Price manipulation in double auction markets using trade-based ramping

Ingvar Thor Gylfason

Faculty of Industrial Engineering, Mechanical Engineering and Computer Science
University of Iceland
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PRICE MANIPULATION IN DOUBLE AUCTION MARKETS USING TRADE-BASED RAMPING

Ingvar Thor Gylfason

30 ECTS thesis submitted in partial fulfillment of a
Magister Scientiarum degree in Financial Engineering

Advisor
Tómas Philip Rúnarsson
Ólafur Pétur Pálsson

Faculty Representative
Birgir Hrafnkelsson

Faculty of Industrial Engineering, Mechanical Engineering and Computer Science
School of Engineering and Natural Sciences
University of Iceland
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Faculty of Industrial Engineering, Mechanical Engineering and Computer Science
School of Engineering and Natural Sciences
University of Iceland
Hjarðarhagi 2-6
107, Reykjavik, Reykjavik
Iceland

Telephone: 525 4000

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First and foremost I would like to dedicate this thesis to my father who has always helped me and believed in me. Without him none of this would have been possible. I would also like to express my love and gratitude to my fiancée and our daughters for their support and understanding.

Abstract

The objective of this thesis is investigating if a trade-based manipulation strategy called ramping can be used in a double auction market to have an increasing effect on price. A reference state is constructed with a population of agent-groups that use known trading strategies to place offers in the market. With these agents placing offers in the market a price-discovery is formed when offers from buyers and sellers are matched. Agents that use ramping are then injected into the market in different proportion of the total population of agents and the market is simulated 1000 times for each state. Various results are collected from the simulations but the price evolution, closing price, frequency of trades and how agents behave is of main interest. With the results in hand, statistical tests are performed in order to reject or accept the hypothesis of a equal medians in the reference state and when ramping agents are injected. This is done in order to find how many of the ramping agents are needed to make a statistically significant effect on the closing price. The behavior of certain agent-groups is investigated as some show signs of a more aggressive behavior than the ramping agents. The conclusions of this thesis are that if 0.125% of more of the trading population, in this version of a double auction market, use ramping strategies, they will have an impact on closing price and also that price changes with different population in the reference state.

Útdráttur

Tilgangur ritgerðarinnar er að rannsaka hvort að hægt sé að nota svokallaða "ramping" aðferð til að hækka lokaverð á markaði þar sem kaupendur og seljendur geta báðir gert tilboð. Viðmiðunarmarkaður samanstendur af hópum af þátttakendum sem nota þekktar aðferðir til að ákveða sín tilboð. Þessir þátttakendur leggja svo inn tilboð sem mynda síðan verðþróun þegar viðskipti eiga sér stað. Þátttakendur sem nota "ramping" aðferðina er síðan bætt inn á markaðinn í mismunandi hlutföllum og markaðurinn er hermdur 1000 sinnum fyrir hvert tilfelli. Ýmsum niðurstöðum er safnað úr hermununum en verðþróun, lokaverð fjöldi viðskipta og hvernig þátttakendur hegða sér er helst til skoðunar. Tölfræðipróf eru síðan gerð á niðurstöðunum til þess að hafna eða samþykkja tilgátuna um jafnt miðgildi viðmiðunarmarkaðar og markaðar með þátttakendur sem nota "ramping". Þetta er gert til þess að finna hversu marga þátttakendur, sem nota "ramping", þarf til að hafa áhrif á lokaverð. Hegðun viss hóps er síðan skoðuð þar sem hann sýnir merki um hegðun sem gæti hækkað lokaverð. Niðurstöður ritgerðarinnar eru að það þarf 0.125% af markaðnum að nota "ramping" til að hafa áhrif á lokaverð og að verð breytist í viðmiðunarmarkaðnum ef að hlutföllum hópanna er breytt.

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1. Introduction

In this study an agent-based simulator of a double auction market is constructed where one asset is traded between agents. The agents represent traders that are of different types so that the population is varied and therefore better replicates the population that occupies real world markets. Agents that seek to manipulate the price are then inserted into the population in order to see how many of them are needed to manipulate the price.

1.1. Motivation and Objective

It was in late September 2008 when the first of the three big banks in Iceland was nationalized. That was only the beginning of the almost total, financial collapse that followed. The two other banks quickly also became victims of necessary nationalization and relative to the size of its economy, Iceland was facing the largest banking collapse any country had seen in recent economic history. The aftermath has today still to fully unravel and life in Iceland has not been the same. The shock the Icelandic population suffered in this collapse ignited a heated debate between all social classes that still occupies a large section of the media coverage. Because of the high emotions, sparked by the lowered quality of life, it is hard to see when healing signs will become apparent both to the economy and to the people. This has inspired both research and investigation of this collapse in a quest to find some reasons for why it happened. The objective of this thesis is to find out how many price manipulating agents are needed in order to be able to manipulate the price in double auction markets of various sizes. That might give some indications that small markets are more sensitive to price manipulation and are, because of that, inefficient in comparison to larger markets.

1.2. Contribution

The main question of the thesis is how the market price can be manipulated, by using a trade-based manipulation strategy called *ramping*, based on its size (number of participants). The impact of how certain trading behavior affects the price discovery and trading frequency, when the market size is varied, is studied. Corporate insiders or traders that have some abnormal agenda or information when trading, might manipulate the market by trading in the *"wrong"* direction (i.e. buying when information on outlook is bad and selling when information on outlook is good). This type of trading behavior reduces the informativeness of the trade performed because the market cannot be sure if a sell (buy) implies bad (good) news. There can be various reasons for this insider behavior but the interest is in the effects rather than the reasons. The consequences of this kind of manipulation can be a smaller bid-ask spread and a less efficient market because of contrarian trades that give false information to the market as stated by (John and Narayanan, 1997).

To investigate, a model is constructed of a market with a changeable number of participants and strategies that trade and produce price discovery. The simulator has its limitations and is built on assumptions to simplify things that were too complex and time-consuming to construct, but it is sufficient enough to investigate the changes in price and frequency of trades with varied market size and strategies. Multiple simulations are run for each state and then the results are compared in a search for answers.

The main contributions this thesis gives to the field of financial market research are the following:

- Shows a way of how a diversified population of trading agents can produce price discovery in a double auction market using a trading method called ramping.
- Gives some answers to how effective trade-based manipulating agents can be in this environment.
- Gives insight into what characterizes small markets that have become inefficient when price manipulating agents enter the market.

1.3. Overview

This thesis is structured as follows. Chapter 2 is a review of some of the previous research that has been conducted on market simulation and also explains the construction and dynamics of double auction markets. Chapter 3 gives an overview of agent-based modeling and its main dynamics as well as the trading behaviors of the agent-groups the market is populated by. Chapter 4 introduces the price discovery process and how it is calculated. Chapter 5 gives a historical review of how regulations in stock markets have evolved and introduces the price manipulating agents that play a significant role in this thesis. Chapter 6 gives an in-depth explanation of how the simulator is constructed and what data is collected. Chapter 7 is where the results from the simulations are analyzed and statistical calculations are performed to produce some answers to the questions that are investigated in this thesis. In particular it shows statistical results for the average closing price of the market in four different scenarios where the involvement of the ramping agents varies. Chapter 8 focuses on the limitations of the model and touches down on which are the most important ones. Suggestions are made on how to improve those limitations in the future. Chapter 9 summarizes the work of this thesis and suggests what would be the first steps in improvements for future research.

2. Market Simulation

This chapter shows how market simulations have evolved over time and gives a description of how the double auction market is today. The double auction market in this study is described in some detail and the dynamics are explained. Some agent-types that have been used in previous studies are also introduced.

2.1. Evolution of Market Simulations

The first market simulations were conducted by Edward Hastings Chamberlin in 1948 and were performed with real human subjects who were recruited by the researchers and often received a small payment for their efforts. As technology evolved and computers became available for use in research, almost all market simulations were done via computer. When arriving at the laboratory where the simulation would be performed, the human traders were assigned a computer that had a trading program installed and was connected to other computers where the other participants would similarly do their trading. After the rules of trading where explained and subjects made aware of their inventory of assets, the trading began. At the end of the trading period all participants were excused and the researchers collected the data and began analyzing it. The researchers quickly became aware of certain problems when trying to simulate a real market with human subjects. Boredom became evident towards the end of the trading period and extreme risk-seeking behavior materialized in some subjects due to the fact that they felt like they had nothing to lose when not trading with their own wealth as stated in a study by (Smith, 1975).

In a study by (Gode and Sunder, 1993) a market simulation with both human subjects and artificial agents was performed and the results were compared. That was the beginning of a vast improvement in market simulations with artificial agents. The first agents were called ZI-agents, which stood for zero intelligence agents as these agents generated random bids or asks. In their simulations human traders traded for 4 minutes in each period compared to 30 seconds of trading for the artificial traders in a total of 6 periods. The time selected for trading periods was enough to ensure that sufficient amount of trades actually occurred. At the start of the trading period each buyer was given the right to buy one or more units of the asset. The buyer was made aware of the asset's redemption value v_i of each unit i, and the profit the buyer made by buying a unit of this asset, at price p_i was then $v_i - p_i$ respectively. An individual buyer's demand function for the asset was defined by the redemption values $v_i, i = 1, 2, ..., n$. Sellers were also allowed to act at the start of each trading period and could sell one or more units of the asset. The sellers were made aware that c_i was the cost of each unit i. Sellers would then make a profit of $p_i - c_i$ when selling the ith unit of the asset at price p_i. The market demand function was not available for the buyers and the market supply function was not available for the sellers. Neither the buyers nor sellers had any costs for units bought or sold. All traders had to trade unit i before trading unit $(i + 1)$. In order to minimize boredom and extreme risk seeking behavior, human traders were stimulated by earning a higher grade in a credit course based on their profits. In the study by (Gode and Sunder, 1993) a budget constraint was used as a part of the market rules as participants had to settle their accounts. Two simulations were run where different budget constraints were placed on the artificial traders. First, the ZI-agents were imposed with a budget constraint that forbade any bids or asks that would yield a loss for the agent and he would therefore not have been able to settle his account. These agents were called "ZI with constraint" (ZI-C). In the second simulation, there were no constraints and agents could place bids and asks without regard to redemption values or costs. They could participate in a trade that would yield a loss for them because they did not need to settle their account at the end of the trading period. These unconstrained agents were called "ZI unconstrained" (ZI-U). The difference in results for the human-market and the ZI-C market is contributed to systematic characteristics of human traders and if ZI-C were considered to have no rationality, this difference in results would be a measure of how human rationality contributes to market performance. When a market with budget constraints and a market without constraints are compared, the difference in results is contributed to the market discipline. A more recent demonstration of the power of stochastic zero-intelligence approaches for understanding market behavior can be found in the paper *"The predictive power of zero intelligence in financial markets"* by (Farmer et al., 2005).

In recent years there has been a big change in computer performance and the traditional perfectly rational, equilibrium or econometric approaches have lost quite a following. This is one of the reasons why new approaches to market simulations have emerged. Simulations with specifically programmed agents with varied decision-making processes, who make up a population that is the market, are now possible and as (Glosten, 1994) states, electronic trading is now more efficient than other mechanisms and its domination will not be prevented. There is a vast number of research studies accessible that provide a comprehensive introduction to how different types of markets work in reality. What sparked many of these important works is the rise and fall of the worlds´ largest markets. Investor activity in the rise and fall of Nasdaq from September 1998 and throughout 2001, was researched by (Griffin et al., 2003) who found that institutions bought shares from individual investors the day after the market moved up and sold when the market took a dip. These trading-patterns contributed to both the rise and the subsequent fall of the market. Markets are constantly changing as prices adjust when new information becomes available; as traders who lose are replaced by those who win, and as new technology evolves. The market-population is versatile. The common household trader with only his gut feeling may be trading against a highly skilled professional that employs advanced trading strategies in his never ending search for profits. The trained traders will ultimately make a profit from investors, gamblers and amateur traders. The stakes in some markets are very high and multi-million-dollar trades can be arranged in seconds or sometimes even milliseconds. It is easy to lose a fortune overnight but the negotiated price that traders agree upon ultimately determines how market-based economies allocate their scarce resources. The wealth and high quality of life we know today owes much to well-functioning and liquid markets as studied by (Harris, 2003).

2.2. The Double Auction

Double auction is when multiple buyers and sellers make offers on the same asset in a continuous market. This type of market institution is important because it allows traders to make offers to buy or sell and to accept other traders´ offers at any moment in the trading period. This is why the double auction is most widely used by financial market institutions as stated by (Friedman and Rust, 1993). On a trading period (trading day), stock markets work as double auctions that are continuous throughout the period and all offers in the market might bring a trade to existence. Buying offers are called bids and selling offers are called asks and these offers are stored in what is called an order book.

The double auction rules can vary somewhat between studies but there are a few simple ground rules. During a trading period, sellers may post any ask order and accept any bid order at any time and buyers can post any bid order and accept any ask order at any time. If a buyer and a seller agree on price, an exchange will happen and the unit exchanged will no longer be available for the duration of the period.

The order book is cleared after each transaction in many double auction experiments and then buyers and sellers have to resubmit bids and asks. A standard practice in these experiments is the assumption that there is a *closed order book* meaning that agents can only observe the best bid and the best ask at any given time in the trading period. For a new bid (ask) to be the best bid (ask), a buyer (seller) must submit a bid (ask) that is higher (lower) than the best bid (ask). This rule is known as the standard bid/ask improvement rule. Throughout the trading period the current *spread* (the difference between the highest bid and the lowest ask) is known to all agents in the market. The history of trades in previous trading periods is also public knowledge. The order book in this study is not cleared after a transaction but at the end of the predefined trading period.

2.3. The Main Dynamics

A study by (Wurman et al., 1998) shows that the dynamics of the double auction market can vary in how prices are set, when price quotes are produced and when the actual trades are computed. The dynamics of the market are a product of the interaction between those agents that trade in a constructed and measurable environment. According to (Darley and Outkin, 2007), in order to understand a marketś behavior, one has to consider the theoretical side as well as the complexity of the marketś infrastructure and the behavior of the populations that make up the market. The double auction has three main factors according to (Wurman et al., 2001): (a) it allows for offers to be made and stored, (b) it produces price information, and (c) it removes offers from the order book when a transaction takes place. The following list gives a more detailed description of each of these factors.

- **Insertion and removal of offers -** When an agent makes a new offer that satisfies all market rules, the offer has to be inserted into the order book (the datastructure of the offers that make the market). When an offer is withdrawn from the market it has to be withdrawn from the order book as well.

- **Price computation -** According to a predefined schedule, the auction will produce price quote information. It can be highly complex to program an algorithm that can deal with the need to maintain price quote information when offers are being inserted and withdrawn from the order book.

- **Clearing -** When offers are paired together to make a transaction, the auction will compute the exchange between the buyer and seller, let the agents know of the transaction, and remove the offers, that make the transaction, from the order book as explained by (Bao and Wurman, 2003).

A study by (Satterthwaite and Williams, 1989) offers a mathematical representation of the double auction mechanics. With slight adjustments to their calculations, the following text gives a mathematical representation of the methods used in this thesis. Traders submit offers that are either bids or asks and these offers are put in two arrays in increasing order $a_1 \leq a_2 \leq ... \leq a_m$ and $b_1 \leq b_2 \leq ... \leq b_n$ where m stands for the number of outstanding asks and n stands for the number of outstanding bids. A trade occurs among those who submitted asks (sellers) when their offers are less or equal to b_n and among those who submitted bids (buyers) when their offers are greater than or equal to a_1.

This study will only give the agents the capacity to either buy or sell a single unit of the asset that is traded on the market in each period of trading and therefore has a tick size of 1. The market may only have one asset to trade as this will allow for theoretical testing and it increases simplification which in turn reduces assumptions that are dubious and unnecessary. The market is frictionless which means that there are no costs, no taxes and no inventory. Another benefit of the single asset/single unit simplification is that it increases the control of the participants by increasing the frequency of the bid/ask offers made by the traders during the trading period. This simplification also enables the manipulation of the ratio of the population. Simply stated, this means that it is possible to change the number of certain types of agents by varying the frequency by which they are allowed to trade by. All the simplifications serve the purpose of sharpening the focus on the price formation process and the frequency of trades like in (Cason and Friedman, 1996) study. Further discussion about assumptions and limitations in the model can be found in Chapters 6.1 and 8. Figure 2.1 shows a simple state chart of the double auction simulation.

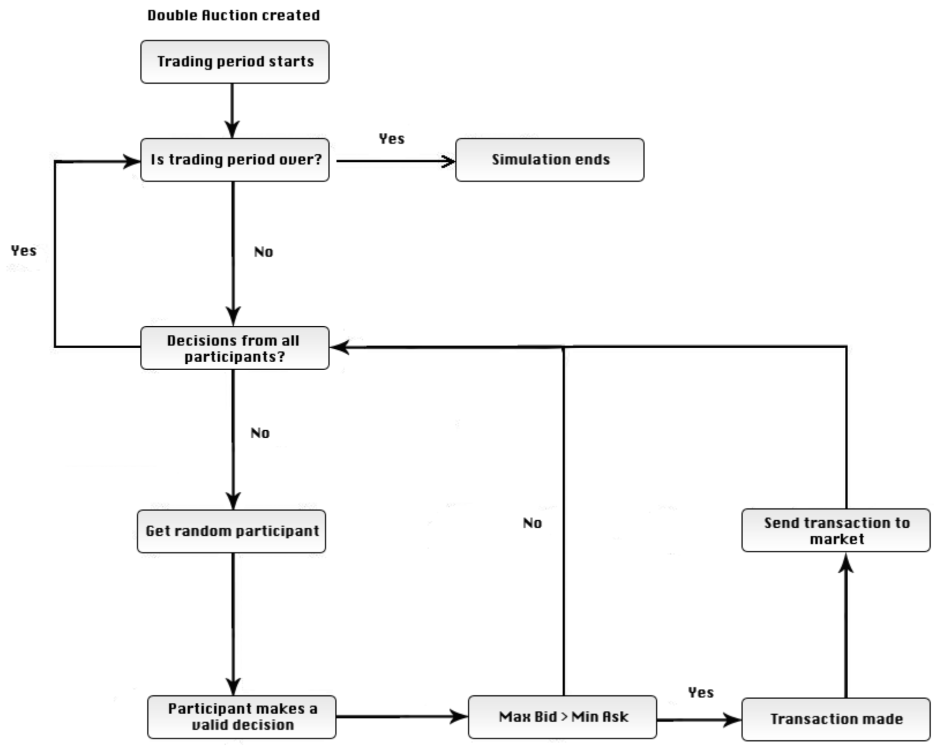

Figure 2.1: A simple state chart of our double auction simulation. Adapted from The Cream in Tristian Ratchford, n.d., Retrieved May 28, 2012, from http://www.cs.mcgill.ca/ tratch/cream/. Copyright 2008 by Tristan Ratchford.

2.4. Summary

This theses uses different types of agents that are programmed so that they will trade for a pre-defined period in a double-auction market environment is. The number of trades in the simulations is not defined in the beginning and is only subject to the interactions between the agents, the decisions they make and the market rules. The market is constructed as a fairly standard version of double auction that uses an order-book to pair offers that then formulate trades and price discovery.

The next chapter will focus on agent-based modeling, both in general and on how the model is constructed in this study. It will also give an overview of all the agent-types that populate the market in the simulation.

3. Agent-Based Modeling (ABM)

In this chapter, some theoretical models, dynamics and agent behaviors will be analyzed from a mathematical point of view. This serves the purpose of proving some elementary results about the dynamics of agent-based models. These results should be used as an introduction to the limits of mathematical analysis when exploring and simulating the complex dynamics formed in real-world markets. This chapter also contains descriptions of how the market is constructed in this thesis as well as describing the behavior of different types of market participants.

3.1. Building an ABM Model

According to (Mainzer, 2004), a successful way of solving problems in the natural sciences is applying the theory of nonlinear complex systems whereas, in social sciences, the linear idea: *that the whole is only a sum of its parts*, has dominated. The realization that the problems of mankind are often complex, global, non-linear and random has made it clear that the linear approach, often praised by economists, is obsolete. Solving problems does not always have to be by computing or predicting what will happen in the future. When dealing with randomness, we understand the dynamical reasons but there may be no way of forecasting. It is often more practical to understand the complex dynamics then to try to compute definite solutions, especially when there is no way of doing so. Such systems may not have behavior that fits with equilibrium conditions that are often assumed in economics and finance. It may well be that the important dynamics lay beyond the equilibria regions and might as well be quite chaotic. The perfectly rational agents that have been so popular in modern economic research are insufficient to describe this kind of system and agents with behavior that has a random component to it would be more appropriate.

The recent developments in agent-based modeling like in (Darley and Outkin, 2007) have produced a practical way of modeling and analyzing complex systems although that can often prove difficult. Agent modeling tools have grown in numbers and have evolved over the years to become very advanced and powerful. Access to micro-data is much more extensive and open and, last but not least, there have been vast improvements in the computational capabilities of computers that make comprehensive simulations possible. All these factors have contributed to the improvements in agent-based modeling and simulation that are so evident today.

When building a typical agent-based model there are three fundamental factors that have to be incorporated. First, the model has to have a set of agents and these agents have to have predefined attributes and behaviors (decision making processes). When the agents have been modeled, the second step is to incorporate the relationships between the agents and how they interact with each other, into the model. Now that the population of agents has been modeled, the third step is to construct their environment. In a study by (Macal and North, 2010), When building a typical agent-based model there are three fundamental factors that have to be incorporated. First, the model has to have a set of agents and these agents have to have predefined attributes and behaviors (decision making processes). When the agents have been modeled, the second step is to incorporate the relationships between the agents and how they interact with each other, into the model. Now that the population of agents has been modeled, the third step is to construct their environment. A study by (Albin and Foley, 1998) shows how to approach economic problems where there is complexity in agent interactions and agents can formulate their own trading strategies and act according to them. In the process of building an agent-based model many difficult questions arise. One of them is how to build agents that replicate human-like trading behavior. This is a question that has inspired many ABM researchers and (Gode and Sunder, 1993) asked the question: *"how much intelligence does an agent require to properly replicate human trading behavior"*. The answer they came up with was surprisingly simple: *little*.

It is assumed that market participants are diversified and are either risk-neutral, risk-averse or risk-seeking. A risk-neutral agent uses a trading strategy that is expressed in terms of expected return without taking the volatility of the asset into account. Agents do not have any inventory in the beginning of trading or at the end of trading and they cannot change the number of units of the asset they are trading; all trades consist only of one single unit of the asset. Agents on the market do not share the amount of information they have access to, and informed traders know the previous prices and spreads on the market whereas uninformed agents only know the current spread.

One of the biggest challenges in this study was to generate a population of agents who interact with each other and for these interactions to produce a price-discovery in the market. At each moment when an agent is called he has to make a decision about whether to post a bid, an ask or to remain neutral and do nothing. The question of how much volume traders could trade is intentionally ignored. The study is instead concentrated on price by allowing traders to exchange only one unit of the asset in each trade. Instead of submitting a supply and demand information to the agents, a simpler price mechanism is opted for. This is explained in greater detail in Chapter 4.

Figure 3.1 gives a visual representation of how an agent interacts with other agents in the market as well as how he interacts with the market structure.

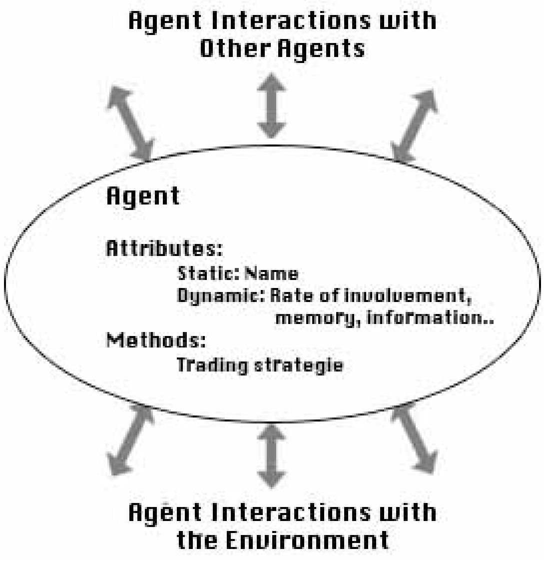

Figure 3.1: A typical agent

3.2. Market Participants

Agents are given one opportunity to submit their offer which can be either a bid or an ask, or they can be neutral and do nothing. The amount offered by the agents is the last price on the market with a stochastic component that serves as an error estimate because they do not have perfect information. The opportunity to submit offers is controlled by the rate by which they are allowed to trade by. It also controls the number of participants in the market. A high rate means more agents in the market and a low rate means fewer. The population in our market is combined of groups of heterogeneous agents. Each group has agents that use the same trading strategy. The following sections give a brief overview of these strategies.

3.2.1. Zero Intelligence

Zero Intelligence traders are unaware, irrational and have near zero intelligence. They submit random bids and asks over some range that is only subject to certain market constraints and they have no means to extract information from the market as described by (Chen and Tai, 2003). In the most basic environment, the buyer's bid and the seller's asks are random draws from a normal distribution. The calculation of the offer is the following:

$$\text{Offer}_{bid,ask} = Scalar \pm 3 * e^{\|N(0,1)\|} \tag{3.1}$$

where $\text{Offer}_{bid,ask}$ is the amount offered as either bid or ask and $Scalar$ is some fixed number (market starting point).

When the market starts, these agents make either bids or asks, randomly and with equal probability. They only trade until there have been enough price discoveries (trades) in the market so more sophisticated agents can join and start to make offers. As previously mentioned, the Zero Intelligence traders make their bids and asks over some range that is fixed and does not change when trades start to materialize. When enough trades are made by these agents, they stop trading and a population of more advanced agents takes over.

3.2.2. Near Zero Intelligence

These agents differ very slightly from the Zero Intelligence agents. They do choose to offer a bid or an ask randomly with equal probability like their closely related agents (Zero Intelligence) but the offers are not selected randomly over a fixed range. Instead, their offers are calculated from the latest spread on the market in the following manner.

$$\text{NZI\_Offer}_{bid,ask,t} = \frac{(Bid_{high,t-1} + Ask_{low,t-1})}{2} \pm 3 * e^{\|N(0,1)\|} \tag{3.2}$$

where $\text{NZI\_Offer}_{bid,ask,t}$ is the amount offered as either a bid or an ask at time t. $Bid_{high,t-1}$ is the highest bid and $Ask_{low,t-1}$ is the lowest ask on the market, in the last trading period, respectively. The knowledge of the latest spread on the market makes these traders just a little more informed, which is the reason for their slight superiority over the ZI-traders.

These agents start trading when there have been enough trades in the beginning of the market and trading strategies can start to form. They are a part of the more advanced agents that populate the market in the long run. Although simple, they represent a considerable part of the market participants.

3.2.3. Simple Trend

This strategy is very simple and may represent the common individual trading on the market. To decide between a bid and an ask this trader only looks at the most recent prices in the market and if the price has risen for two consecutive periods he places a bid. When the price has fallen for two consecutive periods he places an ask. The amount that he places in his offers is calculated in the same way as for the Near Zero Intelligent agent as shown in equation 3.2.

The following shows how the trading signals (bid or ask) are calculated for the simple trend:

$$\text{Signal}_t = \begin{cases} 1 & \text{if } P_1 > P_2 > P_3 \\ -1 & \text{if } P_3 > P_2 > P_1 \\ 0 & \text{otherwise} \end{cases} \tag{3.3}$$

where P_1 is the price from the most recent trade in the market and so forth. Signal_t is the trading signal for period t. The trading signal only takes one number out of the three (-1, 1 and 0) and they are interpreted in the following manner:

- -1 is a signal to sell the asset.
- 0 is neutral and tell the agent to do nothing.
- 1 is a signal to buy the asset.

3.2.4. Exponential Moving Average

These agents use an exponential moving average (EMA) to maximize their expected Sharpe-ratio that was first introduced by (Sharpe, 1966). Using EMA for technical analysis is widely used by traders and organizations that specialize in trading so it is reasonable to assign this strategy to one type of traders in our population. This method involves maximizing a certain performance indicator to get a set of weights that can produce profitable strategies. The method is fairly complex and requires some calculations to select whether to place a bid, an ask or to stay neutral and do nothing. Following is a quick overview of this method and how the calculations are performed.

Almost half a century ago, William F. Sharpe introduced, in his study (Sharpe, 1966), a measure for how well mutual funds performed. He called this the *reward-to-variability ratio*. The definition has evolved over time and now it is defined as a measure of *risk-adjusted-return*. Denoting the trading system returns for trading period t (transactions costs included, zero in the simulation) as R_t, the Sharpe ratio is defined as:

$$S_T = \frac{Average(R_t)}{StandardDeviation(R_t)} \tag{3.4}$$

where the average and standard deviation are computed over returns for periods $t = \{1, \ldots, T\}$.

To incorporate on-line learning, an incremental Sharpe ratio is needed. A *running Sharpe ratio* is defined by using recursive estimates of the first and second moments of the distribution of the returns:

$$A_n = \tfrac{1}{n}R_n + \tfrac{n-1}{n}A_{n-1} \quad and \quad B_n = \tfrac{1}{n}R_n^2 + \tfrac{n-1}{n}B_{n-1} \tag{3.5}$$

With $A_0 = B_0 = 0$. The next step is to extend this definition to an exponential moving average Sharpe ratio on the time scale η^{-1} by using estimates of the moving average of the first and second moments of the distributions for the returns:

$$S_t = \frac{A_t}{(B_t - A_t^2)^{\frac{1}{2}}} \tag{3.6}$$

$$\begin{aligned} A_\eta(t) &= \eta R_t + (1-\eta)A_\eta(t-1) \\ B_n &= \eta R_t^2 + (1-\eta)B_\eta(t-1) \end{aligned} \tag{3.7}$$

The agent uses two exponential moving averages that are called lead and lag. The leading EMA is for a period that is *"forward looking"* and the lag EMA is for a period that is *"backward looking"*, respectively. The trading signal is then acquired by comparing the lead against the lag.

$$\text{EMA\_Signal}_t = \begin{cases} 1 & \text{if } Lead > Lag(Bid) \\ -1 & \text{if } Lag > Lead(Ask) \end{cases} \tag{3.8}$$

This approach only applies to traders who trade a single risky asset. The method can be generalized to the vector case for portfolios as studied by (Moody et al., 1998) but for current purposes, only a single asset case is required. Many expansions that are more complex and robust are possible for this trading strategy and the differential Sharpe ratio has many advantages over this simplified version of this trading method according to (Brabazon et al., 2011). Such improvements are left for future research but the exponential moving average Sharpe ratio suffices in order to get a certain part of our population displaying trading behavior that considers risk in the decision-making process.

3.2.5. Relative Strength Indicator (RSI)

Agents that use the RSI to make their trading decisions, represent the market participants that are concerned with the magnitude of recent gains or losses. The information about gains or losses is then used in an attempt to determine if the asset is oversold or overbought in a predefined period. These agents are therefore quite informed as the have access to how prices have evolved as well as the spread. The RSI is highly effective in chart interpretation and is one of the most widely used technical indicators. The momentum concept is the theoretical basis of the RSI and a momentum oscillator is used to measure the rate of change of price over time. RSI is presented mathematically as follows:

$$\text{RS} = \frac{Average\ of\ L\ day's\ close\ UP}{Average\ of\ L\ day's\ close\ DOWN} \tag{3.9}$$

$$\text{RSI} = 100 - \frac{100}{1 + RS} \tag{3.10}$$

where L is a variable that can be from 1 to 30. Half of the period of the cycle is the ideal setting for the RSI and it is commonly suggested that levels of 70 and 30 signify tops and bottoms respectively. The RSI-index usually leads the market and peaks before the market actually hits top or bottom. Extreme values, such as 90 or 10, show signs of unusual strength or weakness in the market. Support and resistance often show up clearly on the RSI before becoming apparent on the bar chart. The divergence between the price action and the RSI on the chart is a very powerful indicator that a market turning point is imminent. A study by(Liu and Lee, 1997) shows that because of this , RSI is an early warning signal.

Letś have a look at a more detailed explanation of how the calculations are performed. When the $R_{t,p}$ is calculated at time t of period p, only the closing prices are used. It is the ratio of up-closes, U_i, to down-closes, D_i, over the selected time period and is expressed as an oscillator with a range of 0 to 100. The calculation starts with defining an index set $I_{t,p} = \{i : t-p \leq i \leq t\}$ and then defining the up-closes and the down-closes such that:

$$U_i = \begin{cases} C_i - C_{i-1} & \text{if } C_i \leq C_{i-1} \text{ is even} \\ 0 & \text{otherwise} \end{cases} \tag{3.11}$$

$$D_i = \begin{cases} C_{i-1} - C_i & \text{if } C_{i-1} \leq C_i \text{ is even} \\ 0 & \text{otherwise} \end{cases} \tag{3.12}$$

for any $i \in I_{t,p}$ and C_i is the closing price for period i. The next step is to define the average up-close and down-close for period i:

$$\overline{U}_{t,p} = Average\ of\ U_i\ over\ I_{t,p} \tag{3.13}$$

$$\overline{D}_{t,p} = Average\ of\ D_i\ over\ I_{t,p} \tag{3.14}$$

then the Relative Strength is given as follows:

$$\mathrm{RS}_{t,p} = \frac{\overline{U}_{t,p}}{\overline{D}_{t,p}} \tag{3.15}$$

at time t for period t the RSI is then defined as:

$$\mathrm{RSI}_{t,p} = 100 - \frac{100}{1 + RS_{t,p}} \tag{3.16}$$

If RSI is equal to 100 it implies that there are only upward movements in price (overbought market) and a RSI equal to 0 means that there are only downward movements in price (oversold market). In more volatile markets the time period for RSI is shorter than in less volatile markets. Generally, the longer the period, the less frequent and more stable are the trading signals. As an oscillator the RSI is a counter-trend indicator and if used in a trending market, the RSI often becomes entrenched near one end of the range for days (or even weeks), giving a false indication of a market top or bottom as stated by (Wong et al., 2010).

In the simulation, a certain barrier is selected that will determine the trading signals. The calculation for the signals is as follows:

$$\mathrm{RSI\_Signal}_t = \begin{cases} 1 & \text{if } RSI_{t,p} < 30(Bid) \\ -1 & \text{if } RSI_{t,p} > 70(Ask) \\ 0 & \text{else } (Neutral,\ no\,bid/ask) \end{cases} \tag{3.17}$$

The traders that use the RSI indicator in reality are (or at least should be) aware that the RSI can produce false signals when there are surges and drops in the price of an asset and therefore should only use it as a complement to more reliable tools. Such knowledge is absent in these agents and they only use the RSI to make their decisions since that is sufficient for our purposes.

3.2.6. EMA + RSI

A certain part of the market population are agents that combine two trading methods in their decisions. These agents use the most complex trading-decision process in the simulation and could therefore be seen as representatives for the most highly trained and skilled traders in the market. Following is a quick overview of the two methods involved.

When calculating the EMA a *running Sharpe ratio* is defined by using recursive estimates of the first and second moments of the return distribution. This definition is then extended to an exponential moving average Sharpe ratio by using estimates of the moving average of the first and second moments of the distributions for the returns. Further explanation on how EMA calculations are performed was previously discussed in Section 3.2.4.

With the signal from the EMA method calculated, it is time to turn to the RSI method. The momentum concept is the theoretical basis of the RSI and a momentum oscillator is used to measure the rate of how price changes over time. The index usually leads the market and peaks ahead of when the market actually hits top or bottom. The RSI should be looked at as an early warning signal. Further explanation on how RSI calculations are performed can be seen in Section 3.2.5.

A trading signal for the EMA strategy is first calculated and then another trading signal is calculated for the RSI strategy (both methods are described in previous sections). Both signals are either 1, 0 or -1. When both signals have been calculated, they are added together and divided by 2.

$$\text{Signal}_{EMA,RSI,t} = \frac{Signal_{EMA,t-1} + Signal_{RSI,t-1}}{2} \tag{3.18}$$

where $Signal_{EMA,t-1}$ is the trading signal for the EMA strategy and $Signal_{RSI,t-1}$ is the trading signal for the RSI strategy. It is obvious from Equation (3.18) that the trading signal can only be -1, -0.5, 0, 0.5 or 1.

$$\text{Signal}_{EMA,RSI,t} = \begin{cases} 1 & Bid \\ -1 & Ask \\ (0.5, 0, -0.5) & (Neutral,\ no\,bid/ask) \end{cases} \tag{3.19}$$

To make these agents more active it is possible to have only the zero as a neutral signal but the simulation starts like described.

3.2.7. William's %R indicator

The traders in the simulation that use this methodology in their decision making process are concerned about the state of the market. The range of recent highs shows if the market is in a *"bull-state"* and the maximum power is with the buyers. Similarly the range of recent lows shows if the market is in a *"bear-state"* and the power lies with the sellers. The most important factor in the determination of the market-state is always the closing price. This part of the population represents a more speculative type of agent that, is quite informed, having access to the history of prices as well as the spread.

The William's %R momentum indicator, often referred to as %R, is a technical analysis oscillator. It shows the current closing price of the asset in relation to the high and low of a selected range of trading periods N. According to (Zhao, 2007), the indicator was developed by Larry Williams and shows how close the asset is trading to recent highs and lows.

William's %R indicator is denoted as W_n for n periods (e.g days) that are constructed from previous prices. The formula for W_n is the following:

$$W_n = -100 * \frac{H_n - C}{H_n - L_n} \tag{3.20}$$

where C is the last closing price of the asset. H_n and L_n are the highest and lowest prices for the last n periods respectively. As the indicator oscillates between -100 and 0 the range from -100 to -75 is described as undervalued or oversold. When the indicator leaves this range after entering it previously, we use that as a signal to buy the asset. The overvalued or overbought range is from -20 to 0 and if the indicator leaves this range we use that as a signal to sell. This is a very simple method and fairly easy in practice according to (Ilinskaia and Ilinski, 1999). The following is used to determine exactly when to buy or sell. An item is oversold and the agent should buy when %R rises above the -50% mark and an item is overbought and the agent should sell when %R falls below the -50% mark. The trading signal can only be 1 or -1:

$$\text{Signal}_t = \begin{cases} 1 & \text{if } W_n \ < \ -50\%(Bid) \\ -1 & \text{if } W_n \ > \ -50\%(Ask) \end{cases} \tag{3.21}$$

By forcing the agents to place an ask or a bid when the oscillator fluctuates around -50% they become more active market participants. Traders who use this method in reality do not base their decisions on fluctuations around the -50% mark but instead look at when the oscillator enters and leaves a certain range. This simplification is sufficient to incorporate some speculative behavior for this part of the market population.

3.3. Summary

Creating a model of a population of interacting agents, that together trade in a double auction market to produce price discovery is the main goal of this paper. They differ both in how much information they have access to and how advanced their trading strategies are. The interaction between agents is also modeled by market rules and infrastructure. The market dynamics become apparent as a result of interactions between the market participants. The market equilibrium assumption which is so often used in modern economics is not needed. The market contains only a single asset that has a price that is given exogenously in the beginning but is then subject to the trades between the agents. The model is by no means a total replication of reality but the population is varied in order to better replicate the conditions of real world markets. In the beginning of the trading period there are only ZI-traders trading and when enough price discoveries have materialized, a more advanced population can start making decisions and trade. The groups of agents have different trading strategies that are all widely known both in real markets and in academia. The level of information these groups have access to is also varied as some have access to almost no information while others have access to historical information about price and spread. The research will focus on how some modifications to the population and trading strategy diversification will affect both price discovery and the frequency of trade.

The reason why the equilibrium price of economics is abandoned for a stochastic price is explained in the next chapter which also explains how price discovery takes place in the market as well as touching on how price and spread are calculated.

4. Price Discovery

This chapter explains why a stochastic price is used instead of the equilibrium price which is popular in economic research. It also explains how price and spread are calculated and how price discovery takes place in the market.

4.1. From Equilibrium Price to Stochastic Price

The price discovery process is one of the more interesting aspects of market simulation research. As mentioned earlier in this chapter and in a study by (Cason and Friedman, 1996), economists have long been fascinated by the search and study of the perfect equilibrium price in double auction markets and there are hundreds of papers and studies on how effective ZI-agents are in comparison with humans in finding that equilibrium price. In (Gjerstad and Dickhaut, 1998) study, a model of information processing and strategy choice for participants in a double auction market was formulated. Sellers and buyers form beliefs that their offer will be accepted by some counterpart and these beliefs are formed on the basis of observed market data, including frequencies of asks, bids, accepted asks and accepted bids. Armed with this information, the traders make a decision that maximizes their profits. The trading activity that follows is sufficient to achieve transaction prices at competitive equilibrium price, which is the price of an asset in a competitive market, when there is a perfect balance between supply and demand for that asset.

Asset price bubbles and crashes have plagued financial markets throughout history which gives credence to the thought that the equilibrium price does not exist in the real world. A study by (Duffy and Ünver, 2006) examined whether a simple agent-based model with a population of ZI-agents with budget constraints could generate asset price bubbles and crashes, as observed in the real world. The results were that if constrained with the no-loss rule the ZI-agents, operating in the same double auction environments as used in several different laboratory studies with human subjects, asset price bubbles and crashes could be generated. As it is not our intention to search for the competitive equilibrium price of the double auction market, a different way of formulating a market-price in the simulation is needed. This is why price is given as a fixed number in the beginning, and then the ZI-agents make offers around that price since their pricing method is just the fixed price with a stochastic component.

4.2. Price and Spread

In the past decades there has been a big leap in the evolution and usage of screen-based trading and automated order execution in all major markets as well as emerging markets. This leap has produced a big change in information structure and how trades are conducted in financial markets. Research on this new type of trading started fairly recently but studies are growing in numbers according to (Amihud and Mendelson, 1986). One of the first models to simulate this new type of trading was presented in a study by (Glosten and Milgrom, 1985) and is called the Glosten-Milgrom (GM) model. It is a simple model that incorporates most of the features of how adverse selection affects the bid-ask spread. GM-models are generally used by market makers (individuals and companies that quote both bids and asks in order to make profits) to analyze price-discovery from bids and asks in a single asset market where participants are either informed or uninformed heterogeneous agents as explained by (Glosten, 2010). This study will not incorporate market makers into its simulation, as explained in Chapter 8.

Investigating the bid-ask spread in different environments is a study in and of itself but since the spread is something that is important in price-discovery and how price evolves in the market, a brief definition is in order:

$$\text{Spread}_{bid,ask} = Ask_{low} - Bid_{high} \tag{4.1}$$

Spread in double auction markets is the amount that differs between the lowest ask and the highest bid in any given trading period. Essentially, it is the gap between the buyers´ valuation and the sellers´ valuation of the asset. Studies support that the spread consists mainly of three fundamental components. A study by (Huang and Stoll, 1997) shows that the largest component is an order processing component; adverse selection and inventory are the other two. In our study there is no inventory so that will not factor in the spread. It is obvious that the spread is closely related to the actual price-discovery in the market and since that is one of this thesis´ main focuses, it is appropriate to briefly explain how the price is calculated in terms of the spread.

A transaction occurs when the highest bid is matched with a lower, or equally high, ask, and a trade between market participants is realized. If the bid (buying offer) is equal to the ask (selling offer) it is obvious that the transaction price is the amount of these offers because both participants are willing to trade at the same price. This does happen but it is not a very frequent occurrence. When offers are exactly equal in the double auction mechanism and a trade occurs, the amount of the offers is simply defined as $Price_t$ and has the same value as the offers. It is much more likely that the matching offers will not be of the same amount and a spread will be between them. In these situations it is necessary to have a solid, simple and a fair way to calculate the price of the transaction

AURORA is a computerized trading system that was developed by the Chicago Board of Trade and its dynamics are explained in detail by (Rust et al., 1994). According to the AURORA rules only the trader with the highest bid or the lowest ask can make a trade if $Lowest\,Ask_t \leq Price_t \leq Highest\,Bid_t$. The price is set at time t as $Price_t$ and is the midpoint between $HighestBid_t$ and $LowestAsk_t$. A mathematical representation of the price is therefore:

$$\text{Price}_t = \frac{(Lowest\,Ask_t + Highest\,Bid_t)}{2} \tag{4.2}$$

Since $Lowest\,Ask_t \leq Price_t \leq Highest\,Bid_t$ it is clear that either side, or both, would have to trade outside their original quotes. This rationalizes why a trader might be willing to take the risk of quoting a price that is outside the current bid-ask spread. A study by (Chen and Tai, 2003) shows that aggressive quotation like this should therefore be thought of as a strategic behavior instead of a ignorant one and might actually emerge in some traders when the double auction market they trade in, evolves. Another very recent study that supports this methodology in price-determination is one by (Inbuki and ichi Inoue, 2011) who use this point on the bid-ask spread to both determine the price when a transaction takes place, and to calculate time-series of returns from the midpoint during the trading period. This method of price-discovery is adopted in the simulation because it is rational, accepted in the field and will help prevent the price from having an upward or downward trend as a result of biased market mechanics.

When using the GM model it is standard practice to assume an underlying true value of the asset that is selected from a known distribution in the start, but remains fixed after that. It is obvious that prices in markets are not fixed this way in the real world and because of that the assumption has to be broader. Ideally, the price would emerge from trading in the market, powered by supply and demand from the trading population. A situation like that is only possible through far more sophisticated agents than those who populate the modified version of the GM model. Instead of trying to improve the simulation with an overhaul of the whole system, some sort of middle ground is sought by giving the price exogenously and incorporating some fluctuations over time in a random walk. In the general GM model, these fluctuations would only consist of a price-flip between two extreme values, $\overline{P}$ and $\underline{P}$ and would therefore not be all that interesting in the case of random walk. The solution to not getting stuck in the predefined range is to change how offers are made after enough trades have materialized in the market for more sophisticated agents to start trading. The value of the asset, when the market starts, is a random variable over a predefined range, the probability laws of which are known to all agents on the market. The first random offers are only submitted by uninformed agents and trades are made where the price fluctuates around the given *true* value.

When enough trades have been made, new agents populate the market and trade based on the price history that has materialized. The offers the new population makes then fluctuate around the last price realized in the market. A mathematical representation of how the offers are selected can be seen in Chapters 3.2.1 and 3.2.2. In reality the fundamental value of an asset, traded in the market, may be affected by market dynamics but for our purposes, setting it exogenously is sufficient.

4.3. Pre and Post-Trading

A study by (Gonnet, 1983) shows that it is common for stock markets to open with preestablished prices that are formed by operating a *clearinghouse* (a double auction market with a fixed closing time) that closes right before public trading begins. Similar mechanisms can be operated at the end of the trading period and in both cases this pre or post period has the main purpose of finding an opening or closing price for the trading period. This study does not incorporate these mechanisms as no pre or post-trading is allowed before the trading period begins or after it has stopped.

4.4. Summary

The chapter explains why the equilibrium price of economic research is abandoned for a stochastic price and gives an overview of how price discovery takes place in the market, as well as explaining how price and spread are calculated. The AURORA rules are explained in detail and reasons are given why pre and post trading is not allowed in the simulation.

The following chapter explains how regulations have prevented many aspects of price manipulation in real world markets. It also introduces trade-based manipulation strategies and how they have come to pass, as well as giving a detailed description of a trade-based manipulating strategy called ramping. Ramping is used by ramping agents who are inserted into the population to manipulate the price.

5. Price Manipulation

The search for profit is something that drives trade and business around the world and has been around much longer than the double auction markets in which stocks and assets are traded in, today. This hunger for profit has resulted in great advancement in economic improvement and market structures. A side product of these improvements is that there have evolved much more advanced methods to manipulate the price discovery process. This chapter will provide a brief preview of how regulations to prevent price manipulation have evolved, and of the method of manipulation that is investigated in this thesis.

5.1. Regulations and trade based manipulation

According to (Allen and Gale, 1990) the existence of price manipulation of stock prices in stock markets was a great concern prior to the Securities Exchange Act of 1934. By placing many restrictions on how trades were conducted and how information was handled, the act reduced the possibilities for price manipulation. A study by (Allen and Gale, 1990) also states that although the Securities Exchange Act may have eliminated action-based and information-based price manipulation strategies, it did not do anything to limit or prevent trade-based manipulation strategies. Their study gives credence to the theory that agents can use these trade-based strategies to produce favorable price movements in the market.

A study by (Bouchaud, 2010)) points to empirical studies that show that in modern electronic markets, there is a strong correlation between signed order flow and price changes. The impact of the trades is neither permanent nor linear in volume as is assumed by many models, but is instead strongly concave in volume and transient due to the long-memory nature of the order flow. Take a look at a question posed by (Hasbrouck, 2007), do trades *impact* prices or do they *forecast* future price changes? According to (Bouchaud, 2010) there cannot be an obvious difference between $informed$ trades and $uninformed$ trades if the strategies that are used in executing them is similar. The assumption is that the impact of any trade must statistically be the same and it does not matter if it is informed or uninformed and therefore it is very hard to detect offers that are meant to manipulate the price from regular offers.

There are some known methods for manipulating price discovery in real world markets as (deB. Harris et al., 2012) explains. Below is a quick overview of some of them:

- *Pools*: When many agents agree to trade a single asset for a predefined period and then divide the loss or profits that are realized.

- *Churning*: To increase activity and hopefully increase the price, a trader places both an ask and a bid around the same price.

- *Runs*: This is when agents decide to spread rumors that are either good or bad about an asset in order to manipulate the price.

- *Ramping*: When placed bids/asks are placed that match the current lowest ask or the highest bid. This is done to drive the price up or down.

- *Wash trade*: When an agent buys and sells large amounts of the same asset in order to increase price.

- *Bear raid*: By short selling a large amount of the asset, the trader tries to push the price down.

5.2. Ramping

In their article, (Aggarwal and Wu, 2003), presented empirical evidence on the manipulation of stock prices in the United States. By extending the framework proposed by (Allen and Gale, 1992) they consider the effects of an agents´ manipulating behavior in the presence of other traders that are information seeking about the stock´s true value. The information seeking agents play an important role in sustaining price manipulation, and because they buy according to some information, they are the ones who are being manipulated. A market with more information seeking agents will have improved market efficiency because of increased competition for shares, but it will also increase the possibility for manipulating agents to enter the market, which will worsen market efficiency where price transparency is concerned. A study by (Aggarwal and Wu, 2003) also supports that in the real world there are certain groups of agents, such as corporate insiders, brokers, underwriters, large shareholders and market makers, that are more likely to be manipulators. They show that stock prices will rise in the period were manipulation takes place and then fall in the post-manipulation period, having great impact on market efficiency.

There exist many methods for trade-based price manipulation but only one will be studied in this thesis. That method is called *ramping* and is performed by placing offers that match the highest bid or the lowest ask in order to make a trade at that price. Subsection explains in detail how ramping works and how the price manipulating agents in this study are programmed into the simulator.

5.2.1. Ramping agents

After data is collected from the simulations of the reference state where no price manipulating agents are inserted into the population, the configurations are tweaked before running the next simulations. Both the distribution of the agents as well as the density of the population is adjusted and then an investigation on how that affects the output for price and trade frequency is performed. When a *rampingagent* is introduced, how he operates, and why he is of interest is explained below.

This type of agent and the reason for his participation was mentioned in Section 1.2 but now his functionality will be explained in greater detail. An agent with this trading behavior might represent an insider in the real world. An insider is an agent that can benefit from an upward/downward trend in the price evolution process, based on superior information or stock options on the asset being traded. He could therefore buy/sell (submit bids/asks) at a higher/lower price than other agents in the market in order to stimulate an upward/downward trend in the price discovery process.

The agent will not just make high offers randomly but will instead enter the market steadily through each trading period and make his offers then, in order to give a rise/fall to the price that will then close higher/lower than normal. Closing price of a trading period is then the benchmark price that will be used in the start of the next trading period. Each trading period starts with the simplest agents placing offers until exactly 20 trades have materialized. The trading period itself does not have a predefined number of trades to specify its size. The number of trades depends on the population density that makes up the market in this time period as well as the length of the period. The time period in which these traders are allowed to place bids in is, as previously mentioned, all throughout the trading period so they can have maximum effect on the closing price. A simple implementation of ramping agents into the trading period is used as their trading is evenly distributed through the trading period. The portion size of ramping agents, of the whole population or trades that materialized in the trading period, can then be changed in order to see the effects and investigate how many insiders are needed to make an effective upward/downward bump to the price discovery process.

It seems obvious that producing a rise/fall to the closing-price in a current trading period will affect the next trading period so that it starts at a higher/ lower price. The intensions of this type of agent can be seen visually in Figure 5.1 where price follows a random process but abnormal bids are made to increase the closing price by 5%. The figure is not based on a market simulation, but is only an example of how such a strategy might play out based on a stochastic process.

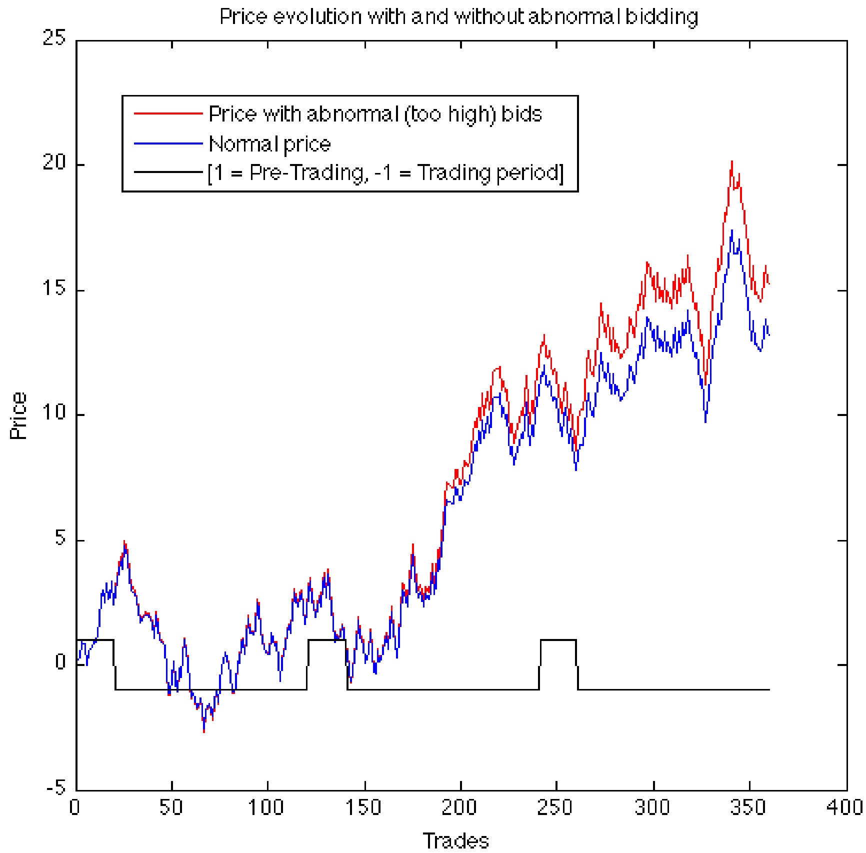

Figure 5.1: A visual example of the intensions of a ramping agent

The size of bid/ask offers placed by the ramping agents will always match the current lowest/highest ask/bid. This will give the price an upward/downward change with each bid/ask as it will always materialize in a trade when it is paired with the lowest/higher ask/bid. The price is equal to the lowest/highest ask/bid and is therefore higher/lower than price usually is when there is a spread between the highest bid and the lowest ask. Mathematical representation of the bid amount for ramping-agents is:

$$\text{Ramping}_{bid} = \text{Ask}_{low} \tag{5.1}$$

The same follows for the ask amount for ramping agents:

$$\text{Ramping}_{ask} = \text{Bid}_{high} \tag{5.2}$$

5.3. Summary

This chapter provides an overview of how price manipulation has evolved and how regulations have reduced price manipulation. Some trade-based manipulation strategies are mentioned and briefly explained but a deeper explanation is given to a method called *ramping* since that is the method the price manipulating agents in our simulator use. The agents themselves and how they work is also explained.

The next chapter will describe how the simulator is constructed and configured. It is not a step-by-step guide to how it is programmed but it will explain how its dynamics work and are constructed. It also gives an overview of what information is extracted from the simulator and explains how efficiency is measured.

6. Simulating a market

Simulations in financial research are used to attempt an imitation of how a real world system or process evolves over time. A simulation generates an artificial history of the system and that observation is then compared to the history of the real system that the simulation was meant to imitate. Using simulation as a problem solving methodology has proved indispensable to the solution of many real world problems, and the financial world is no exception. Simulation is used to describe and analyze the behavior and evolution of systems as well as asking "*what if*" questions about the real system being observed.

Before a simulation is ran it must be decided how the system parameters are configured. The estimate that the simulation creates should be as statistically precise and free of bias as possible. In order to facilitate that, the following questions should be kept in mind for each model design:

- How long should each simulation run be?
- How many independent simulation runs should be executed?
- What is the initial state for each simulation (parameter selection)?
- How many different cases/states should be simulated?

Interpretation of simulation results can be difficult since most outputs are essentially random variables as they are based on random inputs. According to (Banks, 1999) it can be difficult to diagnose whether an observation results from system interrelationships or randomness. A simulation model can only produce a statistical estimate of the *true* performance measure but not the real measure itself. The long run (steady state) behavior of the system is sometimes of main interest for the analyst, but these systems may begin with some unrepresentative state. This is why simulations are often ran for a predefined period called $pre-trading$ period, before the actual simulation starts (Law, 1991).

The simulation does not make use of the pre-trading period as it takes time for all the agent-types to start making offers since they need different amounts of information in order to make trading decisions. In the double auction market model, there are parameters and simplifications that need further explanation. Chapter 2 provides an overview of the dynamics of the double auction markets and explains how these dynamics are addressed in the model. This chapter has, therefore, mainly the purpose to give an overview of parameter selection and how certain dynamics are modified (mainly for simplification reasons) in the simulation.

6.1. Configurations

The following subsections are meant to give a slightly deeper description of how the simulator is constructed, but are not step-by-step instructions on how it is programmed.

6.1.1. Market mechanisms

The market is constructed as a basic double auction market. Agents place offers in the form of bids and asks and these offers are then compared to check if a trade can be made. All bids are sorted into a list that is called *Bidlist* and asks are sorted into a similar list that is called *Asklist*. The lowest ask is called the *outstanding ask (oa)* and the highest bid is called the *outstanding bid (ob)*. If, at any point, we have $outstanding\,ask \leq outstanding\,bid$ then a trade is formed at a $Price = \frac{oa+ob}{2}$. The lists themselves are not cleared after a trade occurs. Only the offers that formulated the trade are cleared from the lists and then there is a new *outstanding bid* and a new *outstanding ask*.

The spread in the market is completely dependent on the agents´ offers since it is the difference between the highest bid and the lowest ask, and no attempt is made to model the size or evolution of the spread in any way.

Figure 2.1 provides a visual representation on how the double auction market works. There is also a much more detailed description of the market dynamics in Chapter 2.

6.1.2. Population

When deciding the size of a population in a simulation, there are many possibilities as the size can be fixed, varied, random, or a function, to name but a few options. The first thing to do is to define the population density. The method for setting population density is performed by selecting the frequency of offers entering the market. The offers come from agents that populate the market so the frequency of those offers represents how populated the market is of active participants. In the simulation, one trading period is defined as $T = 8 * 60 * 60$ (sec) where one trading day is considered to be 8 hours. A decision needs to be made on how many days should be simulated in each run, which is then defined in the variable $NumberOfTradingDays$. With the trading period defined as 8 hours long, the density of the population can be selected by varying the frequency of how often agents are called to make a trading decision over the 8 hour period. The size of the time increment h to when the next agent is called to make an offer is drawn from an exponential distribution so the event occurs randomly between time t and time $t+h$ where h is a small increment and t is the waiting time until the event occurs. The size of h is then the determining factor of the population density. The smaller the h, the more populated the market is. The effect that different population density has on price-manipulation strategies is one of the key topics of this study.

When the size of the population (arrival rate of offers) has been selected it is time to determine whether the offers that come from agents are bids or asks. As mentioned earlier, the simulation starts with not all agent-types being active but post random bids or asks with equal probability, $p = 0.5$. A more comprehensive explanation of how these agents work can be found in Section 3.2.1. After the market starts and enough trades (20) have materialized and all agent-types have started to participate, the rules are different. One type of agents still posts bids and asks randomly with equal probability, but the rest of the population base their trading decisions on various methodologies that are described in Section 3.2.

By having different types of traders, there is some level of diversification in the trading behavior of the population. Although it is not possible to replicate the real market to the fullest extent, this gives a better approximation of reality than having only one type of trading behavior in the model. There are six different types of agents in the trading period and each group has a different type of trading strategy. When an agent is called to make an offer, his *"behaviour-type"* is selected from a uniform distribution. The probabilities the types have is $p = 1/6$ in the first simulation (reference state) but the probabilities can be changed in order to examine the effects each type of agent has on the price-discovery process and the frequency of actual trades.

6.1.3. Size of offers

As explained in Chapter 2 the classical economical approach which gives the agents information about the redemption value of the asset (that they then use to make a profit in the market as they use the information in selecting the size of their offers) is abandoned. In this study, the price-discovery process that formulates from the buy/sell decisions made by the agents that use known methods in their decision making process, is of interest but is not the main topic. The main topic of the thesis is an investigation on the effects that ramping trading behavior has on this process in various market population densities.

In the first trading period, in each simulation, the price is given exogenously as 100 with a random component. The offers will then fluctuate on the range $[97, 103]$ in the trading period and the price will also fluctuate until enough trades have materialized (20) so all agent-types can start placing offers. The offers are calculated as shown in Equation (3.1) but with the scalar taking the value of 100. There is equal probability of the random component being positive or negative. A more general explanation of the agents that start the trading in each period and their behavior can be found in Section 3.2.1. At the start of the second trading period the price is also given exogenously as the last price discovered in the market in the first trading period with the same random component as in the first pre-trading period:

$$\mathrm{Offer}_{bid,ask} = ClosingPrice_{p-1} \pm 3 * e^{\|N(0,1)\|} \tag{6.1}$$

where $ClosingPrice_{p-1}$ is the closing price of the market in trading period $p-1$ as p stands for current trading period. The reason for the delay of certain agent-types in the simulation to start placing offers in the trading period is to generate a certain amount of history on price discovery and spread so that the agents in the population that also trade in the trading period, can start formulating their strategies based on that information.

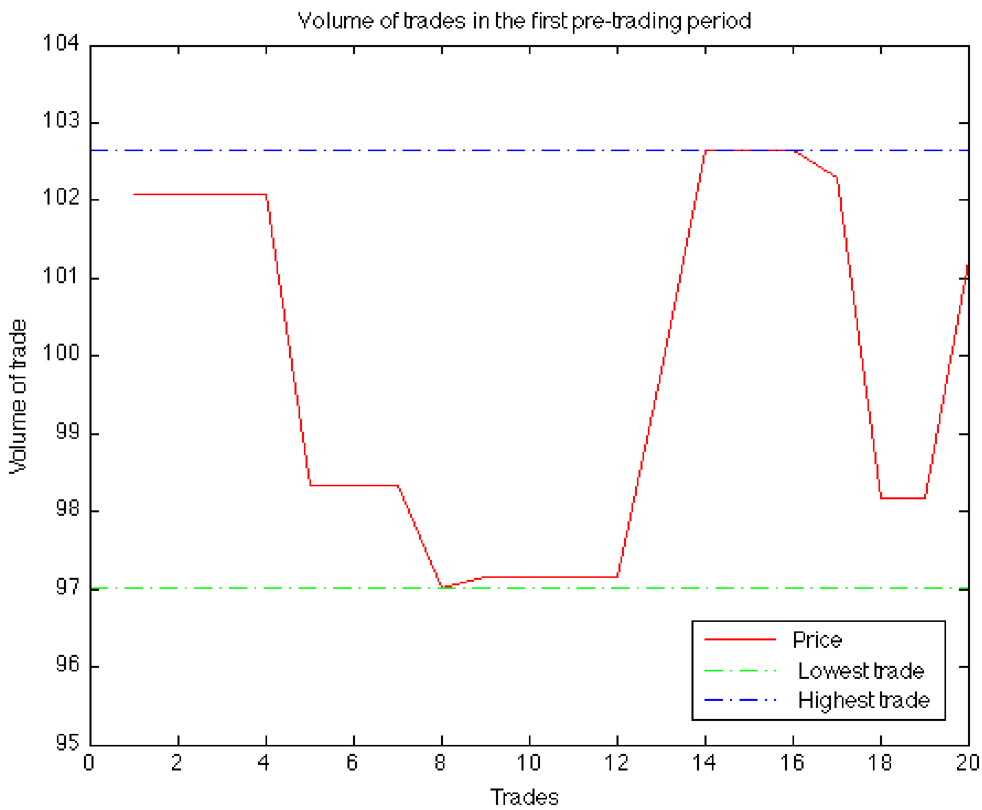

Figure 6.1: An example of price-discovery for the first 20 trades in the first trading period.

When all agent-types are active in the trading period, the price is determined by the trading decisions of the market participants as their offers are based on the latest spread in the market. The offers are calculated using Equation (3.2). Whether agents choose to place a bid, an ask or stay neutral (by not posting an offer) when they are called upon is based on their trading strategies. An overview of those strategies can be found in Section 3.2.

6.2. Runs

Uncertainty, variability and the ability to express more than one interpretation all need to be considered when looking at results from a simulation. There is no way to accurately predict the future so a method that values our predictions in a reasonable manner must be selected wisely. The outcomes of the simulations need to be compared in order to estimate whether the effects of the changes that were made are statistically significant or not. It is a common goal for most statistical research projects to study causality and draw conclusions on the effect of changes in the values of predictions. Experimental studies and observational studies are the two main types of causal statistical studies and obviously our study is an experimental one. This type of study involves taking measurements of the system that is being investigated, manipulating the system, and then taking more measurements with the same method in order to determine if the manipulation has modified the values being measured. This is exactly what is attempted in this study. Applying statistics to a scientific, industrial or a financial problem requires a population or a process to be studied. A population can represent things like "all market participants" but it can also be a composition of observations of a process at various times. When data is collected about this type of "population" it is called a time series.

This experimental study uses a random generator to select, from a uniform distribution, what type of agent should be called on in each time-step. The valuation of when the time-step t actually takes place also has a random component as a time increment h is drawn from an exponential distribution that has a range that can be varied in order to change population density. The amount offered by agents has a random component as well. In order to make statistical calculations, when input has a level of randomness, so that statistical significance can be estimated, a certain amount of output data is needed as explained by (Box et al., 2005).

Exactly 1000 simulations were ran for the original settings of the model. These settings are called *"reference"* states of the market and are considered the benchmark by which the other results are compared. The results of each simulation are recorded and collected to make calculations of statistical significance when all simulations are finished. When the reference state has been simulated and the benchmarks are in order, the population is tweaked and ramping agents added in order to see the effects this has on the price discovery process and frequency of trades when 1000 simulations are ran for each case/state. This is what is investigated in this thesis.

6.3. Outputs

In statistical research it is of the outmost importance to look at the right things and collect the right data from the simulation runs that are performed. When the data from the simulations has been collected it is then a matter of doing some statistical testing on that data and then interpret the results from that testing into some form of a conclusion. This conclusion is then the end product of the research that has been conducted. Let us now think about the problem of analyzing the output of a single simulated system like the one we are looking at in this study. In multiple simulation runs there are different outputs that are independent from simulation replication to replication. The traditional way of handling the outputs has been to focus on the means instead of looking at the distribution of the outputs. The distribution function and/or the values of the statistical parameters of the outputs are usually hidden and unknown from the analyst but there are methods available to gain insight into these attributes. Analytical methods might, for example, indicate that Gaussian, normal, exponential or geometric distributions are appropriate. While giving insight into the distribution of the output, the analytical method may fall short in providing answers to what the precise values of the distribution parameters are. Figure 6.2 shows a framework for analyzing stochastic simulation experiments.

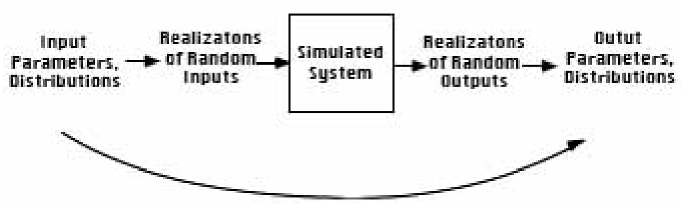

Figure 6.2: A framework for analyzing stochastic simulation experiments. Adapted from "Bayesian analysis for simulation input and output," by C. E. Chick, 1997

According to (Chick, 1997), the process that is visually represented in Figure 6.2, can be summarized with superscript r, used to emphasize quantities specific to replication r. Subscript i stands for the i-th element of a vector.

1. λ^r is a statistical parameter that is selected for replication r.
2. The random variates $x_1^r, x_2^r, ...$ (size of bid/ask, agent types,...) are produced from a distribution that depends on λ^r.
3. The simulation of the system now produces o^r which is a random output.

4. With the output created a parametric distribution $f_{O^r|\theta^r}(o^r)$ is assumed to describe the output. θ^r may depend on λ^r.

5. Now an unknown deterministic function Ξ maps the input to output parameters, $\theta^r = \Xi(\lambda^r; \phi)$ where $\phi = (\phi_1, ...\phi_N)$ are unknown parameters with a another distribution $p_\Phi(\phi)$.

Ξ, Φ and O may either be scalar or vector valued.

Detailed explanations have been provided in previous chapters on what is to be investigated and now an explanation of what data is going to be collected and why, is in order. Most attention is paid to certain parts of the data that the simulation creates, but not all possible outcomes for all possible scenarios are to be investigated. The most important variable in the simulation is the price and how it evolves over time in different settings in the simulation. The frequency of trade is also important as we investigate how different population distributions affect the participation of the agent-groups. The main observations are:

- Number of bids, asks and trades that each group participates in, as well as what prices each group trades in.

- Initial price and closing price for each simulation.

- The changes that are made on the parameters between simulations

- Different amounts of ramping agents that are implemented into the market.

There are other variables to consider but these are the fundamental ones to look at.

6.4. Statistical Testing

The test used is the Mann-Whitney U test which is used to determine whether one of two samples of two independent observations has the tendency to have higher values than the other. According to (Rosner and Grove, 1999), the Mann-Whitney U test is common in statistical practice when comparing the measures of two samples where the assumption of normality can not be made.

When performing the test a statistic usually called U, is calculated when the distribution under the null hypothesis is known. The first thing to do is to arrange all the observations into a single ranked series without regard to which sample they are in. For samples that are greater than 20, the following procedure is used where there is no specification as to which sample is defined as sample 1.

1. First the ranks for the observation from sample 1 are added up. Next the ranks in sample 2 that equal $N(N+1)/2$ where N is the total number of observations, are summed up.

2. U is then calculated in the following manner:

$$U_1 = R_1 - \frac{n_1(n_1+1)}{2} \tag{6.2}$$

where n_1 is the sample size of sample 1, and R_1 is the sum of the ranks in sample 1. A formula that is equally valid for U is:

$$U_2 = R_2 - \frac{n_2(n_2+1)}{2} \tag{6.3}$$

The smaller value of U_1 and U_2 is used when consulting significance tables. Calculating the sum of the two values is straight forward:

$$U_1 + U_2 = R_1 - \frac{n_1(n_1+1)}{2} + R_2 - \frac{n_2(n_2+1)}{2} \tag{6.4}$$

With the knowledge that $R_1 + R_2 = N(N+1)/2$ and $N = N_1 + n_2$ and some algebra calculations the sum is calculated as:

$$U_1 + U_2 = n_1 n_2 \tag{6.5}$$

Maximum value of U is then the product of the sample sizes for the two samples. In such cases the size of the compared U is then obviously zero.

6.5. Efficiency

It is only in recent years that computational capacity has grown to the extent that it can handle complex and extensive simulations of agent-based modeling. Section 3 gives a better overview of how research on agent-based modeling has evolved over time and where it stands today. The efficiency that is looked at in this simulation is simply the time each simulation takes to run because extensive agent-based simulations can still, today, take great amounts of time. In order to improve the model and code, it is important to look at the time it takes for it to run into account and try to minimize it.

Efficiency is not measured by the robustness of the code but by the time it takes to run the simulations. Efficiency is not the prime focus of this thesis but the time that the simulations take is measured, based on different amounts of ramping agents inserted into the population of agents. The answers to how ramping-agents affect the runtime might prove useful in future work and improvements to the current simulator.

6.6. Summary

Simulations of agent-based models where agents trade in a double auction market have only recently been manageable due to the poor computational power of computers in the past. Now, with more powerful computers, it is possible to simulate complex and extensive agent-based models in order to investigate the dynamics and properties of systems. When using simulations in experimental research it is important to clearly define what will be the input and what will be the output as well as selecting what parameters of the system will be changed between simulations. First a reference state is simulated and then the changes are made and simulations are ran again. With the different results in hand it is now the objective to analyze what changed in output with changes in parameters. Due to the randomness in the model, 1000 simulations are ran for each "state" of the model and then, approved statistical methods are used to analyze the results.

A standard double auction market that operates an order book to keep track of current bids and asks on the market is used. The population density of the market is controlled by the frequency used to call upon agents to make their trading decisions. Each trading period starts with ZI-agents posting offers until 20 trades have materialized followed by the "real" trading period of the population of six different types of agents. The calculation of the offers is different between those two periods but the same for all agents within each period.

Ramping agents are then inserted into the population during each trading period to investigate the effects that abnormal trading behavior like "ramping" has on the price-discovery process. Output is then gathered to make statistical calculations in order to analyze and interpret the results. The efficiency of our simulator is also investigated by taking the time of each simulation and comparing the results depending on different amounts of ramping agents being inserted into the population. Increasing efficiency by minimizing the computational time is important in improving the simulator for future work.

The next chapter will show the results of the simulations for price manipulation, frequency of trade and efficiency.

7. Results

The results are split up into three chapters. The main results and the focus of this study is, as mentioned earlier, how price-discovery changes with the introduction of ramping agents to the market. The question of how the frequency of trade is affected by inserting the new agents to the market is investigated and the run time of the simulations is measured and compared.

The results presented in this chapter are based on a population of agents that have different strategies and are representative of the market as it is constructed in this study.

7.1. Price Change

Of particular interest is how the introduction of ramping-agents who have abnormal motivations for trading and might because of that make abnormal trading decisions, affects the price-discovery process. The abnormal behavior that is implemented in these agents is to make a bid that will match the lowest/highest ask/bid that is currently on the market, during the whole trading period. This trading behavior could therefore give an abnormal increase or decrease to the closing price at the end of each period.

As it is computationally very intense to simulate many trading periods, the investigation is constricted to just two trading periods and one insertion of the ramping traders.

7.1.1. Reference State

With the simulation results in hand for the reference market (where there are no ramping-agents) it is in order to have a look at a histogram of the results in order to define its distribution. 1000 simulations were ran to get a decent number of samples to form a distribution to work with.

At first glance we see that the results are not very normally distributed and by looking at the histogram it is quite obvious that there is a peak around 100. The distribution is plotted at the bottom of Figure 7.1.

Although it does not look fitting on the histogram, the normal distribution deserves a deeper look and a QQ plot is used to see how it really fits. By looking at the plot, the distribution seems to fit nicely. The QQ plot can be seen in Figure 7.1. The purpose of determining what distribution fits the results is to be able to select the proper statistical tests of significance to compare the results. This is how

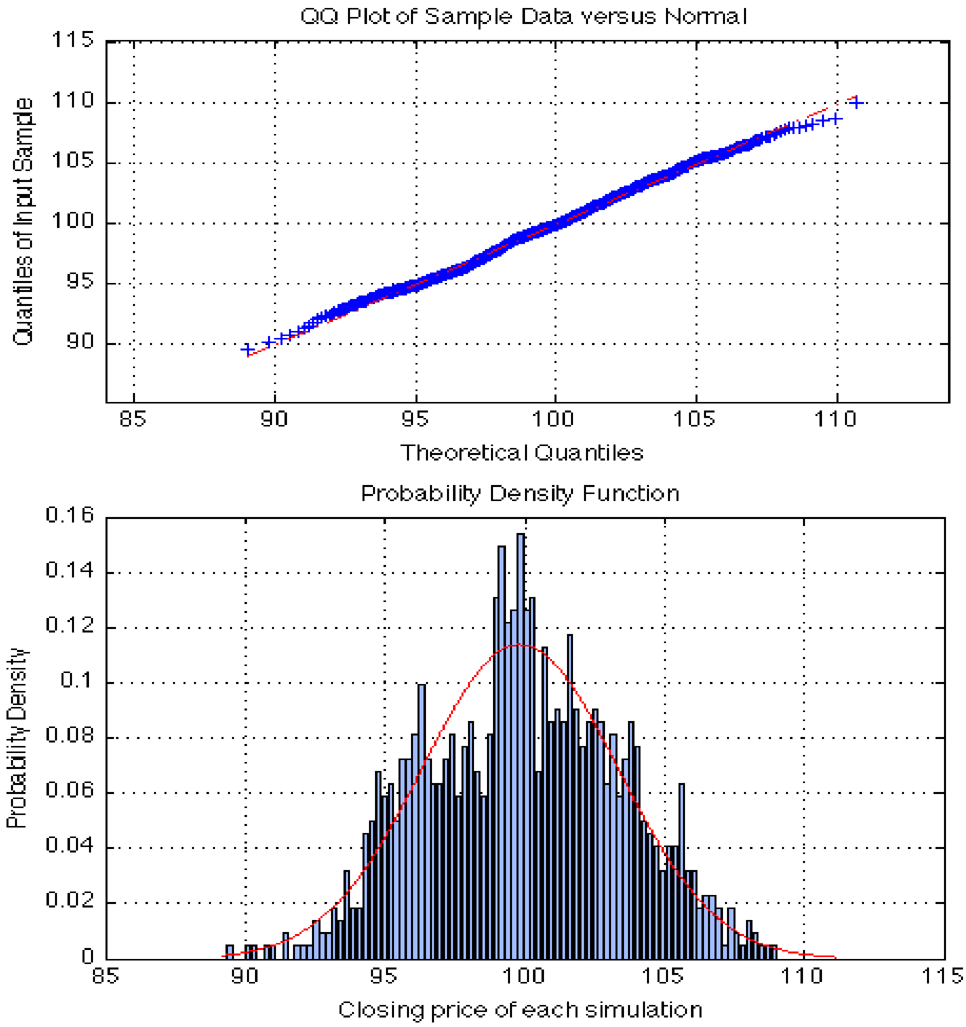

Figure 7.1: Probability Density Funcion fitting to closing price and a QQ plot for normal distribution (reference state)

the effect of the ramping agents is observed in order to see if it is of statistical significance. Other interesting variables were also observed in the simulation to better visualize how the population behaves and whether the ramping agents will have some effect on their behavior, as well as the price-discovery process. The results from that investigation are in Section 7.2.

The average opening price was 100.4 with a standard deviation of 1.95. The average closing price after two trading periods was 99.8 with a standard deviation of 3.5. In order to estimate properly if the closing prices for the reference state are normally distributed a one-sample Kolmogorov-Smirnov test was performed and although it looked fitting from the graphs, the test rejected the hypothesis that the results are normally distributed at a 5% significance level. Results from the Kolmogorov-Smirnov tests for all states can be seen in Table 7.1. P-value was 0 for all scenarios.

Table 7.1: Properties of the results of all ramping states.

Scenario	Opening price (std)	Closing price (std)	Hypothesis (5%)
Reference	100.43 (1.95)	99.83 (3.51)	Rejected
0.1%	100.57 (1.94)	99.96 (3.45)	Rejected
0.125%	100.61 (1.97)	100.24 (3.44)	Rejected
0.25%	100.59 (1.90)	100.62 (3.21)	Rejected

7.1.2. Ramping States

In order to investigate the effects that ramping agents have on the market, the same data has to be collected from the market with the new population as was done for the reference state. The number of new agents that are inserted into the population is varied as a fraction of the initial (reference) population. Markets that have ramping agents in the amount of 0.25%, 0.125% and 0.1% percent of the initial population are simulated in order to investigate how many are needed to produce a price manipulation effect. How and when they are inserted into the market to make offers as well as how their offers are determined, is explained in detail in Section 5.2.1.

By looking at the histogram of the results for the market with an insertion of ramping agents in the amount of 0.25%, 0.125% and 0.1% of the market, it can again clearly be seen that the results seem to be normally distributed. The distribution of the results is quite similar to the reference state.

Establishing whether the results are normally distributed or not is what is needed in order to choose the appropriate statistical test for comparison that will follow in the next section. The QQ plots in Figure 7.2 show how the distributions might seem to be normal but the results from the Kolmogorov-Smirnoff tests are shown in Table 7.1 for all ramping states. Normal distribution for the closing price was rejected for all states.

Again, a one-sample Kolmogorov-Smirnov test is used to test if the results are normally distributed. Table 7.1 shows average opening and closing price of the results for all scenarios as well as the results of the Kolmogorov-Smirnov test for the hypothesis of normally distributed results at a 5% significance level.

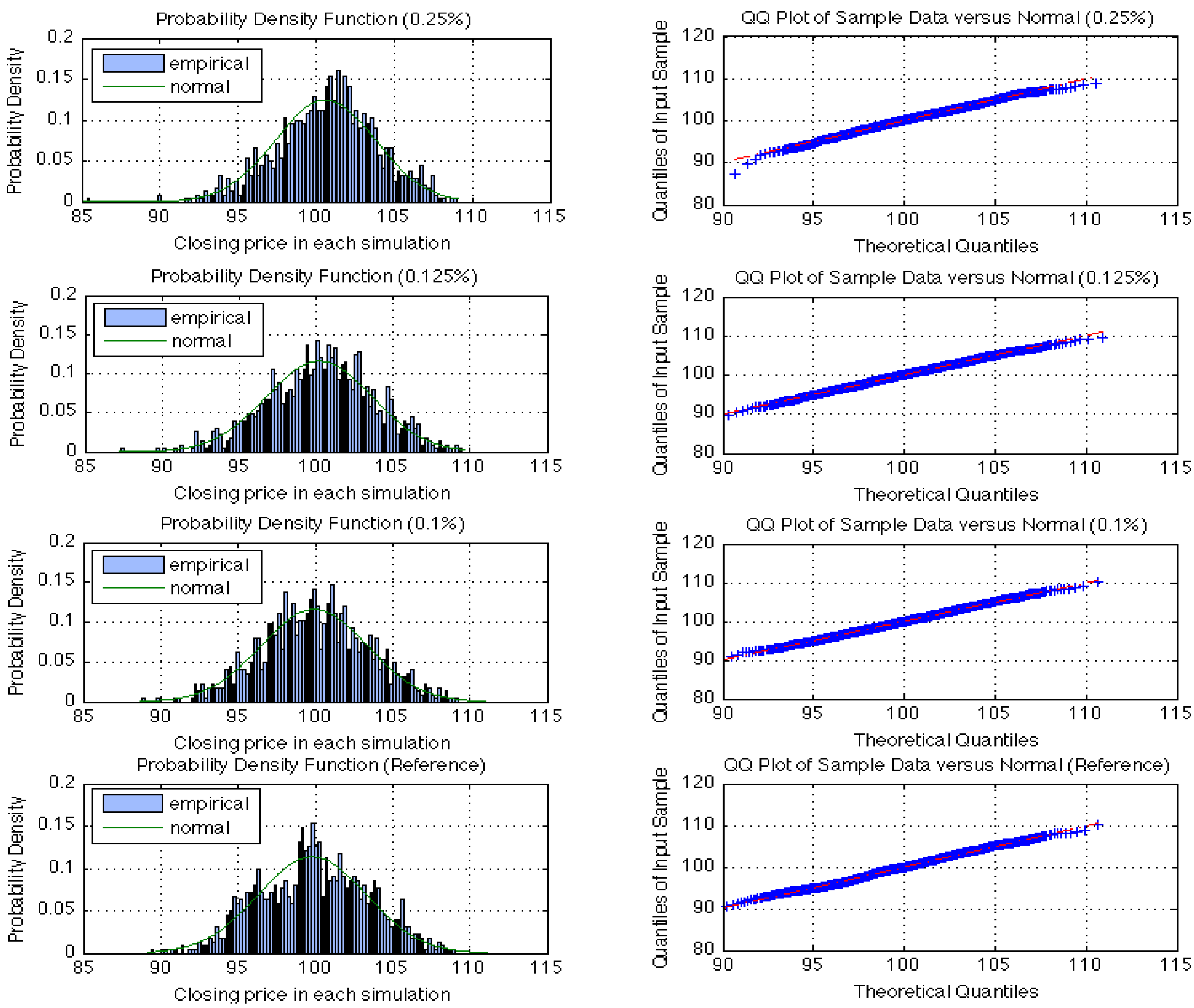

Figure 7.2: Probability Density Funcions fitting to closing price and a QQ plot for the normal distribution (All states)

Like the reference state, although they looked fitting from the graphs, the test rejected the hypothesis that the results are normally distributed at a 5% significance level for all ramping-states. With the results for the three different states, where ramping-agents are inserted into the market in different numbers, the next step is statistical comparison in order to justify that the new agents really have the suspected effects.

7.1.3. Statistical Comparison

Having ruled out that the results are normally distributed (only more fitting were Inverse-Gaussian, Nakagami and Rician distributions), a non-parametric statistical hypothesis test is used to assess if the ramping agents have price-increasing effects on the price-discovery process in the market.

The results from the Mann-Whitney U test for the results, where the three ramping states are compared to the reference state under the null hypothesis that the samples have equal median (insertion of ramping agents has no effect on the closing price), are collected in Table 7.2.

Table 7.2: Results from null hypothesis results for equal median.

Scenario	1% significance	P-value
0.25%	Rejected	$5.83 * 10^{-10}$
0.125%	Rejected	0.0048
0.1%	Not rejected	0.47

The hypothesis was rejected for two of three scenarios at a 1% significance level. This gives the statistical facts needed to state that inserting ramping agents with the trading behavior of "buying up" the lowest asks in order to increase the closing-price of the market, works if the ramping-agents are 0.125% or more of the population. Many scenarios were tested in order to find where the ramping-agents started to have an impact on the price and it is safe to state that inserting a number of ramping agents that is only 0.125% of the initial market population is inserting just enough to have an impact on the closing price. It also gives reason to believe that in small markets, manipulation is easier for a single agent that has the means to "buy up" the asks at the end of each trading day in order to keep the price of the asset increasing.

7.2. Frequency of Trades

When inserting a group of ramping-agents that make trading decisions that are serve the purpose of stimulating a price-increase in the market, it is interesting to investigate how the market reacts to it. In this section there is investigated if and how trading behaviour of the market participants changes with the introduction of the ramping agents and also if there is a change in number of trades that the "reference" market participants take part in.

7.2.1. Reference State

As before, the first thing to do is to collect data from the simulations of the reference state in order to compare them to the ramping states. Table 7.3 lists a variety of information about the trading behavior of the population. All numbers are averages from the 1000 simulations.

Table 7.3: Trading behavior of the population in the reference state.

Strategy	Bids	Asks	Trades	Average trade (std)	Total volume
NZI	210.8	233.7	245.9	100.8 (3.10)	24779.8(29.1%)
Simple Trend	9.1	9.6	9.1	100.6 (3.01)	916.5(1.08%)
EMA	186.6	255.4	239.3	100.6 (3.14)	24082(28.3%)
RSI	169.2	273.5	241.1	100.7 (3.25)	24264.9(28.5%)
EMA+RSI	**166**	**0.9**	**90.2**	**101.7 (3)**	**9167(10.2%)**
% R	21.9	12	17.9	101.2 (3.02)	1811.2(2.1%)
Total	769.6	791.2	**843.4**	**100.8 (3.16)**	85021.4

Looking at Table 7.3, it is clear that not all the agents are equally active in the market. They vary in their frequency of how often they place offers, the ratio between bids and asks that they place, and the average price of the trades they participate in. The average number of trades (843.4) for each simulation is the most crucial number since the intentionis to see if it changes with the introduction of the ramping agents.

Another interesting behavior belongs to the EMA+RSI agents but they almost only place bids, and the average trade they participate in is higher (101.7) than for any other agent group. This is evidence of a very aggressive behavior that stimulates the price upwards. In order to see if there is a statistical difference in the closing price with and without this type of agent present in the market, a simulation without them is performed. The results from that simulation are collected in Table 7.4. With the EMA+RSI agents excluded from the population, the average trade

Table 7.4: Trading behavior of the population in the reference state (without the EMA+RSI agents).

Strategy	Bids	Asks	Trades	Average trade (std)	Total volume
NZI	246.2	247.6	275.2	99.9 (3.27)	27483.9(32.4%)
Simple Trend	9.7	10.5	9.9	99.9 (3.11)	988.4(1.16%)
EMA	230.6	260.1	273.6	99.8 (3.35)	27310.2(32.2%)
RSI	214.4	276.8	272.2	99.8 (3.4)	27166.9(32%)
EMA+RSI	**0**	**0**	**0**	**0**	**0**
% R	27	12.4	19.2	100.3 (3.22)	1928.5(2.3%)
Total	733.9	813.4.2	**850.2**	**99.8 (3.33)**	84899.9

decreases as expected from 100.8 to 99.8, but the number of trades does not change much although they are slightly higher without the EMA+RSI agents. In order to see if the drop in the average trade is of statistical significance, some more testing is required. The Kolmogorov-Smirnov test rejects the hypothesis that the closing-price results are normally distributed for the state without the EMA+RSI agents, which is the same result as for the reference state. Next a Mann-Whitney U test is performed to test the null-hypothesis that the mean, from the two states being compared, is the same. The hypothesis is rejected at a 5% significance level and that gives credence to the assumption that price will change between different populations, and that the results in this study only apply to the population that is used in the simulations and cannot be assumed to apply for other populations that are constructed in a different way.

7.2.2. Ramping States

Now that the data from the simulation of the reference state has been collected, the same is done for all three ramping states in order to make some comparison and see if the introduction of the new agents had some effect on the number of trades or the trading behaviour of the reference population. The data for the 0.25% state is collected in Table 7.5.

Table 7.5: Trading behavior of the population in the 0.25% state.

Strategy	Bids	Asks	Trades	Average trade (std)	Total volume
NZI	209.3	166.5	227	101.3 (2.81)	22991.6(25.7%)
Simple Trend	10.9	8.9	9.4	101.4 (2.83)	955.5(1.1%)
EMA	192.8	246.6	229.7	101.3 (2.91)	23269(26.1%)
RSI	154.1	283.8	228.3	101.1 (2.98)	23089.4(25.8%)
EMA+RSI	**168.6**	**0.8**	**88.1**	**102.2 (2.67)**	**8991.8(10.1%)**
% R	18.6	13.2	14.3	101.6 (2.62)	1456.5(1.6%)
Ramping	**84.3**	**0**	**84.3**	**101.6 (2.74)**	**8563.5(9.6%)**
Total	845.9	726.8	**881.1**	**101.4 (2.87)**	89323.3

First the 0.25% scenario is observed and the average number of trades, formed by our reference population, has dropped 5.5% from 843.4 to 796.8 (trades that ramping-agents participate in are subtracted from the total sum of trades). It is no surprise that the amount of the average trade is also up as it rises 0.595%, which validates the findings in Section 7.1.3, that the insertion of ramping agents that "buy up" the lowest asks will have price-increasing effect in the 0.25% state. With an aggressive trading strategy, the EMA+RSI agents are also increasing the average price by participating in trades at the highest price of all the agent groups which is the same behavior as in the reference state. The diversification of the population was the same in all the simulations (except when the EMA+RSI were completely dropped, Table 7.4) as each group was kept in even proportions, which is how we can see the trading behavior in each group of agents. In order to observe how active our groups are, we may start by looking at the Simple Trend agents, who might represent the common individual trading in the market. These agents seldom trade but at around the average price of the whole population in both the reference state and the 0.25% state. Then there are three groups of agents (NZI, EMA and RSI) that are the most active as they trade very often (together make up for almost 80% of the market in trades in the reference state) and at an average price that is close to the average price for the market as a whole. It is interesting to see that their "market-share" drops in the 0.25% state at a similar level to what the ramping agents gain of the "market-share". The remaining two groups also show interesting behavior as the EMA+RSI agents trade aggressively at a relatively high price but almost never place asks and only place bids in both the reference and the 0.25% state. In both states it is obvious that the %R agents trade at high prices despite being involved in relatively few trades. Overall the market is well diversified with much variation in activity price at which trades are made. Inserting ramping agents in the amount of 0.25% of the overall market does not seem to affect the frequency of trades all that much. A possible reason for this is that they do not participate in trades every time they are inserted (or they would have a higher market share) because they may enter the market when there is no outstanding ask. They seem to have some effect on the price of trades as there is a smaller gap between the lowest group and the highest.

When the amount of ramping agents is cut in half and only what amounts for 0.125% of the market population, inserted, it produced the results that can be seenin Table 7.6. When looking at the overall results it becomes apparent that they are

Table 7.6: Trading behavior of the population in the 0.125% state.

Strategy	Bids	Asks	Trades	Average trade (std)	Total volume
NZI	204.6	200.8	236.1	101 (3)	23845.6(27.5%)
Simple Trend	10.3	9.1	9.8	101 (2.87)	987.5(1.1%)
EMA	185	249.4	235.2	101 (3.08)	23748.5(27.4%)
RSI	161.7	271.8	231.1	100.9 (3.15)	23311(26.9%)
EMA+RSI	**164**	**0.7**	**87.7**	**101.9 (2.9)**	**8932.1(11.1%)**
% R	20.5	11.8	15.1	101.5 (2.77)	1534.8(1.8%)
Ramping	**43.5**	**0**	**43.5**	**101.2 (2.96)**	**4401.5(5.1%)**
Total	784.6	750.5	**858.4**	**101.1 (3.06)**	86761

very similar to the results from the 0.25% state, although the average trading price drops from 101.4 to 101.1 as is to be expected if any wisdom has been drawn from Section 7.1. A small increase in the frequency of trades is also noticeable for the whole population as the number of trades rises 2.27% from 796.8 to 814.9 (trades that ramping-agents participate in are subtracted from the total sum of trades). With the number of ramping agents inserted into the market, cut in half, the trading activity of the ramping-agents drops by half as well. This is quite surprising as there is not a linear relation between the number of agents and their trading activity as agents can be inserted into the market at a time when there is no outstanding ask.

The results from the last (0.1%) state are collected in Table 7.7 in order to see if there are any significant changes to the number of trades or the trading behavior of the market participants. The results are pretty similar to the 0.125% state as

Table 7.7: Trading behavior of the population in the 0.1% state.

Strategy	Bids	Asks	Trades	Average trade (std)	Total volume
NZI	207.7	229.8	235.2	100.7 (3.06)	2682.7(28.7%)
Simple Trend	9.1	10.1	9	100.7 (3)	904(1.1%)
EMA	183.8	256.1	231.5	100.6 (3.12)	23291.9(28.2%)
RSI	171.3	270.9	233.8	100.6 (3.21)	23513.2(28.5%)
EMA+RSI	**164**	**0.8**	**89.1**	**101.7 (2.97)**	**9061.5(11%)**
% R	21.8	12.9	16.7	101.2 (2.95)	1692.6(2.1%)
Ramping	**3.6**	**0**	**3.6**	**101 (2.94)**	**366(0.4%)**
Total	767	878.7	**819**	**100.8 (3.13)**	82511.8

is to be expected. The main variables do change in the same direction as before, as the average trading price drops from 101.1 to 100.8 and the frequency of trades slightly increases as there is a rise of 0.061% from 814.9 to 815.4 in the numbers of trades (trades that ramping-agents participate in are subtracted from the total sum of trades). When the trading activity of the ramping-agents is observed we see that it drops to 3.6 trades on average from 43.5 in each simulation, which is far more than their drop in numbers from the 0.125% state to the 0.1% state. This gives credence to the assumption that their trading activity is not linearly related to their numbers.

7.2.3. Comparison

The difference in number of trades between the ramping states is quite small but it seems that with the insertion of the ramping agents there is a decrease in the number of trades that the reference population participates in. The fall in trades from the reference state to the most extreme ramping state (0.25% state) is 5.5% which shows that inserting the ramping agents into the reference population does decrease their participation in trades. The drop is less drastic from the reference market to the 0.1% state compared to when these agents have been introduced to the market, since increasing their number has a more powerful effect.

A rise in the average amount of trades (price) comes as no surprise as that is in contrast with the findings in Section 7.1.3. It is interesting, however, that the introduction of the new agents does not have any drastic effects on the trading behavior of the population besides the drop in trading frequency and the increase in price. The groups themselves do not seem to change their number of offers or the amount offered all that much.

Another interesting observation is the trading behavior of the EMA+RSI agents as they seem to have a more aggressive and price increasing trading behavior than the ramping agents. When involved in the reference state market, they trade at the highest price of all agent-groups and almost only place bids, which is a very similar behavior as that of the ramping agents. Although they trade in a similar way, the decision-making process is different and because of that it is interesting to look a bit further into the impact of the EMA+RSI agents on the reference market. The results from a simulation without the EMA+RSI agents revealed that there was a drop in price from 100.8 to 99.8 but the number of trades for the market actually went up from 843.4 to 850.2.

7.3. Efficiency

Since efficiency is not part of the main investigation, this section mainly serves the purpose of giving a quick overview of the runtimes of the simulation for the different scenarios in order to see if any significant difference is between runtimes when the new agents are introduced. In future studies this might become a more important topic as the time it takes to run the simulations can be a limiting factor.

Table 7.8: The runtime for 1000 simulations for all states.

State	Runtime
Reference	9978 sec
0.1%	10634 sec
0.125%	9045 sec
0.25%	9819 sec

Unexpectedly, the runtime first increases as the ramping agents are introduced and then decreases against the number of trades decreases with the participation of the ramping agents in the market. The drop in runtime from the reference state to the 0.25% state is small and less than the drop in number of trades. This difference, as well as the fact that the runtime is longer for the 0.25% state thn it is for the 0.125% state, could be a consequence of the dynamic nature of the market. In the dynamic market, some variation of how different groups behave in different scenarios is normal. Although the number of trades does not change significantly between states, the agent types do differ in the time it takes to calculate their decisions.

7.4. Summary

After looking at the price change in all the states that were simulated and some statistical measuring and calculating has been done, the conclusion was reached that introducing enough ramping agents who make bids that match the lowest asks, during the trading periods has a statistically significant effect on price-discovery. When the number of the ramping agents was increased, the price got higher as was to be expected. These findings support the initial suggestion that in small markets it is easier to have price-increasing effects with this type of behavior. The behavior of the EMA+RSI agents was interesting because they practiced a more aggressive trading behavior than the ramping agents; trading both more often and at a higher price. As a result they had an increasing impact on the price as the price dropped when a simulation was ran without the EMA+RSI agents in the population.

Next there was a brief look at how the introduction of the ramping agents affected the frequency of trades that the reference market participants were involved in, as well as how the individual groups behaved. There was a drop of 5.5% in the number of trades from the reference state to the 0.25% state. It supports the idea that simply by introducing agents who behave like the ramping agents, will have quite an impact on the decision making of the reference population as they participate in fewer trades. Any other behavior of the groups did not seem to change significantly between states.

The runtimes for the simulations were collected for the different states to gain a little insight into whether the difference between the states would result in different runtimes. The difference in runtime between the reference state and the other states did fluctuate to the degree that no conclusion could be drawn from the results.

8. Future Work

Computer simulation is a popular way of analyzing various types of problems. Although powerful, they can only give an approximation of the problem when humans are involved. Simulating human behavior with a computer program can only ever be an approximation since it is impossible to completely replicate human behavior with code. This chapter provides a brief overview of the main limitations to the model as well as some ideas on how to improve those limitations.

8.1. Real World and Simulation

The largest financial markets in the world are double auction markets with millions of participants where trades occur in milliseconds in amounts that can vary from a few dollars to many billions of dollars. In the modern world there is a global economy where each market affects the other so what happens on one side of the planet can cause an effect on the other. It is not only the many markets that are intertwined but the participants are as well. Humans are known to be affected by, for instance, the herding effect and mass panic, both of which can completely erase rational thought and cause market participants to trade irrationally. No attempt will be made to identify all the factors that make the global economy such a complex system with the many abnormal aspects to it, because that is simply impossible.

When using simulation to replicate such complex systems, simplifications are inevitable and many of them are made in this study. Simplifications of complex things can give the researcher the ability to focus only on the problem meant to investigate, given that his reasons for the simplifications are rational. The reason for using dynamic simulation is to get an idea about how agents trade and behave when time passes. Their features change over time with some predefined probabilities and the outcome of their behavior changes as well. The limitations in this study when modeling these agents are mainly that the behavior of each agent is modeled in terms of six predefined trading decision-making processes, each of whichhas an equal chance of being selected when an agent is called upon to make a trading decision. The decision-making processes that are used are all known and frequently used both in the real markets as well as in similar studies. There has been very little effort made to justify them in terms of individual preferences, decisions, plans, emotions, etc. as that is almost impossible and would at least require a comprehensive research on trading behavior. A study by (Davidsson, 2001) states that there are also limitations in the interactions between agents as each agent is considered individually with no interactions with other agents and no ability to learn from past decisions. The population is split into 6 different groups where each group has its own trading decision-making process and the probabilities for each group to be selected for participation are equal.

Pre and post trading is something that takes place in real world marketplaces. This study does not try to implement pre or post trading in any way in its simulations, but that is clearly something that would make the simulation more realistic. With that said, it is obvious that pre and post trading is something that should be integrated in a more advanced version of this study.

It is almost an impossible task to name everything that is limiting when using code to simulate the real world marketplace and the point of this chapter is only to provide a brief overview of some of the things that were encountered in building the model. When faced with limiting factors of the computer, the best efforts were made to simplify things by still keeping the main dynamics of a real market intact. Thereby, an investigation was possible and some answers, to the questions that inspired this this study, might just materialize. Improvements of the model would then be to incorporate more complexity and sophistication into the model instead of the simplifications that were made.

8.2. Agent Scheduling

The participation of agents in the simulation is not based on their own will but the frequency that they can be called and the probabilities that are assigned to each group. This means that the agents are called up by the mechanism and forced to make a decision to buy, sell or do nothing in a time that they do not control. This is a simplification of the real world were market participants make offers at times that are based on their free will.

To be able to make the agents enter the market based only on their own dynamics and decision making process, the simulator would have to be changed somewhat. Each agent would then be constructed as an object that would have its own timer and would be able to enter the market at times that would not be dependent on anything else: no other agents or the market mechanism. This would be much more complex and computationally heavier as many agents could be participating at the same time and all agents would constantly have to check the conditions of the market in order to decide whether to make offers or not. Many agents making offers at the same time or at very small time intervals creates a problem of queuing those offers, in order for every agent to get a valid place and to be paired with counter offers should they arise. Another factor that is disregarded in the simplification is the option for agents to withdraw their offers if market conditions change. Once they make their offer, it stays in the order book until the end of the trading period.

Clearly there are limitations in the simulation regarding the independence of the agents but the simplifications do still serve the purpose they were meant to serve. The population size of our market is controlled and the price-discovery process is fairly similar to the one that is observable from real market data. By using the simulations we can investigate what the effects are of inserting agents that do not trade by the same principles of any of the agent groups that populate the reference market.

8.3. Inventory, Transaction Costs and Multiple Assets

In the real world, agents and institutions have more than one unit of asset at a time to trade at any given time. They could have more than one unit of the asset and that could have an impact on their trading decisions. Transaction costs are also a part of the real world market place that impacts trading decisions of the market participants. The ability to keep a portfolio of different assets is also something that is fundamental in real world trading.

These things are not allowed in the simulation as they are very complex to implement and because using a single unit/single asset simplification does not eliminate the chance to investigate the questions asked in this thesis. Another justification of this simplification is that it is not the intentionto investigate how certain trading behavior of a single asset effect the price-discovery process of that same asset. With no inventory allowed, the decision of simplifying by not adding transaction costs to each trade is justifiede.

8.4. Real Data

How market participants calculate the amount of their offers in the real market is based on many things and the variations of these calculations are almost infinite. Historical data, predictions, information and hindsight are among the tools that traders use to make offers. It seems obvious that when a market is simulated with a computer program these calculations need to be simplified because of the endless methods available.

When called upon, the agents make a trading decision that can have three possible outcomes. The agent can decide to place an ask, place a bid, or stay neutral by not placing an offer. In the cases where the agents do make an offer, the amount that constitutes that offer is calculated as the latest market price with a random component to it. That in and of itself is a very known and valid simplification but in order to make it even more realistic, it could be compared to real data. With that comparison available, the agents could better adjust their offers to what is happening in the real market. The ability to learn by using a genetic algorithm is also something that could be programmed into the agents and that could be accomplished by using real data.

Mixing simulation with real data has many possibilities but it is not intended to name them all but to point out that the lack of the use of real data in the study is a limiting factor as it could improve the model, if used right.

9. Conclusions

9.1. Conclusions

When looking at the results it is clear that when inserting ramping agents that intend to increase the price by placing bids matching the lowest asks during the trading periods, there is an increase in price. It was also discovered that this happened between the 0.1% and 0.125% states as the price increase was statistically significant in the 0.125% state but not the 0.1% state in comparison to the reference state of the market. The main conclusion that can be drawn regarding the main topic of the study is that in small markets it is possible for individuals or institutions to manipulate the price-discovery process more easily than in larger markets because of the enormous amounts of volume needed when the market is highly populated.

When the simulation results were analyzed it was obvious that one agent group of the reference population showed signs of a very aggressive trading behavior and that was clearly something of interest to this study. The EMA+RSI agents practiced a more aggressive trading behavior than the ramping agents, trading both more often and at a higher price. As a result they had an increasing impact on the price as the price dropped when a simulation was ran without the EMA+RSI agents in the population.

It is also apparent that with the insertion of the ramping agents there will be a slight decrease in the number of trades that the reference population participates in. There can be many reasons for this change in behavior but it is fair to say that the abnormality that the ramping agents bring to the price-discovery process, does impact the trading decisions of the reference population.

The runtime of the simulations was also investigated but the runtimes between different states did fluctuate to the degree that no clear conclusion could be drawn from the results. It is something that was quite surprising as the number of trades decreased between these scenarios and so it seems that the number of trades is not the only thing that contributes to the runtime.

9.2. Improvements

The next step in improving the study is to improve the simulator. Chapter 8 provides a review of a number of factors that are limiting to the model; factors which an attempt should be madeto eliminate. With more time it would have been practical to begin improving how and when the agents participate in the market as explained in Section 8.2. This is only one of many improvements that could be made, but just to name what should be on top of the list, this would be it.

Researching the double auction market and its features by using agent-based simulation is a fairly new phenomena and the literature in this field is still pouring in. The method used in this research and in programming the simulator is just one way of many that are available in order to investigate the double auction market.

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A. Matlab Simulator

This is the code for our simulator of the double auction market:

```
clear all
close all
tic;
Simcounter = 0;
Simulations = 1000;

global Random_Ask_Container Random_Bid_Container ...
    Two_Trend_Ask_Container
global Two_Trend_Bid_Container EMA_Ask_Container EMA_Bid_Container
global Williams_Ask_Container Williams_Bid_Container ...
    EMARSI_Ask_Container
global EMARSI_Bid_Container RSI_Ask_Container RSI_Bid_Container
global EBA_Ask_Container EBA_Bid_Container
global Total_Bid_Container Total_Ask_Container
global Total_S1_Trades Total_S2_Trades Total_S3_Trades ...
    Total_S4_Trades
global Total_S5_Trades Total_S5_Trades Total_S6_Trades ...
    Total_S7_Trades

Random_Ask_Container = 0;Random_Bid_Container = 0; ...
    Two_Trend_Ask_Container = 0;
Two_Trend_Bid_Container = 0; EMA_Ask_Container =0 ; ...
    EMA_Bid_Container = 0;
Williams_Ask_Container = 0; Williams_Bid_Container = 0; ...
    EMARSI_Ask_Container = 0;
EMARSI_Bid_Container = 0; RSI_Ask_Container = 0; ...
    RSI_Bid_Container = 0;
EBA_Ask_Container = 0; EBA_Bid_Container = 0;
Total_Bid_Container = 0; Total_Ask_Container = 0; ...
    Total_S1_Trades = 0;
Total_S2_Trades = 0; Total_S3_Trades = 0; Total_S4_Trades = 0; ...
    Total_S5_Trades = 0;
Total_S6_Trades = 0; Total_S7_Trades = 0;

while  (Simcounter < Simulations)
    Simcounter = Simcounter + 1;

global AskList BidList n teljari k TradePrice2 t Price ...
    EMA_BUYorSELL r
```

```
global s lead lag sh RSI_BUYorSELL RSI EMA rs PriceClose_EMA ...
    Spread signal
global w EMA_RSI_BUYorSELL_plot TwoTrendSignal Simcounter ...
    Simulations Price2
global BidAsk_Listi Trades_And_Strategy EBA_ON

Periodcounter = 1;
NumberOfPeriods = 2;
t = 8*60*60;
T = (16*60*60)*Periodcounter;
teljari = 0;
k = 1;
n = 0;
AskList = [];
BidList = [];
Price = [];
EMA_BUYorSELL = 0;
EMA = 0;
RSI = 0;
EBA_ON = 0; %0 = Normal state - 1 = EBA on
EBA_BidorAsk = 1; %1 = Place bids (increase price) - 0 = Place asks
                  %(decrease price)
HlutfallEBA = 0.00; % How many EBA as a precentage of total pop
warning off
while (t<T*NumberOfPeriods)
    k= k+1;
    t(k) = t(k-1) - 1*60*log(rand(1));
    Randomnumber = rand(1);

    %Offers are random until 20 trades have materialised in the ...
        market
    %Then the "real" agents take over

    if (length(Price2) ≥20 && length(AskList)>1 && ...
        length(BidList)>1)

        %Agent places an ask

        if (Randomnumber < 0.10)
            BidAsk_Listi(k,1) = [-(Tilbodsreiknir(Price))];
            BidAsk_Listi(k,2) = [1];
            BidPrice(k) = NaN;
            AskPrice(k) = Tilbodsreiknir(Price);

            %Send offer to orderbook where it is compared in ...
                order to
            %check if a trade has materialised

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),1);

        end
```

```
        %Agent places a bid

        if (Randomnumber ≥ 0.10 && Randomnumber < 0.20)
            BidAsk_Listi(k,1) = [Tilbodsreiknir(Price)];
            BidAsk_Listi(k,2) = [1];
            AskPrice(k) = NaN;
            BidPrice(k) = Tilbodsreiknir(Price);

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),1);

        end

        %Simple Trend Agent

        if ((Randomnumber ≥ 0.20 && Randomnumber < 0.40))
            TWO_TREND_BUYorSELL = TWO_TREND_Agent(Price);

            %Agent places bid

            if (TWO_TREND_BUYorSELL == 1)
            BidAsk_Listi(k,1) = [Tilbodsreiknir(Price)];
            BidAsk_Listi(k,2) = [2];
            AskPrice(k) = NaN;
            BidPrice(k) = Tilbodsreiknir(Price);

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),2);

            end

            %Agent places ask

            if (TWO_TREND_BUYorSELL == −1)

            BidAsk_Listi(k,1) = [−(Tilbodsreiknir(Price))];
            BidAsk_Listi(k,2) = [2];
            BidPrice(k) = NaN;
            AskPrice(k) = Tilbodsreiknir(Price);

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),2);

            end
        end

        % EMA Agent

        if ((Randomnumber ≥ 0.40 && Randomnumber < 0.60))
            EMA_BUYorSELL = EMA_Agent(Price);

```

```
            %Agent places bid

            if (EMA_BUYorSELL == 1)
            BidAsk_Listi(k,1) = [Tilbodsreiknir(Price)];
            BidAsk_Listi(k,2) = [3];
            AskPrice(k) = NaN;
            BidPrice(k) = Tilbodsreiknir(Price);

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),3);

            end

            %Agent places ask

            if (EMA_BUYorSELL == -1)
            BidAsk_Listi(k,1) = [-(Tilbodsreiknir(Price))];
            BidAsk_Listi(k,2) = [3];
            BidPrice(k) = NaN;
            AskPrice(k) = Tilbodsreiknir(Price);

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),3);

            end
        end

        %Williams Agent

        if ((Randomnumber ≥ 0.60 && Randomnumber < 0.80))
        WILLIAMS_BUYorSELL = WILLIAMS_Agent(Price,Spread);

            %Agent places bid

            if (WILLIAMS_BUYorSELL == 1)
            BidAsk_Listi(k,1) = [Tilbodsreiknir(Price)];
            BidAsk_Listi(k,2) = [4];
            AskPrice(k) = NaN;
            BidPrice(k) = Tilbodsreiknir(Price);

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),4);

            end

            %Agent places ask

            if (WILLIAMS_BUYorSELL == -1)
            BidAsk_Listi(k,1) = [-(Tilbodsreiknir(Price))];
            BidAsk_Listi(k,2) = [4];
            BidPrice(k) = NaN;
            AskPrice(k) = Tilbodsreiknir(Price);
```

```

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),4);

            end
        end

        %EMA+RSI Agent

%         if ((Randomnumber ≥ 0.68 && Randomnumber < 0.84))
%             EMA_RSI_BUYorSELL = EMA_RSI_Agent(Price);
%
%             %Agent places bid
%
%             if (EMA_RSI_BUYorSELL == 1)
%             BidAsk_Listi(k,1) = [Tilbodsreiknir(Price)];
%             BidAsk_Listi(k,2) = [5];
%
%             AskPrice(k) = NaN;
%             BidPrice(k) = Tilbodsreiknir(Price);
%
%             [BidList, AskList] = ...
    samfellt_double_auction(BidPrice(k), AskPrice(k),5);
%
%             end
%
%             %Agent places ask
%
%             if(EMA_RSI_BUYorSELL == -1)
%             BidAsk_Listi(k,1) = [-(Tilbodsreiknir(Price))];
%             BidAsk_Listi(k,2) = [5];
%
%             BidPrice(k) = NaN;
%             AskPrice(k) = Tilbodsreiknir(Price);
%
%             [BidList, AskList] = ...
    samfellt_double_auction(BidPrice(k), AskPrice(k),5);
%
%             end
%         end

        %RSI Agent

        if (Randomnumber ≥ 0.80)
           RSI_BUYorSELL = RSI_Agent(Price);

           %Agent places bid

           if (RSI_BUYorSELL == 1)
           BidAsk_Listi(k,1) = [Tilbodsreiknir(Price)];
           BidAsk_Listi(k,2) = [6];
           AskPrice(k) = NaN;
```

```
            BidPrice(k) = Tilbodsreiknir(Price);

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),6);

            end

            %Agent places ask

            if (RSI_BUYorSELL == -1)

            BidAsk_Listi(k,1) = [-(Tilbodsreiknir(Price))];
            BidAsk_Listi(k,2) = [6];
            BidPrice(k) = NaN;
            AskPrice(k) = Tilbodsreiknir(Price);

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),6);

            end
        end
%           if (Randomnumber < HlutfallEBA)
%
%           if (EBA_ON == 1)
%
%               EBA_BUYorSELL = EBA_Agent(EBA_BidorAsk);
%               if (EBA_BUYorSELL == 1 && length(AskList)>0)
%                   BidAsk_Listi(k,1) = [AskList(1)];
%                   BidAsk_Listi(k,2) = [7];
%
%                   AskPrice(k) = NaN;
%
%                   BidPrice(k) = AskList(1);
%
%
%                   [BidList, AskList] = ...
    samfellt_double_auction(BidPrice(k), AskPrice(k),7);
%               end
%               if (EBA_BUYorSELL == 0)
%                   BidAsk_Listi(k,1) = [-BidList(end)];
%                   BidAsk_Listi(k,2) = [7];
%                   BidPrice(k) = NaN;
%                   AskPrice(k) = BidList(end);
%
%                   [BidList, AskList] = ...
    samfellt_double_auction(BidPrice(k), AskPrice(k),7);
%               end
%
%           end
%           end
```

```
    %If not enough trades have materialized on the market for ...
        the more
    %advanced agents to start trading we use agents that place ...
        offers that
    %fluctucate around 101.5

    else

        if (Periodcounter ≤ 1)

        %Agent places ask

        if (Randomnumber < 0.5)
            BidPrice(k) = NaN;

            if (rand(1) < 0.5)
                AskPrice(k) = (100+randn(1)*3);
            else
                AskPrice(k) = (100-randn(1)*3);
            end

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),0);

        end

        %Agent places bid

        if (Randomnumber ≥ 0.5)
            AskPrice(k) = NaN;

            if (rand(1) < 0.5)
                BidPrice(k) = (100+randn(1)*3);
            else
                BidPrice(k) = (100-randn(1)*3);
            end

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),0);

        end

        else
            %Agent places ask


        if (Randomnumber < 0.5)
            BidPrice(k) = NaN;

            if (rand(1) < 0.5)
                AskPrice(k) = (Price(end)+randn(1)*3);
            else
```

```
                AskPrice(k) = (Price(end)−randn(1)*3);
            end

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),0);

        end

        %Agent places bid

        if (Randomnumber ≥ 0.5)
            AskPrice(k) = NaN;

            if (rand(1) < 0.5)
                BidPrice(k) = (Price(end)+randn(1)*3);

            else
                BidPrice(k) = (Price(end)−randn(1)*3);
            end

            [BidList, AskList] = ...
                samfellt_double_auction(BidPrice(k), AskPrice(k),0);

        end
        end

    end


%If the bid/ask list is not empty we huse the lowest ask and ...
    highest bid.
%If not we use NaN for plotting purposes.

if (¬isempty(BidList) && ¬isempty(AskList))
        Spread(k,:) = [BidList(end) AskList(1)];
else
        Spread(k,:) = [NaN NaN];
end




% if(t(end)≥(T*Periodcounter) && Periodcounter<2)
%     if (EBA_ON == 1)
%     FjoldiEBA = floor(k*HlutfallEBA);
%     for (i=1:FjoldiEBA)
%     EBA_BUYorSELL = EBA_Agent(EBA_BidorAsk);
%     if (EBA_BUYorSELL == 1 && length(AskList)>0)
%         AskPrice(k) = NaN;
%
%         BidPrice(k) = AskList(1);
%
```

```
%
%          [BidList, AskList] = ...
    samfellt_double_auction(BidPrice(k), AskPrice(k),7);
%      end
%      if (EBA_BUYorSELL == 0)
%          BidPrice(k) = NaN;
%          AskPrice(k) = BidList(end);
%
%          [BidList, AskList] = ...
    samfellt_double_auction(BidPrice(k), AskPrice(k),7);
%      end
%      end
%      end
%      if(Periodcounter<NumberOfPeriods)
%          Periodcounter = Periodcounter +1;
%
%          Price2 = 0;
%
%          clear Price2;
%          global Price2;
%
%      end
% end

end

Startprice(Simcounter) = Price(1);
Endprice(Simcounter) = Price(end);
Toflureiknir(BidAsk_Listi,Simcounter,Simulations,Startprice,Endprice);


end

toc;
```

This is the code for the order-book of our double auction market:

```
function [BidList,AskList] = ...
    samfellt_double_auction(tilbod_fra_kaupendum, ...
    tilbod_fra_seljendum,strategy)

global Price2 AskList BidList TradePrice TradePrice2 n teljari k ...
    t Price Trades_And_Strategy


%If the bid is higher than zero we put it on the bidlist. We ...
    then sort it
%a the way that the highest bid is the "last".
if (tilbod_fra_kaupendum ≥ 0)
    %disp('Test');
    BidList = [BidList; tilbod_fra_kaupendum];
```

```
    BidList = sort(BidList);
end
%If the ask is higher than zero we put it on the asklist. We ...
    then sort it
%a the way that the highest ask is the "last".
if (tilbod_fra_seljendum ≥ 0)
    AskList = [AskList; tilbod_fra_seljendum];
    AskList = sort(AskList);
end
%If the lists are not empty then we compare the higest bid and ...
    the lowest
%ask. If the highest bid is greater or equal to the lowest ask ...
    then a
%trades materializes.

if (¬isempty(BidList) && ¬isempty(AskList))
    if (BidList(end) ≥ AskList(1))
        n = n+1;
        TradePrice(n) = (BidList(end)+AskList(1))/2;
        teljari(n) = t(k);
        TradePrice2(n) = (BidList(end)+AskList(1))/2;
        %Trade materializes and we remove the offers from their ...
            lists.
        BidList(end) = [];
        AskList(1) = [];
        Price(n) = TradePrice(n);
        Price2(n) = Price(n);
        Trades_And_Strategy(n,1) = Price(n);
        Trades_And_Strategy(n,2) = strategy;
    else
        %If a trade does not materialize we put NaN as the ...
            trading price
        %(done for plotting purposes) If this is the first trade to
        %materialize we put the price as a 101.5 with a small random
        %component, if not the previous price. This is done to ...
            always have
        %a price.
        n = n+1;
        teljari(n) = t(k);
        TradePrice2(n) = NaN;
        if (n == 1)
            Price(n)= 100+rand(1)*3;
            Price2(n) = Price(n);
        else
        Price(n)=Price(n-1);
        Price2(n) = Price(n-1);
        end
    end
end
```