log-overshoot



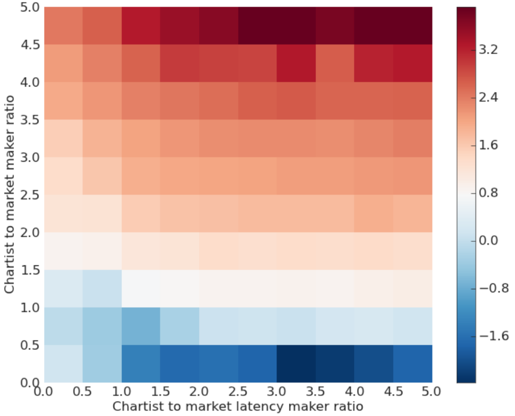
Market response time



Summary of results

- Market makers have a stabilizing effect of the market by reducing price movements
- Chartists increase price movements
- The influence was larger for faster agents
- The market will only crash if *both* chartists *and* market makers are present.
- The market was more likely to crash if the chartists were much faster than the market makers

Log-overshoot



Conclusions

Fast trader pros and cons Fast agents both provided benefits to the market (faster response, lower price flickering), and caused some dangers (crashes, misvaluation)

Stability/speed trade-off The market was found to have a trade-off between speed and stability

Relative agent latencies The results illustrated the importance of allowing different agents to have different latencies.

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