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MASTER'S THESIS

Thesis Title

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UNIVERSITY NAME (IN BLOCK CAPITALS)

Abstract

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Doctor of Philosophy

Thesis Title

by John SMITH

The study found that having agents which are orders of magnitude faster than human traders is not in itself a problem. By simulating the advent of bad news as an instantaneous decrement of the stock price, it was found the fast algorithmic traders did provide the market with some benefits, such as a reduce responsible time to the shock, a smoother descent of the traded to the

However, it was also found that making the market more stable, and by increasing the responsiveness of the market after a

It was also found that

Acknowledgements

The acknowledgements and the people to thank go here, don't forget to include your project advisor...

Contents

Abstract	i
Acknowledgements	ii
Contents	iii
List of Figures	vi
List of Tables	viii
Abbreviations	ix
Physical Constants	x
Physical Constants	xi
Symbols	xii
1 High Frequency Trading	2
1.1 Overview of High Frequency Trading	2
1.1.1	2
2 Model	3
2.1 Model	3
2.1.1 Asynchronous vs game theoretic model	3
2.1.2 Overall architecture	3
2.1.3 Modeling delays	4
2.2 Market components	4
2.2.1 Stocks	4
2.2.1.1 Fundamental price	5
2.2.2 Messages	5
2.2.2.1 Market information	6
2.2.2.2 Orders	7
2.2.2.3 Transaction receipts	7
2.2.2.4 Order cancellations	8
2.2.3 Order book	8

2.2.3.1	Price updating	8
2.2.3.2	Order matching	10
2.2.3.3	Empty order book	10
2.2.4	Market	10
2.2.4.1	Short selling	10
2.3	Agents	11
2.3.1	Slow traders	12
2.3.1.1	Arrival of orders	14
2.3.2	Market makers	14
2.3.3	HFT Chartists	15
2.4	Simulation rounds	15
2.5	Implementation	15
2.6	Overview of model parameters	15
2.7	Experiments	15
3	Parameter tuning	16
3.1	Motivation and overall procedure	16
3.1.1	Selecting fixed parameters	18
3.2	Inverse simulation with a genetic algorithm	18
3.2.1	Representing parameters as genes	19
3.2.2	Model fitness	19
3.2.3	Genetic algorithm parameters	20
3.2.4	Controlling market behavior	21
3.2.5	Filtering parameters	21
3.2.6	Handling failed simulations	21
3.3	Applying the genetic algorithm	23
3.3.1	Time complexity	23
3.3.2	Experiments: Dividing the search into parts	24
3.3.3	Gene pool as data set	24
3.3.4	Convergence of parameters	25
3.4	Data analysis tools	25
3.4.1	Data visualization	26
3.4.1.1	Color toned scatter plots	26
3.4.2	Preprocessing	26
3.4.2.1	Handling outliers	26
3.4.3	Clustering algorithms	28
3.4.3.1	GMM	28
4	Experiments	29
4.1	D3	29
4.1.1	Section summary	32
4.2	D9: Fixing the number of high frequency traders	33
4.2.1	Parameter and fitness evolution	33
4.2.2	Visualizing the data set	33
4.2.3	Analysing scatter plots	35
4.2.3.1	f_m vs f_σ	35
4.2.3.2	f_m vs. f_s	35

4.2.3.3	f_σ vs. f_s	37
4.2.4	Looking for parameters causing certain behavior	38
4.2.5	Section summary	39
4.3	D10	39
4.3.1	Fitness and parameter evolution	39
4.3.2	Correlation between fitness measures	43
4.3.3	Parameter-fitness correlations	44
4.3.3.1	Number of chartists	47
4.3.3.2	Chartist- to market maker ratio	47
4.3.4	Clustering	48
4.4	Hall of fame	51
A	Additional tables	52
A.1	Dataset 1	52
B	Third party software	53
C	Additional figures	54
C.1	Scatter plots for d10	54
C.2	Correlation plots of $\lambda_{c,\sigma}$ and $\lambda_{m,\sigma}$	54
Bibliography		59

List of Figures

2.1	:	5
2.2	6
2.3	When an agent wants to submit an order it has to go through several steps of interaction with the market. The process is comparable to how real traders communicate with markets via a network, such as the Internet.	7
2.4	9
2.5	The HFT agent submits a sell order for 100 stocks, and another agent submits a price-matching buy order which fills the sell order. Before the transaction receipt reaches the seller, the seller decides to cancel the order, and submit another order at a different price. When the transaction receipt reaches the seller, the agent promptly sends out a cancellation of its second sell order, as it knows it cannot fulfill the order. However, before the cancellation reaches the market, a third agent fills the sell order, and a receipt is send to the seller who ends up being short.	11
2.6	Slow trader order arrival	14
3.1	Motivatoin for tuning: the two	17
3.2	Example of a simulation which is assigned fairly good fitness values, but which was executed with clearly unrealistic parameters: $N_m = N_c = 0$. The simulation reaches the new fundamental price fairly quickly without any undershoot, and stays within the stability margin. The only point where it scores badly is the standard deviation which is slightly high due to the fluctuating trade price.	22
3.3	Color toned scatter plots of f_s , f_σ and f_m taken from dataset d1after applying log-scaling and manually removing outliers	28
4.1	Evolution of time delay parameters common both HFT agent types, and of the number of agents in experiment d1	30
4.2	Evolution of chartist-specific strategy parameters in experiment d1	31
4.3	Evolution of the four fitness measures in experiment d1	31
4.4	Evolution of time delay parameters common both HFT agent types in experiment d1	32
4.5	Evolution of chartist-specific strategy parameters in experiment d9	32
4.6	Evolution of the four fitness measures in experiment d9	33
4.7	Scatter plots of fitness measures in experiment d9.	34
4.8	Scatter plot of $\log f_\sigma$, $\log f_m$ and f_s	35
4.9	Scatter plot of $\log f_\sigma$, $\log f_m$ and f_o	35
4.10	Scatter plot of f_m , f_s and f_σ	36
4.11	Scatter plot of f_o , $\log f_m$ and f_s	36

4.12 Scatter plot of f_m , f_s and f_σ	37
4.13 Scatter plot of f_m , f_s and f_o	38
4.14	38
4.15 Evolution of the four fitness measures in experiment d10	40
4.16 Evolution of the model parameters in experiment d10	41
4.17 Correlation matrix of the four fitness measures in the first generation of dataset d10	44
4.18 Correlation between $\lambda_{c,\mu}$ and the four fitness measures in experiment d10 .	45
4.19 Correlation between N_m and the four fitness measures in experiment d10 .	46
4.20 Correlation between $\lambda_{c,\mu}$ and the four fitness measures in experiment d10 .	48
4.21 Correlation between $\lambda_{c,\mu}$ and the four fitness measures in experiment d10 .	49
4.22 Scatter plots in fitness space showing the grouping of data points when using a GMM with 12 clusters.	50
4.23 XXX	51
C.1 Scatter plot of $\log f_\sigma$, $\log f_m$ and f_s	54
C.2 Scatter plot of $\log f_\sigma$, $\log f_m$ and f_o	55
C.3 Scatter plot of f_m , f_s and f_σ	55
C.4 Scatter plot of f_o , $\log f_m$ and f_s	56
C.5 Correlation between $\lambda_{c,\sigma}$ and the four fitness measures in experiment d10	57
C.6 Correlation between $\lambda_{c,\sigma}$ and the four fitness measures in experiment d10	58

List of Tables

2.1	TABLE ILLUSTRATING ORDER BOOK	8
3.1	Overview of parameters used in the genetic algorithm	21
3.2	Overview of experiments	21
3.3	An example data matrix containing the parameters of ten individuals who lived sometime during the execution of the genetic algorithm. In this case, each individual contained parameters for the number of HFT agents, as well as the latency and thinking time parameters. Hence, the data matrix has a column for each parameter.	25
3.4	This table contains the fitness values for each individual in table 3.3. Note that, in order to increase the reliability of the fitness measure of an individual, the recorded fitness-values are the average of the fitness-values obtained by evaluating each individual ten times	26
4.1	Mean for each fitness-cluster.	50
4.2	Standard deviation for each fitness-cluster.	51

Abbreviations

HFT	High Frequency Trader
ST	Slow Trader
OB	Order Book
MM	Market Maker
SD	Standard Deviation
GD	Gaussian Distribution
GMM	Gaussian Mixture Model
GA	Genetic Algorithm

Physical Constants

Term	Explanation
ask price	
bid price	
fitness	
fundamental	
limit order	
market order	
liquidity	
match	When a sell order and a buy order happen to have the same listed price, they are said to match.
order book	
partial match	Two orders which match, but have different volumes.
share	A fraction of ownership of an asset, such as a stock.
spread	
standing order	A market order registered at an order book and waiting for a matching order.
tick	
volatility	

Physical Constants

$E_p[\mathbf{x}]$	The sample mean of vector \mathbf{x}
$Var_p[\mathbf{x}]$	The sampe variance of vector \mathbf{x}
$Cov_p[\mathbf{x}, \mathbf{y}]$	The sample covariance between vector \mathbf{x} and \mathbf{y}
$M_p[\mathbf{x}]$	The sample median of vector \mathbf{x}
p^m	Time delay in rounds from agent i to market j . Note that $\tau_{i,j} = \tau_{j,i}$.
s_r	Spread at the end of round r
p_r^a	The lowest askprice in the order book at the end of round r
p_r^b	The highest bidprice in the order book at the end of round r
p^m	Match price, i.e., the price at which a trade is executed
f_r	Fundamental price at round r
p_{fas}	Fundamental price after shock
m_{stable}	Size in ticks of the stability margin around each side of p_{fas}

Symbols

Symbol	Description	Unit
n_{rounds}	Number of simulation rounds	
$\text{***}\lambda$	Average number of ST orders per round	
N_c	Number of HFT SC agents	
N_m	Number of HFT MM agents	
$\lambda_{c,\mu}, \lambda_{c,\sigma}$	Mean and SD parameters of the GD for HFT SC latency	
λ_c^i	Latency of HFT SC agent i where $\lambda_c^i \sim \mathcal{N}(\lambda_{c,\mu}, \lambda_{c,\sigma})$	
$T_{c,\mu}, T_{c,\sigma}$	Mean and SD parameters of the GD for HFT SC thinking time	
T_c^i	Thinking time of HFT SC agent i where $T_c^i \sim \mathcal{N}(T_{c,\mu}, T_{c,\sigma})$	
$H_{c,\mu}, H_{c,\sigma}$	Mean and SD parameters of the GD for HFT SC time horizon	
$H_{c,\sigma}$	Standard deviation of the Gaussian distribution for HFT SC time horizon	
$W_{c,\mu}, W_{c,\sigma}$	Mean and SD of the GD for the HFT chartist wait time	
$\lambda_{m,\mu}$	Mean and SD of the GD for HFT MM latency	
λ_m^i	Latency of HFT MM agent i where $\lambda_m^i \sim \mathcal{N}(\lambda_{m,\mu}, \lambda_{m,\sigma})$	
$T_{m,\mu}$	Mean and SD of the GD for HFT MM thinking time	
T_m^i	Thinking time of HFT MM agent i where $T_m^i \sim \mathcal{N}(T_{m,\mu}, T_{m,\sigma})$	
V_c^i, V_m^i	Volumes of orders submitted by HFT SC and HFT agents, respectively.	

For/Dedicated to/To my...

FOREWORD As such, this project turned out to be just as much about software engineering as Many models of artificial markets resemble typical game theoretic models in that all trading is round based. Typically all agents receive the market information and evaluate their strategies once every round. Such models are very useful when all agents are more or less equally fast, since it is then reasonable to assume that they have access to the same information.

The model proposed in this work is different from such models in that it assumes that agents generally do *not* have access to the same information when they evaluate their strategies.

Chapter 1

High Frequency Trading

1.1 Overview of High Frequency Trading

1.1.1

In the literature,

Chapter 2

Model

2.1 Model

As explained in section 1, perhaps the most distinguishable aspect of high frequency trading is the speed with which agents can react to new market information. It is therefore essential that a model should capture this aspect, if it is to be used to draw generalized conclusions about the influence of high frequency trading in the markets.

What are the goals of this model

What are not the goals of this model.

2.1.1 Asynchronous vs game theoretic model

In this work, we have tried emulate the asynchronous nature of a continuous auction by

As such, our model bears little resemblance to models derived from a game-theoretic basis, which typically

This work resembles a real-time simulation.

2.1.2 Overall architecture

The model consists a market and agents. Agents and the market communicate by exchanging messages which all arrive one or several rounds after they were issued. A

complete simulation consists of several consecutive rounds. In each round, some agents submit orders, while others wait for new market information. Order messages arrive at the order books, and trades are executed when prices match. The following sections will describe the model in detail.

2.1.3 Modeling delays

Although each round corresponds to a period of real-time, it is not particularly important to specify how long that period is. Instead, what matters is that there is a difference in speed between the agents. In other words, the important thing is that some agents are much faster than other agents. If one thinks of each round as a millisecond of real-time, one realizes that an agent simulating a human trader will require several thousands of simulation rounds to react to market news. On the other hand, fast algorithmic traders may only require a few rounds, making them several orders of magnitude faster than the slow traders.

This focus on the extremely

Another issue when simulating

2.2 Market components

Sending/receiving orders, supply liquidity

2.2.1 Stocks

A stock is an asset which is traded on a market. The price of a stock is a mysterious thing. A stock is only worth as much as people are willing to pay for it, and the price at which it is traded thus goes up and down according to what beliefs people hold. In financial markets, every trader is supposed to have access to the same information. However, two traders might disagree on the meaning of some piece of information. The way in which a trader evaluates market information and reaches a conclusion on how to trade is called a strategy. While any function which takes some information relevant to the market as input and gives a decision of how to trade (or not trade at all) can be termed a strategy, it is useful to divide strategies into two broad categories. In the first category are strategies which are dubbed chartist strategies, which basically tries to extrapolate on the past price movements. In the other category are strategies which

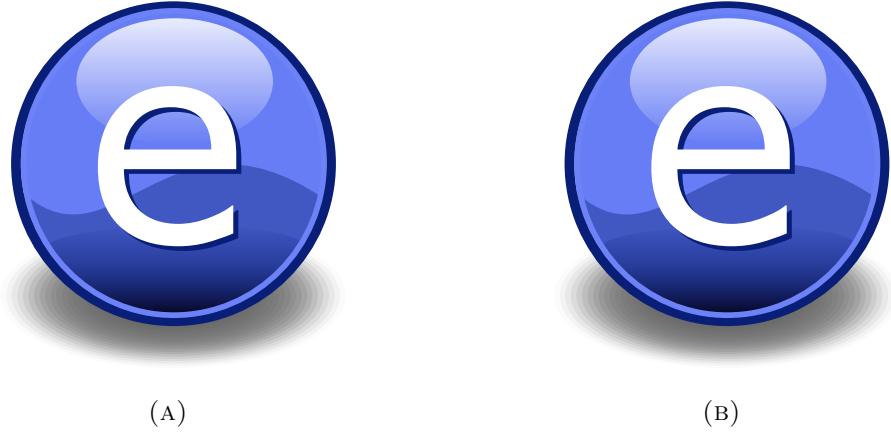


FIGURE 2.1: :

are based on some analysis of the true value of the stock, called the fundamental value. Not surprisingly, these are called fundamentalist strategies.

Whether or not one type of strategy is more accurate than the other, it is a fact that both types are employed by traders. Hence, a model of such an environment needs to simulate both a traded price and a fundamental price.

2.2.1.1 Fundamental price

A common way to model the development of the fundamental price is to use a stochastic random walk process. The idea is that, assuming that markets are efficient, any available information about the stock is already reflected in the fundamental price. When some news arrive, this will quickly cause the price to change according to the nature of the news, as rational traders act to adapt to the new situation. The justification for modeling this with a random walk is that, since the fundamental price already reflect whatever news is available, it will only change as new information is released. In other words, the fundamental price is independent of past information. Since new information is fundamentally unpredictable, a random walk model seems suitable.

The idea behind this is that

2.2.2 Messages

All communication between the market and agents is transmitted in messages. A message sent from agent i to market j (or the other way around) has a transmission time of $\tau_{i,j} = \tau_{j,i}$. The smallest possible transmission time is $\tau_{i,j} = 0$. This means that no information is transmitted instantly between agent and market. $\tau_{i,j}$ is constant through

the simulation. Several message types were implemented in order to accommodate the various types of communication.



FIGURE 2.2

2.2.2.1 Market information

One of the key points of simulating delays is that agents always trade on old information. Before an agent can evaluate its strategy, it has to request the most recent market information. In a model without delays, an agent would simply receive the state of the market in the current round, but when information is delayed the process is somewhat more cumbersome. First the agent sends off a request to obtain the information about the market state. When the request arrives at the market some rounds later, the market serves the request and by sending back another message containing the information. The contents of this message depends on the agent strategy, as the various agent strategies require different information. In the case of a single market, it is reasonable to simplify the model such that the market serves the request instantaneously, since any delay inherent in the market is common for all agents. After a further delay, the message containing the market state finally arrives at the agent, and the agent can then start evaluating its strategy. Figure 2.3 summarizes the procedure.

This is analogous to how



FIGURE 2.3: When an agent wants to submit an order it has to go through several steps of interaction with the market. The process is comparable to how real traders communicate with markets via a network, such as the Internet.

2.2.2.2 Orders

An order is a message which is sent from an agent to a market when the agent has decided to trade. An order is an offer to buy or sell a specified number of shares at a certain price at a certain market. Orders can either be limit orders or market orders. A limit order will only result in a trade to be executed if there is a matching order when it arrives to the market. A market order will stay in the order book until a matching order arrives, or until it expires after a number of rounds set by the submitting agent.

When an agents submits an order, it has to decide on the trade price, the number of shares, limit or market order, and whether to buy or sell. Details on how each type of agent does this can be found in section 2.3.

2.2.2.3 Transaction receipts

When two orders match, a receipt is sent to each of the two agents involved in the trade. The seller receives a receipt specifying the number of shares that it has to deliver, and the buyer gets a receipt for the amount of cash to be paid. Because of the transmission

ASK-volume	Price	BID-volume
------------	-------	------------

TABLE 2.1: TABLE ILLUSTRATING ORDER BOOK

delay, the agents do not update their portfolios when the trade actually happens, but when they receive the receipt. In the case that an agent does not have enough shares or cash in its portfolio, the agent is allowed to borrow the necessary assets, thus bringing its portfolio into negative. An agent cannot submit new sell orders while holding a negative number of shares. Similarly, an agent cannot submit any new buy orders while having a negative amount of cash. In the case that the agent has neither cash nor shares, it simply becomes inactive.

2.2.2.4 Order cancellations

It can happen that an agent wants to change a previously submitted order, or cancel it entirely. In fact, this is what the market maker agent does frequently, as described in section 2.3.2. In this case, the agent issues a message to the market requesting that the order should be removed. Due to the presence of delays, the agent's order might be filled before the cancellation reaches the market, in which case the market will ignore the request to cancel.

2.2.3 Order book

The order book is a record of all unmatched orders for a single stock. Since any buy-and sell orders submitted at the same price will cause a trade to be executed, and the matched orders to subsequently be removed, there must at point of time during the simulation be a non-negative price difference between the sell order with the lowest price and the buy order with the highest price. This difference is called the *spread*, and is denoted as follows

$$s_r = p_r^a - p_r^b \quad (2.1)$$

where p_r^a is the lowest ask price and p_r^b is the highest bid price, both at round r . These prices are also frequently referred to as the *best* ask and bid prices.

When an agent

2.2.3.1 Price updating

Each time an order is added or removed, the order book has to update the best bid and ask prices. Since it often happens that several orders arrive in the same round. This

means that the order book spread can fluctuate within a single round. However, since one round is considered the minimum quantum of time, these within-round fluctuations are not recorded in the order book history. Instead, after all orders have been processed, the resulting best bid and ask prices are registered as the best prices for that round. Agents who look at the market will therefore only be able to see the state of the order book after the book has finished processing all price changes due to the arrival or removal of orders. The subscript denoting time equation 2.1 therefore refers to the prices at the end of that round. This difference between the traded prices and the best prices is shown on figure 2.4



FIGURE 2.4

When no orders arrive or are removed from the order book, the prices are updated as $p_{r+1}^a = p_r^a$ and $p_{r+1}^b = p_r^b$.

Since orders can be removed due to cancellations or because they expire, the order in which incoming messages are processed matters to the outcome of p_r^a and p_r^b . Messages are therefore processed in random orders, so that no agent is favored.

2.2.3.2 Order matching

When a trade is executed between orders o_1 and o_2 , the traded volume is

$$\Delta v = \min(v_{o_1}, v_{o_2})$$

If $v_{o_1} = v_{o_2}$ the orders are *fully matched*, and both are removed from the order book. In the case of a *partial match*, that is, if the volume of one order is larger than the volume of the other, then the order with the smaller volume is removed, and the volume of the other order is subtracted by Δv . The price of the transaction is the price of the market order which was already in the book.

Each agent knows the volume of every order that it submitted, when the order was dispatched. However, when an order is partially filled by a matching but smaller order, the volume of the order at the market changes. Since it takes time for the order to be transmitted for the agent to the market, the agent cannot immediately update its knowledge of the order volume. In this case the order has one volume at the agent side and another in the market side. The momentary disparity of agent market side and agent side volumes can have several consequences, such as agents short-selling without, agents submitting cancellations for orders which have already been filled. Rules that handle these situations are described in section ???. Unlike volumes, the price of a standing market order does not change, and hence the situation of a disparity between market-and agent-side price knowledge does not occur.

2.2.3.3 Empty order book

Since orders are removed when their volume is depleted, it can happen that one or both sides of the order book is empty. XXXWRITE SOME MORE HERE

2.2.4 Market

2.2.4.1 Short selling

Although some market do allow deliberate short selling, this practice is not allowed in the simulation. That is, an agent is not allowed to place a sell order for more stock than it has in its portfolio at the time it places the order. However, due to the presence of delays, it can happen that an agent is required to deliver on a sell order for more stocks than it holds when notified of the order. A sequence of events which causes this to happen is illustrated on figure 2.5. The agent who is short is required to deliver

the stocks, and thus goes into negative on its portfolio, and has to buy back the stocks before it can place further sell orders. Although the sequence of events shown in figure 2.5 may seem unlikely, it did in fact occur frequently, making it necessary to implement handling of this special case.



FIGURE 2.5: The HFT agent submits a sell order for 100 stocks, and another agent submits a price-matching buy order which fills the sell order. Before the transaction receipt reaches the seller, the seller decides to cancel the order, and submit another order at a different price. When the transaction receipt reaches the seller, the agent promptly sends out a cancellation of its second sell order, as it knows it cannot fulfill the order. However, before the cancellation reaches the market, a third agent fills the sell order, and a receipt is send to the seller who ends up being short.

2.3 Agents

The model contains three types of agents, each employing a different strategy. Each strategy has several parameters which greatly impact the behavior of the agent.

The purpose of this work is to model a market in which some agents are much faster than other agents. To this effect, we divide the agents into two groups. The first one is the group of slow traders, which are meant to represent human traders, and algorithmic traders using long-term strategies. The other group is the strategies representing the high frequency traders.

[1]

During the work, HFT agents will often be referred to as being “fast” or “slow” when talking about agents with small or large latencies to the market. While an agent’s latency to the market is unrelated to how fast or slow an agent is (other parameters, such as T_m^i , T_c^i is more related to an agent’s speed), the agent’s latency does determine the delay with which the agent received market information. By fast and slow agents is therefore meant agents that can or cannot respond quickly to new market events.

2.3.1 Slow traders

The purpose of this agent type is to include agents which

The stylized trader model used in this work is inspired by the model used in [1] and [6]. However, due to the fundamental differences in the way that the simulation works, the model has been modified significantly.

Since the stylized trader model is so predominant in the market simulation literature (see [?], [?] etc.), we feel that we need to justify our choice of not using it.

The basic idea of the model is that there are basically three basic techniques that any trader mixes draws upon to form his own strategy.

Fundamental analysis Traders subscribing to this way of thinking believe that they can know the true value of a stock by estimating the fundamental price (see section 2.2.1.1). Furthermore, such traders believe that any deviation from the fundamental price is due to other traders misinterpreting the market, and that such deviations will eventually disappear. In other words, given enough time, the traded price will converge towards the fundamental price.

Technical analysis Traders using technical analysis do not care whether or not the stock is over valued. Instead, they believe that they can predict future price movements from past data. Traditional technical analyst approaches extrapolates on price movements by using simple mathematical models and a good deal of heuristics.

Noise trading Some traders are in possession of insider knowledge, which means that they think that they know something about the stock that others do not. They use this information to trade the stock, for better or for worse. Such traders were dubbed noise traders, since it is highly unlikely that any one individual would come in possession of information which actually gives that person an advantage

in the market. Any such belief is therefore naive, and might as well inflict a loss on the agent than generate a profit.

Whether or not one strategy is better than the others is not for this thesis to discuss. The point is that all three techniques are commonly used among traders, and that rather than subscribing solely to one way of thinking, most people use a mix of all three.

In this model, it is assumed that all slow traders know the true fundamental value of the stock at some time in the past.

aspects of human behavior which influences their decisions to trade. The first one

with the one significant alteration that it uses no historical data. In other words, the model does not simulate the contribution made by chartist speculation. This is justified because of the short time-scales at which the HFTs operate.

As mentioned, chartist strategies work by extrapolating on historical price movements to predict future price movements. However, due to the short span of real-time which the simulation covers, it hardly makes sense to

In our model we preserve the fundamental and noise trader characteristics, but dispose of the chartist element. Although this is contrary to common practice, we justify it as follows. Most chartist strategies operate on a timescale of days to weeks to months. However, the simulation proposed in this work merely simulates a few minutes of real-time¹. Any chartist strategy based on the accumulated history of price movement over a long period of time will simply be too sluggish to follow with the high frequency price fluctuations occurring within the simulation.

It is possible that some traders utilize chartist algorithms on a very short time scale, but any trader employing such a strategy must be fast enough to react to the rapid changes. In order for the model to cope with the presence of such agents, a HFT-chartist agents was implemented as described in section 2.3.3.

Secondly, we are not interested in long term market dynamics. The model is limited to simulating only periods which are of key interest, as is discussed in section 2.7.

However, remembering that the time resolution at which slow traders are observing the markets is so low, that the information that they are watching is close to constant during the simulation. The contribution from a chartist strategy can therefore be represented by a random number. The strategy is therefore simply

¹This is not entirely accurate as each round can be interpreted as an arbitrary length of real-time. However, since we are interested in what phenomena occur when we have some agents which are several orders of magnitude faster than other agents, we need a high time resolution, effectively capping the length of real-time which can be simulated

The stylized traders play the same role as the slow trades in [3]

The orders submitted by the stylized traders throughout the run of the simulation should be thought of as being submitted by a variety of different agents, all observing the same date, but interpreting it differently using different strategies. As for the timing of the order, the same argument goes. In the simulation, a constant number of orders arrive at each round, and sent to the buy- and sell side with equal probability. Thus no attempt is made to model any kind of herding phenomenon, since there is no time in which such a thing could occur.

2.3.1.1 Arrival of orders



FIGURE 2.6: Slow trader order arrive randomly according to a Poisson process. The bars show the volume generated by slow traders. XXXWRITEMORE

2.3.2 Market makers

For the sake of simplicity, each market maker is only allowed to have one order at each side of the order book at the same time. The agent can therefore not stack orders on either side of the order book.

2.3.3 HFT Chartists**2.4 Simulation rounds****2.5 Implementation****2.6 Overview of model parameters****2.7 Experiments**

WRITE ABOUT KEY POINTS OF INTEREST IN TIME

Chapter 3

Parameter tuning

The model has several parameters which must be selected carefully before the simulation can be used to infer knowledge about market behavior.

The parameter tuning turned out to consume a significant amount of time, and simple using a genetic algorithm to optimize over the entire space of parameters was not enough. Instead, the process was a slow and iterative one of running the genetic algorithm to create a data set, analyze the data set to find out what was discovered in the search, and then run the genetic algorithm again with different parameters. Thus several data sets were created, each with the purpose of examining some aspect of the simulation, or of the parameter tuning method itself.

This chapter will cover the instruments used in the optimization of the model parameters, and also mention the machine learning tools used in the analysis of the data sets.

The parameter tuning has two overall goals, which are covered in the following section.

3.1 Motivation and overall procedure

First of all, the model must be calibrated such that it mimics the behavior of real markets. Since virtually every aspect of the simulation behavior depends on the values on the various parameters, these must be chosen carefully in order for the simulation to produce realistic behavior. An example of a simulation untuned parameters causing unrealistic behavior is given in figure 3.1a. Selecting realistic parameters is by far a simple task. First of all, it requires a way of quantifying the quality of each simulation. The choice of such a quantification is discussed in section 3.2.2. Secondly, there might be several different parameter configurations which produce seemingly realistic behavior,

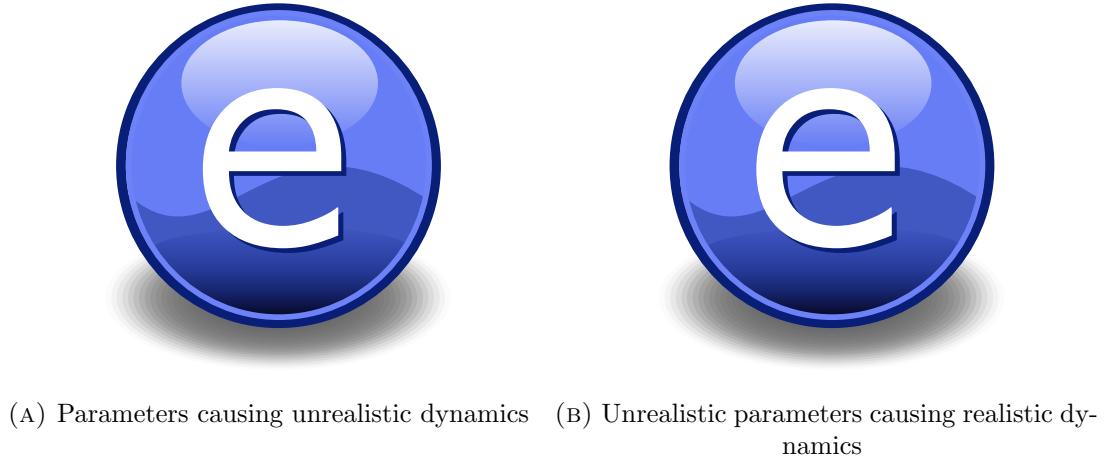


FIGURE 3.1: **Motivatoin for tuning:** the two

but do not correspond to a realistic market setting. An example for this is given in figure 3.1b, and section 3.2.5 briefly discusses this point.

The second goal of the parameter tuning is to find parameters which promotes certain desirable behaviors. For instance, we might be interested in determining which parameters causes the traded price to stabilize faster after a shock to the fundamental price. Metrics for doing this is discussed in section 3.2.2

The selection of parameters is a fairly complicated process because of the large parameter space, and because it takes a significant time to evaluate the fitness of a given set of parameters¹. amount of time to execute a simulation. Because of this, the following three-step parameter selection procedure was used.

1. Fix some of the model parameters in order to reduce the search space for the optimization algorithm. This requires us to consider which parameters can be fixed without losing opportunity to gain insight into market behavior. Essentially this step is a question of prioritizing the optimization of some parameters over the optimization of others.
2. Use an optimization algorithm to find sets of parameters which yield realistic model behavior. A genetic algorithm was chosen for this purpose, and the details are explained in section 3.2.
3. From the set of parameter combinations found by the optimization algorithm, remove the parameter combinations which obviously do not correspond to a realistic setting.

¹The calculation time depends largely on the parameters, such as the number of agents and how active these are. Typically one to several minutes are required to evaluate a single set of parameters.

3.1.1 Selecting fixed parameters

The main parameters of interest are the ones that control the latency and speed of the agents. The agent strategy parameters are less important, since

n_{rounds} Due to the computational cost of running the simulation for a large number of rounds, the the number of rounds is fixed at 10^5 for all experiments.

Order volumes As with most of the other agent parameters, the

The remaining model parameters will either be fixed for each experiment, or varied by the genetic algorithm.

3.2 Inverse simulation with a genetic algorithm

Inverse simulation refers to the technique of specifying metrics measuring model behavior, and then using an optimization algorithm to search for parameters resulting in desirable (or undesirable) behavior.

In this work, a genetic algorithm was used to search the parameter space. The algorithm proceeds as explained below.

1. Generate a population of healthy individuals, e.g., individuals with valid parameters.
2. Evaluate fitness for every individual in the population.
3. Repeat n_{gen} times
 - (a) Generate offspring by crossing existing individuals.
 - (b) Apply mutation to with a certain probability to each individual (parents as well as children)
 - (c) Evaluate fitness of children and mutated parents.

Mutation and crossover are the operators responsible for generating variation in the population, while the selection is responsible for propagating promising individuals to future generation where they might be improved. Several possible methods of performing each of these three steps exist in the literature (see[?], [?]), and section 3.2.3 briefly covers the method and parameters of the genetic algorithm.

3.2.1 Representing parameters as genes

Since the choice of mutation and crossover operators depends on the nature of the genes, the first step towards utilizing to search the model parameters is to decide on how to encode the parameters as individuals. A set of parameters is represented by an individual, i , consisting gene for each parameter, represented by a floating point $g_{i,j}$, where j denotes the index of the parameter. When the population is initialized, each $g_{i,j}$ is drawn from a uniform distributed in the range $g_j \in [0; 1]$:

$$g_{i,j} \sim \mathcal{U}(0, 1) \quad (3.1)$$

Some of the model parameters are integers, such as N_m and N_c , and these are rounded after being scaled and before they are passed to the simulation.

3.2.2 Model fitness

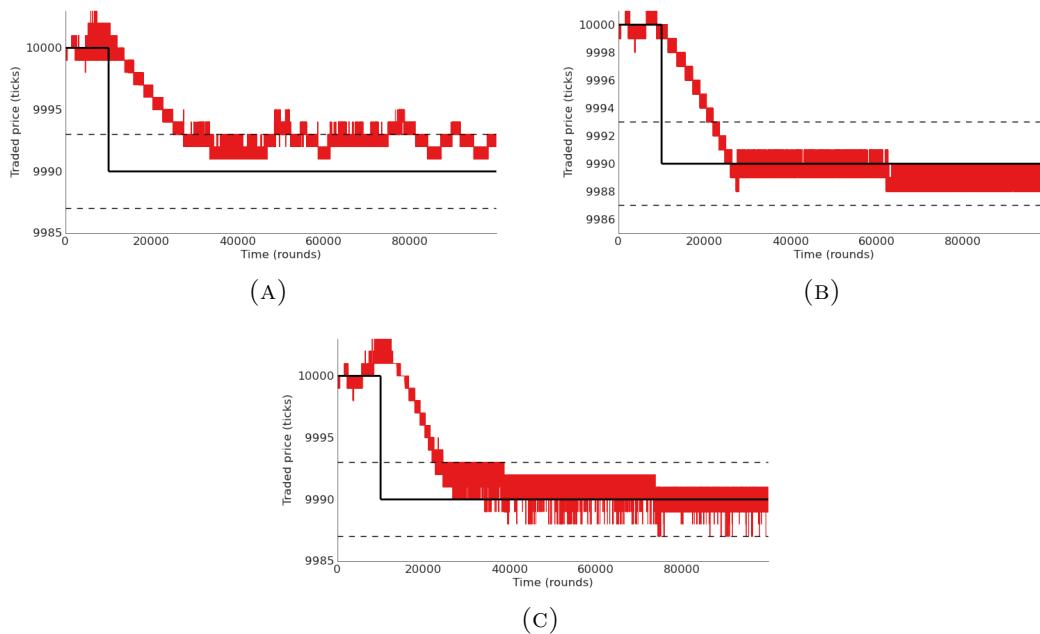
In order to use inverse simulation, it is necessary to decide on how to measure the quality of an instance of the simulation. In this work, the overall goal is to examine which parameter values cause the market to be stable, and which cause it to be unstable.

Another interesting point is the speed with which the market responds to the shock to the fundamental price, and which parameters influence this property. Furthermore, we are interested in investigating whether or not

- 'fit
- Are there certain parameter combinations which cause the market to behave in certain ways. S

In particular the parameters controlling various time delays are of interest. The search space of the parameters is very large, which makes an exhaustive search impossible. To this end, four fitness measures were defined. The balance between the number Several parameters influence the number of orders submitted by the high frequency traders.

f_{mi} f_s This happens when the traded price never leaves the stability margin after reaching the new fundamental price. Note however that this case does not necessarily mean that the prices do not flicker.



f_m or f_s This happens when the traded price leaves the stability margin once or more after reaching the new fundamental. The traded price can be close to the fundamental, but flickers in and out of the stability margin as on Figure 3.2a shows an example where the trade price fairly stable and with no overshoot, leading to good (low) f_σ and f_o fitness values to be assigned to the parameters. However, even though the traded prices are mostly within the stability margin, occasional flickers out of the margin causes the simulation to score a bad (high) f_m fitness. Note also that f_s is undefined in this case.

$f_m = f_s$. This happens if a trade is executed at price $m_{\text{stable}} - p_{\text{fas}} < p^m < m_{\text{stable}} + p_{\text{fas}}$, and another trade is executed at price $p^m = p_{\text{fas}}$ in the same round.

f_o

It is possible for a simulation to be considered stable even before

3.2.3 Genetic algorithm parameters

Although this is a basic version of genetic algorithm, using it correctly is not necessarily easy, as was encountered. First of all, the parameters for the genetic algorithm itself must be established. The larger and more complex the search space, the more resources the search will require, since the evaluating the fitness function (i.e., the running the simulation) will have to be done a larger number of times.

Table 3.1 presents an overview of the parameters used in the genetic algorithm.

Parameter	Assignment
Number of generations	200 to 1000
Number of individuals	100 to 1000
Cross-over points	2
Tournament size	3
Mutation probability	0.1
Mutation distribution	$\mathcal{N}(\mu = 0, \sigma = 0.1)$

TABLE 3.1: Overview of parameters used in the genetic algorithm

Parameter	Range
N_m	
N_c	

TABLE 3.2: Overview of experiments

3.2.4 Controlling market behavior

The four fitness measures defined in section 3.2.2 make it possible to specify the type of market behaviour that is favoured by the genetic algorithm. gives 16 combinatinos for how to optimize the model.

First of all, we are interested in establishing which parameters cause the market to return to a stable state after the fundamental price has incurred a shock

3.2.5 Filtering parameters

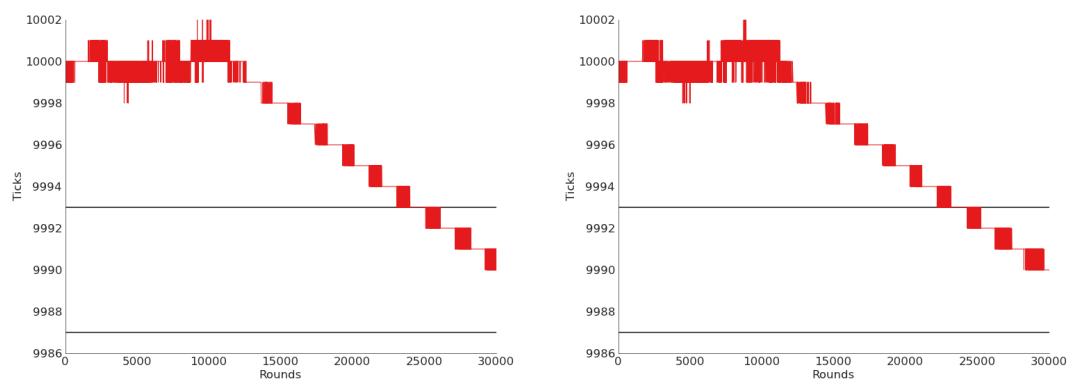
As mentioned earlier, it is not enough simply to define a fitness function which assigns high values to parameters causing realistic behavior. In addition, it is important to discard parameters which obviously do not correspond to a realistic setting. Imagine that the simulation scores high fitness values when executed without any market makers. Since it is known that real markets do in fact contain market makers, nothing can be inferred from such a result. Indeed this might be a consequence of poorly designed fitness measures, but since it is easier to use domain specific knowledge to filter out the unrealistic parameters

3.2.6 Handling failed simulations

Some parameters cause the simulation to act in strange ways, and even crash in some cases. For instance, the the order book becomes empty, the simulation throws an exception and terminates. Similarly, if the best bid/askprices drops to zero, the simulation exits. As such



FIGURE 3.2: Example of a simulation which is assigned fairly good fitness values, but which was executed with clearly unrealistic parameters: $N_m = N_c = 0$. The simulation reaches the new fundamental price fairly quickly without any undershoot, and stays within the stability margin. The only point where it scores badly is the standard deviation which is slightly high due to the fluctuating trade price.



(A) $\lambda_{m,\mu}=49$, $\lambda_{m,\sigma}=8$, $\lambda_{c,\mu}=32$, $\lambda_{c,\sigma}=19$, $f_o=1.0$, $f_s=29210.0$, $f_m=23970.0$, $f_\sigma=0.482$ (B) $\lambda_{m,\mu}=7$, $\lambda_{m,\sigma}=17$, $\lambda_{c,\mu}=21$, $\lambda_{c,\sigma}=17$, $f_o=1.0$, $f_s=28229.0$, $f_m=23146.0$, $f_\sigma=0.5$

The most common odd phenomenon was the market

3.3 Applying the genetic algorithm

Applying the genetic algorithm to produce markets with desirable behavior turned out to be more difficult than one could have hoped for. First of all, the high computational costs was a hurdle.

Secondly, many of the data sets (see section 3.3.3) produced did not contain any useful information.

The model parameters do influence the fitness values as they control model behavior, but they are not directly weighted into the fitness-values. This means that even after the parameters of the genetic algorithm was properly tuned in such a way that higher-fitness individuals were produced, these individuals often turned out to be of no interest. Such individuals were discarded according to the filtering criteria described in section 3.2.5 would have to be discarded. An example of such a case is discussed in section ??

3.3.1 Time complexity

The high time complexity stems from several factors

- Running a simulation for a given set of parameters required up to several minutes of computation on a single CPU core.
- Large number of model parameters increase the size of the search space. The more parameters Unfortunately there is no magic to the way the genetic algorithm works, and optimizing in a larger search means a larger time complexity.
- Large range of parameters. Some of the parameters are integers while some are real numbers. While most of the parameters have a lower bound, none of the parameters have upper bounds.
- Unstable fitness parameters. Since the same set of parameters can produce varying model behavior, the fitness-values may also vary. Therefore it is necessary to evaluate the simulation several times for each set of parameters.
- The model parameters also influence the time complexity. For instance, evaluating a simulation with many agents takes more time than evaluating a simulation with fewer agents.

Genetic algorithms are naturally suited for parallel computation. Two servers with a total of 40 cores and enough memory to evaluate as many simulations were utilized. With this equipment, evaluating a single strategy (see section 3.3.2) for generating data sets could take

reaching a point where the genetic algorithm began to produce useful output turned out to be somewhat of an iterative process.

First of all, the computational cost of running the genetic algorithm was high, which meant that the algorithm was not always able to find better individuals.

Det tager lang tid -*i* faerre params skod resultater -*i* nye eksperimenter

Second of all, even when the genetic algorithm did manage to improve the fitness of the population, this did not always result in useful data.

3.3.2 Experiments: Dividing the search into parts

As mentioned earlier, the number of parameters and the range of each parameter influences the complexity of the search. Because of this, it is desirable to keep the number of parameters that are included in each individual as small as possible. However, fixing parameters means that some interesting properties about the model might not be discovered. Furthermore, varying all parameters at the same time makes the analysis and interpretation of the results more difficult. In an attempt to overcome this dilemma, several “experiments” were carried out ². Instead of trying to optimize all the model parameters at once, the search was split into several parts, each of which we call an experiment. Each of these experiments produce a data set, each of which were analyzed using the methods described in section 3.4. Some of the data sets produced interesting results, while others did not. Chapter ?? focuses on the analysis and presents the findings. A brief overview of the experiments is presented in ??, but since the motivation for creating each data set is best understood in the context of the analysis of each data set, the details are deferred until chapter ?. The next section will explain exactly what a data set is.

3.3.3 Gene pool as data set

The previous sections contain the details of each of the steps undertaken in order to produce data sets. To summarize, the list below enumerates the steps.

²The reason for the quotes is that the term experiment might be stretching the common understanding of what an experiment is a little.

	$\lambda_{c,\mu}$	$\lambda_{c,\sigma}$	N_c	$T_{c,\mu}$	$T_{c,\sigma}$	$H_{c,\mu}$	$H_{c,\sigma}$	$W_{c,\mu}$	$W_{c,\sigma}$	$\lambda_{m,\mu}$	$\lambda_{m,\sigma}$	N_m	$T_{m,\mu}$	$T_{m,\sigma}$
0	84	11	14	98	9	1071	445	38	17	3	2	48	8	1
1	23	21	74	49	24	529	554	45	13	9	0	8	5	3
2	51	13	53	47	13	3586	536	10	11	9	4	14	4	2
3	18	21	213	70	39	793	1179	33	15	7	2	43	6	3
4	94	41	144	10	25	2668	893	12	15	6	1	49	7	4
5	19	4	130	15	38	1085	1165	39	4	2	3	11	4	4
6	65	15	91	81	46	3867	1991	48	1	7	2	21	4	4
7	36	38	143	77	19	2805	1870	10	9	7	0	3	2	4
8	43	8	10	19	19	3384	1706	33	4	8	4	5	5	0
9	11	33	127	94	49	3597	723	12	2	7	1	33	5	4

TABLE 3.3: An example data matrix containing the parameters of ten individuals who lived sometime during the execution of the genetic algorithm. In this case, each individual contained parameters for the number of HFT agents, as well as the latency and thinking time parameters. Hence, the data matrix has a column for each parameter.

1. Initialize a population in the genetic algorithm with healthy individuals.
2. Evaluate the fitness for every individual several times and obtain fitness-values by calculating averages.
3. Stack all individuals that ever lived into a $N \times \mathcal{L}_i$ parameter data matrix \mathbf{P} , where N is the number of individuals, and \mathcal{L}_i is the length of each individual. Likewise, stack the fitness values into a $N \times \mathcal{L}_f$ fitness-data matrix \mathbf{F} , where \mathcal{L}_f is the number of fitness values calculated.
4. Filter the data by removing rows in \mathbf{P} with parameters which can be deemed not to correspond to real markets, and by removing rows in \mathbf{F} with fitness values that are not realistic. Please refer to section 3.2.5 for details. Naturally, when a row is removed in \mathbf{P} , it is also removed in \mathbf{F} , and vice versa.
5. Likewise, data points which were generated by a simulation crashing before it could complete were removed.

Tables 3.3 and 3.4 contain the first rows of \mathbf{P} and \mathbf{F} for one of the data sets.

3.3.4 Convergence of parameters

3.4 Data analysis tools

Using inverse simulation merely creates a lot of data. This data has to be analyzed before any

Data normalization

	f_o	f_m	f_σ	f_s
0	3	25359	0.382092	29838
1	7	99999	1.289659	23373
2	6	99999	1.253363	18748
3	7	99997	1.695150	22819
4	6	94343	1.329276	22703
5	16	99999	2.439084	31860
6	6	93378	1.287235	25645
7	10	99997	1.858166	19417
8	3	24039	0.935465	27381
9	19	99995	4.092439	24845

TABLE 3.4: This table contains the fitness values for each individual in table 3.3. Note that, in order to increase the reliability of the fitness measure of an individual, the recorded fitness-values are the average of the fitness-values obtained by evaluating each individual ten times

3.4.1 Data visualization

It is useful to be able to plot the data points

3.4.1.1 Color toned scatter plots

Scatter plots are useful for initial data analysis, as one can quickly detect problems such as outliers, and maybe even detect clusters of data points.

3.4.2 Preprocessing

3.4.2.1 Handling outliers

The term outliers is often used as a label for data which is considered “invalid” in the sense that is not a product of the true data generation process, but due to various sources of noise. In this report, data that was caused by failing simulations corresponds to the usual understanding of outliers. However, as was already explained in section 3.2.6, data from such simulations are never included in \mathbf{P} and \mathbf{F} to begin with. Instead, outliers in this report refer to entries in \mathbf{P} and \mathbf{F} deviate significantly from the majority of the data points by having extreme values.

Such data points caused problems when applying data analysis techniques which rely on a fairly normal distribution of the data points, such as Principal Component Analysis (PCA). PCA looks for a rotation of the data space, such that the axes of the new basis are aligned with the directions of the largest variance in the original space. Since a few

points with extreme values come to account for a large portion of the data set variance, the new basis computed by PCA will be aligned along these few data points. When PCA is used to extract lower dimensional features from the data set, outliers will degrade the quality of these features. In the case that PCA is used for data visualization, the scatter plots of the first few principal components will not be very informative, as they merely show the projection of the data onto the axes aligned with the outliers.

In all experiments, outliers were present in both the parameters space and in the fitness space. Outliers in the parameter space occur because of abnormally large mutations, and any dimension of the parameter space is susceptible to such an event. In the fitness space, only a few of the features suffered from the occurrence of outliers. The feature f_m cannot contain outliers, because the shock to the fundamental occurs at round $r = 10^4$, and because the simulation is terminated at round $r = 10^5$, hence $f_m \in [10^4, 10^4 + 1, \dots, 10^5]$. The same is true for f_s . f_σ and f_o , on the other hand, are susceptible to outliers, because the two features have no upper bound.

1. Apply a monotonically increasing transformation $f(x)$ to some or all of the features for every data point in the data set. A common choice of f is $f(x) = \log x$, as it efficiently reduces the impact of data points with extremely high values. Figure ?? illustrates the effect of applying the log-transform. The log-scaling does a fairly good job of reducing the importance of the outliers in the f_σ feature, while the change is less dramatic in f_s . While the left scatter plot does not really reveal any structure of the data, the transformation makes it possible to spot to rough clusters when inspecting the right plot.

Another simple method is to manually remove

2. Manually select one or more criteria for when a data point is to be considered an outlier. It is worth noticing that f_o and f_σ
3. Use a one-class support vector machine to calculate a probability for each data point that said point is an inlier or an outlier. In this case, inliers

In the parameters data set, outliers can occur due to abnormally large mutations. Some parameters cause the simulation to act in strange ways, and even crash in some cases. For instance, the the order book becomes empty, the simulation throws an exception and terminates. Similarly, if the best bid/askprices drops to zero, the simulation exits. As such

The most common odd phenomenon was the market

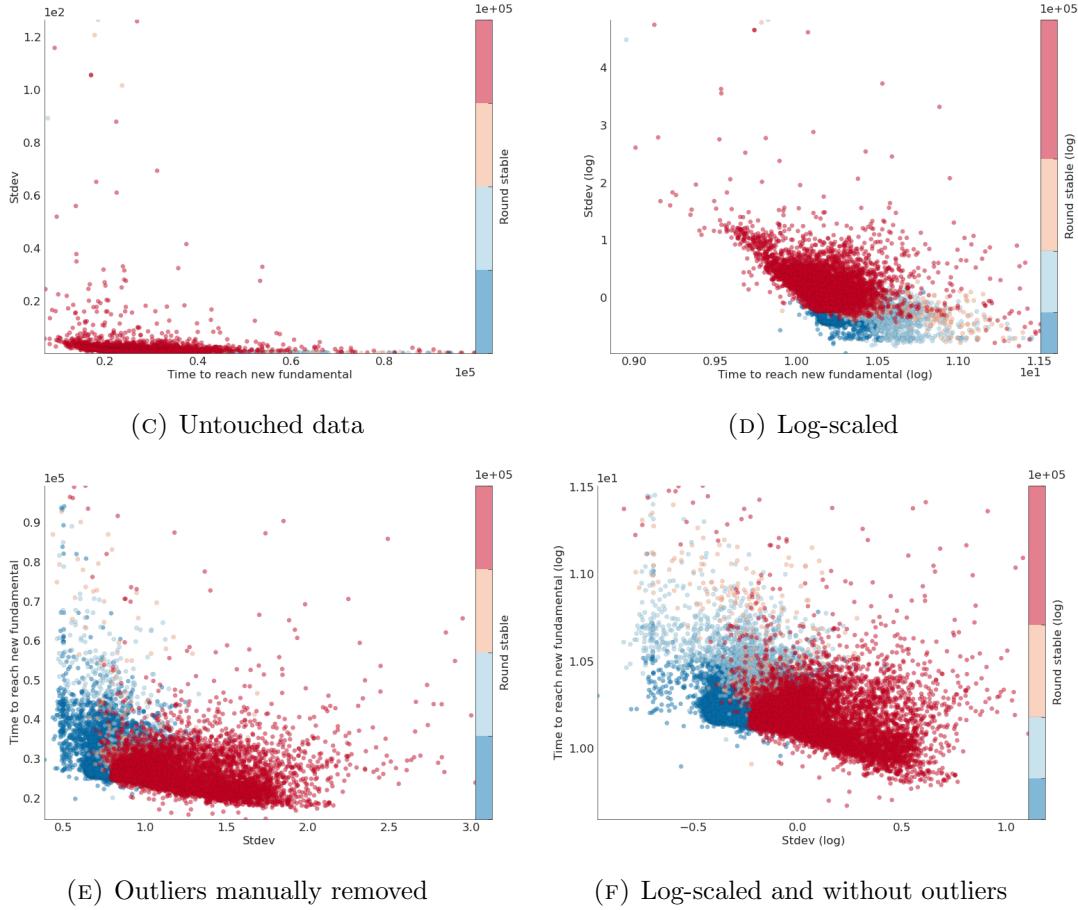


FIGURE 3.3: Color toned scatter plots of f_s , f_σ and f_m taken from dataset d1 after applying log-scaling and manually removing outliers

3.4.3 Clustering algorithms

3.4.3.1 GMM

covariance type:full

Chapter 4

Experiments

As mentioned in the previous chapter, the process of finding was an iterative one of running an experiment, analyzing the generated data, draw conclusions and then repeat the steps with a new experiments designed to amend the mistakes of the previous experiment. This chapter will go through each of these steps and explain the insights that were gained.

This chapter presents the flow of analysis as it was carried out, rather

A summary and discussion of the results is found in chapter ??.

4.1 D3

In this experiment, the number of N_m and N_c as well all the latency parameters were included in the individuals. The genetic algorithm was run for 1000 generations with a population size of 200. A total of

This data set was generated by including all the model parameters concerning time latency as well as the number of agents into the individuals in the genetic algorithm. Due to the high number of variables, the data turned out to be difficult to analyze, as too many factors pertaining to the simultaneous change of several parameters influenced the fitness values. Thus, not many definitive results concerning the impact of time latency of market behavior were derived from this data set. The reason why it is still included in the thesis is that the data did provide hints on how to proceed with the analysis of the model. Furthermore, the data set proved useful for developing the tools used to analyze the data sets that were generated later, and hence this section is intended to illustrate the motivation for applying these tools.

Dataset id	Parameters in genes
d1	$\lambda_{c,\mu}, \lambda_{c,\sigma}, N_c, T_{c,\mu}, T_{c,\sigma}, H_{c,\mu}, H_{c,\sigma}, W_{c,\mu}, W_{c,\sigma}, \lambda_{m,\mu}, \lambda_{m,\sigma}, N_m, T_{m,\mu}, T_{m,\sigma}$

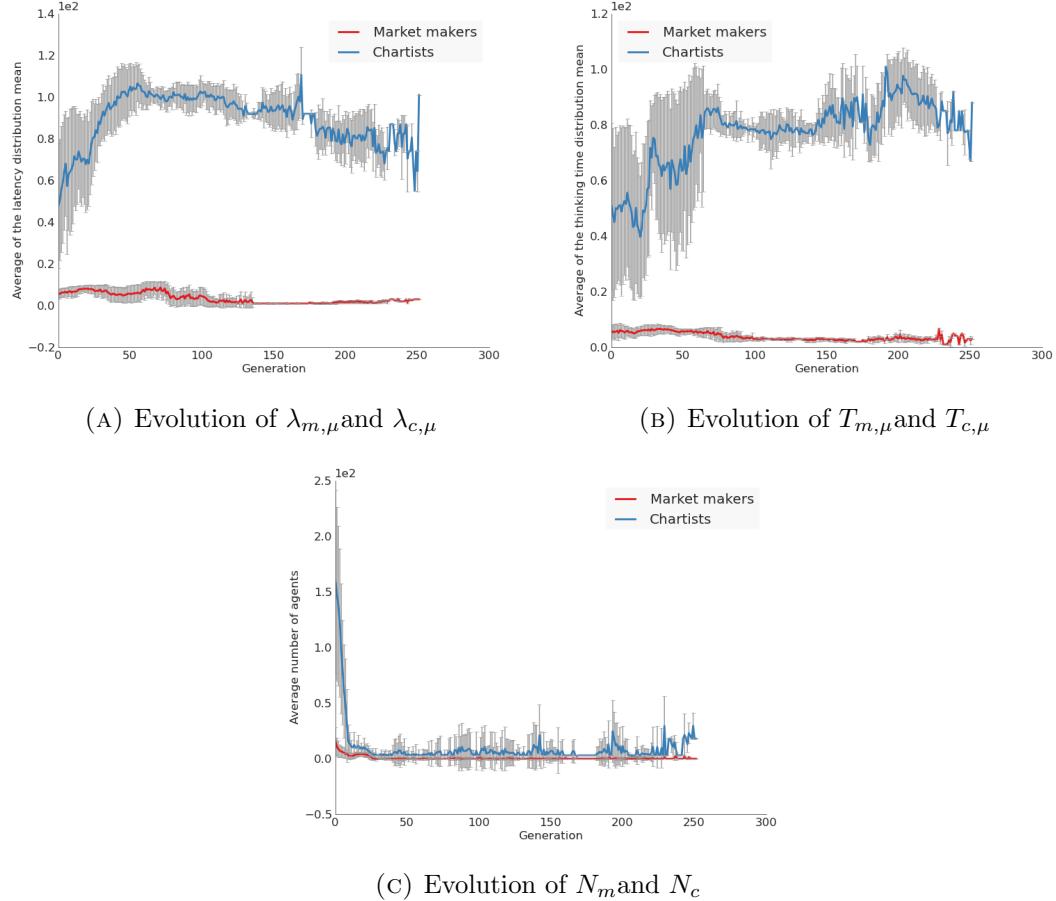


FIGURE 4.1: Evolution of time delay parameters common both HFT agent types, and of the number of agents in experiment d1

Scatter plots of the fitness data before and after preprocessing were already shown in figure ??.

Free parameters:

Data set d1 was the first run of the genetic algorithm that actually produced something that looked like results. The following parameters were included in the genetic algorithm individuals:

$$\lambda_{c,\mu}, \lambda_{c,\sigma}, N_c, T_{c,\mu}, T_{c,\sigma}, H_{c,\mu}, H_{c,\sigma}, W_{c,\mu}, W_{c,\sigma}, \lambda_{m,\mu}, \lambda_{m,\sigma}, N_m, T_{m,\mu}, T_{m,\sigma}$$

Fixed parameters:

EVEN THOUGH ROUND STABLE AND TIME TO REACH NEW FUNDAMENTAL SEEM SIMILAR, THEY ARE NOT CORRELATED SO MUCH. WRITE ABOUT

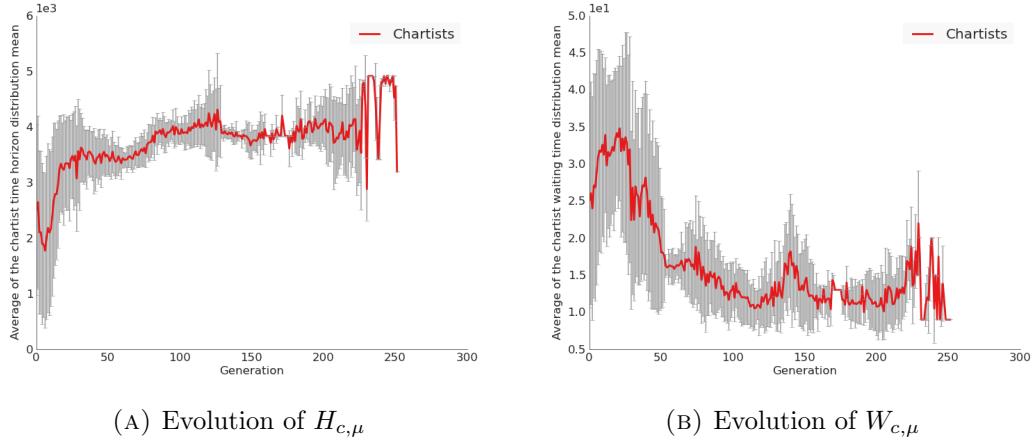


FIGURE 4.2: Evolution of chartist-specific strategy parameters in experiment d1

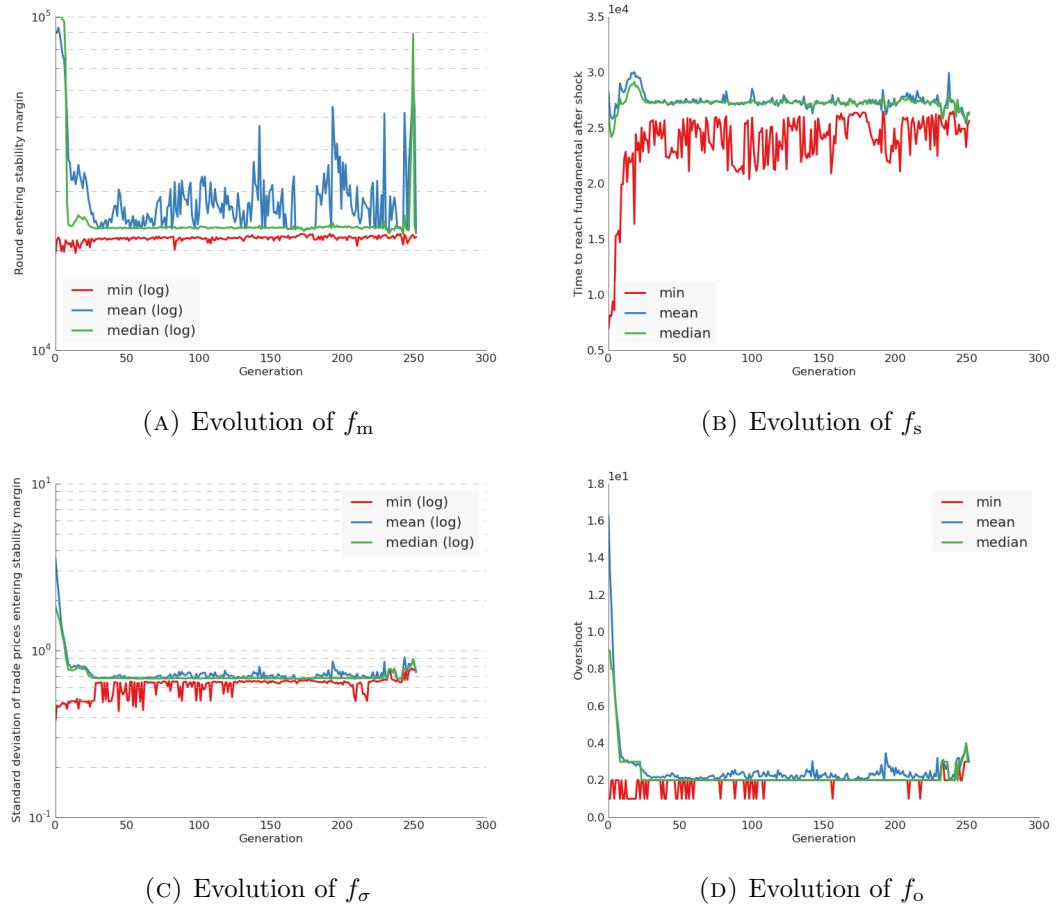


FIGURE 4.3: Evolution of the four fitness measures in experiment d1

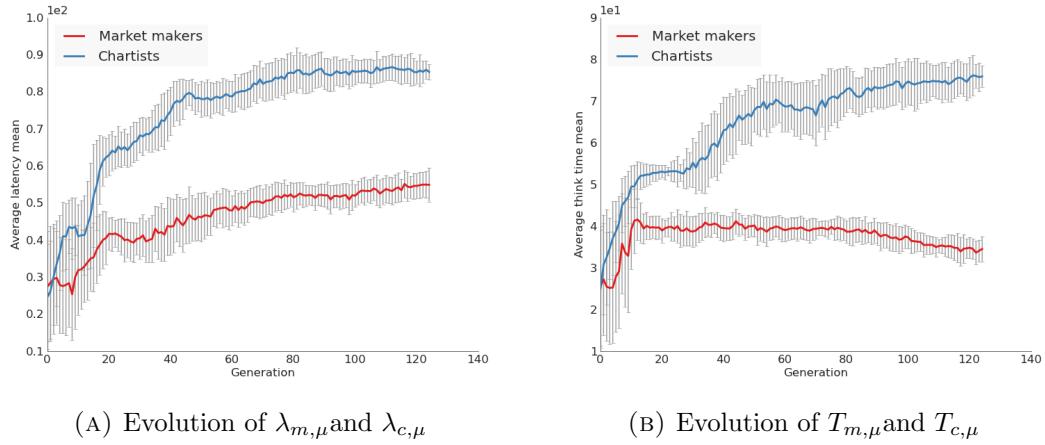


FIGURE 4.4: Evolution of time delay parameters common both HFT agent types in experiment d1

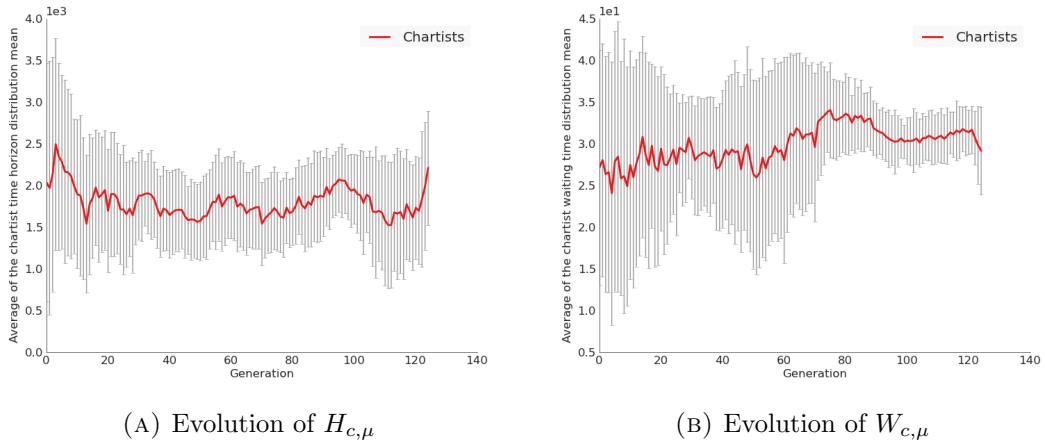


FIGURE 4.5: Evolution of chartist-specific strategy parameters in experiment d9

WHAT THIS MEANS (e.g. some markets reach new fundamental quickly, but never become stable, etc.)

4.1.1 Section summary

In summary, the main problem with this data set was that it contained mostly simulations with few or no high frequency traders.

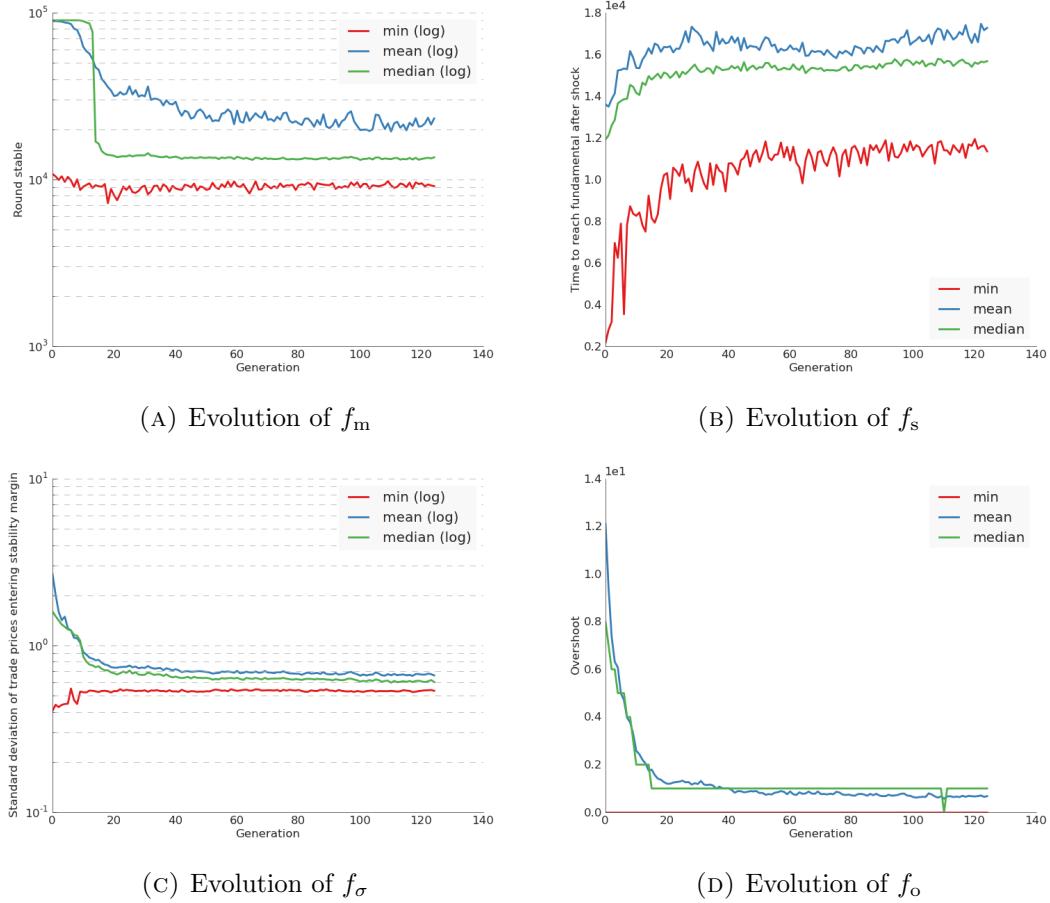


FIGURE 4.6: Evolution of the four fitness measures in experiment d9

4.2 D9: Fixing the number of high frequency traders

4.2.1 Parameter and fitness evolution

4.2.2 Visualizing the data set

Scatter plots are probably among the most rudimentary of techniques for data analysis, yet they can be incredibly informative, especially when the data that is visualized is low-dimensional. The two plots in figure make two things clear. First of all, extreme values occur in f_σ . Even log scaling does not seem to fix this problem entirely. Second of all, XXXissue109XXX

The high correlation between f_σ and f_o can be interpreted in two ways. The sparsity of points with extreme values shows that it rarely

1. It rarely happens that a market has a large overshoot, and then returns to a stable state (large f_o , small f_σ)

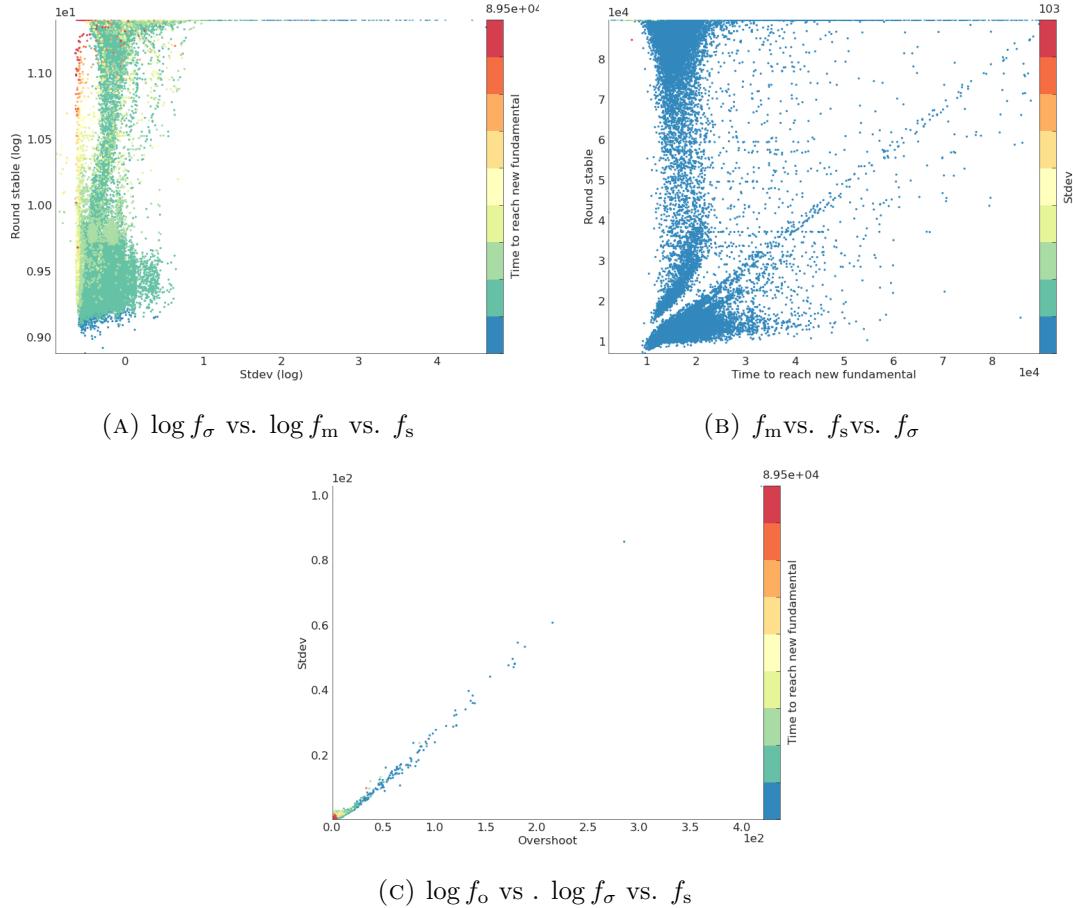
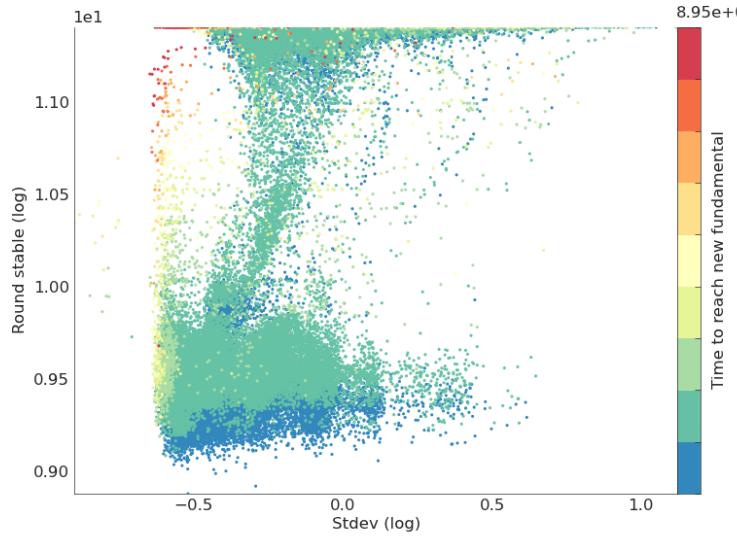
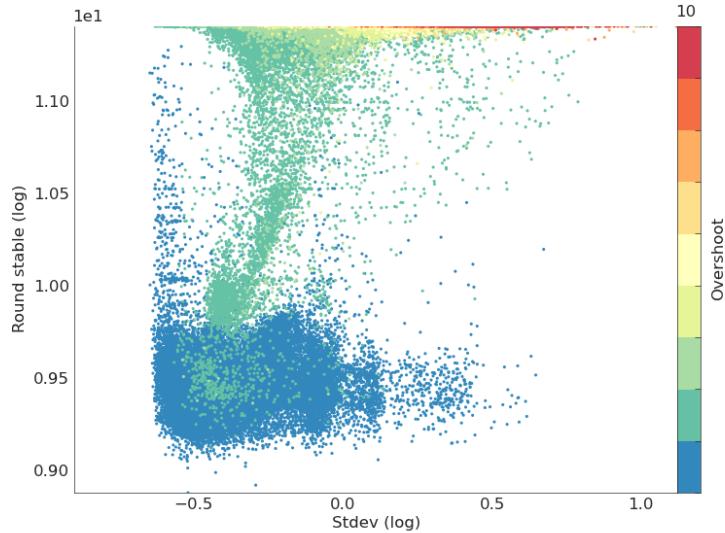


FIGURE 4.7: Scatter plots of fitness measures in experiment d9.

2.

For the purposes of data analysis, the high correlation between f_σ and f_o means that it is possible to reduce the number of dimensions in the fitness space from four to three without loosing any significant classification power. This can be done by discarding either f_σ or f_o .

The scatter plots do seem to reveal some structure, the presence of large values in the f_σ feature obscures the nature of this structure, in spite of the logarithmic scaling. The plot showing $\log f_\sigma$ vs. $\log f_m$ is squeezed to the left, and the color grading on the scatter plot for $\log f_o$ vs. $\log f_\sigma$ reveals no variety in the f_σ feature. In an attempt to get some more information out of the scatter plot, data points with a more than 100 % overshoot (corresponding to $f_o > 10$) are removed. The resulting scatter plots for the reduced data set are shown and discussed in the section 4.2.3.

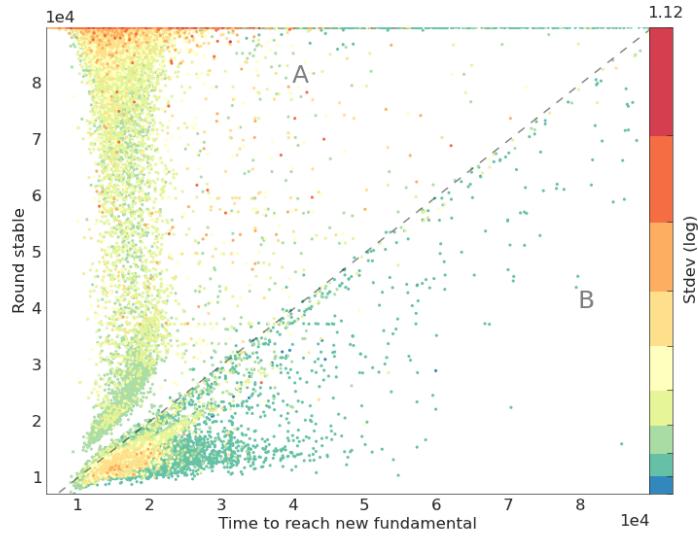
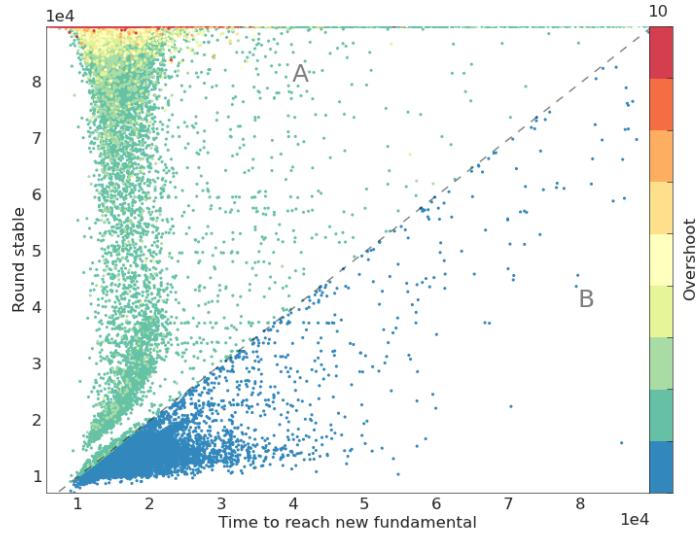
FIGURE 4.8: Scatter plot of $\log f_\sigma$, $\log f_m$ and f_s FIGURE 4.9: Scatter plot of $\log f_\sigma$, $\log f_m$ and f_o

4.2.3 Analysing scatter plots

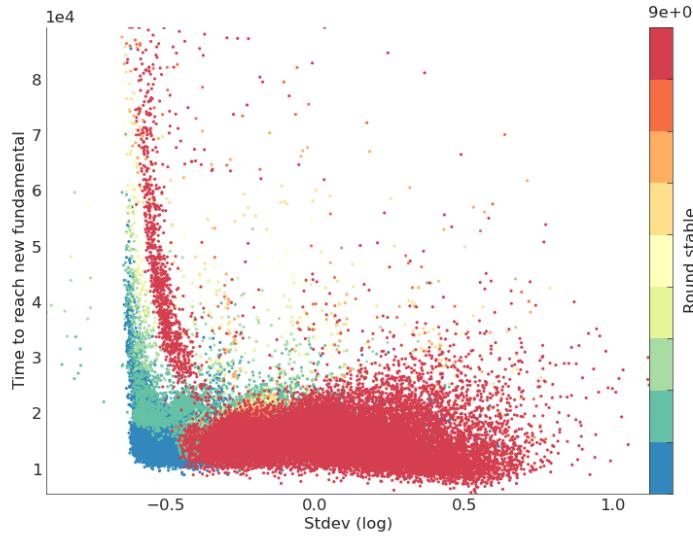
4.2.3.1 f_m vs f_σ

4.2.3.2 f_m vs. f_s

The line $f_s = f_m$ (black dashed line) divides figure 4.10 into region A, (upper left triangle) and region B (lower right triangle). Region A contains the fitness-points of the simulations which are counted as stable *after* they reach the new fundamental, and region B contain those that become stable before. Comparing with

FIGURE 4.10: Scatter plot of f_m , f_s and f_σ FIGURE 4.11: Scatter plot of f_o , $\log f_m$ and f_s

1. In figure 4.10, the density of points is slightly higher around the region defined by $f_m = f_s$. This is true both for small and large values of f_s and f_m . Furthermore, these points all have small values for f_σ . The same points can be identified by looking at figure ??, where a cloud of points lay around the vertical line $\log f_\sigma \approx -0.6$.
 - (a) The low f_σ also means that the traded price is stable after entering the stability margin. Furthermore, the simulations represented by these same points are among the ones with the most stable traded prices.

FIGURE 4.12: Scatter plot of f_m , f_s and f_σ

- (b) Since $f_s \approx f_m$, the traded does not leave the stability margin once it has entered. This is true for both small and large values of f_s and f_m .
- 2. In figure 4.10 The density seems high in the region defined by the inequalities $0.2 < f_s < 0.3$ and $f_m > 0.25$.
 - (a) Simulations in this group reach the new fundamental quickly (less than $2 \cdot 10^4$ rounds after the shock), but then leave the stable region again.
 - (b) The simulations which take a longer time to become stable also have less stable traded prices (higher values of f_σ)

4.2.3.3 f_σ vs. f_s

- 1. The two large clusters of red points in figure ?? are all the simulations which never became stable during the simulation. The horizontal cluster contain the simulations which responded quickly to the shock by taking only between 10.000 and 20.000 rounds. This cluster contains simulations with both high and low f_σ values, indicating varied behavior.
- 2. The spike of points on the right side of the cluster are simulations that did become stable, but did so slowly and with no overshoot, as is seen by observing that all the points in the cluster are blue when the color indicated the value of f_o as in figure 4.13.

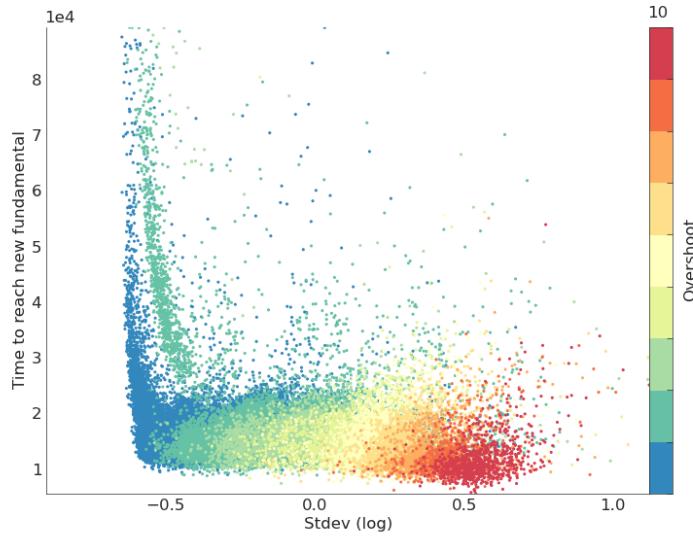
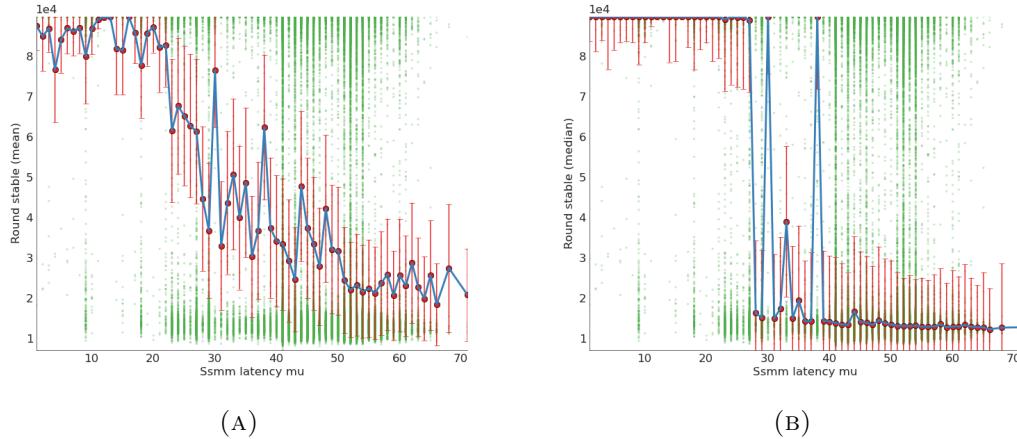
FIGURE 4.13: Scatter plot of f_m , f_s and f_o 

FIGURE 4.14

The next section seeks an answer to the question of whether or not there are model parameters which cause the model to behave in certain ways. In other words, is it possible to make predictions about the model behavior based of the model parameters?

4.2.4 Looking for parameters causing certain behavior

In order to answer the question posed in the end of the previous section, we can divide the data points into groups based on their fitness values, and then calculate descriptive statistics for the parameters of the points belonging to each group.

The easiest first step is to do that for the outliers and inliers.

As manually labeling hundreds of thousands of data points is not really an option, clustering algorithms were used to separate the fitness data into groups with distinct characteristics.

4.2.5 Section summary

4.3 D10

In the previous section, some weak tendencies The scatter plots for d10 are somewhat similar to those of d9, and they have therefore been placed in appendix C

Note that the definition of “nice” market behavior is, of course, qualitative in nature. In this experiment, as well as in d9 and d10, the search for such nice behavior was carried out by minimizing all four fitness measures, as nice market behavior was taken to be a market that . Whether this can be accomplished by the model or not is a question that can only be answered by running the

If, say, a fast reaction on the cost of a larger overshoot, one could search for such behavior by omitting f_o from the optimization criteria.

Figure 4.15 shows the evolution of the four fitness measures. The population wide mean is plotted along the median and minimum statistics. Since all four fitness measures were minimized, the curve for the minimum value shows the best individual alive during each generation, with respect to each fitness measure. While the mean reflects how the overall population is evolving, the median is useful as it gives an insight into how skewed the population wide distribution of parameters is.

4.3.1 Fitness and parameter evolution

Figure 4.15 show the evolution of the population wide mean, median and minimum statistics for each of the four fitness-measures.

Model stability Figure 4.15a: shows that the GA quickly manages to find some parameters which cause the simulation to stabilize quickly. However, these individuals do not manage to dominate the population evident by the mean and median curves remaining almost the same until generation 30 or so. In the next 20 generations the population undergoes a rapid change, as the population wide average of f_m drop from close to 10^5 to around $2 \cdot 10^4$ rounds on average. The disparity between the mean and the median indicates that the population undergoes a rapid

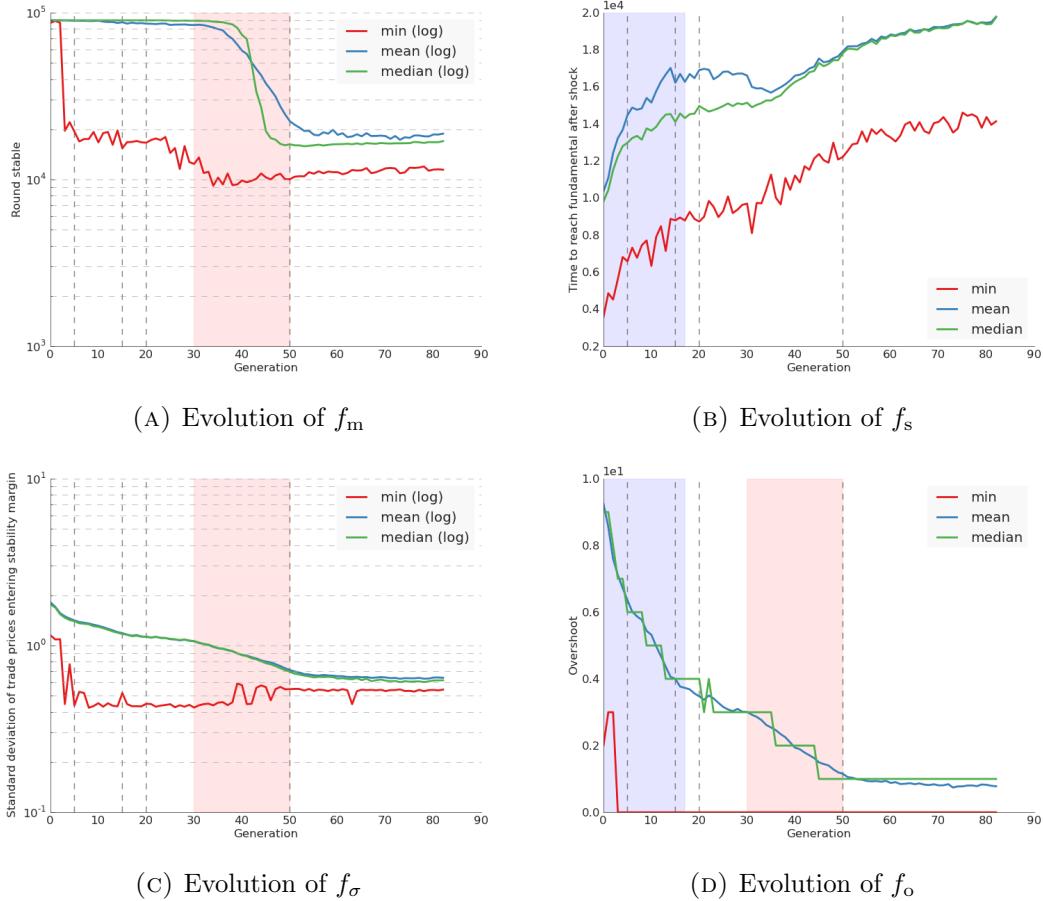


FIGURE 4.15: Evolution of the four fitness measures in experiment d10

change in the same period, from mostly containing unstable individuals to mostly containing stable individuals. In generation 42, the median curve crosses the mean curve, which means that the population contain as many stable simulations as it contain unstable simulations. From that point on the unstable simulations are quickly replaced by stable individuals.

Price fluctuations and overshoot During the same period, the population average f_σ also decreases fairly rapidly, but the drop is less pronounced than the drop in f_m . As figures 4.16a and 4.16b show, the number of market makers rapidly increased during this period, as did the average latency of the market makers. Since the mean and median are close in both figure¹, the mean is representative of the evolution of the entire population.

Responsiveness f_s measures the time it takes for the model to react to the shock in the fundamental, and the evolution of the population wide statistics is shown on figure 4.15b. Although the GA is instructed to minimize f_s in order to look for more

¹Since f_o is discrete, the median and min statistics are also discrete

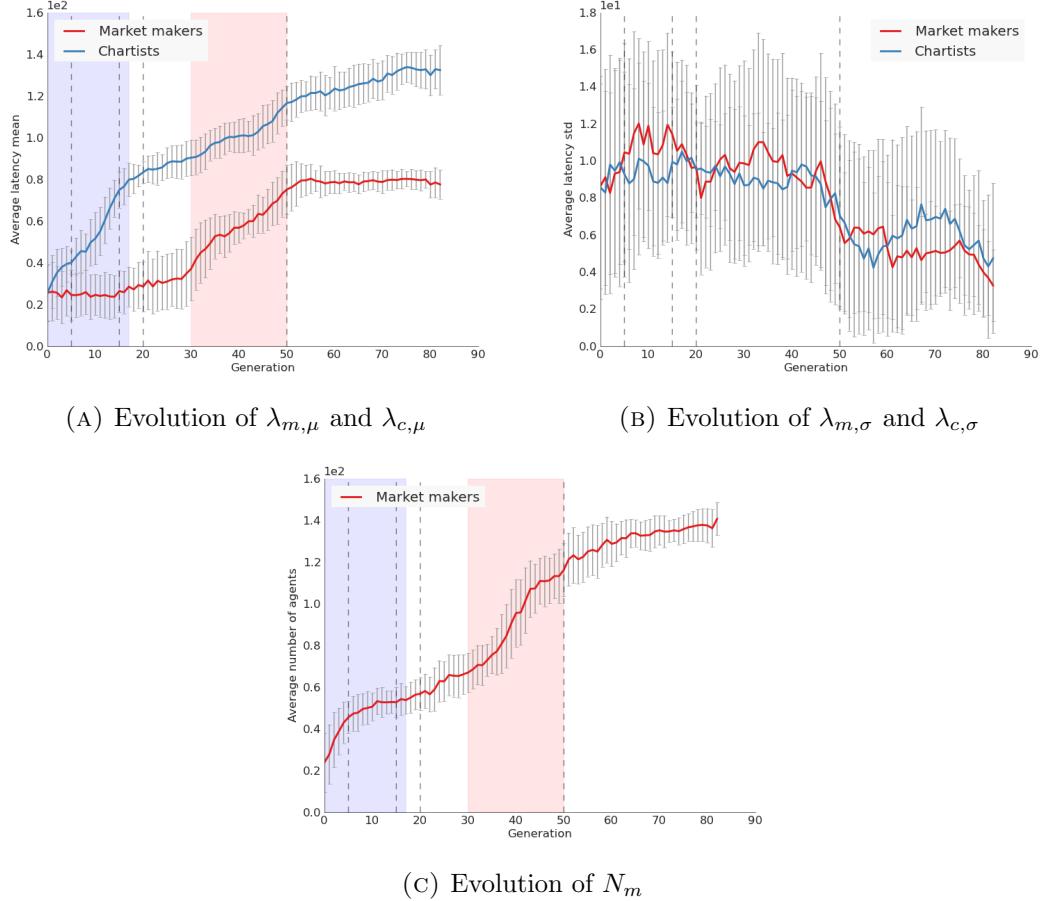


FIGURE 4.16: Evolution of the model parameters in experiment d10

faster models, it clearly fails to do this. Indeed, the most responsive simulation took only about 4000 rounds to reach the new fundamental, but this individual died out in favor of slower individuals. In the last generation the most responsive simulation took around 14000 rounds to reach the new fundamental. The reasons for this failure to locate responsive models is discussed in section 4.3.2. In the A large change of the average of f_s happens in the rounds five to 15. In this period, the median is lower than the mean, which means that the growth in the mean can be attributed to a minority of individuals.

On figures 4.15 and 4.16, the two areas shaded in a light blue and light red respectively show the two periods during which there was a drastic change in parameters and fitness-values. By comparing the time at which parameters and fitness-values change, it is possible to get an idea of how parameters influence the fitness-values. To that end, figure 4.16 shows the evolution of each of the parameters that were varied by the GA².

²Since the median was found to follow the mean nicely for all the parameters, the medians are not displayed. Also, the gray error bars show the population wide variance

The two periods indicated by the shaded squares seem to reflect some sudden changes in the parameters.

Average agent latency As is shown on figure 4.16a, individuals containing large latency parameters are selected for both HFT market makers and HFT chartists. $E_p[\lambda_{c,\mu}]$ grows quickly during the first 20 rounds (blue shade). Referring back to figure 4.15, it is seen that $E_p[f_s]$ and $E_p[f_o]$ grows and shrinks respectively. As for $E_p[\lambda_{m,\mu}]$, it grows from rounds 20 through 50 (red shade), and this seems to be strongly reflected in the growth of $E_p[f_m]$, and to a lesser degree a decline in $E_p[f_o]$ and $E_p[f_\sigma]$. Furthermore, the small size of the error bars on both curves show that the population consistently moves towards containing more individuals with larger latency parameters for both HFT agent types. While initially $E_p[\lambda_{m,\mu}] \approx E_p[\lambda_{c,\mu}]$, the population wide mean $E_p[\lambda_{c,\mu}]$ ends up being roughly 1.5 times larger than $E_p[\lambda_{m,\mu}]$. Finally, note also that the growth of $E_p[\lambda_{c,\mu}]$ and $E_p[\lambda_{m,\mu}]$ seem to be somewhat independent, as they sometimes grow together, sometimes not.

Number of market makers The number of market makers increases almost every generation, but grows especially quickly through rounds 20 to 50 (red shade)

Agent latency variance Figure 4.16b: The trends for $E_p[\lambda_{c,\sigma}]$ and $E_p[\lambda_{m,\sigma}]$ are less clear, as the population-wide variances $\text{Var}_p[\lambda_{c,\mu}]$ and $\lambda_{m,\mu}$ illustrated by the large error bars are high compared to the change in $E_p[\lambda_{c,\mu}]$ and $E_p[\lambda_{m,\mu}]$. While this could mean that the simulation behaves more nicely when the difference between the latency parameters of the trading agents is smaller, further experiments would have to be carried out to confirm this fact. XXX

In summary, the genetic algorithm prefers simulations with many, but relatively slow market makers. Apparently simulations with slow chartists also outperformed those with fast chartists, but since the number of HFT chartists was fixed at $N_c =$, this experiment does not reveal how the simulation would perform with more (or less) chartists. It is possible to imagine that the market would perform just as well with a few and fast chartists. Section ?? contains the analysis of an experiment in which the number of chartists were varied. The discussion above can be summarized as follows:

1. The responsiveness of the market is influenced by latency of the chartists. Slower chartists made the market require more time to respond to the fundamental shock.
2. The time it takes for the market to become influenced by the number of market makers and on the latency of the market makers. More but slower market makers seems to make the market settle within the stability margin faster.

3. The overshoot, as well as the average size of the price fluctuations of the market, are both influenced by the latency of both agent types, as well as the number of market makers.
4. The market was more stable but reacted slowly when the chartists were slower than the market makers.

The accuracy of the above analysis is limited as it only looks at population wide statistics at a given point in the duration of the GA. The following section contain an analysis in which the generation to which each data point belongs is considered irrelevant. The analysis will try to confirm each of the four statements above.

4.3.2 Correlation between fitness measures

A factor which influences the evolution of parameters is correlation between the fitness-measures. If two or more fitness measures have non-negative correlation coefficients, individuals will be statistically more likely to get good scores in the correlated fitness measures at the same time. Since all fitness measures are given equal weight in the selection process, individuals scoring well in the correlated fitness-measures will win over individuals which score well on another, statistically independent fitness measure. It is therefore important to compare the selection tendencies with the correlation between fitness-measures. Figure 4.17 shows a plot of the correlation matrix for d10. Since later generations will be affected by the biased selection and therefore contain more individuals which did well on the correlated fitness measures, the correlation coefficients in the figure were calculated over individuals in the first generation only.

For instance, the correlation between f_o and f_σ means that an individual which scores a good f_o -fitness will be statistically likely to also score a good f_σ -fitness. Since all four fitness measures are weighed evenly in the selection, models with behavior which is assigned good values for f_o and f_σ will score a better overall fitness than a simulation with a good fitness

In other words, the correlation between f_σ and f_o means that stable individuals will outlive fast individuals as they are selected for breeding more often. This is not a property of a model itself, but rather a problem with the definition of the fitness measures. This problem can be circumvented by not using of the correlated fitness values. XXX

Both f_o and f_σ were used for the GA selection, and although these two fitness measures do reflect different properties of the simulations, they were found to be somewhat correlated. That is, a simulation which tends to have a small overshoot also tends to have stable traded prices.



FIGURE 4.17: Correlation matrix of the four fitness measures in the first generation of dataset d10

(simulations with a small overshoot also tend to have more stable trade prices), and there work together towards selecting the same type of simulations. f_s and f_m both The same is not the case for f_s and f_m , as it is possible that a simulation responds quickly to the shock, but does not stay within the stability margin.

4.3.3 Parameter-fitness correlations

This section will

Each of the four fitness measures has been plotted against $\lambda_{c,\mu}$, $\lambda_{m,\mu}$ and N_m on figures 4.18, 4.20 and ??, respectively. Each green dots are the data of a single simulation. The solid curve shows the estimated conditional mean of the fitness given the parameter, and the error bars show the estimated conditional variance. Figures of the four fitness plotted against $\lambda_{c,\sigma}$ and $\lambda_{m,\sigma}$ did not reveal anything of interest, but have been included in appendix ?? for reference.

It is important to keep in mind that the statistics were calculated by conditioning over just a single parameter. As such, it is not possible to deduce anything about the way that the parameters work together.

Chartist latency

The list below briefly summarizes the results shown by figure 4.18.

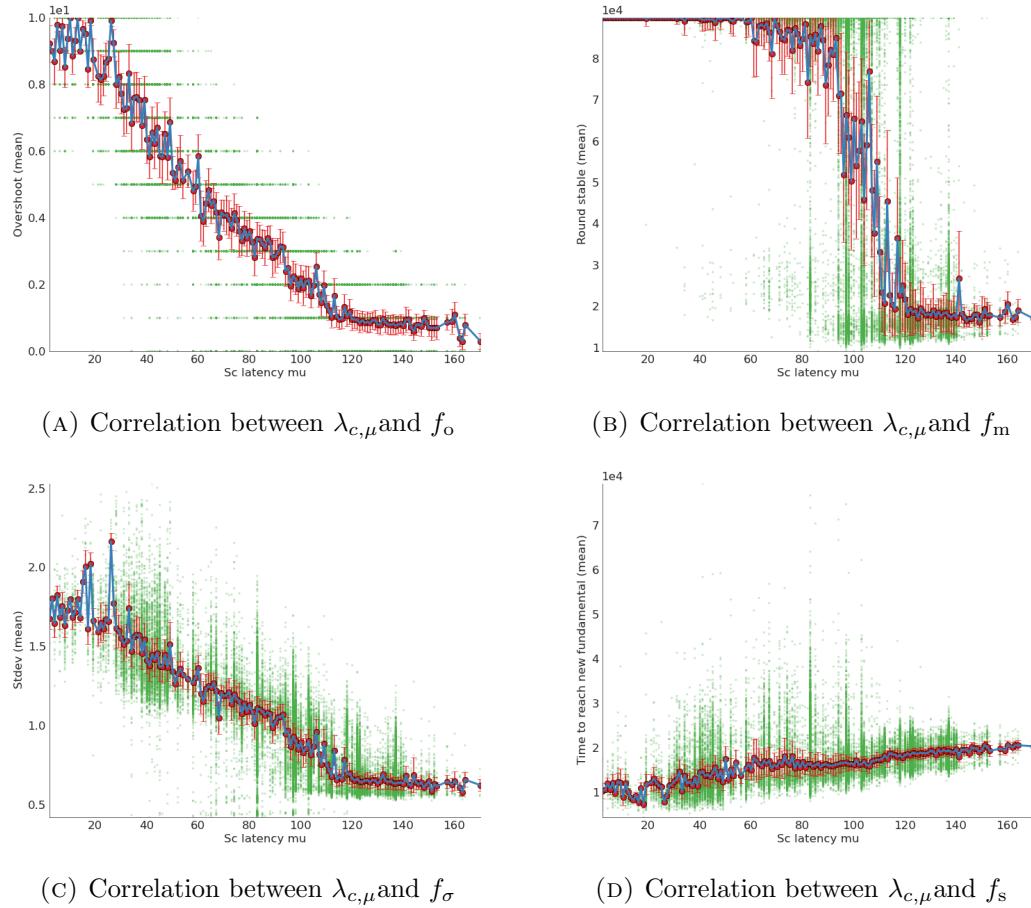
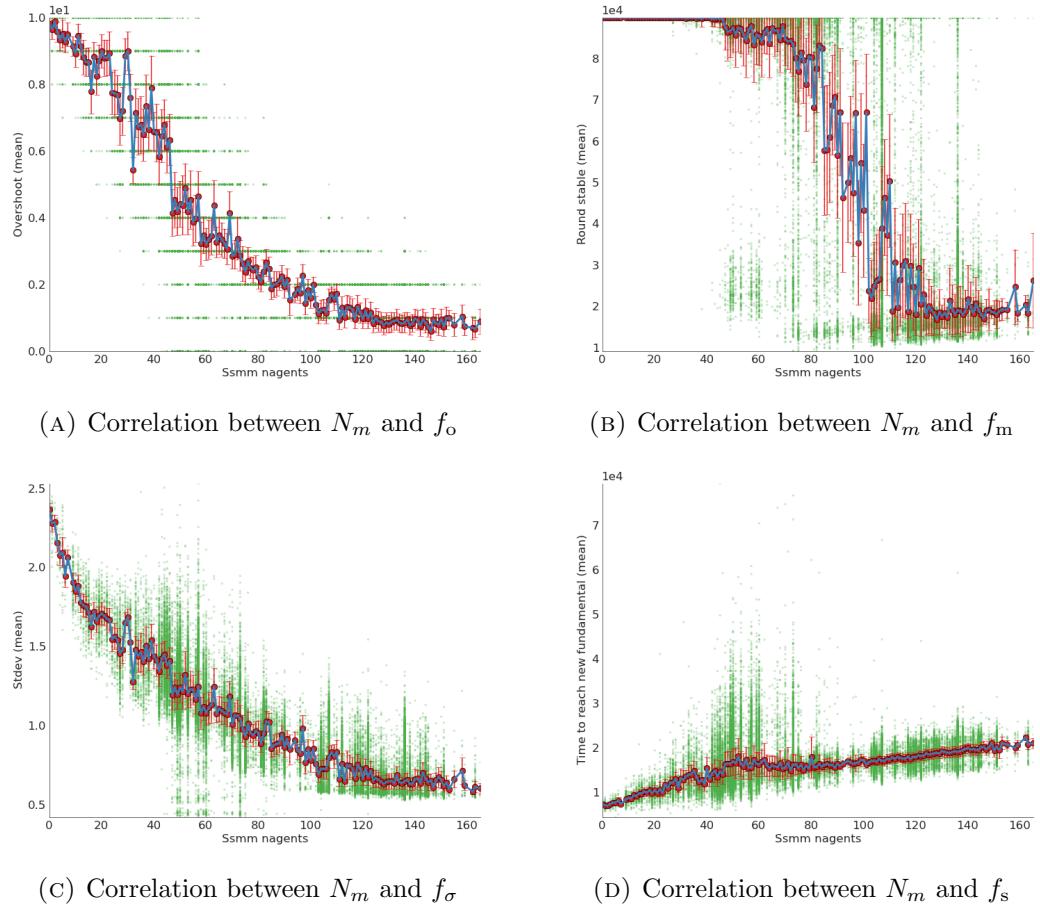


FIGURE 4.18: Correlation between $\lambda_{c,\mu}$ and the four fitness measures in experiment d10

Figure 4.18a shows that $\lambda_{c,\mu}$ is negatively correlated with f_o , such that markets with faster chartists are more likely to have a larger overshoot. Since all simulations with $f_o > 10$ were considered outliers and therefore removed, the vertical axis is limited to $f_o = 10$. Next, figure 4.18 shows that $\lambda_{c,\mu}$ is negatively correlated with f_σ , such that markets with faster chartists are more likely to have flickering trade prices.

As for the market responsiveness, it is seen that $\lambda_{c,\mu}$ is positively correlated with f_s , such that markets with faster agents are more likely to have a shorter response time to the market. Figure 4.18d confirms that markets with fast chartists did actually manage to reach the new fundamental price faster than those markets having slow chartists. The average response time of markets in which the chartists had a latency of less than 30 rounds was around 18000 rounds, whereas it was around 25000 rounds with chartists with more than 100 rounds of latency. The market response time is most sensitive in the range $20 < \lambda_{c,\mu} < 60$, and does not change much for larger latencies.

The plots of f_o , f_σ and f_s show that predicting the three fitness measures in markets with slow chartists would be more accurate than for markets with fast chartists, as the

FIGURE 4.19: Correlation between N_m and the four fitness measures in experiment d10

correlation of f_o , f_σ and f_s with $\lambda_{c,\mu}$ is stronger for larger values of $\lambda_{c,\mu}$.

Figure 4.18b shows that $\lambda_{c,\mu}$ is positively correlated with f_m , but also that the relationship between $\lambda_{c,\mu}$ and f_m seems highly non-linear. The figure illustrates the binary nature of the stability criteria, that is, that a simulation is either stable or not stable. This causes f_m to have a high conditional variance of f_m given $\lambda_{c,\mu}$ in the region $50 < \lambda_{c,\mu} < 120$, meaning that prediction of f_m from $\lambda_{c,\mu}$ in this region would not be very accurate. What this means is that the stability of a simulation is highly dependent on factors other than $\lambda_{c,\mu}$, when the parameter is within 50 to 120 rounds. When the chartists are faster than 50 rounds, the market is almost always unstable, and when the chartists are slower than 120 rounds the market is almost always stable.

Number of market makers

Figure 4.20, showing the how the number of market makers correlates with the model fitness, is quite similar to figure 4.18. A large number of market makers reduces the overshoot, whereas the virtually always have an overshoot when there are little or no

market makers. The same is true for the flickering of the trade prices: few market makers always means flickering prices. A higher number of market makers makes the market less responsive, while fewer market makers makes the market more responsive. Finally, the number of market makers also influences how quickly the market settles within the stability margin, as markets with more market makers become stable faster than markets with few agents. However, figure 4.20b shows that it sometimes happens that a market with few market makers becomes stable quickly.

1. When the market has fast chartists, it needs more market makers to keep the market stable, but these may be slow.
2. When the market has fast chartists, the market first of all needs fast market makers to be stable.
3. A market with few market makers can be stable if the market makers are fast, or if the chartists are slow.

Market maker latency

The market almost never has any overshoot, irregardless

The tricky thing about this

2. The time it takes for the market to become stable depends on the number of market makers and on the latency of the market makers. More and slower market makers seems to make the market settle within the stability margin faster.

4.3.3.1 Number of chartists

4.3.3.2 Chartist- to market maker ratio

3. The overshoot of the market seems to be influenced by all three factors, as did the fluctuations of the traded prices.

As figure 4.18a shows, the overshoot seems to be highly correlated with the latency of the chartists.

4.18c and 4.19a 4.19c

and somewhat true for

4.19a and 4.19c

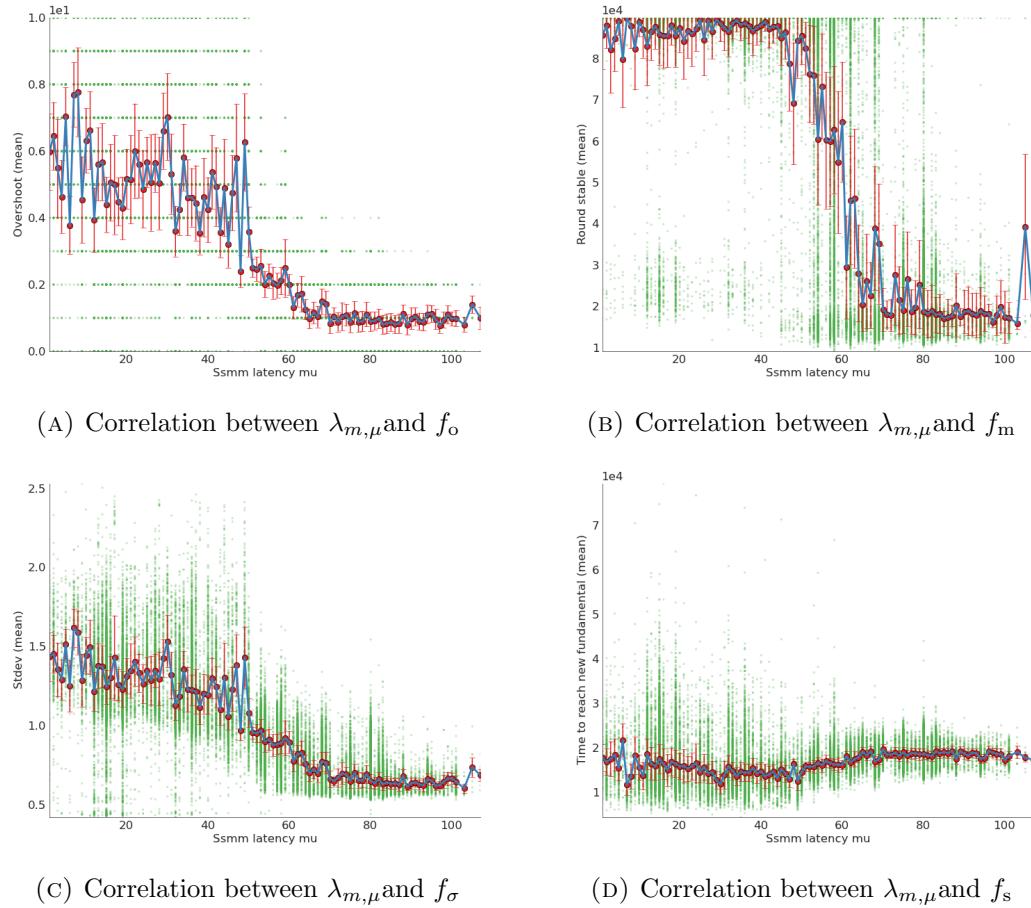


FIGURE 4.20: Correlation between $\lambda_{c,\mu}$ and the four fitness measures in experiment d10

4. The market was more stable but reacted slowly when the chartists were slower than the market makers.

4.3.4 Clustering

In this section, the focus is shifted from looking at population wide statistics to analysis sub-groups within each population. Whereas the previous sections showed that there do indeed exist statistical relationships between the latency of the agents and the behavior of the model, each discovered correlation was calculated over the entire population.

For instance, even though prediction of, say a negative correlation between f_s was $\lambda_{c,\mu}$ was found, there might be configurations of the model in which faster chartists were actually beneficial to the market. In order to investigate this, a Gaussian mixture model (GMM) was used to find clusters in the fitness space. All four fitness measures were used for the clustering. After discarding simulations with undefined fitness values and removing outliers, the data set contained 80813 data points. The large number of data points and

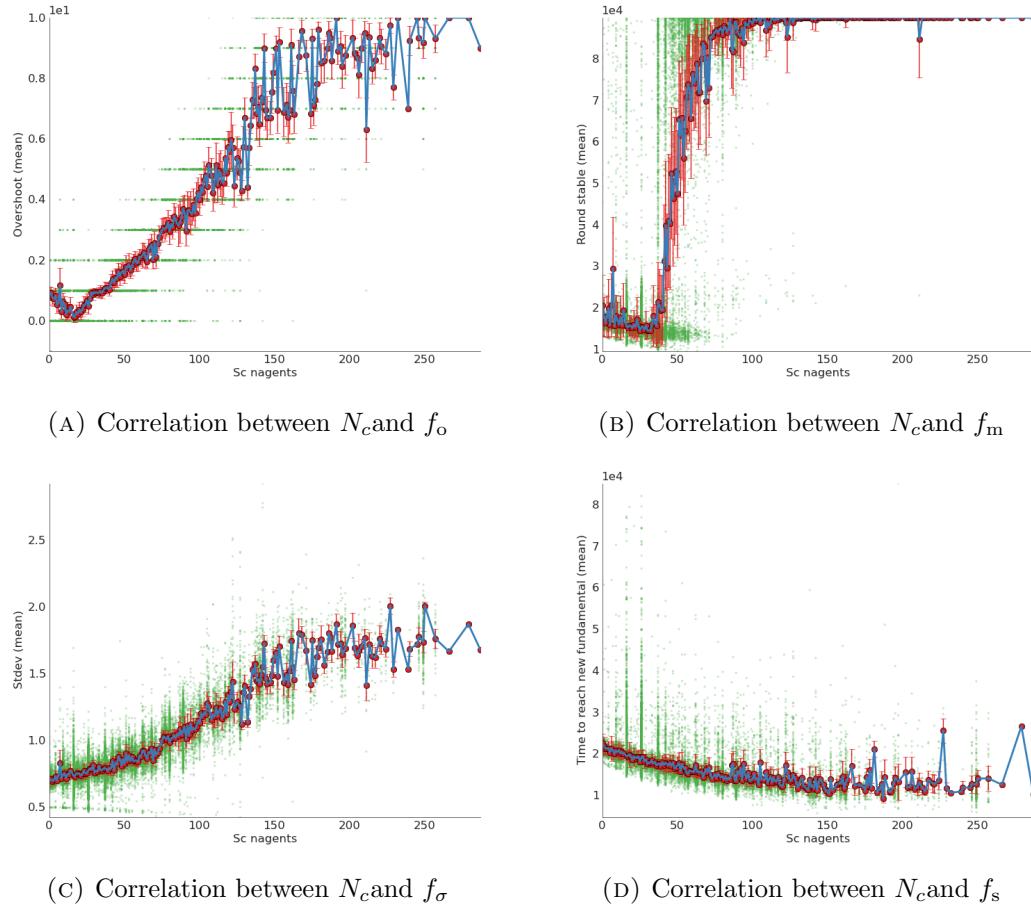


FIGURE 4.21: Correlation between N_c and the four fitness measures in experiment d10

the low number of dimensions made it possible to allow each Gaussian component to have a full covariance matrix, giving the model a high level of flexibility. Figure 4.22 shows scatter plots of the data after it has been grouped. Tables ?? and ?? respectively show the mean and standard deviation calculated over each cluster. The tables are sorted by the average value of f_o .

$\text{Var}_{\text{C}8}[f_m]$ and $\text{Var}_{\text{C}11}[f_m]$ and $\text{Var}_{\text{C}5}[f_m]$ are large. The points in this cluster have parameters which

Chartist latency and market response time

As was noted earlier, the evolution of $\lambda_{c,\mu}$ and f_s indicates that slow chartists made the market slow, and fast chartists made the market fast. C1 is the cluster with the $E_{\text{C}1}[f_s]$

C2 contains the fastest simulations, which take an average of 11.5×10^3 rounds to reach the new fundamental. This group is also the one with the largest overshoot.

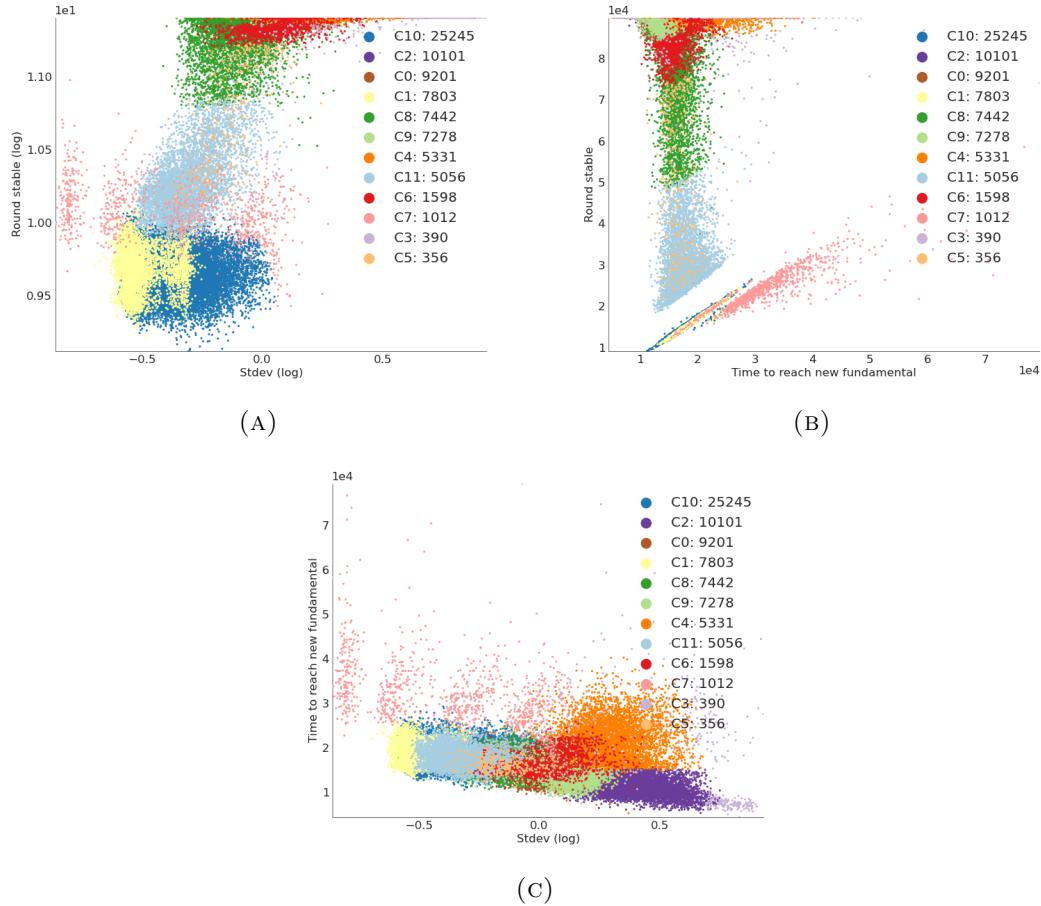


FIGURE 4.22: Scatter plots in fitness space showing the grouping of data points when using a GMM with 12 clusters.

	f_o	f_m	f_σ	f_s	$\lambda_{c,\mu}$	$\lambda_{c,\sigma}$	$\lambda_{m,\mu}$	$\lambda_{m,\sigma}$	N_m	Count
C1	0.0	16301.2	0.6	19217.4	127.2	6.2	78.4	5.2	132.2	7803
C7	0.3	24383.1	0.7	32005.5	87.0	9.5	25.8	10.5	66.7	1012
C10	1.0	15832.8	0.7	18602.8	121.9	6.5	76.3	6.0	126.3	25245
C8	2.0	81599.7	0.9	16333.6	101.8	8.7	56.4	9.2	91.3	7442
C11	2.0	30515.0	0.7	17822.9	114.2	7.3	71.7	7.0	117.5	5056
C0	3.0	89015.0	1.1	14687.5	89.0	9.2	39.5	10.0	66.8	9201
C5	3.0	51306.4	0.9	16508.7	102.2	9.0	59.2	8.8	96.0	356
C6	3.0	83914.2	1.1	16820.9	92.3	9.2	40.6	10.0	72.4	1598
C9	4.0	89496.0	1.2	14459.8	77.7	9.6	29.9	10.4	56.7	7278
C4	5.0	89896.6	1.4	22034.2	62.4	9.4	21.5	10.3	51.6	5331
C3	6.7	86440.9	1.8	18692.7	54.9	9.2	26.2	10.5	38.0	390
C2	7.9	89996.1	1.6	11574.7	36.4	9.2	26.4	9.6	36.4	10101
Outliers	11.5	89998.8	2.2	8835.1	17.8	9.3	24.3	8.5	19.4	740

TABLE 4.1: Mean for each fitness-cluster.

	f_o	f_m	f_σ	f_s	$\lambda_{c,\mu}$	$\lambda_{c,\sigma}$	$\lambda_{m,\mu}$	$\lambda_{m,\sigma}$	N_m	Count
C1	0.0	2142.8	0.0	2220.9	10.9	4.7	7.1	3.3	11.3	7803
C7	0.5	4827.7	0.2	7424.7	18.4	3.8	18.7	5.4	23.2	1012
C10	0.0	2150.8	0.1	2261.1	12.7	4.7	9.3	4.1	14.7	25245
C8	0.0	10563.6	0.1	1926.7	10.3	4.0	12.2	5.3	20.0	7442
C11	0.0	6952.5	0.1	2276.1	13.8	4.7	11.6	4.7	18.3	5056
C0	0.0	1380.7	0.1	1479.2	9.7	3.4	14.7	5.0	12.7	9201
C5	0.0	17151.2	0.1	2087.1	11.2	4.2	12.5	5.2	21.4	356
C6	0.0	3961.3	0.1	2646.9	10.3	3.5	16.9	5.2	16.0	1598
C9	0.0	1048.5	0.1	2368.7	13.0	3.4	12.7	4.9	9.4	7278
C4	1.4	423.6	0.2	4246.5	21.3	4.3	11.6	5.3	10.4	5331
C2	1.6	211.8	0.2	1943.0	16.0	5.2	11.7	5.5	13.7	10101
C3	2.9	7387.0	0.4	11884.0	26.0	4.5	15.0	5.5	30.6	390
Outliers	0.8	0.6	0.3	2691.9	11.3	6.1	13.4	5.7	14.2	740

TABLE 4.2: Standard deviation for each fitness-cluster.

	$\lambda_{c,\mu}$	$\lambda_{c,\sigma}$	$\lambda_{m,\mu}$	$\lambda_{m,\sigma}$	N_m	γ
0	0.53	-0.24	0.54	-0.24	0.56	0.57
1	-0.0	0.74	-0.01	-0.67	0.03	0.18
2	0.23	0.63	0.16	0.7	0.19	0.17

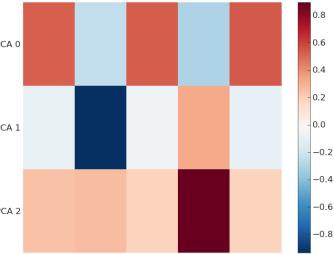


FIGURE 4.23: XXX

The point of the clustering is not that all groups should have distinctly different parameter statistics.

4.4 Hall of fame

Appendix A

Additional tables

A.1 Dataset 1

Write your Appendix content here.

Appendix B

Third party software

Deap scoop sklearn matplotlib numpy, scipy and pandas geometric brownian walk

Appendix C

Additional figures

C.1 Scatter plots for d10

C.2 Correlation plots of $\lambda_{c,\sigma}$ and $\lambda_{m,\sigma}$

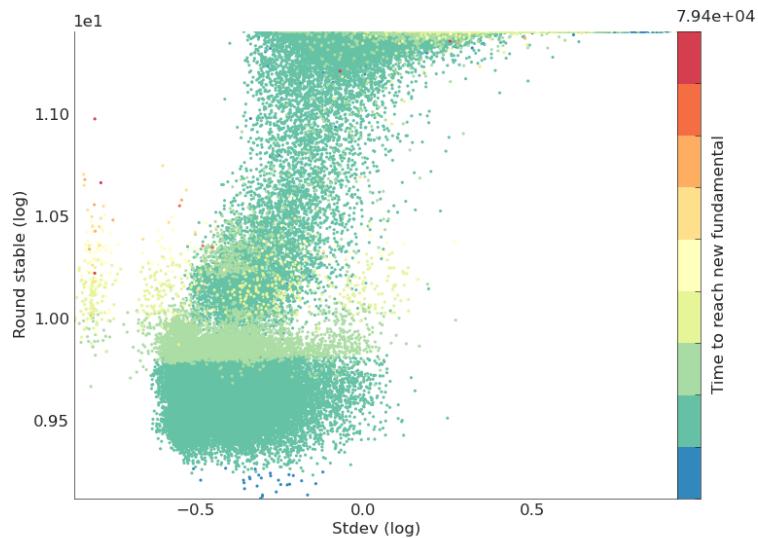
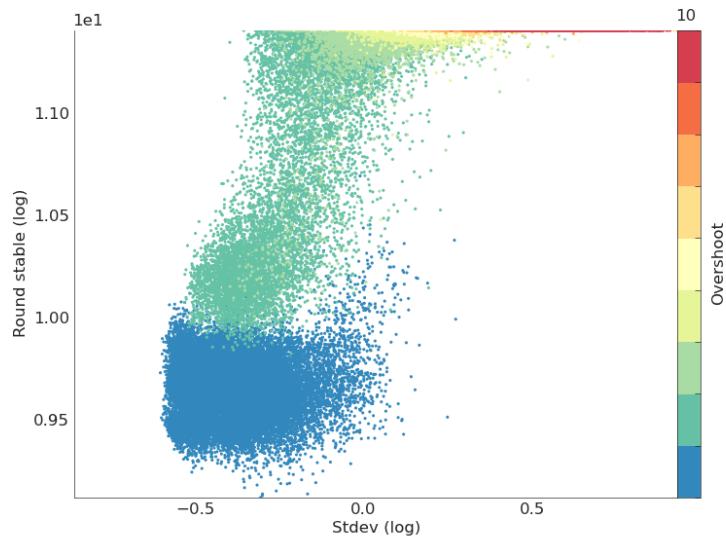
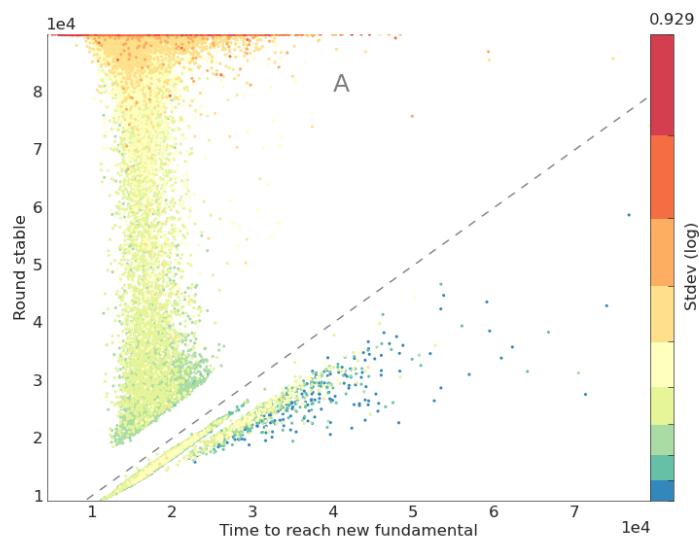
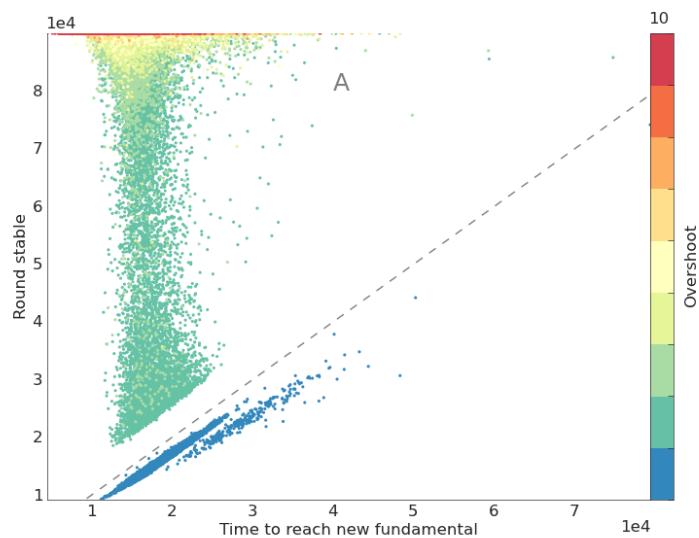


FIGURE C.1: Scatter plot of $\log f_\sigma$, $\log f_m$ and f_s

FIGURE C.2: Scatter plot of $\log f_\sigma$, $\log f_m$ and f_o FIGURE C.3: Scatter plot of f_m , f_s and f_σ

FIGURE C.4: Scatter plot of f_o , $\log f_m$ and f_s

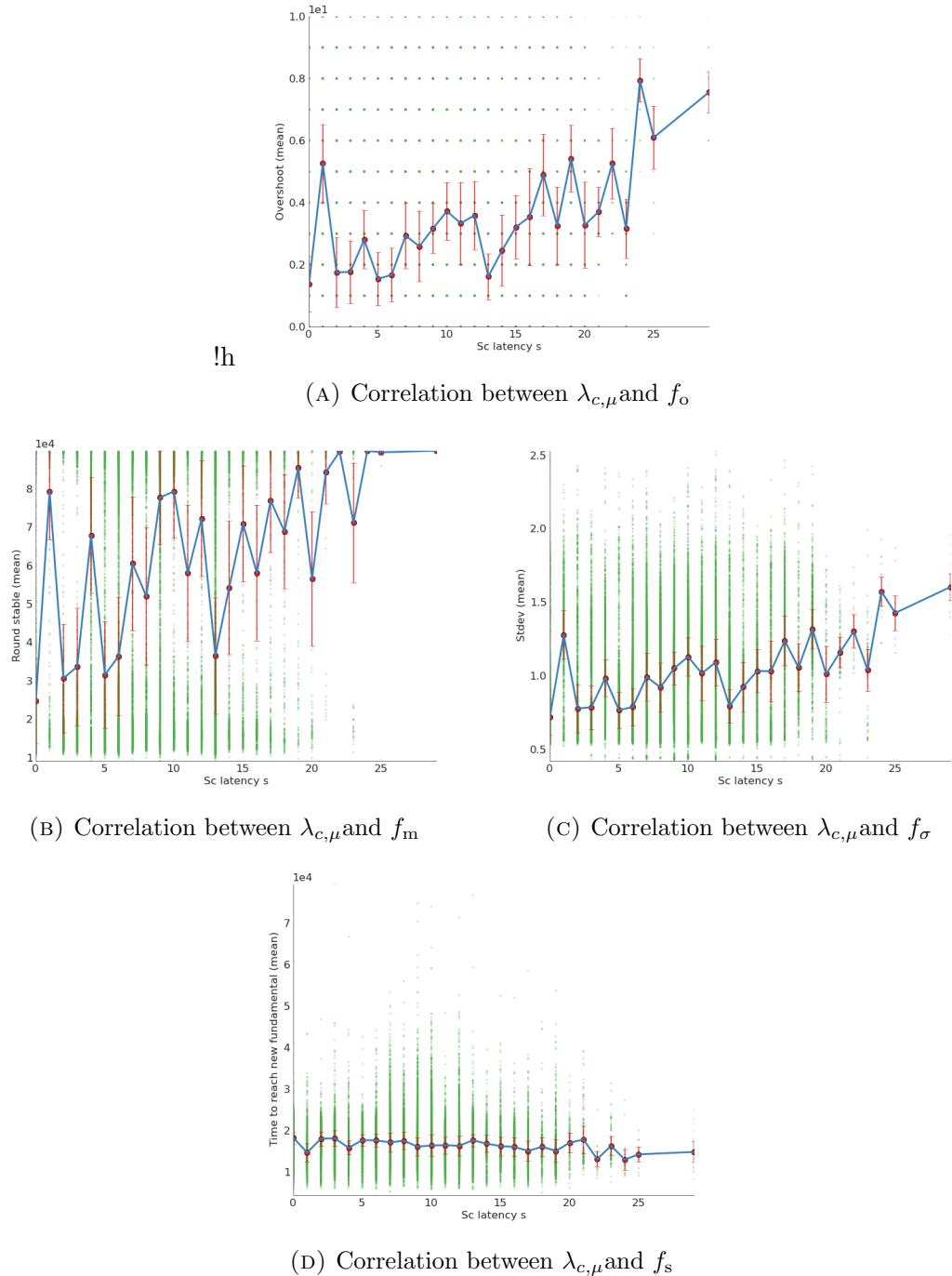


FIGURE C.5: Correlation between $\lambda_{c,\sigma}$ and the four fitness measures in experiment d10

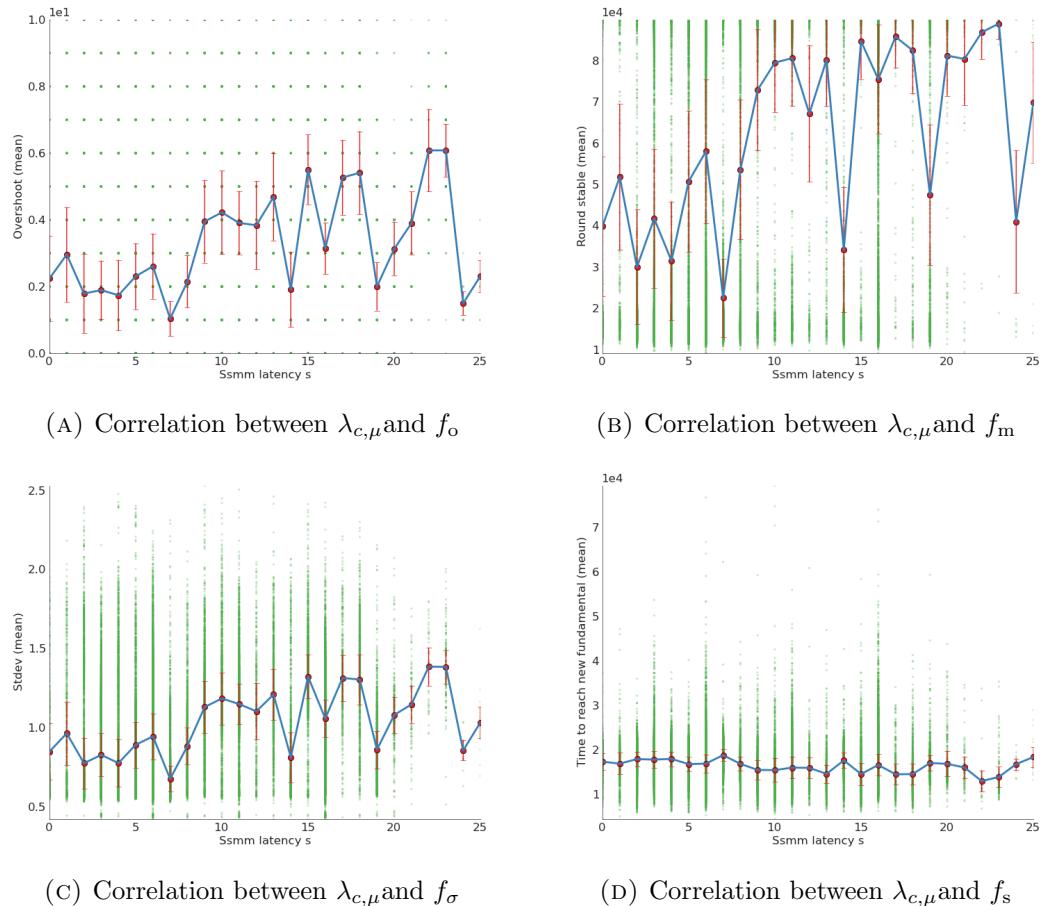


FIGURE C.6: Correlation between $\lambda_{c,\sigma}$ and the four fitness measures in experiment d10

Bibliography

- [1] C. J. Hawthorn, K. P. Weber, and R. E. Scholten. Littrow configuration tunable external cavity diode laser with fixed direction output beam. *Review of Scientific Instruments*, 72(12):4477–4479, December 2001. URL <http://link.aip.org/link/?RSI/72/4477/1>.

Bibliography

- [1] Chi Wang, Kiyoshi Izumi, Takanobu Mizuta and Shinobu Yoshimura: “Investigating the Impact of Trading Frequencies of Market Makers: a Multi-agent Simulation Approach” *SICE Journal of Control Measurement, and System Integration, Vol. 4, No. 1, pp. 001-005, January 2011.*
- [2] Michael J. McGowan: “The Rise of Computerized High Frequency Trading: Use and Controversies”, *2010 Duke L. & Tech. Rev., 2010.*
- [3] Thomas McInish and James Upson: “Strategic Liquidity Supply in a Market with Fast and Slow Traders”, *Available at SSRN 1924991 (2012).*
- [4] Niel Johnson, Guannan Zhao, Eric Hunsader, Jing Meng, Amith Ravindar, Spencer Carran and Brian Tivnan: “Financial Black Swans Driven by Ultrafast Machine Ecology”, *Available at SSRN (2012).*
- [5] Kiyoshii Izumi, Kiyoshi, Fujio Toriumi, and Hiroki Matsui: “Evaluation of automated-trading strategies using an artificial market”, *Neurocomputing 72.16 (2009): 3469-3476.*
- [6] Chiarella, Carl, Giulia Iori, and Josep Perelló: “The impact of heterogeneous trading rules on the limit order book and order flows” *Journal of Economic Dynamics and Control 33.3 (2009): 525-537.*
- [7] Peter Gomber, Björn Arndt, Marco Lutat, Tim Uhle: “High-frequency trading.” *Available at SSRN 1858626 (2011).*
- [8] J. Doyne Farmer and Spyros Skouras: “An ecological perspective on the future of computer trading” *Quantitative Finance 13.3 (2013): 325-346.*