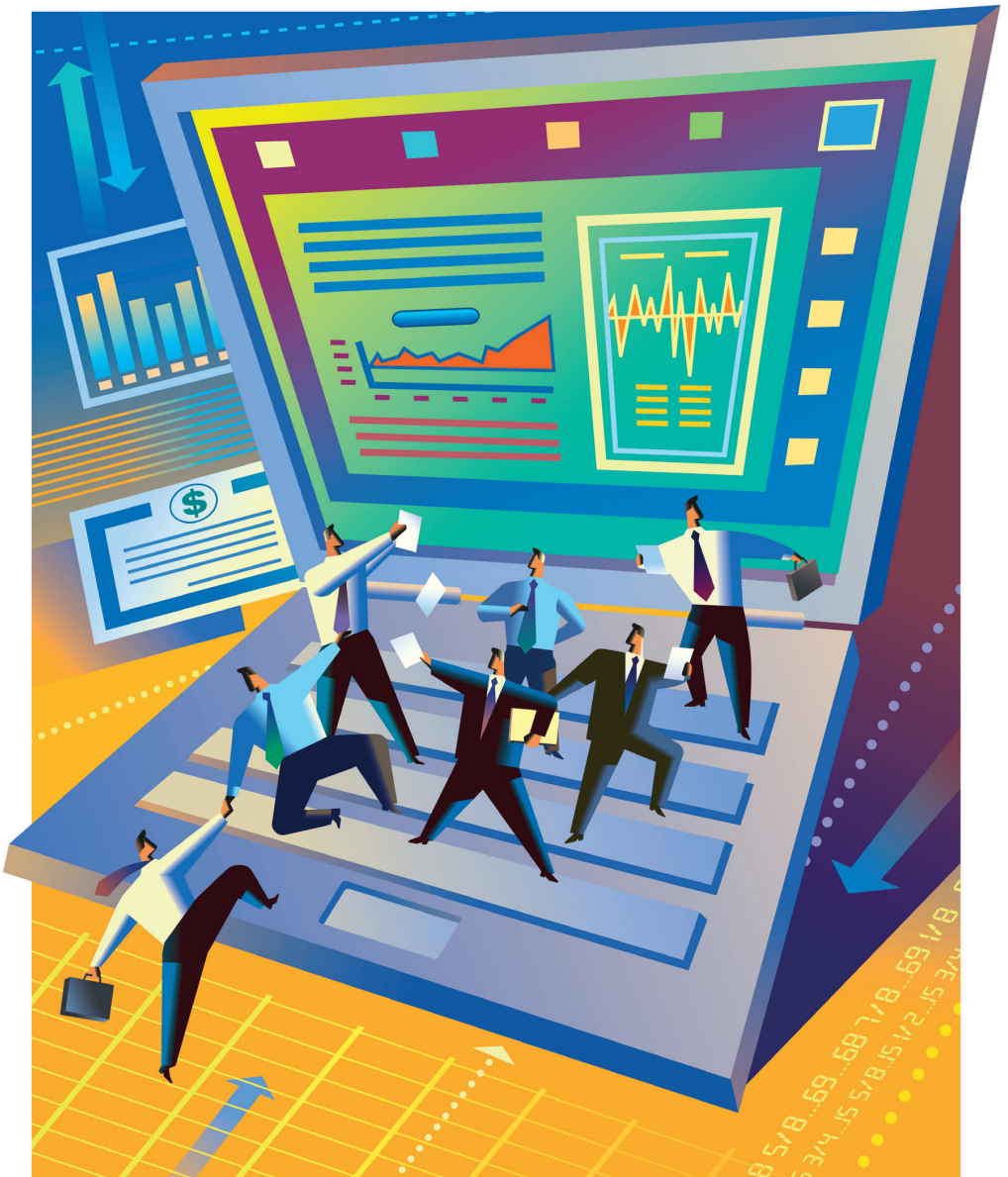KATALIN BOER-SORBÁN

Agent-Based Simulation of Financial Markets

A Modular, Continuous-Time Approach

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A modular, continuous-time approach

Agent-Based Simulation of Financial Markets

A modular, continuous-time approach

**Simulatie van financiële markten
gebaseerd op agent theorie**
Een modulaire, continue benadering

Thesis

to obtain the degree of Doctor from the
Erasmus University Rotterdam
by command of the
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Prof.dr. S.W.J. Lamberts

and in accordance with the decision of the Doctorate Board.

The public defence shall be held on
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by
Katalin Boer-Sorbán
born at Miercurea-Ciuc, Romania

ERASMUS UNIVERSITEIT ROTTERDAM

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To
my mother, my father, my husband Csaba and my son Danó

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One of the central questions in studies on market dynamics is whether price series are random or whether some patterns can be revealed. I believe that many of us ask ourselves similar questions when facing certain events in our life. For instance, when we run across a friend by chance, a dream of ours comes fortuitously to fruition, or unexpected events happen to us. A long series of planned and spontaneous events forewent the publication of this dissertation. I am grateful to many people who triggered or participated in some of these events helping me to carry out a Ph.D. research.

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Katalin Boer-Sorbán
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Chapter 1

Introduction

1.1 Motivation

The dynamics of financial markets is subject of much debate among researchers and financial experts trying to understand and explain how financial markets work and traders behave. Diversified explanations result from the complex dynamics of markets and its various hardly observable aspects, such as decisions behind price formation mechanisms, or investors' motivation behind trading actions. All this causes researchers to base their studies on diverging assumptions.

There are two main, contradictory views regarding market mechanisms. On the one hand, **theoretical studies** idealistically describe market dynamics. They suggest that markets are efficient and assume rational, homogeneous behavior of traders. As the Efficient Market Hypothesis (EMH) states, efficient markets are markets in which all available information is immediately reflected in the prices, and thus, it is not possible for anyone to consistently outperform the market, other than by chance. Further, rational traders are defined as traders who take the optimal trading decision based on all the information they posses.

In contrast to the theoretical models, **empirical and experimental studies** suggest that several assumptions made by theories (such as homogeneity, rationality, or the absence of transaction costs) do not correspond to reality. They claim that traders are heterogeneous and "boundedly rational". Bounded rationality arises not only from cognitive boundaries, but rationality is mostly limited by the complexity of the environments. This approach suggests that the standard finance models based on rational behavior and profit maximization, can be true within specific boundaries. They are, however, incomplete, since they do not capture the details of behavior (Reilly and Brown, 2003). Traders' behavior, the way humans interpret and act on information is the central topic studied within the area of **behavioral finance**. Within behavioral finance alternative paradigms, such as the prospect theory and the heterogeneous market hypothesis (HMH), are proposed to explain empirical patterns (referred to as market anomalies by EMH believers) that are not supported by theoretical explanations. Although behavioral factors play an important role in the decision-making process of individual investors, it is not clear how this phenomena influences the market as a whole (Brabazon, 2000).

There is, thus, much controversy about the market mechanisms that lead to price developments of the assets that can be observed in practice. There are two main aspects that cause discussion: the **rationality** of traders, and the **efficiency** of markets. In relation to this discrepancy, opinions regarding the properties of the time series on a market are not univocal as well. Some people argue that prices follow a random walk, and that this property suggests that markets are efficient. Several analysts, however, seem to find patterns, or so-called "stylized facts", in time series and benefit from them. The question is whether these patterns occur by chance or whether there is some predictability in the prices. There are obviously a multitude of factors that might influence in multiple ways the way prices develop, but there is no general consensus regarding which aspects effectively play a role in the formation of market prices and in the possible predictability of future returns.

In recent years, the **agent-based approach** to economic and financial analysis has grown into an important research field for developing and understanding the complex patterns and phenomena that are observed in economic systems. The **agent-based computational economics (ACE)** (Tesfatsion, 2001; LeBaron et al., 1999), and, alternatively, the **microsimulation** (Levy et al., 2000) approaches have been proposed, emphasizing the need to represent traders as individuals and to study the way macro features emerge from individual interactions. These approaches attempt to model financial markets as evolving systems of competing, autonomous interacting agents and emphasize their learning dynamics (Tesfatsion, 2001, 2002; LeBaron, 2000). Agent-based models offer the possibility to transparently model behavioral issues and to study in this way the effect of agents' behavior on the market prices. Further, in agent-based models prices can be endogenously formed by the system itself as the result of interaction of market participants. By using agents for studying market dynamics, heterogeneous, boundedly rational, and adaptive behavior of market participants can be represented and its impact on market dynamics can be assessed.

Both the benefits and the drawback of agent-based artificial stock markets, as LeBaron (2001) notices, lie in the "large number of parameters for which our priors are extremely diffuse". Two important features of agent-based artificial stock markets in relation to other market models and real stock markets are emphasized here: diffuse priors, and the ability to handle large number of parameters. Diffuse priors refer to the fact that the identity and value of the parameters that describe real markets are uncertain or not known, and therefore market modelers make different assumptions regarding them. Taking into account a large number of parameters, on the one hand, generates market models that contain more representative elements of the de facto microstructure of stock markets. This strengthens their validity, in the sense that the probability that they have any connection to the real world increases. On the other hand, the changing and large variety of market organizations and the occurrence of several "hardly observable" features, such as details behind price formation mechanisms and traders' decision, imply broadly diffuse prior assumptions. Consequently, the dilemma that one has to deal with when representing markets is, which parameters and values to choose for, and how to assess the validity of one's assumptions and the way the choices influence the dynamics.

Given the complexity of real stock markets, agent-based market models need to contain as well assumptions and choices related to the market organization and to the traders' behavior. We observe several common choices made in these models. For instance, most of the early agent-based artificial markets represent call markets. Further, often only investors are

modeled. From implementation point of view the investors are centrally coordinated, and a predefined set of trading strategies is considered.

In artificial stock markets (ASMs) in the literature a common choice is to study call markets. Further, in these models, in relation to call markets, equilibrium type of price formation mechanisms are typically studied. Although, **continuous trading sessions** are much more common in real markets (Demarchi and Foucault, 2000; Harris, 2003), these have been rarely focused on in early ASMs, and have gained attention only recently.

With respect to the behavior of market participants, in ASMs attention is rarely paid to the representation of **financial traders** involved in setting prices, such as market makers or brokers. Usually, the only market participants considered are investors, who are moreover modeled as being centrally selected and making trading decisions simultaneously. In contrast to this representation, in reality investors take decisions **autonomously and asynchronously**.

The modeled strategies across the different AMS's vary on a wide scale, given the fact that investment strategies are hardly observable, and the fact that arbitrary many possibilities exist to forecast future values. However, by far the most ASMs are one shot models with a predefined set of trading alternatives. This means, that if we want to study other strategies, or slightly other type of models, we need to build a new model from scratch. It is not possible to easily **plug in new alternatives** in existing models.

In an attempt to provide a better understanding of market dynamics, in this thesis we propose a trading environment that addresses the above mentioned shortcomings. We aim to represent markets from bottom-up, and to continuously follow the trading behavior of market participants, including financial traders, portrayed as individual, autonomous agents. In order to accomplish this goal we apply the ACE methodology. We strive for a modular representation of markets and trading behaviors, in the sense that we try to support multiple market structures and arbitrarily many trading strategies in a flexible way. We primarily focus on studying dynamics in relation with continuous trading sessions by using continuous time simulation.

Based on the considerations above, we start with formulating our research objective and research questions followed by a discussion of the applied research methodology.

1.2 Research objective and research questions

Research objective:

Contribute to the study and understanding of market dynamics by providing a computational agent-based continuous-time simulation approach that supports a flexible representation of stock market organizations and traders' variable behavior.

Several approaches exist to study and understand market dynamics. Theoretical studies try to find explanations through analytically tractable models. Empirical research analyzes historical data and tries to find correspondence between various factors. Experimental studies focus on analyzing the trading behavior and its consequences on the dynamics of well-observed players in a usually stylized environment of simplified market models, players being either humans or computer programs. Experimental studies are closely related to

the behavioral finance literature.

The common feature of the approaches used to study market dynamics is, that a model of the market is created. In order to create somewhat realistic models, however, one should look at how markets are in fact organized. Therefore, in order to provide an improved approach for studying market dynamics, first, we should examine and summarize what is known about market organizations and market dynamics. Further, we should pinpoint and analyze the aspects that make market dynamics difficult to understand or can cause controversial explanations. For instance, an important aspect that leads to controversial explanations of market dynamics is the assumption regarding the characteristics of market participants. Are they rational, boundedly-rational, heterogeneous, or homogeneous?

Accordingly, the first question that arises in relation to our objective is:

Research Question 1.

Which are the relevant common and variable aspects of stock markets that should be taken into account when studying them?

After having gained insight into the workings of real markets we should survey how artificial stock markets from literature compare to them. Therefore, we need to study several ASMs, compare these and analyze what kind of common and variable aspects are taken into account by them. Accordingly, the second main research question that we aim to answer is:

Research Question 2.

To what degree do ASMs from literature reflect the workings of real markets and how do they deal with the common and variable aspects of real stock markets?

Our final objective is to improve the understanding of market dynamics. We aim to do this with the help of an environment that supports the representation of common and variable aspects of markets found when answering Research Question 1, irrespective of whether they are considered or not by the ASMs studied. The question is:

Research Question 3.

How can we design and develop a modular, flexible agent-based environment using which one can study both the common and the varying, hardly observable features of stock markets, as well as their aspects that have been rarely or not represented in existing ASMs?

Our aim is at the one hand to provide a design methodology for flexible, modular representation of stock markets. On the other hand, we aim to build such an environment. Once we know how to build this environment, and we build it, we need to evaluate it.

In order to evaluate the environment we need to conduct case studies, i.e. implement specific ASMs on top of the environment. The case studies serve to evaluate whether the environment possesses the suggested properties, particularly the ability to embed varying aspects in a flexible way. Further, they are used to prove the correct functioning of the environment. Further, case studies can help us to answer questions related to the added value of the proposed environment:

Research Question 4.

What is the added value of the proposed environment as compared to existing ASMs, and how can it improve the understanding of market dynamics?

1.3   Research methodology

As we remarked in the previous subsection, the first step to take in our research is to study the relevant aspects of real stock markets. To be able to answer Research Question 1, we study first, the literature on market microstructure and we analyze the organization of several markets. In order to be able to describe the generic behavior of traders and to determine the varying aspects that differentiate individual participants we discuss the various trading possibilities by tracing orders on the various routes they can follow, from the moment they are placed till they are executed and confirmed back. Based on the literature survey and analysis conducted in this way, we compose a conceptual framework that consists of a structured classification of the common and varying aspects of markets with the help of which market organizations and traders' behavior can be described and differentiated. This framework forms a guideline for the rest of the thesis. So far, the research approach that we apply can be characterized as qualitative and inductive: we start with detailed observations of part of reality, namely the structure and the workings of stock markets, and move towards a more abstract, general representation of the observed features (theory building).

After having gained insight into the workings of real markets we conduct a literature survey on artificial stock markets. In order to answer Research Question 2 we give a structured overview of several ASMs from the literature in terms of the conceptual framework that we build in answering Research Question 1. First, we analyze which aspects of the taxonomy are modeled in the ASMs, and which aspects are omitted. Then, we also investigate implementation issues, i.e. we investigate how the represented aspects are modeled. This comparative study on ASMs leads to a new taxonomy of ASMs that enriches the conceptual framework for describing real stock markets with modeling details.

The frameworks and the results on the analysis of stock markets and ASMs enables us to take a generic approach for modeling stock markets, leading to an environment that should be flexible and modular in order to support the representation of multiple market structures and trading strategies. The question that arises at this stage is, how to combine all these aspects into one environment. The next step of our research is thus, to answer Research Question 3.

As reflected by the research objective, there are already some decisions we have made in advance related to the design of this environment. These decisions refer to the continuous-time simulation and the agent-based computational approach. By applying the agent-based computational economic approach we can achieve constructive development of market models, and we can study dynamics as arising from the interaction of individual agents. Continuous-time simulation and asynchronous, autonomous trader representation will be achieved with the help of the JADE environment, that supports non-preemptive scheduling of agents' tasks, that are part of agents' behavior. We choose for software agent-based simulation experiments, since it gives us the freedom to manage various parameters, and the possibility to observe traders' behavior. This in turn helps us to study the influence of traders' decision on the dynamics.

After designing and developing the proposed framework, it should be evaluated and its added value should be assessed. There are several aspects to evaluate in relation to a framework. First of all it should be tested whether it serves its purpose, and additionally its correctness needs to be investigated. In order to evaluate the agent-based framework that we build, we try to replicate already tested models. In one of the case studies, we go further than

replicating experiments and conduct additional experiments by taking advantage of specific features (such as continuous-time simulation and autonomous representation of traders) of the trading environment that we propose. The case studies help us to evaluate the environment and to illustrate the added value of it, thus answering Research Question 4. Further, the case studies also serve to investigate whether and in which measure the choices made with respect to the aspects of the real markets we choose to model, and the way these aspects are modeled influences the dynamics of the model.

Our research objective goes further than building a market model. By introducing this environment we aim to provide a methodological advancement, that, as stated in our research objective, can aid the study and understanding of market dynamics. We provide a framework that can be used to model many types of markets and trading strategies and as such, can help to investigate market dynamics using these models.

1.4   Outline of the thesis

The structure of the thesis is directed by the research questions stated above. To start with, in Chapter 2 we present a synthesis on market organizations and the behavior of market participants. We analyze the structure of market organizations and abstract out factors that we think are important to consider when modeling markets. Further, we study the trading behavior of market participants with different roles, such as investors, brokers and market makers and identify the common and varying aspects of individuals within each group. This analysis is aimed to answer Research Question 1, and results in a conceptual framework, a taxonomy of real markets and market participants.

In the second part of Chapter 2 we present an overview of approaches used to describe and understand market dynamics. We briefly discuss ideas behind analytical, empirical and experimental research conducted in this direction and compare them. We elaborate on how they try to provide means for understanding market dynamics, briefly mention the findings they lead to, and discuss the advantages and shortcomings of each. Further, we motivate why we choose to apply the agent-based computational approach.

Based on the conceptual framework for a taxonomy of stock markets, in Chapter 3 we study several artificial stock markets from the literature. We investigate the aspects that these ASMs represent, and the aspects they omit or rarely represent. Further, we study how the represented aspects are modeled within these ASMs. The analysis conducted in this way helps us to answer Research Question 2 and results in a taxonomy of artificial stock markets. This taxonomy extends in fact (with modeling aspects) the taxonomy of real markets proposed in Chapter 2.

The results obtained so far, i.e. the structured description and classification of stock markets and ASMs are mapped to an agent-based framework in Chapter 4. In this chapter we propose an approach, i.e. the ABSTRACTE modular trading environment, that aids the understanding of market dynamics. During the design phase of the trading environment we strive to take into account both the common features and the varying aspects of real markets. We also want to incorporate features that are rarely focused on in the ASMs studied. Through the presentation of this environment we aim to answer Research Question 3.

In order to evaluate the environment and to answer Research Question 4 we try to replicate and extend ASMs from the literature. As a first stage we choose to replicate two simple

models. The first case study (the Roll model) is analytically tractable, and represents continuous quote-driven markets. The second case study models a simple call auction with prices set at equilibrium. Our primary aim with these ASMs is to illustrate the modularity of ABSTRACTE and to prove its correct functioning. A success in replicating an existing model can be seen as a positive evaluation of the environment.

At the second stage of evaluation, we illustrate how microstructure models can be represented and studied within the proposed framework. In Chapter 5 we consider the extended Glosten and Milgrom model presented by Das (2005), and try to replicate its findings. Our research goal goes beyond replicating these experiments however. We primarily aim to improve the understanding of market dynamics. Therefore, taking advantage of the properties of our proposed environment, we extend and improve the replicated model, and analyze the market dynamics within it. The main focus of the analysis is whether and how continuous-time simulation influences the outcomes and what its added value is in comparison to discrete time simulation. Through the various experiments conducted we aim to answer Research Question 4.

Finally, in Chapter 6 we evaluate our research objective, and analyze to what degree we managed to answer the research questions. We finish the thesis with suggestions for future research.

Chapter 2

Dynamics of Stock Markets

One of the few characteristics that advocates of the various research approaches agree on is that stock markets are complex systems and that models are needed to study their dynamics. In order to find out how to design such models insight in the structure and workings of real stock markets is required.

In this chapter we aim to give insight into the organization and workings of stock markets. We start with introducing some concepts from the market microstructure literature. Market microstructure literature studies the institutional structure behind price formation in markets, analyzing the process by which investors' demands are translated into transactions and prices. Inspired by this area we propose a conceptual framework to differentiate stock markets. The framework provides a taxonomy for market structures and trading aspects. These proposed aspects will then serve as a guideline for comparing ASMs from the literature and for an overview of the structural and behavioral representation possibilities. Further, they provide the main design line one should consider when building new market models.

The way a market is represented and organized influences the quality of a market. High quality, good functioning markets are what all traders ultimately strive for. In the second part of this chapter we discuss how quality of a market is defined, and how it can possibly be measured. We round off with a brief overview of the approaches used to study market dynamics, and the findings thereof. A preliminary version of this chapter has been reported in (Boer et al., 2005b).

2.1 Market microstructure

The central topic in studies on market dynamics is price dynamics, that is the process by which prices change as a reaction to changes in the state of the market. Market prices are directly determined by the price formation mechanism that applies on a specific market. Prices are formed basically as a result of executing orders. As a consequence, prices are indirectly influenced by several other factors that trigger orders, such as economy, news, financial situation of equity issuers, personal opinions (Figure 2.1).

The importance and influence of the market structure on price formation is ignored in many studies. The primary aim in market microstructure literature, however, is to study

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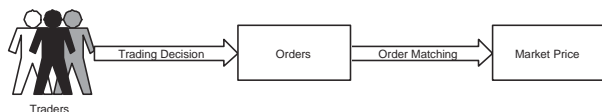
Figure 2.1: Price formation at high level

this relationship (O'Hara, 2002). The institutional structure behind price formation might be ignored for some purposes, like when longer investment horizons are involved. However, for many purposes (measurement of execution costs, market liquidity, comparison of alternative market making mechanism, etc.) market microstructure should be a central issue (Campbell et al., 1997).

It is not difficult to observe the trading actions that participants take. What is more problematic is to define what governs these actions, such as when, how and why participants take these actions, how they determine the parameters of the orders. How traders solve these problems depends on their role in the market, on the market structure, and on individual characteristics. The difficulty of understanding market dynamics arises from the presence of such hardly observable aspects. Generally speaking there are two main hardly observable aspects on stock markets: the price formation mechanism and the decision-making mechanism of the traders. We denote these as cloudy areas in Figure 2.2. The former hardly observable aspect is related to the organization of the market, the latter to the behavior of market participants. They are however, strongly related to each other, given that market participants might be involved both in placing orders and executing them.

The literature on market microstructure investigates trading and the organization (structure) of markets. The structure of a market is defined by trading rules and trading systems and determines who can trade, what, when and how can be traded, and further what traders can know and do in a market (Harris, 2003). The structure provides the framework within which the market functions, i.e. trading takes place. Microstructure literature focuses on research related to:

- price formation and price discovery,

- market structure and design issues,

- information and its disclosure.

Markets are often referred to as black boxes because of the hardly observable aspect of these issues. Market microstructure literature is concerned in a natural way with "black box" related problems, such as (Madhavan, 2000):

- looking inside the "black box" in order to analyze how latent demands are translated into the prices and volumes realized,

- analyzing how different rules and structures affect the "black box", and

- studying how revealing the workings of the "black box" affects the behavior of traders and their strategies.
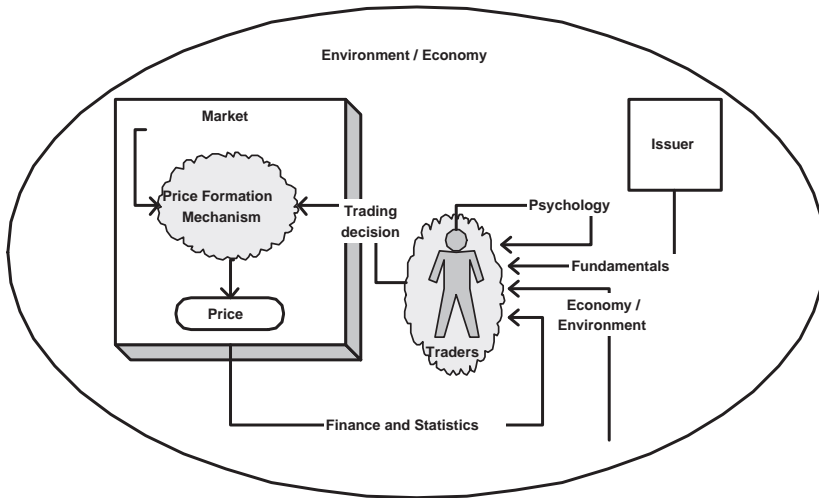
Figure 2.2: Processes that determine market dynamics at high level

Being interested in understanding the dynamics of stock markets we are inevitably concerned with these black box related problems. In order to be able to study market dynamics, first we take a closer look at the (static) structure of real markets. Then, we try to watch markets in action and look inside the black boxes.

2.2 The organization of stock markets

In order to understand how stock markets work, first we focus on their **static, visible side**. In this section we aim to identify the main *organizational factors* that characterize real markets and influence market dynamics, and, as such, should be taken into account when designing artificial stock markets. In order to achieve our aim we analyze various market organizations. Based on the aspects discussed by Harris (2003) and Madhavan (2000) we identify the following main factors that describe a market structure: traded instruments, order forms, market participants, trading sessions, execution systems, and market rules. We elaborate on each of them in the remainder of this section.

2.2.1 Traded instruments

Instruments are the objects traded in a market. At every market it is well-defined which instruments can be traded. Instruments include several types of assets and contracts. Real assets represent physical commodities. Financial assets are instruments that represent ownership of real assets and the cash flows that they produce. *Stocks* are financial assets that represent ownership of corporate assets (Harris, 2003). A given stock can be traded on a market only if it qualifies for listing, which is the case if it, and the corporation that issued it, satisfies certain financial and governance criteria stated by market rules. On the NYSE

instruments of approximately 3600 companies were listed in January 2007 according to the official site of NYSE Group, Inc. (http://www.nyse.com). Certain stocks can be traded on more than one market.

Stocks traded on a given market are priced according to the rules that are established on that specific market. Price, however, does not necessarily reflect the real value of a stock. The value of a stock depends on the valuation of corporate assets, liabilities and income of the corporation that they represent, and further it depends on the traders' expectation regarding how well they expect corporate managers will use corporate assets in the future (Harris, 2003). In this sense, stocks are not an integral part of a market where they are traded, but, they exist "outside" the market. That is: they represent the issuer company, dividends are payed on them, and their value depends on the issuer's performance and future plans.

2.2.2 Orders and quotes

Trading intentions are expressed by means of trade instructions called orders or by means of willingness to trade in the form of quotes (Harris, 2003). *Orders* specify which instrument to trade, how much to trade (size of an order), whether to buy or sell (side of an order). All this information is contained in the most simple orders, called *market orders*. Orders might also specify additional conditions that the trade must satisfy. Conditions might refer to the ultimate price (limit price) that the trader accepts for an order, in case of *limit orders*, and they might further indicate for how long the order is valid (expressed in time or related to change in the market price), whether the order can be partially executed, etc. If price is not included in the order, the order will be executed at the market price that is valid when the order is received on the market.

Buy and sell orders that can not be executed for the moment are entered in a so-called *order book*. There is a separate order book for every stock. Order books that contain limit orders are *limit order books*. Whether, and in which measure the content of an order book is available to the market participants, and other restrictions regarding order placement are determined by the trading rules that hold in a market. Availability of such information has impact on the grade of transparency of the market.

Generally, on markets traders are operating having a specific role, for instance they need to execute orders, motivate trading, or ensure an orderly market (see Section 2.2.3). Traders with a specific role on a market do not issue trading instructions, but they arrange their own trades. In order to indicate that they are willing to buy or sell they *quote* prices and quantities. Willingness to buy is referred to as a *bid quote*, while willingness to sell is referred to as an *ask quote* or *offer*. Quotes include information about the name of the instrument, the trading side, the quantity and price that the traders will accept. The difference between the best (i.e. lowest) offer price and the best (i.e. highest) bid price on a market is the *bid-ask spread*. Traders *offer liquidity* when they make bids or offers, and they *take liquidity* when they accept bids or offers (for a definition of liquidity see Section 2.4).

2.2.3 Market participants

In every market it is well-defined what kind of traders can operate, their number, role, obligations and restrictions. Depending on their tasks and role in the market we classify market participants (traders) in two main groups:

- investors and

- financial traders.

We refer to traders who are not part of the market organization itself as *investors*. They can be individuals, mutual funds, money managers or corporate pension funds (Harris, 2003). *Financial traders* (or financial agents) are traders endowed with special role in financial markets. They act as intermediaries, i.e. third parties in trading (Schwartz and Francioni, 2004).

Financial agents need to conduct special tasks. They need to execute orders on behalf of the clients, or need to execute orders for own account in order to give other traders the opportunity to trade (i.e. to provide *liquidity*). Accordingly, we differentiate two types of financial traders:

- brokers and

- market makers.

Brokers are primarily required to handle orders for customers. They might be allowed at some markets to trade for their own account as well. Financial traders responsible for a good, orderly market are called *market makers*. Market makers allow other traders to trade when they want to trade, and make money by buying low and selling high. Market makers often are known by other names. Market makers who have the obligation to commit capital to a trade in order to contribute to a liquid, orderly market are defined as *dealers*. Further, the expression market maker can be used for the "Specialist" from the NYSE, for the "Hoekman" from the Amsterdam Stock Exchange, for the "Kursmakler" from the Deutsche Börse AG, and for the *dealers* from the NASDAQ.

To each stock one (e.g NYSE) or more market-makers can be assigned. They are responsible for the liquidity of the assigned stock. In most markets, market makers have to provide bid and ask quotes for the stocks they are responsible for. If more market-makers are assigned to a certain stock (e.g. dealers on NASDAQ), they are competing with each other by trying to provide the best bid-ask quotes.

Figure 2.3 depicts the relations that are possible between the different types of market participants. Market makers function only on the market itself. Brokers, however, can work both on the market and independently, trading through member brokers from the market organization or directly with market makers. Investors typically contact a specific broker or brokerage firm if they want to sell or invest, and ask their advise and help to place orders. However, it is also possible that investors trade directly with a market maker, for example, if they are member firms, or they trade via electronic trading systems. A common scenario is that brokers are contacted by investors to execute an order, and they then try to trade with other brokers or market makers, like the specialist on NYSE, and the dealer with the most attractive quote on NASDAQ. Market-makers have the obligation to execute orders that

arrive from outside the market-place, and need to overtake unexecuted orders from brokers. It is not always possible to execute an order immediately. The time of execution depends on market requirements, and on the market makers' strategy and belief. Orders that cannot be immediately executed are stored in the limit order book of the market maker.
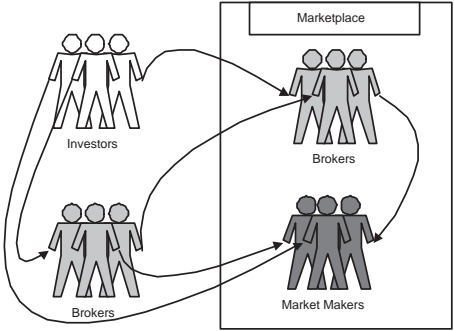
Figure 2.3: Relation between traders

Financial traders are, in fact, not always needed. Their tasks can be performed by *automated order execution mechanisms* as well, that do not require human intervention.

2.2.4 Trading sessions

Trading at stock markets takes place in trading sessions (Harris, 2003). There are basically two types of trading sessions, based on the degree of continuity (Madhavan, 2000):

- call market sessions and
- continuous sessions.

On *call-markets* trading occurs at well-specified times. During a call all trading requests placed for a stock are aggregated and a single price is set, usually such that the trading volume is maximized. On *continuous markets*, trading can occur at any time the market is open. The advantage of call markets is that traders interested in a given instrument at the same time and place can easily find each other. The advantage of continuous trading is that it allows traders to arrange their trades whenever they want.

Although there are several types of stock markets, there is a tendency to converge towards similar organizations, often towards a structure with call markets used to open and close the trading day, and with continuous trading session in between (Demarchi and Foucault, 2000). Continuous trading markets are very common. In the past few years many national equity markets switched from call market sessions to continuous trading with opening calls, but none has changed from continuous trading to exclusive call trading (Harris, 2003).

2.2.5 Execution systems

The procedures used for matching buyers and sellers defines the execution system of a market. The execution system is the kernel of a market. There are two primary market structures

distinguished based on the execution system applied (Harris, 2003; Schwartz and Francioni, 2004):

- quote-driven markets, and

- order-driven markets.

Often two or more execution systems are applied on a market. Such kind of markets are referred to as hybrid markets. Both limit and market orders can be placed on any of these markets.

On **quote-driven markets** market makers must participate in every trade. This means that investors and brokers cannot trade with each other, they need to involve the market maker in every trade. Market makers trade for their own inventory by placing quotes at which they are willing to buy and sell. In pure quote-driven markets all liquidity is supplied by market makers. Quote-driven markets in which more market makers supply the liquidity for a given stock are also called dealer markets.

On **order-driven markets** the orders of buyers and sellers can be brought together and cleared directly without the intermediation of market makers or dealers. Buyers and sellers have to arrange their trades based on the trading rules (see Section 2.2.6) applied on the market. Trading requests are submitted to a central location, where they are matched (Reilly and Brown, 2003; Madhavan, 2000). There are many forms of order-driven markets, most of them being auction type of markets.

- *Oral auctions.*

  In an oral auction traders offer and take liquidity by calling out and accepting bids and offers. Traders must publicly express their bids, offers and acceptance. In this way all traders can participate fairly in the market. One of the best known forms of oral auction is the "persistent shout double auction" applied on the NYSE. During double auction on NYSE the current bids and offers persist. Any new bid or offer must improve on the existing one. Call outs that are improved become invalid.

- *Rule-based order matching systems.*

  On markets that apply rule-based order matching systems traders negotiate with each other by submitting and canceling orders. If the market is organized around call sessions, then orders will be collected before a call and there is one attempt made to arrange all trades at the end of a call. In continuous trading markets the system attempts to arrange trades whenever new orders arrive. Based on the rule applied to determine prices of trading arrangements, three main types of markets are distinguished: single price auctions, continuous two-sided auctions and crossing networks.

  - *Single price auctions.*

    In a single price auction, all trades take place simultaneously at the same market clearing price. If the buy and sell order in a feasible trade have different prices (i.e. the price of the buy order is higher than the price of the sell order), the orders can be filled at any of these prices, or at any price between them. The final price in this case will be determined by trading rules. Single price auctions are applied in call sessions.

In (Schwartz and Francioni, 2004) single price auctions are further classified as price scan auctions, sealed bid auctions or open limit order books. During a *price scan auction* the market maker indicates a market clearing price. Traders respond to the indicated price with orders. These processes are repeated until an acceptable balance can be found. During a *sealed bid auction* orders are not revealed to other participants. If a single price auction is characterized as *open limit order book*, orders are made public, and, at each instant a clearing price is indicated that would be set if the call were to be held at that instant. The final market price is set when the call is conducted.

– *Continuous two-sided auctions*.

In a continuous two-sided auction, orders that cannot be filled are stored in an order book. Incoming sell orders are compared with the best bid and incoming buy orders are compared with the best offer from the order book. If a match is possible trade is conducted at the price of the order from the order book. If the trade does not completely fill the new order, the system matches the remainder of the order from the next highest ranking order from the order book on the corresponding side.

– *Crossing networks*.

In crossing networks all trades take place at prices determined elsewhere. Crossing networks are the only order-driven markets that are not auction markets. They are all call markets: traders submit orders to them before the call. The system matches buy order to sell orders based on some precedence rules. All possible trades are arranged at a so called crossing price. The crossing price, can be for example the closing price of some market, or at a price of a trade chosen randomly from trades immediately following a call.

Order-driven markets are very common. On call markets typically single-price auctions are conducted. These type of call-sessions are referred to as call-auctions. On many continuous markets it is possible to arrange trades via electronic continuous two-sided auctions (Harris, 2003).

Both quote-driven and order-driven markets can be further characterized as **brokered markets** if brokers actively search to match buyers and sellers. Brokers are either asked by investors (their clients) to fill their orders or initiate orders themselves by suggesting trades to their clients. Brokers are, for example, often needed on order-driven markets for an effective creation of liquidity.

Most of the markets cannot be characterized as pure quote-driven or pure order-driven, but are **hybrid markets**. Hybrid markets do not apply a single execution system, but they combine them. In such a case, the dominating system defines the market type. The NASDAQ Stock Market is, for example, a quote-driven market, but sometimes traders can directly trade together. Many continuous markets are basically order-driven markets but if there is not enough activity intermediaries need to intervene as dealers (Reilly and Brown, 2003). This is the case if there is order imbalance (there are no orders on one of the trading sides), or if the bid-ask spread becomes too wide (Schwartz and Francioni, 2004).In the Amsterdam Stock Exchange, the most liquid stocks, those belonging to the AEX and AMX indexes, are traded in a continuous order-driven market with automatic matching. For medium and less

liquid stocks, execution is not automatic but controlled by the Hoekman who enters quotes manually (Demarchi and Foucault, 2000). The NYSE is essentially an order-driven market as well, but has elements of quote-driven market, since market makers (called Specialists) are required to commit capital in order to offer liquidity when no one else will do so.

2.2.6 Market rules

On every market rules specify how buyers and sellers can arrange their trades. The set of rules adopted on a market is called the protocol. Rules can vary not only from market to market but from stock to stock within a market as well. Rules regulate the organization of trades, the trade prices, and determine the quantity and quality of information provided to market participants.

Rules specify, for example, the time of the call-auctions on call and hybrid markets, and the conditions that imply trading suspensions. They also impose restrictions on the orders and quotes that traders can place (Madhavan, 2000). On the Amsterdam Stock Exchange, for example, there is a minimum threshold of shares determined for which quotes can be placed (Demarchi and Foucault, 2000). Rules restrict the allowed minimum and maximum difference between the bid and ask prices of a dealer's quote, called as *bid-ask spread*, the minimum and maximum difference between two consecutive bid quotes and ask quotes, the unit by which traders can vary their quotes (e.g. decimals) called *tick-size*. The order in which orders can be filled also depends on regulations: earlier placed orders, or orders at better prices might have priority.

The quantity and quality of information provided to the market participants during the trading process (Madhavan, 2000), the extent of dissemination and speed of dissemination (Demarchi and Foucault, 2000) are all regulated by market rules. Information is classified as pre-trade or post-trade based on the timing of its availability. Pre-trade information refers to information a-priori available for traders, such as: quotes, the content of the limit order book, degree of anonymity. Post-trade information refers to the transactions made, to the publication of prices, etc. An example of post-trade information is transaction data. On many markets there must be some delay before transaction data is published (especially if it represents a large transaction). The way information is disseminated on a market influences the degree of transparency of that market.

The organizational factors described above state how trades can be conducted and thus, how prices can be formed on a market. Accordingly, the type of execution system by which the final price is determined on a specific market is known. However, the detailed process behind the actual price formation is in general not public but hardly observable. This problem is strongly related to the hardly observable aspect of price formation discussed in Section 2.1. The other hardly observable aspect we mention in that subsection refers to the participants' behavior. The presence and behavior of traders is constrained by the way a specific market is organized. Their actual behavior is, however, individual and is influenced by the de facto functioning of a market. In the next section we discuss the generic trading behavior of market participants based on their role and the market organization where they interact, and we speculate on the actual behavior of the participants within the constraints indicated in this subsection.

2.3 Price formation and behavioral aspects

Now that the static, visible side of stock markets has been described we can let them operate and make an attempt to observe their dynamics. We need thus, to discover somehow hardly observable aspects or speculate on their content. In this section we aim to describe processes and to identify behavioral aspects that influence market dynamics. Fort this reason, we zoom in on the tasks and responsibilities of market participants. By behavioral aspects we mean factors related to the trading behavior of market participants, such as the way market participants decide which stocks to trade, the way they determine the parameters of their orders and quotes, their timing regarding when to place orders, when and how to determine the parameters of a transaction, if that is not unequivocally defined by the trading rules, and so on. The method that we apply for deriving the behavioral factors is to watch markets in action. That is, we elaborate on possible ways of price formation through the behavior of market participants by tracking step by step how orders might be formed and how they might trigger market prices. In order to succeed we build mainly on observations of these processes as described in the literature (e.g. (New York Stock Exchange, Inc., 2000; Demarchi and Foucault, 2000; Reilly and Brown, 2003)).

2.3.1 Order initiation and the behavior of investors

Orders can be initiated by investors or by financial agents trading for their own account, trying to keep or reallocate a certain level of inventory, or trying to ensure liquidity. The instruments that a trader holds constitute the portfolio of the trader. Traders aim to keep the composition of their portfolio appropriate. They do this by means of portfolio management. Portfolio management often involves that the composition of a portfolio needs to be changed. The main question is how traders determine the desired content of a new portfolio. The way investors manage their portfolio is in fact a hardly observable process as discussed in Section 2.1.

In general, as described by Reilly and Brown (2003), the portfolio management process involves four main, highly interrelated tasks:

- construction of a policy statement,

- determination of the investment strategy to meet the policy statement guidelines,

- construction and maintenance of the portfolio, and

- continual monitoring of the needs and conditions.

These tasks provide a guideline to the remainder of this section. By taking a closer look on how these tasks can be possibly conducted we try to identify generic and varying aspects of traders' behavior when placing orders.

2.3.1.1 Policy statement

The policy statement is a road map that specifies the investment goals, constraints and risks investors are willing to take. It depends on the expectations and experience of the investors and it is determined taking into account the investors' short-term and long-term needs. The

policy should be updated from time to time given that needs change over time. Three main factors drive the policy statement: the investment goals, investment constraints and risk.

Investors can have a variety of **objectives** changing over *time*. Objectives are stated for different time-horizons and are of varying importance. Objectives vary from near-term high priority goals (such as, accumulating funds to make a house down payment or pay college expenses) and long-term high-priority goals (like the ability to retire at a certain age) to lower-priority goals (like to take a luxurious vacation every year).

There are several **constraints** that influence investment objectives, including: liquidity needs, time-horizon, tax concerns, legal and regulatory factors, unique needs and preferences. A close relationship exists between the investors' time-horizon and liquidity needs: near-term goals might require quick conversion to cash and thus more liquidity.

In order to achieve their objectives, investors need to take risk. People are willing to take different grades of risk. That is, they have different **attitudes to risk**. An investor's attitude to risk is influenced by personality, financial constraints, and personal preferences. In addition, the priority and the time-horizon of an objective might exert a big influence on the attitude to risk: long-term investment horizons can usually tolerate more risk, while investors with short-term time horizons favor less risk.

2.3.1.2 Investment strategy

In order to achieve the investment objectives stated in the policy statement, traders can develop a variety of investment strategies. The development of a strategy includes the study of financial, economic, political and social conditions and aims to **forecast future prices** at a certain time-horizon. Many indicators (measures) exist that traders use for analysis in this sense. Many studies are devoted to analyze how and whether various indicators can be used to describe and forecast financial time series. A thorough overview of measures and (possible) relationships between these is given by Haugen (2001). Indicators are characterized as either technical or fundamental. **Fundamental** indicators are related to the basic intrinsic value, also referred to as *fundamental value* of a stock, and as such, depend mainly on the underlying economic factors (Reilly and Brown, 2003), like the performance of the issuer. **Technical** indicators refer to assumed statistical features of the historical data. Arbitrary many ways exist to consider and combine diverse indicators in order to have a possible projection into the future. Based on the type of data that is used by traders for forecasting, two main types of investors are differentiated: *fundamentalists* and *technical analysts* (or chartists). In the literature they are also referred to as informed traders and noise traders, respectively .

2.3.1.3 Portfolio maintenance

Based on the policy and forecast, traders or their advisors implement the investment strategy by determining how to allocate available funds across different markets, asset classes, and assets depending on the investor's attitude to risk. Trading instruments of different types are categorized in asset classes, such as real assets, risk-free assets paying constant interest rate, and stocks paying varying dividends. Regardless of the investment strategy used, the portfolio construction results in **asset allocation**, that is, the determination of the required **asset classes and weights** for each class, and the **specific assets and weights** of them within

each asset class. The difference between the current portfolio and the required portfolio determine the parameters of the **orders** that traders will place: the identity of the traded assets, the size and side of the orders.

When placing an order traders should have in mind an ultimate **price** at which they are willing to buy/sell the selected stocks. The price depends heavily on the expectations given by the investment strategy. At markets where limit orders can be placed, traders can quote a price (limit price) at which they are willing to trade in the worst case. Traders might also decide to place market orders, and then, the price that they are not willing to exceed can be determined by the right **timing** of the placement of the order.

2.3.1.4   Monitoring

Monitoring is, in fact, conducted in combination with all the other processes of portfolio management. Monitoring implies periodic reconsideration of the various phases. Investors monitor their needs and the market conditions, and evaluate the portfolio performance from time to time, compare it to expectations, and modify the policy statement and/or the investment strategy if they think it is necessary. Monitoring includes thus, **performance analysis**, and assimilation of new **information**. Modified statements and strategies reflect the **adaptive** behavior of the traders.

2.3.1.5   Time

During the various stages of the portfolio management process a variety of **time factors**, related to different decision problems, play an important role. The time factor in this sense has multiple aspects. It can refer to the time-horizon of the investment objectives, to the forecast horizon of the investment strategies, to the time interval traders look back in past for relevant historical data in order to forecast, to the time at which they decide to place an order for a certain stock, their waiting patience for the execution of a limit order, to the time they monitor changes and decide to reconsider their strategies and objectives, and so on. Decisions related to timing can be influenced by current market conditions but also by individual factors, such as goal, belief and portfolio composition. The timing with respect to the placement of an order is, for example, determined by the preferences of a trader, the signals/information perceived and by the market regulations. Alternatively, brokers might advise their clients (investors) when they think it is advantageous to place an order for a certain asset.

We have analyzed, so far, the order placing behavior of investors, in view of the portfolio management process. Based on the market organization where they interact, brokers and market makers might deal with similar decision problems. Order-placing behavior in their case is mainly related to, and can be entailed by the order execution behavior required by their role. In the next subsections we continue to trace the orders on the various routes they can follow, based on the organization of the market where they are placed and executed, and on the role and behavior of financial traders who overtake and execute them. First, we focus on markets in which brokers can interact and the way orders might be processed by brokers. Then, we spend a few words on automated execution mechanisms and finally, we elaborate on the tasks of market makers.

2.3.2 Order execution and the role of brokers

According to their role, brokers are committed to clear orders on behalf of the investors. Their main task is thus to **receive and execute orders** placed by investors. In addition, they might also place orders for their own account if allowed. In relation to their role in the market, brokers are faced with two main decision problems:

- which received order(s) to select for execution; and

- how to execute the received orders.

Like investors, brokers continually **monitor** and analyze the market conditions which influences them in making decisions. The way brokers decide to select and execute orders depends on the execution system(s) applied on the market where they interact.

2.3.2.1 The order selection strategy

Brokers might try to execute orders one by one or in an accumulated way. Orders that are not immediately executed are stored in an order book, and selected from there later, for further execution. The selection choice can be based on the order of arrival, price (orders with higher probability for execution might be chosen first) or several orders can be aggregated into a new order that contains and represents them. It is not clear how brokers solve this problem in reality. Arbitrary many possibilities exist, which depend on several individual and financial features. Further, the way selection is made is influenced by the execution system that is applied on a market.

2.3.2.2 The order execution mechanism

For an easier overview assume $Broker\_A$ receives and executes orders one by one. Suppose he receives $Order\_X$ from $Investor\_X$ and thus needs to execute it. The broker needs to decide through which available execution mechanism to execute the received order. There are basically three main possibilities he can choose from (Figure 2.4) depending on the rules and the execution system that apply on that market (U.S. Securities and Exchange Commission, 2001; Schwartz and Francioni, 2004):

1. cross the trades: execute the order or part of it internally (represented by $Order\_X^I$), for example with an earlier received order from another trader;

2. try to negotiate: find other traders that are willing to take the other side of the order preferably at an improved price ($Broker\_A$ can take the $Order\_X^N$ form of the received order and try to negotiate with $Broker\_B$ and with $Broker\_C$ who try to fill $Order\_Y^N$ and $Order\_C$ respectively);

3. submit the order, or part of it for further execution to a central execution system ($Order\_X^C$). Central execution might be either automated or supervised by a market maker.

The first two choices can be made for example on order-driven markets, where participants can directly trade with each other. The central execution system where orders can be

sent to and cleared can be, for instance, automated central matching system on call-auctions, or might represent and be driven by market makers, who quote bids and asks and maintain a limit order book on quote-driven markets. Usually, all trades must be reported to, and approved by the market maker (or the central system).
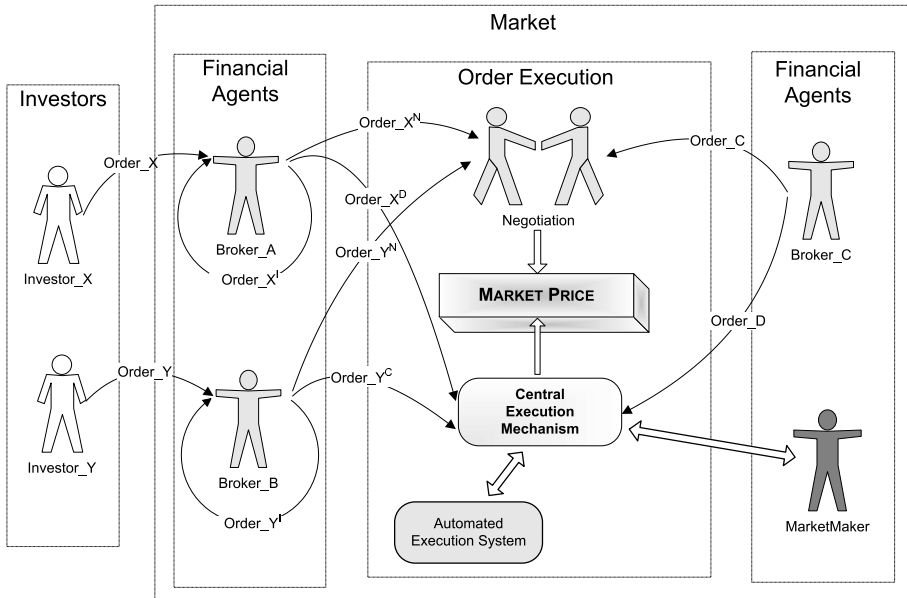
Figure 2.4: Tracking orders

Depending on the decision of the brokers, an order might be transformed into more orders before final execution. Transformation might be applied to volume and/or price. It is often possible to improve the execution price of an order. It might also happen that in first instance only part of an order can be executed. The rest will be then filled later, most probably at a slightly different price. Finally, it can also occur that parts of an order are executed through different execution mechanisms.

Depending on the execution mechanism selected, brokers are faced with additional decision problems.

1. If a broker is allowed to, and chooses to execute the order internally, he needs to decide whether to match the order with orders sent by other traders (that could not have been executed previously) or to execute it for his own account. Taking the other side of an order might lead to surplus or deficit in the inventory of a broker. Brokers who are required to keep a certain level of inventory are faced with a portfolio management problem similarly to the investors. Order execution might thus trigger additional orders.

2. If the market organization allows and the trader chooses to find other financial agents to trade with, he can either accept an offer of the others or try to negotiate. If traders

choose negotiation they further need to set up some kind of **negotiation strategy**, that involves decisions regarding:

- timing related to the length of negotiation: for how long to try to negotiate an item?

- the negotiation steps: how to define the negotiation prices?

- timing related to negotiation patience: how long to wait before making the next bid/offer?

- negotiation limit: when to accept an offer and when to stop with negotiating?

3. If the broker routes the order for execution to a central order execution mechanism he can still send it with an improved price quote. In this case it is up to the execution system how it clears the order. How this can be done is discussed in the next section. Basically there are two main decision-problems brokers are faced with in this case. They need to decide the degree of price improvement. Further, they need an appropriate **timing** for forwarding the order: they need to decide for how long to keep an order before sending it to a central matching mechanism. In most of the cases the latter is in fact not a difficult problem since often rules specify for how long brokers at the trading floor are allowed to keep an unexecuted order.

Regardless of the choice made, brokers have to determine the **transaction price** at which to execute the orders in case of actual execution, or a **price limit** in a way similar to investors, in case of routing the order. The price depends on the price quote that the requesting investors set, in case of a limit order, but also on the current market conditions and regulations.

Similar to the variety of investment strategies that can be applied by investors, arbitrary many realizations of the order selection and the execution strategy of the brokers exist. Several possible variants (of e.g. negotiation strategies) are described in the literature, however, except for the constraints defined by market organizations, details of the applied strategies are not revealed by the brokers themselves. This hardly observable feature again is a reason why market dynamics are difficult to understand.

2.3.3   Order execution and the role of market makers

While placing an order always involves traders, the execution of orders does not necessarily require a trader, but can be automated. Central order execution at call sessions, for instance, might be conducted by a special financial trader, e.g. a market maker but often an automated system is used to match orders and find an equilibrium point. Similarly, a mechanism on continuous markets where limit orders are stored if they cannot be executed and new orders are matched against the best quotes, can be solved by an automated order matching systems, like a continuous electronic system operating 24 hours a day. In this section we elaborate on the role and behavior of market makers when executing orders. We can state without loss of generality that the descriptions below also cover price formation mechanisms and decision problems within automated execution systems. The reason is that we can think of an automated system as an execution system carried out by a trader, the decision of which is determined only by a computer program and it is not influenced by other behavioral factors.

2.3.3.1 The role of market makers

The role of market makers as summarized in (Madhavan, 2000; Reilly and Brown, 2003) and (Demarchi and Foucault, 2000) consists primarily of the following tasks:

- supply immediacy in order to permit continuous trading by overcoming the asynchronous timing of investor orders;

- monitor the market through quoting bid and ask prices at which they buy and sell stocks, so that traders do not need to spend resources to do that;

- set prices: adjust the bid-ask spread to the changing market conditions;

- provide liquidity: provide additional liquidity for less liquid stocks;

- in some cases (must) complement the supply of liquidity at the time of call-auctions: this can lead to equilibrium and liquidity;

Summarizing the tasks above, market makers are responsible for a good functioning of the markets. For this reason, they need to place additional orders and to execute received orders as soon as possible. Further, they need to maintain bid and ask quotes on continuous markets that on the one hand reflects market conditions, and on the other hand encourages trading.

2.3.3.2 Execution of orders on call markets

During call market sessions where, as described in Section 2.2, trading takes place at well defined times when all interested traders need to send their orders during a given time interval to a central execution system. In case of call auctions orders are accumulated and matched at a single price at some equilibrium. The equilibrium point can be defined in different ways but in most of the cases the aim is to maximize trading volume, or to minimize excess demand. The key factor distinguishing the mechanisms of call-auctions, and the main decision problem to be solved by market makers or by automated execution systems on these type of markets is thus, how to **determine the equilibrium price**.

2.3.3.3 Execution of orders on continuous markets

During continuous trading sessions market makers need to determine bid and ask quotes. When market makers receive an order they check whether it matches the quoted bid (in case of a sell order) or ask (in case of a buy order). If it matches they clear the order at the quoted price and charge the actual transaction costs, otherwise they enter the new order into the limit order book. Besides new order arrivals, inactivity on the market, competitive behavior, belief, or the arrival of some information can cause the market maker to update the bid and ask quotes.

The main decisions that market makers face on continuous markets is thus related to:

- **determination of the new quotes**: what should be the values of the new quotes so as to reflect the content of the limit order book, the position of the market makers and to ensure a liquid and fair market?

- **timing of the new quotes**: that is when to change the quote. How to decide that there is not enough liquidity? How to be competitive without loosing in case of competitive markets?

- **management of the limit order book**, that is how and when to execute orders entered in the limit order book? This problem is related to the way new quotes are determined, since market makers can take the other side of an order before they make new quotes, or after some quotes are executed, in order to "recover" their position.

The most simple solution for defining a quote is to take the highest bid and lowest ask orders from the order book, as quotes. However, most likely, real bid-ask setting strategies of market makers are more complicated, as they depend, among others, on the content of the limit order book and on the position of the market maker. How each market maker determines the quote can vary a lot, and again it is not revealed.

2.3.4 Summary

In this section we have discussed the details of price formation. It is important to make a clear distinction between the originally quoted price of an order and the final price that an order triggers. We refer to a limit price that investors (or other participants initiating orders) define as a *price quote* or quoted price, and to a price that is a result of a transaction as the *market price*. We discussed the details of placing orders and quoting prices in the first part of this section. In the second part we elaborated on the possible forms of execution of an order and the market prices that the original order could trigger.

Price formation is strongly related to the behavior of traders. The decisions behind traders' behaviors are by definition hardly observable. Given this property it is not obvious how prices are actually determined by the participants. The organization of markets imposes constraints on how prices can be set but does not provide all the details behind the price formation mechanism. Based on the organization and the actual conditions on the market a final market price might be set:

- by brokers within their own account;

- by brokers through negotiation;

- by market makers at quote;

- by market makers at equilibrium;

- by automated electronic systems based on submitted quotes;

- by automated matching mechanisms at equilibrium.

The difficulty to understand market dynamics is caused by the fact that the details behind these alternatives are hidden.

By tracing the path an order takes till it is executed we could observe that a multitude of factors might influence the value of the resulting market price. The final market price does not only depend on the originally quoted price of an order placed by an investor but might go through slight changes based on the market structure, financial agents' role and behavior.

So far we have identified several organizational and behavioral factors that are often hardly observable, and often vary, underlying the differences between various markets and traders' behavior respectively. The hardly observable aspects of the market mechanisms, and their complexity, are reasons behind the difficulty to understand market dynamics. This is why representations of markets have to be designed incorporating assumptions regarding hardly observable aspects.

2.4 Market quality

The organization of markets influences their quality. Therefore, organizational aspects are adapted from time to time to improve market quality. Various people perceive the quality of a market differently depending on their priorities. In this section we describe the attributes which are considered relevant in deciding how well markets function. Further, we discuss how, and through which organizational aspects these attributes can be manipulated to improve market quality.

2.4.1 Characteristics of a good market

The most important characteristics of a good market, according to Reilly and Brown (2003) are timely and accurate information, liquidity, low transaction costs and informational efficiency. In this subsection we explain these notions and introduce related ones.

- **Transparency.** Traders expect **timely and accurate information** on the prices and volume of past transactions, and on the current outstanding bids and offers in order to be able to determine an appropriate price.

- **Liquidity.** Liquidity refers to the ability to buy and sell an instrument quickly at a fairly certain price, that does not differ substantially from previous transaction prices assuming no new substantial information is revealed. The likelihood of an asset of being sold quickly is referred to as **marketability**, while the fact that prices do not change much from one transaction to the next is referred to as **price continuity**. Continuity of prices can be achieved if there is enough **depth**, that is if there are buyers and sellers who want to trade at prices above, and respectively, below, the current market price.

- **Low transaction costs (internal efficiency).** Traders prefer markets with lower transaction costs to markets with higher transaction costs. Investors do not want to pay much in addition for their orders being executed. They will normally not trade if the costs of the trade are higher than the difference in value between what they give up and what they receive. Markets where minimal transaction costs are charged are characterized as internally efficient.

- **Informational efficiency (external efficiency).** Finally, traders expect to be treated honestly and not to be misled, that is they want to trade at a price that *fully reflects* all the information available regarding the asset. A market in which prices reflect all available information is characterized as being informationally efficient.

2.4.2   Manipulating market quality through the organizational aspects

The first three measures of a good market, namely transparency, liquidity and low transactions costs, can be more ore less directly manipulated through the organizational aspects of the market, such as trading rules, execution systems and trading sessions.

The degree of transparency of a market depends on the trading rules applied. This is entailed by the fact that the part of the information on prices, volume, bids and offers, and the timing of the information that is revealed is constrained by trading rules. Information that is withhold can be made available for extra cost. Prices with respect to information as well as transaction costs are again formulated in form of trading rules.

The liquidity of the assets is influenced by the rules applied on a market, and can be enhanced by employing specific financial traders, since these traders are required to trade for own account if necessary, initiate orders, and update quotes if there is not enough activity. The relationship between liquidity and organization of markets is in fact bidirectional. The liquidity of certain assets often determines the type of trading sessions and execution systems applied on a market to trade them: liquid stocks are mainly traded on continuous order-driven markets, while less liquid stocks are traded on call markets (Demarchi and Foucault, 2000).

While there is a direct, univocal relationship between organizational aspects, and the first three attributes mentioned above, it is not evident how external efficiency can be improved through altering aspects of a market organization. The main reason behind this problem is that it is not well-understood how information is reflected into prices. This problem is strongly related to the hardly observable aspect of the price formation process and has led to many conflicting and controversial discussions around market efficiency.

All the aspects of market quality are strongly related to information. Therefore, in the next subsection, we define what the term information might cover. Then, we would like to elaborate on the efficiency of the markets, one of the most discussed topics in the literature on financial markets.

2.4.3   Information in markets

We can state without any doubt that one of the main, if not the main, driving forces of market dynamics is information. The main questions all market participants face are all related to information, i.e. is some specific information available or can it be acquired for extra cost, is the available information accurate, is someone in the possession of some valuable information, and can he make advantage of it.

Information on markets is classified along two dimensions: its source and its grade of dissemination.

Based on their source, two categories of information are differentiated, namely:

- market information, and

- fundamental information.

Market information, also known as trading information, refers to currently available information generated by the market and historical values. It includes knowledge of the current quotes, last transaction data, contents of the limit order book.

Fundamental information pertains to the determinants of future share value. It includes information concerning current earnings, forecasts, strategic business and economic condition (Schwartz and Francioni, 2004).

Information can be also differentiated based on its availability. Three categories of information are defined accordingly, based on the extent to which information is disseminated:

- public information;

- private information; and

- inside information.

Public information refers to information that is widely disseminated and is readily available to everyone (freely or for cost). It includes market information, and fundamental information such as earnings and dividend announcements, price-to-earnings (P/E) ratios, dividend-yield (D/P) ratios, price-book value ratios (P/BV), stock splits, news about the economy, political news. Private information is fundamental information possessed individually based on own analysis. Finally, inside information is only known by people in a special position.

2.4.4   Market efficiency

The efficiency of financial markets is a central question in economic studies. An efficient market is defined as a market in which *prices always "fully reflect" all available information* (see (Fama, 1970)). This definition is known as the efficient market hypothesis (EMH). Depending on the type of information, that is to be reflected into prices, three variants of efficiency have been proposed by Fama (1970) in the form of hypotheses:

- The **weak-form EMH** is concerned with the full reflection of all **past market information**.

- The **semistrong-form EMH** is concerned with the full reflection of all **public information**.

- The **strong-form EMH** is concerned with the full reflection of all **information from public and private (including inside) sources**.

The problem with this definition of efficiency is that, because the term "fully reflects" is not operational, there is no common agreement on what it means. This problem gave rise to many different interpretations and controversial discussions on what an efficient market is. We enumerate the most common interpretations:

1. In an efficient market prices **adjust rapidly to the release of new information** (e.g. in (Reilly and Brown, 2003)).

2. In an efficient market prices reflect all information so that **no one can predict future price changes**(e.g. in (Harris, 2003)).

3. In an efficient market investors cannot realize **excess returns**.

4. In an efficient market investors are not able to consistently derive **above-average risk-adjusted profits**.

5. In a (perfectly) efficient market prices follow a **random walk**.

Notice that three types of EMH are distinguished based on the type of information reflected in the prices. Similarly, all interpretations of the EMH given above, except for the last one, can have three forms, each form being parameterized with the type of information investors base their decision on, i.e. past, public and all information.

The various interpretations of the EMH illustrate that, as (Lo and MacKinlay, 1999, pg.6-7) state "the Efficient Markets Hypothesis, by itself, is not a well-defined and empirically refutable hypothesis." On the other hand, interpretations of the EMH, such as "adjust rapidly", "excess returns", "above-average", are not well-defined either. Therefore, in order to make the EMH operational, "one must specify additional structure, e.g., investor preferences, information structure, business conditions, etc." However, the additional structure implies additional difficulties, since: "then a test of the Efficient Markets Hypothesis becomes a test of several auxiliary hypotheses as well, and a rejection of such a joint hypothesis tells us little about which aspect of the joint hypothesis is inconsistent with the data. Are stock prices too volatile because markets are inefficient, or is it due to risk aversion, or dividend smoothing? All three inferences are consistent with the data. Moreover, new statistical tests designed to distinguish among them will no doubt require auxiliary hypotheses of their own which, in turn, may be questioned."

Based on the reasoning above, we do not discuss here the first interpretation because it is as vague as the original. Interpretations 2 to 4 can be treated as being equivalent. Most of the studies on testing EMH are based on one of these three interpretations combined with the last interpretation. These studies are mainly concerned with analyzing the predictive power of traders relying on some specific information. Accordingly, the grade of efficiency of a market is often determined by examining whether some traders can realize excess returns by trading on a given set of information, i.e. if there are any traders who can to realize above-average profits by using trading rules based on past price movements (in relation to the weak-form EMH), public information (in relation to the semi-strong EMH), and private information (in relation to the strong-form EMH).

In the literature, in general the weak-form EMH is tested. For a description and discussion on various tests of different forms of efficiency we direct the reader to Campbell et al. (1997). Studies that are aimed to test the weak-form efficiency try to find successful strategies that are based on past data. In relation to this approach two possibilities are differentiated with respect to the properties of the time series: price series are either random, or contain some pattern, i.e. there is some linear or non-linear relation between the various past data values. Accordingly, in order to find successful strategies based on past data, it is analyzed whether price changes are random or some sort of "pattern" can be observed in the past data. If someone cannot make above normal profits by exploiting a certain regularity, that regularity, indeed, is not enough proof to reject the hypotheses that a given market is efficient. It does not mean however, that no other patterns might exist, which have not been discovered. If someone is able to make above normal profits by exploiting these regularities, it has to be further analyzed whether this successful strategy is persistent or it is there only by chance. There are contradictory views whether this is indeed the case.

Tests on the successful behavior of traders are thus, strongly related to the 5th interpretation of market efficiency, according to which in an efficient market price changes are random. This is in fact the only mathematical formulation that can be operationalized. Many people claim that in a perfectly efficient market prices follow a "random walk". However, critical remarks on this claim have been voiced. Alexander et al. (2001) emphasize for instance, that "stock prices do not need to follow a random walk in order for them to fully reflect information and for markets to be efficient."

Schwartz and Francioni (2004)[pg.33] comment on the relation between efficiency and randomness with the following argumentation: "Information is the input that drives investment decisions and therefore also trading. Security prices are a result (output) of the process. In efficient markets, information should be reflected in prices with an accuracy that leaves no investor an incentive to search for additional information or to trade. If information is perfectly reflected in prices and if trading is frictionless (seamless and costless) process, then security prices will follow a random walk (i.e., a stock's price will change randomly over time). However, when the realities of actual markets are taken into account, it is clear that trading is not frictionless and that share prices do not follow random walks."

Our conclusion is that random walks and efficiency are not equivalent properties. While the proof for randomness might be enough to accept efficiency, efficiency does not necessarily generate only random time series. If price changes prove to be random, and thus, no pattern can be found, probably no successful strategy can be found either. It can also happen however, that price changes are not random, but no successful strategy can be found based on the patterns found. If no such a strategy can be found the weak-form EMH cannot be rejected. However, if one couldn't find a successful strategy, it does not mean that a strategy that leads to above-average risk adjusted profit does not exist. If a strategy exist that is based only on past information can persistently outperform the buy-and-hold strategy, the market is probably not weak-form efficient.

2.4.5   Summary

By definition in a high quality market we expect timely and accurate information; liquidity; low transaction costs and informational efficiency. While there is a desire to achieve all these requirements of a good market, sometimes a trade-off between them is inevitable. There are certain policies, like restrictions on insider trading, which may make prices less informative while increasing market liquidity. Further, if information is expensive, or the market is not liquid, prices will not be able to fully and rapidly reflect information. As Harris (2003, pg.243) states: "How informative prices are depends on the costs of acquiring information, and on how much liquidity is available to informed traders. If information is expensive, or the market is not liquid, prices will not be very informative."

Well-functioning markets produce prices that accurately reflect the fundamental values of the instruments they trade (Harris, 2003). Achieving a highly efficient structure for markets is, however, a challenge (Schwartz and Francioni, 2004). In order to improve efficiency in particular, and market quality in general, sources of efficiency should be brought to light and the workings of financial markets should be better understood.

2.5 Schools of thought and approaches for studying market dynamics

In order to understand and explain the dynamics of financial markets price dynamics are analyzed. Several methods have been proposed that try to describe the properties of price (or rather return) series. Approaches include analytical models, empirical testing, experiments and computer simulations. Approaches base their theories on assumptions that are needed given the hardly observable properties of market organizations and traders' behavior. In this section we present a brief summary of the views formed on market dynamics, the approaches used to study it and the ensuing controversial findings. Given that the literature on various aspects of market dynamics is very broad, and given that many detailed overviews of the surveys, findings, and descriptions of the historical development of the specific areas exist (such as (Campbell et al., 1997), (Alexander, 2001), (Haugen, 2001), (Hommes, 2006), among others) our aim is not to give a full description, but just to provide some insight into the views and central ideas.

2.5.1 Theories of modern finance

The very first models proposed to explain market dynamics use mathematics as a tool to describe traders' behavior and financial time series. These models of financial markets have been mainly introduced in the modern era of economics, in the 1960's and 1970's, and form the pillars of financial economic theory. The most popular paradigms developed include the portfolio optimization theory by Markowitz (Markowitz, 1952), the capital asset pricing model (CAPM) (Sharpe, 1964), the option pricing model (OPM), the expected utility theory (EUT) and the efficient market hypothesis (EMH) (Fama, 1970).

When we investigate how these paradigms deal with the hardly observable aspects of financial markets we find that they simply ignore the many options behind them and take the most ideal variant. Accordingly, in the models that are concerned with trading behavior it is assumed that *all traders are rational*. Rational traders always make the most optimal choice in a given situation.

As far as order execution mechanisms and price formation is concerned, in theoretical market models *equilibrium* is central, and the mechanics of trading is ignored. Equilibrium is most often defined at the price at which demand equals offer. This is the price at which orders are executed, i.e. the market is cleared. Implicit in this approach is the assumption that the trading mechanism does not affect the resulting equilibrium: that is, whatever trading mechanism is employed, the same equilibrium would arise (O'Hara, 2002).

With respect to the quality of markets, in modern theoretical studies it is often claimed that *markets are efficient*. Efficiency is commonly used in relation with external efficiency. Proponents of efficiency claim that in financial markets it is not possible to earn abnormal profits (other than by chance) by exploring some set of information. In these studies market efficiency is often interpreted as being equivalent to *random price changes* or to *the impossibility to earn above average risk-adjusted profits*.

According to the theoretical models, one might assume about the operation of markets that participants are rational, prices are formed at equilibrium, and markets are efficient. Many people question however, whether these models are right about the assumptions they

make with respect to the hardly observable aspects, and whether trading on real markets takes place as assumed and claimed by them. A number of approaches have been proposed to test whether markets operate as described by modern finance theory. Approaches include empirical studies, experimental economics, and the market microstructure approach. Empirical studies primarily focus on market quality, in particular on efficiency. Traders' behavior is central in experimental economics. Finally, market structures and the effect of trading mechanisms on the price dynamics are closely analyzed and described in the market microstructure literature.

2.5.2 Market anomalies and empirical studies

In order to determine how efficient various markets are numerous empirical studies have been and are conducted. Empirical studies test whether theoretical models correspond to reality by taking real (i.e. empirical) data and trying to fit them to the model tested. In contrast to the theoretical approach empirical studies do not assume and ideal world but investigate the real one. This approach aims to describe and analyze properties of market data.

In general, early empirical tests supported the theoretical models. However, in the late 1970's unfavorable evidence began to appear against the modern financial paradigms because empirical regularities have been uncovered in the pricing of stocks, these being not predicted by traditional models. Accordingly, they are referred to as *anomalies* (Alexander et al., 2001).

One of the most widely known anomalies is the *January effect*. It has been observed that in general stocks have higher returns during the month of January than during other months. Another interesting seasonal anomaly is the Monday effect: in general returns on Monday turn to be lower than on other days of the week.

Empirical studies test the random walk property of price changes. Randomness implies that successive price changes should be statistically independent and identically distributed (IID). Consequently, most efficiency tests are concerned with statistical tests of independence between rates of return. Autocorrelation tests or runs test are used for this reason. If the autocorrelation of rates of returns is not significant, return series are statistically random, supporting weak-form efficiency. Similarly, the number of runs (one ore more consecutive increases or decrease) being similar to what one expects in random series, supports the hypothesis that the series is random.

Statistical properties that reveal non-random features of historical data are referred to as **stylized facts**. A wealth of interesting stylized facts have been discovered which seem to be common to a wide variety of markets, instruments and periods. Examples are excess volatility, heavy tails, no autocorrelation, volatility clusters and volume-volatility correlation (Cont, 2006).

When conducting empirical analysis on historical data, it turns out also, that the returns in many financial markets are not well-modeled by an IID process. Very high frequency returns often show signs of autocorrelation, meaning that they are not independent. And although, low-frequency data is in generally not autocorrelated at first order, there is, often a strong autocorrelation in squared returns. Autocorrelation in squared returns indicates that return series are not independent, but that "volatility comes in clusters where tranquil periods of small returns are interspersed with volatile periods of large return" (Alexander,

2001). **Volatility clusters** (or autoregressive conditional heteroscedasticity, i.e. ARCH) have been reported already in the sixties by Mandelbrot (1963, pg. 418), who noted that "large changes tend to be followed by large changes -of either sign- and small changes tend to be followed by small changes." Various versions of GARCH (generalized ARCH) models have been proposed that manage to reproduce volatility clusters which are observed in empirical data.

Volatility clusters are an example of stylized facts. Another stylized fact often reported is the presence of **heavy tails**, meaning that the distribution of returns displays fat tails with positive excess kurtosis. It has been also observed that trading volume is positively correlated to market volatility.

For a thorough overview of surveys, approaches and (contradictory) findings on testing paradigms of modern finance theory we recommend the reader (Campbell et al., 1997). A thorough overview of approaches applied to test the various forms of efficiency is presented in (Alexander, 2001) and (Campbell et al., 1997).

Findings of empirical research are contradictory and the significance of anomalies is controversial. While the existence of anomalies is well-accepted, the question whether they are persistent, and whether investors can exploit them to earn excess return in the future is subject to debate. On the one hand, proponents of it claim and believe that anomalies contradict accepted theoretical predictions (e.g. (Haugen, 2001)). On the other hand, advocates of theoretical finance, sustain that anomalies are "not of a sufficient magnitude to suggest that richer are to be made by exploiting them. Indeed, transaction costs would devor most if not all of any profits that might be made" (Alexander et al., 2001).

Despite this controversy, empirical findings rarely support theoretical models, and they suggest that there is predictability in the prices. The question is whether this proves that markets are not efficient, or predictability is the consequence of other properties, such as market structure, frictions, or changing conditions (Campbell et al., 1997).

2.5.3 Behavioral finance and experimental economics

Empirical findings suggest that markets do not necessarily behave according to the theoretical models suggested. A possible reason behind this phenomenon might lie in the simplifying assumptions behind these models. Behavioral finance and experimental economics investigate whether the assumptions on homogeneous rational decision-making, utility maximization and a priori knowledge of utility functions and alternatives are valid (Simon, 1997).

In order to test these assumptions, experiments have been conducted. The aim of experiments is to evaluate a theoretical model by examining investors' behavior in a laboratory (Levy et al., 2000). Experimental studies try to describe human behavior and reasoning behind decision-making. During experiments artificial market conditions are set up in a laboratory. Description of behaviors is based on observations and surveys.

The main advantages of experimental studies are the possibility to replicate them and to control them (Davis and Holt, 1992):

- *Replicability* refers to the possibility that other researchers can reproduce the experiment, and thereby verify the findings independently;

- *Control* is the capacity to manipulate laboratory conditions so that observed behavior can be used to evaluate alternative theories and policies. In laboratory, relations and effects of certain settings can be isolated, and thus analyzed without the interference of other variables.

Experiments and surveys form the basis of **behavioral finance**, the area of economics that is concerned with the effects of market decisions, and with the empirical validity of the neoclassical assumptions about human behavior (Simon, 1997). Behavioral finance is largely influenced by psychological research, in particular by "cognitive models of decision-making under risk and uncertainty", and by "the prospect theory" of Kahneman and Tversky (1979).

Behavioral finance not only investigates assumed or contradictory behavior, but it also analyzes the implications of departures of actual behavior from assumptions. It tries to discover "the empirical laws that describe behavior correctly and as accurately as possible". It aims to better understand economic decisions and the way they affect market dynamics.

While recent behavioral approaches are all concerned with theory testing, it is interesting to know that many of their ideas date back from before the introduction of the rational expectations and efficient market hypothesis (Hommes, 2006) [1]. Some of the key elements of this approach "are related to Keynes' view that *'expectations matter'*, to Simon's view that economic man is *boundedly rational*, and to the view of Kahneman and Tversky in psychology that individual behavior under uncertainty can best be described by simple *heuristics and biases*" (Hommes, 2006).

Findings of experiments suggest heterogeneity and *bounded rationality* of traders. Results are, however, often questionable because of biased features included in the experimental process, which can influence the subjects' behavior even if only subconsciously. For example, as argued by Phelan and Reynolds (1996): "The mere observation of people may lead them to modify their behavior and if information about behavior is to be published this may also have an effect." Other possible biases are discussed in (Roth, 1994). Another question that arises with respect to experiments is whether and how findings can be calibrated to real data.

2.5.4   Market microstructure

While experimental economics try to reveal the hardly observable aspects of traders' behavior, market microstructure literature is concerned with the hardly observable price formation mechanisms. Traditional theoretical models assume that prices are formed at equilibrium and markets are cleared at this price. In these models it is not of interest how this market clearing was achieved, i.e. what it is in the economy that coordinates the desires of demanders and suppliers so that a price emerges and trade occurs.

In contrast to the traditional equilibrium models, that ignore the mechanics of trading, market microstructure literature analyzes how specific trading mechanisms affect the price formation process (O'Hara, 2002). According to the market microstructure theories, prices need not equal full-information expectations because of a variety of frictions. A central question of this approach is concerned with how various frictions and departures from symmetric information (i.e. the fact that participants do not possess the same information) affect

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[1] see also http://www.behaviouralfinance.net/

the trading process (Madhavan, 2000). The best known theoretical microstructure models are the Kyle model (Kyle, 1985) and the Glosten and Milgrom model (Glosten and Milgrom, 1985), which study the process by which prices come to impound new information. Findings point out that market structure and information asymmetry influence the grade of efficiency of a market.

2.5.5 The constructive approaches

Recent promising approaches propose a bottom-up understanding of financial markets. In contrast to other approaches they pay attention to individual interactions and study the emergent properties generated as the results of these interactions. The main observation behind the constructive approaches is that economies are recognized as *complex dynamic systems*. This feature is underpinned by Tesfatsion (2006) as follows: "Large numbers of micro agents engage repeatedly in local interactions, giving rise to global regularities such as employment and growth rates, income distributions, market institutions, and social conventions. These global regularities in turn feed back into the determination of local interactions. The result is an intricate system of interdependent feedback loops connecting micro behaviors, interaction patterns, and global regularities."

As part of the constructive approach, recently the evolutionary approach has gained attention, according to which economy is viewed as a *complex evolving system* (see (Hommes, 2006) for a thorough overview). What is evolving is mainly the set of applied trading strategies, and because of the "feedback loops" in fact a co-evolution of strategies and markets can be observed.

Proponents of the constructive approach argue that although classic models can reproduce basic macroscopic features, they fail to reproduce emergent features of markets that cannot be directly deduced from the microscopic interaction producing them (Muchnik et al., 2005). There are three main approaches that we classify as being constructive: the nonlinear economic dynamics approach, microscopic simulation and agent-based computational economics (ACE). The area of nonlinear economic dynamics assumes nonlinear price formation and boundedly rational traders, whose belief about efficiency co-evolves with price. In microscopic simulation and ACE, the focus is on individual interactions. The latter two approaches have emerged from different areas, namely econophysics and agent-based simulation, but are based in fact on similar ideas and apply the same method to study market dynamics.

2.5.5.1 The nonlinear economic dynamics approach

The complex evolutionary view on economics motivated researchers to apply nonlinear dynamics, chaos theory and complex systems to economic theory. Proponents of this approach attack traditional models on the fact that they assume simple (linear) economics. Hommes points out that in those simple environments it is not surprising to have rational traders: "In a simple (linear) stable economy with a unique steady state path, it seems natural that agents can learn to have rational expectations, at least in the long run. A representative, perfectly rational agent model nicely fits into a linear view of a globally stable and predictable economy." (Hommes, 2006)

In contrast to the linear view on economics, a central question of the nonlinear approach is: "how could agents have rational expectations or perfect foresight in a complex, nonlinear world, with prices and quantities moving irregularly on a strange attractor?" Hommes argues that "A boundedly rational world view with agents using simple forecasting strategies, perhaps not perfect but at least approximately right, seems more appropriate within a complex, nonlinear world." Models within the nonlinear approach are referred to as dynamic heterogeneous agent models.

Summarizing, within this approach price formation is based on nonlinear rules rather than linear equations. Further, traders are assumed to be boundedly rational. Moreover, traders' strategies co-evolve with markets. Studies for describing and analyzing market dynamics within this area, typically apply a mixture of analytic and computational tools. A number of dynamic heterogeneous agent models is described in (Hommes, 2006). One of these, the ABS model, will be subjected to a deeper analysis in the next chapter.

2.5.5.2   Microscopic simulation

Microscopic simulation emerged from physics and is part of the so-called econophysics research. The idea behind microscopic simulation is to model the system in question as a set of microscopic elements and define microscopic interactions between them. This approach then investigates how observed macroscopic features emerge from the interaction of these microscopic elements. Being frequently and successfully exploited in physics, this method is now being applied in social sciences as well. In the specific context of the stock market, a variety of simplified microscopic models have been introduced over the last decade. (Levy et al., 2000; Muchnik et al., 2005).

2.5.5.3   Agent-based computational economics

Another approach to constructive understanding of economic theory, is the rapidly expanding area of agent-based computational economics (ACE). ACE is defined by Tesfatsion as "the computational study of economic processes modeled as dynamic systems of interacting agents" (Tesfatsion, 2001, 2002, 2006). Agent-based market models attempt to explain the origins of observed properties of market prices in terms of simple, stylized behavioral rules of market participants.

In recent years, studying stock markets using multi-agent based models has become a promising research area due to the fact that this methodology reflects the nature of the stock market where heterogeneous investors with various expectations and different levels of rationality interact with each other through the market (Chen and Liao, 2005).

Microscopic simulation and agent-based computational economics ultimately apply the same paradigm: constructive understanding, the importance of individuals and their interactions; they just emerged from different areas of science.

In contrast to laboratory experiments with humans, in pure computational experiments, the simulated behavior of represented traders is completely observable. The reasoning behind decision making, the relation between cause and effect is more trustable in this sense.

Approach	Price formation	Traders' behavior	Market efficiency
Theoretical (analytical)	- simple, linear at equilibrium	- assumed to be rational	- yes
Empirical	- no special attention paid - analyze statistical properties of real historical data	- no special attention paid	- anomalies found
Experimental (Behavioral finance)	- assume simple models or real markets	- observe traders' behavior in action and conclude that they are "boundedly rational"	- anomalies found
Market microstructure	- analyze price formation in function of specific trading mechanisms	- investors with asymmetric information or inventory management, and learning market makers	- grade of efficiency is analyzed with respect to well-defined fundamental values
Nonlinear economic dynamics	- complex nonlinear at equilibrium	- boundedly rational evolving groups of investors	- measured in convergence to strange attractors - stylized facts generated
Microscopic- and agent-based simulation	- varying: emerges from interaction of individuals	- boundedly rational, heterogeneous individuals	- depends on settings and heterogeneity

Table 2.1: Comparison of approaches proposed to study market dynamics

2.5.5.4   Overview

In Table 2.1 an overview is given on how various approaches handle the hardly observable aspects, and what they conclude about the efficiency of markets.

Theoretical models assume that prices are formed at equilibrium, traders are rational and that markets are efficient. Within empirical studies price formation mechanisms and traders' behavior are not of interest, but the statistical properties of historical data are studied instead. Analysis of data results in interesting patterns in time series, suggesting that prices are not random, and thus might be exploited to earn excessive returns. Further, the possibility to earn excessive profits might indicate that markets are not efficient.

Other approaches try to find out what kind of behavior and/or market organization can lead to the stylized facts observed by empirical studies, and in which circumstances markets are efficient as suggested by theoretical models. While the area of behavioral finance focuses on revealing the behavior of traders, market microstructure literature is mainly concerned with the hardly observable aspects of the price formation details.

Based on the observed behavior of market participants, experimental studies in the area of behavioral finance conclude that traders are not homogeneous and rational as presumed by theoretical models, but rather "boundedly rational". They attribute to this property the discrepancy between theoretical predictions and empirical findings with respect to market efficiency.

The market microstructure literature studies the structure of various real markets analyzing the effects of differences in the various market organizations on the quality of markets. Several types of price formation mechanisms are studied and it is analyzed how information is reflected into prices. Efficiency is characterized by whether market prices converge to a well-defined fundamental value.

Finally, the constructive approaches represent the details both behind price formation and behind individual traders' behavior. A variety of price formation mechanisms and behaviors are represented and analyzed. Stylized facts are often reproduced, but it is also found that efficiency of markets can emerge from individual interactions within these market models.

2.6   Summary

In this chapter we gave insight into the dynamics of stock markets. It is well-known that findings with respect to market dynamics are not univocal. Further, there is a lot of discussion going on with respect to market quality in general, and market efficiency in particular. The reason behind these discussions and contradictory findings is caused by the complexity of the markets and particularly the hardly observable aspects that drive market dynamics. By hardly observable factors we mean values and processes that are not revealed directly to the outside world. We have pointed to two important hardly observable aspects that make market dynamics difficult to be understood. One represents the actual price formation and the decisions behind it, the other represents the behavior of traders.

In order to be able to determine the aspects that drive the dynamics we have applied a microstructure based approach. We elaborated on the possible route of orders in different market organizations. In the first part of this chapter we proposed a list of aspects that are important to consider when studying market dynamics. We differentiated organizational factors from aspects related to price formation and traders' behavior. The former are mainly static and describe the structure of a market, the latter are mainly dynamic.We concluded the first part with a discussion on the quality of markets, and its relation to the market aspects we distinguished.

In the second part of this chapter we briefly presented approaches and theories about market dynamics and we discussed how they deal with problems related to the hardly observable aspects, and what they say about market quality. In order to study and understand market dynamics, assumptions regarding the content of the hardly observable aspects are inevitable. The various approaches make different assumptions and consider diverging levels of detail when representing or describing market organizations. These differences are at the root of the contradictory, and often controversial findings.

Analytical models form the pillars of economic theory. They have been criticized however, on the simplifying assumptions made (such as investors' homogeneous rational behavior, price formation at equilibrium). The advantage of these assumptions is that they lead to analytical tractability. Furthermore, advocates of classical theoretical models claim that it is

not important whether these assumptions are realistic, it is more important how predictive the models are. Indeed, these studies form the basis of modern finance, and in fact, they led to the appearance of new finance and alternative theories.

Alternative theories reveal a number of "anomalies". However, there is no agreement on whether these are strong enough to reject the EMH. The reason is that it is questionable whether investors can earn consistently above average risk-adjusted profits based on these anomalies, and whether these anomalies will persist at all in the future.

Concluding we can say that, the "large range of empirical financial puzzles (...) remain difficult to explain using traditional asset pricing models" (LeBaron, 2006). This fact motivates more and more researchers with different views on markets, from different areas of science (such as econometrics, psychology, physics, computer science) to continue to study and understand market dynamics. In the next chapter we describe and analyze some of the studies that use constructive approaches. As we aim to study how market structure and traders' behavior influences market dynamics, in the remainder of this thesis we focus especially agent-based approaches and, in relation to it, on agent-based artificial stock markets.

Chapter 3

Agent-Based Artificial Stock Markets

In general market dynamics are studied through market models. A market model is, like any other model, an external and explicit representation of part of reality (in this case of financial markets) as seen by the people who wish to use that model *to understand, to change, to manage and to control that part of reality* (Pidd, 2003). An overview of the approaches used to study stock markets has been given in the previous chapter. The approaches include theoretical analytical models, empirical studies, experiments, market microstructure, nonlinear economic dynamics, microsimulation and agent-based computational economics. Many market models within these approaches are referred to as artificial stock markets (ASMs), moreover recently the term agent-based ASM (ABASM) has became popular. There is however no commonly accepted definition of these terms.

In this chapter first we discuss what the term ASM might cover. Then, we elaborate on what agents are, and give definitions from different areas; Further the agent-based aspect of ASMs is brought to light. In the second part of this chapter we study a number of ASMs and place them in a taxonomy based on the conceptual framework derived from the organizational and behavioral aspects listed in Chapter 2. A preliminary version of this chapter has been reported in (Boer et al., 2005*b*).

3.1   Agent-based artificial stock markets

3.1.1   Artificial stock markets

Artificial stock markets are models of financial markets used to study and understand market dynamics. They are more advanced than traditional market models however. They are **"markets"**, and as a consequence, they incorporate a well-defined price formation mechanism and a representation of market participants. The key property is that in ASM environments prices should emerge internally as a result of trading interactions of the market participants represented.

Chen and Yeh (2002) make a more strict distinction between ASMs and conventional models pointing out that ASMs are composed of *many heterogeneous interacting adaptive traders*. They further remark that ASMs are "a promising way to study the stock market as a *complex adaptive system*", because they are *rich in dynamics*, and they are *rich in emergent properties*.

There are several keywords here to be elaborated upon:

- *many* traders: more than one market participant or behavior or strategy thereof is thus represented in ASMs;

- *heterogeneous* traders: in contrast to classical theoretical models which assume homogeneous behavior, in ASMs heterogeneity is taken into account;

- *interacting* traders: traders are interacting in order to achieve their objectives, in the sense that they communicate and trade with each other;

- *adaptive* traders: they can perceive the changes in their environment and act upon it (Kaymak and Boer, 2001);

- *rich in dynamics*: a variety of dynamics can emerge as a result of interaction between traders;

- *rich emergent properties*: prices emerge as a result of interaction among market participants. Various studies manage to explain emergent properties of ASMs from the interaction between heterogeneous traders. For an overview see for example LeBaron (2000).

The definition above indicates that modeling using ASMs falls within the constructive approaches applied for studying stock markets. As introduced in Section 2.5.5 the constructive approach aims to study how emergent properties arise from the interaction of market participants who are represented either in mass, or as molecules, or as agents.

Nowadays most market models are characterized as agent-based artificial stock markets (ABASMs). However, there is not a definition of this notion that is commonly agreed upon. People associate various meaning to the terms "agent-based" and "agent-based artificial stock markets". Therefore, before we describe some ASMs we elaborate on a number of definitions concerning these terms.

3.1.2 Agents

Agent-based modeling is characterized by the existence of *many agents* who *interact* with each other with *little or no central direction* (Axelrod, 2003).

Nowadays we meet agents more often than not as far as human agents are concerned. If we do not contact them ourselves, they call us during dinner time and want to arrange our pension or life annuity, they want us to borrow money and want to arrange that for us, they want to look for a new house on our behalf and negotiate on the price. If you do not want to apply for their service, but you are frequently using the Internet, and searching for something, then you still have to do with them, or, better said, with their artificial version.

Internet agents compare prices for us, they look for houses and jobs for us, and notify us whenever new offers appear in which we are interested in.

While the "trendy" term *agent-based* is widely used in many areas to characterize models and systems, there is no commonly accepted definition of what an *agent* is. It has a different meaning for different people even in the same area. In this section we discuss some widely used definitions.

The origins. The term agent has its roots in the Latin "agere" which means "to do". In everyday life we think of an agent as a mediator that arranges something for us.

The economic view. Agents have been originally used in the context of economics. The classical definition of an agent is as follows: an agent is "an individual or firm authorized to *act on behalf of another* (called the principal), such as by executing a transaction or selling and servicing an insurance policy." [1] We refer to an agent that corresponds to this description as a *financial agent*.

The "broad" view. Russell and Norvig (2003) define an agent very broadly as *anything that can be viewed as perceiving its environment through sensors and acting upon that environment through effectors*. In (Wooldridge, 1999) a mathematical formalization of agents is given. For the time being, assume that the agent's environment can be characterized as a set of *environment states* $S = \{s_1, s_2, \ldots\}$ that the agent can influence only partially. The influence of the agent is effected through a set $A = \{a_1, a_2, \ldots\}$ of actions that the agent can perform. The agent can then be viewed as a function

$$action : S \to A$$

that maps environment states to actions (Wooldridge, 1999). The (non-deterministic) behavior of the environment can also be modeled as a function:

$$env : S \times A \to \mathcal{P}(S)$$

which maps the current environment state and the action of the agent into a set of environment states. The range of the env function is always a singleton in case the environment is deterministic. Note that this definition of an agent completely parallels the definition of a decision maker in a decision environment. Hence, one could argue that this is a decision-theoretic approach to agents.

Typically, the agents observe the environment states only partially. (This is one of the aspects that hinders them from being perfectly rational.) Therefore, the agent's actions will depend only on a set P of percepts, which consists of a subset of the environment states and quantities that can be derived from the environment states. It is part of the agent's design to determine which percepts it can derive from the available states. In the formalism of this section, this mapping can be represented as a function:

$$see : S \longrightarrow P.$$

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[1] http://www.investorwords.com/154/agent.html

The agent's decision-making mechanism now maps (sequences of) percepts to the actions of the agent. Let f denote this mapping. Then we have:

$$f(P, \Theta) : P \longrightarrow A$$

where Θ denotes a set of parameters with which the mapping f can be parameterized.

An agent's function can now be specified by defining its set P of percepts, set A of actions and the mapping $f(P, \Theta)$ from the percepts to the actions as shown in Figure 3.1. It is assumed for simplicity that the specification of P also implies the specification of the function see.
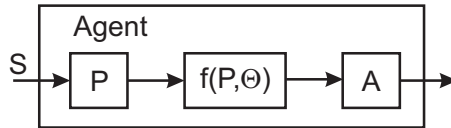
Figure 3.1: An agent maps its percepts to its actions.

The software engineering view.   In software engineering agents are specific computer programs. Wooldridge and Jennings (1995) define an agent as "a computer system that is situated in an *environment*, and that is capable of *autonomous* action in this environment in order to meet its design *objectives*."

In this definition the notion of environment mentioned in the broad view of Russell and Norvig comes back. New in this context is the *autonomy* and the fact that agents have their own *objective*. Although there is no agreement on what autonomy precisely means for agent-based systems, people agree that autonomy should be central to the notion of agency.

Tesfatsion (2006) tries to associate agents' autonomy to humans' autonomy. She claims that "autonomy, for humans, means a capacity for self-governance". According to Franklin and Graesser (1996) "an autonomous agent is a system situated within and part of an environment that senses that environment and acts on it, over time, in pursuit of its own agenda and so as to effect what it senses in the future." This definition is not sufficiently strict however. As Tesfatsion (2006) argues: "the standard neoclassical budget-constrained consumer who selects a sequence of purchases to maximize her expected lifetime utility could be said to satisfy this definition in some sense".

The most widely accepted definition of autonomy is probably the one given by Jennings (2000), according to which the property autonomy means that agents have control both over their internal state and over their own behavior. The question is how and to what degree this property of agents is realized in models. What does "having control" mean? Does it mean that they can not be controlled by another computer system? On the other hand, the way autonomy is implemented does not seem to be an important detail. According to Tesfatsion (2006) "the important issue is not whether agent-based tools permit the modeling of agents with autonomy, perse, but rather the degree to which they usefully facilitate the modeling of agents exhibiting substantially more autonomy than permitted by standard modeling approaches."

The fact that there is no general agreement on the terms "agent" and "autonomous agent" is illustrated by the discussion in (Franklin and Graesser, 1996) on the many ways these terms are used. The authors give an overview of many definitions, and, based on these definitions, they propose a taxonomy of autonomous agents.

The "intelligent agent" view.   In the area of computer science, many people, among which Russell and Norvig, associate agents to artificial intelligence (AI). Russell and Norvig (2003) are of the opinion that AI cannot exist without agents, defining AI as "the study of agents that receive percepts from the environment and perform actions." They differentiate several types of agents based on their qualities. Examples include rational agents, adaptive agents, and so on.

In (Poggio et al., 2001) we see a more restricted view. Here AI-related agents are explicitly referred to as intelligent-agents, and they are defined as "computer programs that contain certain heuristics and computational learning algorithms, with the intention of capturing particular aspects of human behavior." The authors compare the agent-based approach to study financial markets with the experimental one, and emphasize the added value of software agents above humans, claiming that "their preferences and learning algorithms are transparent and, unlike experimental subjects, can be carefully controlled and modified. Using AI-agents, we can conduct a far broader set of experiments involving more complexities than with human agents."

While Russell and Norvig associate agents to the area of artificial intelligence, and they define them as adaptive agents that use artificial intelligence techniques (such as genetic algorithms, neural networks) to learn and adapt, according to Jennings and Wooldridge it doesn't need to be necessarily so. So, they introduce the notion *"intelligent agent"* and they define this as "a computer system that is capable of *flexible autonomous* action in order to meet it's design *objectives*" (Wooldridge and Jennings, 1995).

What differentiates an intelligent agent from a simple agent is its flexibility. According to Wooldridge and Jennings (1995) a flexible agent has the following properties:

- *responsive:* agents should perceive their environment and should be able to respond in a timely fashion to changes that occur in their environment;

- *proactive:* they should be able to exhibit opportunistic, goal-directed behavior and take the initiative where appropriate; and

- *social:* they should be able to *interact* with other agents in order to achieve their goals.

The question is whether AI techniques are necessary for achieving these properties. A Genetic Algorithm, for example, is viewed as a key component in many agent-based financial markets for modeling responsive behavior, i.e. learning and adaptation. Besides AI tools however, more traditional approaches exist as well, such as Bayesian learning and adaptive linear models (LeBaron, 2006).

The agent-based computational economics view.   In the agent-based computational economics (ACE) literature "agent" refers broadly to a bundle of data and behavioral methods representing an entity constituting part of a computationally constructed world. Examples

of possible agents include individuals (e.g., consumers, producers), social groupings (e.g., families, firms, communities, government agencies), institutions (e.g., markets, regulatory systems), biological entities (e.g., crops, livestock, forests), and physical entities (e.g., infrastructure, weather, and geographical regions). Thus, agents can range from active data-gathering decision makers with sophisticated learning capabilities to passive world features with no cognitive function. Moreover, agents can be composed of other agents, permitting hierarchical constructions (Tesfatsion, 2006).

3.1.3   Agent-based environments

Regardless of the agent-definition that one is willing to accept, we certainly all agree, that "agents are situated and interact in an environment". Let us know focus on the possible properties of an environment where agents might interact. Russell and Norvig (2003, pg. 41) list six dimensions along which an environments can be categorized. In the list below the explanation of properties is based on the interpretation and examples given by Wooldridge (2005).

- **fully observable** vs. **partially observable**:

  An environment is fully observable if the complete state of the environment is observable. That is: complete, accurate, up to date information can be obtained about the environment's state. An environment is partially observable if the observer cannot get complete insight into the environment either because he is hindered given the properties of the environment or because of his own capabilities. Partially observable environments have some degree of uncertainty.

- **deterministic** vs. **stochastic**:

  In a deterministic environment any action has a single guaranteed effect. In a stochastic environment a variety of effects can occur each with some probability. The probability that a certain effect will take place might be known, but even so, it can lead to actions failing to have the desired result. Thereof stochastic environments entail uncertainty as well.

- **episodic** vs. **sequential**:

  In an episodic environment decisions must be taken periodically, in episodes. The state of the current episode does not depend on actions in the previous episodes. An episodic environment can be viewed as an environment with isolated decision problems, that could be solved in any order in fact because they do not affect each other. In sequential environments the current decision generally affects the state of the environment, and as such, all future decisions. The order of decision problems in sequential environments can thus not be varied, because when the order would be varied that would change the characteristics and outcomes.

- **static** vs. **dynamic**:

  The state of a static environment is guaranteed to stay the same while decisions are being made. In a dynamic environment there are many processes that operate concurrently to modify the environment in ways that are beyond our control. A dynamic environment might thus change while decisions are being made, entailing uncertainty.

  A dynamic agent-based environment, for example, has the following consequence on the agents' decisions and actions: "if an agent performs no external action between times t_0 and t_1, then it cannot assume the environment at t_1 will be the same as it was at time t_0. Thus if an agent checks that the environment has some property ϕ and then starts executing some action α on the basis of this information, it cannot in general guarantee that the environment will continue to have property ϕ while it is executing α" (Wooldridge, 2005). As a consequence, participants in a dynamic environment will need to synchronize or coordinate their actions with those of other processes in the environment.

- **discrete** vs. **continuous**:

  "Discrete ideas or things are separate and distinct from each other". (Sinclair, 2001, pg. 435) "A continuous process or event continues for a period of time without stopping." "A continuous line or surface has no gaps or holes in it." (Sinclair, 2001, pg. 327) "The discrete/continuous distinction can be applied to the *state* of the environment, to the way *time* is handled, and to the *percepts* and *actions* of the agent. For example, a discrete-state environment such as a chess game has a finite number of distinct states. Chess also has a discrete set of percepts and actions. Taxi driving is a continuous-state and continuous-time problem: the speed and location of the taxi and of the other vehicles sweep through a range of continuous values and do so smoothly over time. Taxi-driving actions are also continuous." (Russell and Norvig, 2003).

- **single agent** vs. **multiagent**:

  Based on the number of agents, an agent-based environment can be classified as single agent or multiagent. Most problems require or involve *multiple agents* which will need to *interact* with one another, either to achieve their individual objectives or to manage the dependencies that ensue from being situated in a common environment. Interactions can vary from simple information interchanges, to requests for particular actions to be performed and on to cooperation, coordination and negotiation in order to arrange interdependent activities (Jennings, 2000).

A most complex environment is one that is partially observable, stochastic, sequential, dynamic, continuous, with many participants or decision makers. One can easily agree that financial markets are such kind of environments. On the one hand, conventional financial models, being constrained by mathematical feasibility, are not capable of modeling all these features (Chen and Yeh, 2002). On the other hand, computational agent-based techniques proved to be able to model these sort of environments. We point the reader again to (Russell and Norvig, 2003) and (Wooldridge, 2005) for a detailed description and reasoning on this potential of agent-based modeling.

3.1.4   Agent-based modeling of financial markets

The goal of agent-based modeling is to enrich our understanding of fundamental processes that may appear in a variety of applications. The emergent properties of an agent-based model are the result of "bottom-up" processes, rather than a "top-down" direction. (Axelrod, 2003). While the topics being investigated by the agent-based approach may be complicated, the assumptions underlying the agent-based model should be simple. The complexity of agent-based modeling should be in the simulated results, not in the assumptions of the model (Axelrod, 2003). The promising property of agent-based approaches to model and study complex systems is at the basis of the area of agent-based computational economics.

3.1.4.1   Agent-based computational economics

Agent-based computational economics (ACE) is the computational study of economic processes modeled as dynamic systems of interacting agents. (Tesfatsion, 2006).

Tesfatsion (2006) elaborates on a number of advantages of ACE modeling above standard modeling approaches.

- In ACE events are driven solely by agent interactions once initial conditions have been specified. ACE does not aim to focus on the equilibrium states of a system. The idea behind it is rather "to watch and see if some form of equilibrium develops over time." Thus, it is possible to study in what case equilibrium will establish, and if so, how such an equilibrium is realized. Further, "modeling can proceed even if equilibria are computationally intractable or non-existent."

- Agent-based tools facilitate flexible social communication. "Agents can communicate with other agents at event-driven times using messages that they, themselves, have adaptively scripted."

- Agent-based tools facilitate the design of agents with relatively more autonomy than standard modeling approaches. in the sense that agent-based tools facilitate the modeling of cognitive agents with more realistic social and learning capabilities than standard models. These capabilities include:

  - social communication skills;
  - the ability to learn about ones environment from various sources (such as gathered information, past experiences, social mimicry, and deliberate experimentation with new ideas);
  - the ability to form and maintain social interaction patterns (e.g., trade networks);
  - the ability to develop shared perceptions (e.g., commonly accepted market protocols);
  - the ability to alter beliefs and preferences as an outcome of learning; and
  - the ability to exert at least some local control over the timing and type of actions taken within the world in an attempt to satisfy built in (or evolved) needs, drives, and goals.

As Tesfatsion (2006) observes: "A potentially important aspect of all of these modeled capabilities is that they can be based in part on the private internal methods of an agent, i.e., internal processes that are hidden from the view of all other entities residing in the agents world. This effectively renders an agent both unpredictable and uncontrollable relative to its world."

3.1.4.2 Agent-based computational finance

Agent-based computational finance is a subfield of agent-based computational economics, which focuses on agent-based modeling of stock markets. Models in the realm of agent-based computational finance view financial markets as *interacting* groups of *learning*, *boundedly rational agents*. In agent-based financial markets, *dynamic heterogeneity* is critical. This heterogeneity is represented by a distribution of agents, or wealth, across either a fixed or changing *set of strategies*. Bounded rationality is driven by the complexity of the state space more than the perceived limitations of individual agents (LeBaron, 2006).

According to LeBaron (2006): "Financial markets are particularly appealing applications for agent-based methods for several reasons.

- First, the key debates in finance about market efficiency and rationality are still unresolved.

- Second, financial time series contain many curious puzzles that are not well understood.

- Third, financial markets provide a wealth of pricing and volume data that can be analyzed.

- Fourth, when considering evolution, financial markets provide a good approximation to a crude fitness measure through wealth or return performance.

- Finally, there are strong connections to relevant experimental results that in some cases operate at the same time scales as actual financial markets."

Agent-based computational finance allows us to explore new areas of economic theory, especially in dynamic markets with asymmetric information, learning, and uncertainty - a combination that poses many insurmountable technical challenges from a theoretical perspective (Poggio et al., 2001).

3.1.4.3 Is agent-based modeling the perfect approach?

Based on the above properties agent-based modeling seems almost perfect. Although it is the most promising approach so far to model complex dynamic systems, unfortunately, agent-based models are not perfect either, they also entail problems. The most commonly criticized aspects include:

- validation / calibration: how do models and data relate to reality and real data?

- too many parameters, the impact of which is not well understood;

- the stability of the results with respect to the addition of new trading strategies. The question as LeBaron (2006, pg223) states is: "Specifically, are there strategies that would smoke out obvious patterns in the data and change the dynamics?"

- a small number of assets, which is a simplification that may eliminate many interesting features;

- a small number of agents. The question is what happens when the number of agents is increased? Can the dynamics change dramatically as the number of agents becomes large?

- timing (of learning, decisions, information and trade). To which degree do the results depend on arbitrary timing decisions?

The reason for all these drawbacks, as Poggio et al. (2001) argue, is that agent-based models contain "new and untested algorithms, parameters that *must be calibrated*, and other ad hoc assumptions that are likely to be controversial". This "ad hoc assumption" problem is in fact the same problem that occurs in other approaches used to study stock markets, and is entailed by the hardly observable aspects of financial markets. One way to address these concerns, as proposed by (Poggio et al., 2001) is to use data from human experimental markets to validate and calibrate the agent-based models.

3.1.5   Are all ASMs agent-based? - a discussion

In the literature on studying market dynamics, most authors prefer to refer to their market model as an ASM and to characterize it as agent-based. Most notably, the three constructive approaches i.e. the nonlinear dynamic approach, microscopic simulation, and ACE often talk in terms of agent-based methods, agent-based artificial stock markets. The approach that explicitly mentions agents in the naming is the ACE approach (agent-based computational economics), all three approaches refer however to the market participants they represent as agents. The idea behind these methods is also very similar: they represent individual market participants or groups of market participants and aim to study the emergent properties that are the results of their interactions. The difference is that they root in different areas: the first one in chaos theory, the second one in physics, and the last one in the literature on agents.

The question that we aim to answer in this subsection is whether the models in the realm of these approaches are artificial stock markets and whether they are agent-based. Given that there is no commonly accepted definition of these two terms (agent and ASM) more answers might be possible to this question. Our answer is based on two definitions, namely the definition of ACE (or strictly speaking agent-based computational finance) by (LeBaron, 2006), and the strict definition of ASMs by (Chen and Yeh, 2002).

Let us recall the (strict) distinction between standard models and ASMs. Chen and Yeh (2002) describe ASMs as models composed by "*many heterogeneous interacting adaptive traders*". They claim that an ASM is a promising way to study the stock market as a complex adaptive system, because it is rich in emergent dynamics and it is rich in emergent properties.

Let us now turn to the ACE view on financial markets. According to LeBaron (2006) models in the realm of agent-based computational finance view financial markets as *inter-*

acting groups of *learning*, *boundedly-rational agents*, in which *dynamic heterogeneity* is critical.

There are many similarities in these two definitions. First of all, interaction of participants is central in both of them. Secondly, one definition requires adaptive, the other learning behavior. Learning is in fact a form of adaptation in a computational sense, and these two terms are often used interchangeably. Further, both definitions emphasize the need for heterogeneous behavior. In addition the ACE view emphasizes bounded-rationality. One important criticism on the "homogeneous literature" is, that there all traders are assumed to be "rational", whereas experiments point out that bounded-rationality is an important aspect leading traders to behave heterogeneously. The main property thus that makes a group of agents heterogeneous is bounded-rationality.

This leaves just a slight difference in the definitions above of an ASM and an ACE model. They differ in the naming of the participants in the models. The first definition refers only to traders, and does not talk about agents, or about how traders are represented. Traders might be modeled as computational agents (whatever the term covers) but not necessarily.

Chen and Yeh (2002) is talking, thus, about "traders", and LeBaron (2006) about "agents", but do they really mean different type of participants? In agent-based modeling of financial markets, agents are particularly used to represent traders. Further, in the finance literature the term agent refers to financial traders, such as brokers or market makers. In that sense the two expressions thus might cover the same meaning. If so, ASMs can be considered as market models in the realm of agent-based computational finance and the expression agent-based ASM becomes redundant. If not, still the question remains which definition of the term agent the various researchers adopt. How does the ACE literature define an agent? Do the definitions and implementations correspond to the characteristics mentioned by Axelrod (2003), i.e. do these agents interact with little or no central direction? We have to mention, that the definition of ASMs is not a computational definition, but it cover also experimental laboratories. According to this view, models in the realm of ACE are a subset, a specific case of ASMs. Finally, some people who apply the ACE methodology might call their model an ASM without adhering to Chen's definition.

Once again there is no common agreement on what the concept agent covers. The explanatory power of the model is ultimately more important, than the form of representation. Therefore, in the remaining of this chapter we drop the adjective "agent-based" for the moment, and refer to all the models from the presented literature as artificial stock markets. Whether and to what degree one considers them agent-based ASMs is a topic for further discussion and depends on the definition of the notion agent.

Based on the many definitions and contexts in which agents, ASMs and ABASMs are referred to, we conclude this discussion with our own definition. We define artificial stock markets as market models that have at least a well-defined price formation mechanism for at least one asset for which prices emerge internally trough the interaction of market participants. Agent-based artificial stock markets are artificial stock markets where market participants (but possibly other elements as well) are represented as agents. The term agent is widely used in various areas in different context. Our definition is that, in the literature on ASMs, it is a representation of a market participant (or a group of market participants using similar strategies), having a form that varies from a simple equation to complex software components endowed with human-like artificial-intelligence based adaptive behavior.

3.2   An overview of ASMs

In the remainder of this chapter we present some artificial stock markets from the literature. The criteria for selecting the ASMs that we study here is, that they should incorporate an endogenous price formation mechanism, and a representation of the behavior of traders. More precisely, we select market models that have at least a well-defined price formation mechanism for at least one asset to the extent that prices emerge internally trough the interaction of represented market participants. Whether these can be characterized as ASMs was the topic of discussion of the previous section, and depends on the definition adopted.

When searching for ASMs we took into account the references from the ACE website[2], references from the papers we studied, and we additionally made use of search engines. The list is certainly selective and incomplete, but it reflects the main research directions and the market organizations represented in literature. We focus here on the following artificial stock markets:

1. *SSM*: the stochastic simulation model introduced in (Lux and Marchesi, 1999), and further studied in (Lux and Marchesi, 2000) and (Chen et al., 2001);

2. *ABMI*: the agent-based model for investment proposed in (Farmer, 2001);

3. ABS: the Adaptive Belief System as described in (Brock and Hommes, 1998) and (Hommes, 2001);

4. *GASM*: the Genoa artificial stock market introduced in (Raberto et al., 2001) and extended in (Raberto et al., 2003) and (Cincotti et al., 2003);

5. *LLS*: the "Levy, Levy and Solomon" microsimulation model introduced in (Levy et al., 1994), and studied in (Levy et al., 2000) and (Zschischang and Lux, 2001);

6. *SF-ASM*: the Santa Fe ASM as described in (LeBaron et al., 1999), (LeBaron, 2002) and (Tesfatsion, 2004);

7. *BS*: the business school representation in (Chen and Yeh, 2001) and (Chen and Yeh, 2002);

8. *MDS*: the microscopic dynamical model from (Daniels et al., 2002), (Daniels et al., 2003), (Blume and Durlauf, 2005) and (Smith et al., 2002);

9. *OMP*: the opinion, media and past-based financial market in (Franci et al., 2001) and (Matassini and Franci, 2001);

10. *CTAM*: the continuous time asynchronous model introduced in (Shatner et al., 2000) and extended in (Daniel et al., 2006), (Muchnik et al., 2005) and (Muchnik and Solomon, 2005) to an asynchronous simulation platform under the name of NatLab;

11. *EGM*: the extended Glosten and Milgrom microstructure model in (Das, 2003) and (Das, 2005);

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[2]http://www.econ.iastate.edu/tesfatsi/ace.htm

12. *EMM*: the ASM based on an electronic market maker in (Chan and Shelton, 2001);

13. *KapSyn*: the KapSyn framework described in (Loistl and Vetter, 2000), (Loistl et al., 2001), (Loistl and Veverka, 2004) and (Landes and Loistl, 1992);

The first seven artificial markets implement single-price call auctions. The rest of the studies focuses on continuous execution mechanisms.

1. **SSM**: the stochastic simulation model

   SSM is based on the nonlinear approach, to be more precise, to represent investors a *mass-statistical approach* is used. The method considers a few key behavioral variants and models agents in groups (as a mass), switching the proportion of agents over the alternatives in a stochastic manner. The dynamics covers switches within the prevailing mood among various types of traders, such as within noise traders (from optimistic to pessimistic) as well as switches of agents between the noise trader and fundamentalist group. Switching groups happens in response to observed differences in profits. Switches between different groups is modeled by means of Poisson transition probabilities. The model resembles call trading sessions with single-price auction mechanisms. Prices are determined by a market maker. The market maker adjusts prices in reaction to imbalances between demand and supply.

   The aim of the studies around *SSM* is to investigate the time series properties (especially nonlinear features thereof) of simulated data and its dependence on market settings.

   On the one hand, tests give unstable results in that both acceptance and strong rejection of IID series can be found in different realizations of the model. On the other hand, when testing for volatility clusters, a good fit is reported both to theoretical and empirical data, in the sense that when estimating GARCH models, the results appear robust and the chosen GARCH specification closely resembles the typical outcome of empirical studies

2. **ABMI**: the agent-based model for investment

   The goal of this paper is to illustrate how simple agent-based systems can be used for modeling and studying stock markets. There are a few types of investors and a market maker, all represented as agents. The role of the market maker is to adjust prices as a function of the order imbalance.

   The study shows in what sense the market mechanism matters. Risk-averse behavior of the market maker, for example, introduces trends in prices. This is caused by the fact that if the market maker acquires a position he wants to get rid of it. Structure in price series creates opportunity for technical traders.

   In the model there is a point at which the market is efficient (i.e. everyone breaks even). The authors analyze under which conditions the market will converge to this point.

3. **ABS**: the Adaptive Belief System

The ABS is based on the nonlinear dynamic approach. The aim of the studies around the *ABS* is to investigate the dynamics in simple asset pricing models with traders having heterogeneous beliefs. Within *ABS* financial markets are modeled as evolutionary systems. In this model investors are represented in similar way as in the *SSM* in the sense that investors with different forecast functions form groups of traders (typically fundamentalists and chartists), and the fraction of traders in various groups evolves over time. The difference between the *SSM* and the *ABS* is that in the former the probability of a change is stochastic, in the latter the transition is deterministic. The evolution of fractions is based on the idea that most investors choose the prediction strategy that generates the highest past performance. The results point out that heterogeneous beliefs may lead to market instability: a large fraction of fundamentalists tends to stabilize prices, whereas a large fraction of chartists tends to destabilize them.

4. **GASM**: the Genoa artificial stock market

The Genoa artificial stock market was introduced in (Raberto et al., 2001). The main problem studied in the *GASM* is how the market microstructure and the macroeconomic environment affect market prices. In order to address this problem a multi-agent framework has been proposed using which it would be possible to perform computational experiments with various types of artificial agents. The three papers analyzed here underpin this property of the *GASM*. The experiments presented in these papers differ with respect to the type of the traders used. From this point on we denote the variants of the Genoa stock market as *GASM-1* (the version described in (Raberto et al., 2001)), *GASM-2* (the version described in (Cincotti et al., 2003)), and *GASM-3* respectively (the version described in (Raberto et al., 2003)). In *GASM-1* all investors generate orders stochastically as a function of historical volatility, whereas in *GASM-2* and *GASM-3* intricate technical trading strategies are introduced additionally. Moreover, in *GASM-3* fundamentalist traders are also represented. In all versions it is taken into account that agents have finite resources. In *GASM-2* and *GASM-3* additionally the dynamics of markets in case of cash inflow is analyzed.

In the *GASM* the limit price of the orders depends on the quoted bid and ask prices. By making limit orders dependent on volatility, the model introduces correlations of price and volatility. All three models are able to exhibit some of the stylized facts of financial time series, such as fat tails and volatility clustering. The volatility clustering effect in *GASM-1* is sensitive to the size of the model. If the number of agents becomes very large, volatility clustering tends to disappear.

In *GASM-2* price processes exhibit strong reversion to the mean. Mean reversion is a tendency for a stochastic process to remain near, or tend to return over time to a long-run average value. Given this property mean-reversion traders perform better than other type of traders. On the long-run the performance of the strategies depends critically on the market condition (steady or growing) and on the periodicity of portfolio reallocation. Finally, this model rejects the random walk hypothesis.

In *GASM-3* the long-run wealth distribution of agents with different trading strategies is studied. In this model fundamentalist traders are also investigated. Results show

that a trading strategy cannot be judged solely on the basis of the strategy itself. Its success depends also on the market conditions.

5. **LLS**: the Levy-Levy-Solomon microsimulation model

   The *LSS* model is a pioneering work applying the microscopic simulation approach to the study of financial markets. Investors have a limited memory span of a number of periods on which they base their forecast functions. They use similar utility functions, but they have different risk aversion parameters and a different memory span. To make the expectation of investors with an identical memory span heterogeneous, the utility value to be maximized is altered with a normally distributed random number.

   Studies based on *LLS* show an extreme dependence on initial conditions. The conditions varied one by one are the random price history given at the start of the simulations, alternative utility functions, different attitudes to risk, different memory span, and the initial distribution of wealth.

   If all the traders have identical memory span, price series tend to follow a cyclic behavior with booms and crashes. With respect to the traders' wealth and to the market efficiency, results based on the *LLS* suggest that investors with constant shares of stocks in their portfolio perform better than other strategies. Further, results suggest that those ready to accept a higher risk will also earn higher returns (on average) so that as a group (irrespective of individual failures) they will increase their share of wealth. In general, the outcomes in terms of the dominance of one group (with similar memory span) over other ones depends on the overall number of agents.

6. **SF-ASM**: the Santa Fe ASM

   The Santa Fe ASM is one of the most heavily cited, and one of the first sophisticated agent-based financial market models that applies a bottom-up approach for studying stock markets. The approach applied in the model is ACE. The goal of the *SF-ASM* is to understand the dynamics of relatively traditional economic models. Investors base their orders on a set of strategies that evolves over time by means of genetic algorithms (GA). Results suggest that the efficiency of the market and the performance of the traders depends on the speed with which traders update their set of strategies.

7. **BS**: the business school representation

   The *BS* is an agent-based model of a so-called "school". The idea behind this school is similar to the approach used in the SF-ASM in that the set of strategies (here the school) used to forecast future values evolves over time as a function of their performance. Investors update from time to time the forecast function they use if it does not predict satisfactorily. Forecast functions are selected from the school. The population of forecast functions in the school is evaluated and evolves over time using a GA-based technique. Experiments in the *BS* result in random IID return series in a world with technical traders. Consequently, this study cannot reject the efficient market hypothesis.

8. **MDS**: the microscopic dynamical model

   MDS is a microscopic dynamical statistical model for the continuous two-sided auction under the assumption of IID random order flow. The goal is to understand how prices depend on order flow rates, without paying attention to the problem of what determines these order flow rates. In *MDS* both limit and market orders are generated. Similarly to the *GASM* model the price of limit orders depends on current bid and ask quotes. This coupling provides a nonlinear feedback in the model that makes the price process complex. One of the main findings within the model is the property that the liquidity for executing a market order can be characterized by a price impact function, i.e. properties like depth, bid-ask spread, the time and probability of filling orders, can be expressed as a function of the shift in the price and the size of the order that caused the shift.

9. **OMP**: the opinion, media and past-based financial market

   In *OMP* the microscopic simulation approach is applied. In this model, when formulating their trading intentions, traders do not only analyze historical data but also take into account the forecast of other, successful agents, and they might receive news.

   In the papers based on the *OMP* the most successful trading strategy is derived. Then, the robustness of this optimal strategy, its performance and the applicability to real markets is discussed. In the studies conducted based on the *OMP*, distribution with fat tails and volatility clusters are found. The alternation in the volatility is explained by the imbalance between demand and supply.

10. **CTAM**: the continuous time asynchronous model

    CTAM is a continuous, asynchronous model where individual traders interact. This model is based on the microscopic simulation approach. Continuous, asynchronous interaction is achieved, applying event-based simulation (Markov Nets in extended versions), i.e. by paying special attention to the timing and the frequency of orders. Traders in *CTAM* are not continuously active, but they "sleep" and "wake up" either at predefined time intervals, or after the execution of an order, or in reaction to some market event, such as news or price change. Recently, the *CTAM* has been extended to a generic asynchronous simulation platform, namely NatLab (Natural Asynchronous-Time Event-Lead Agent- Based Platform). The NatLab platform supports experiments with multiple trading strategies. In addition, it supports behavioral experiments, as most of these strategies are designed and maintained by humans competing in a continuous double-auction market on NatLab. Simulations conducted on the NatLab platform show, among others, that market dynamics can be drastically changed by a small fraction of trend followers. Further, winning strategies are studied and discovered. These depend, however, on market conditions.

11. **EGM**: the extended Glosten and Milgrom microstructure model

The *EGM* and *EMM* (see below) belong to the few studies that focus on the market-makers' quote-adjusting strategy. Both ASMs are inspired from the market microstructure literature. They are designed with the aim to show the influence of informational asymmetry on the bid-ask spread in financial markets. *EGM* extends the Glosten and Milgrom (1985) information-based model. In the *EGM* model, the market maker tries to discover the fundamental value of a stock by means of Bayesian learning. He determines the bid and ask quotes based on his expectation of the real value, the order flow, and his prior knowledge regarding the ratio of informed and uninformed traders. In the articles on *EGM* a nonparametric density estimation technique is proposed for maintaining a probability distribution over the true value that the market-maker can use to set prices. Discrete time simulation is applied in the model, and a probabilistic representation of order flows is considered. In the papers the performance of the market-maker in markets with different settings is evaluated. Findings suggest that the market is very volatile and spreads are high in periods immediately following a price jump. However, the learning algorithm applied by the market maker resolves the informational asymmetry rapidly. The market settles soon into a regime of homogeneous information with small spreads and low volatility.

12. **EMM**: the ASM based on an electronic market maker

The *EMM*, like the *EGM* focuses on the market-maker's quote-adjusting strategy. It is an information-based computational model based on the market microstructure literature. A Poisson process is applied to change the true value of the stock, and to generate market orders that represent decisions of informed and random traders. The goal of the paper is to model the market-making problem in a reinforcement learning framework, to explicitly develop market-making strategies, and to discuss their performance. Reinforcement learning is a learning technique in which agents aim to maximize their long-term accumulated rewards. No knowledge of the market environment, such as the order arrival or price process, is assumed. Instead, the agent learns the fundamental value from realtime market experience and develops explicit market-making strategies, achieving multiple objectives including maximizing of profits and minimization of the bid-ask spread. The simulation results show initial success in using learning techniques to build market making algorithms.

Two situations are analyzed. In the basic model the market-maker quotes a single price (bid and ask are the same), in the extended model bid and ask quotes differ from each other. In the basic model the optimal strategies are determined analytically and it is shown that the reinforcement algorithms successfully converge to these strategies. While in the basic model the market-maker only needs to control the direction of the price, in the extended model both the direction of the price and the size of the bid-ask spread has to be considered. It turns out that, in this model, there is one strategy (the actor-critic algorithm) that generates stochastic policies that correctly adjusts bid/ask prices with respect to order imbalance and effectively controls the trade-off between profit and spread. Furthermore, the stochastic policies are shown to outperform deterministic policies in achieving a lower variance of the resulting spread.

13. **KapSyn**: the KapSyn framework

In studies describing the *KapSyn* framework the importance of representing market microstructures is emphasized. The model imitates the microstructure of various stock exchanges, especially with respect to their price-finding procedures. The stock markets focused on are the XETRA and the NASDAQ. Investors are represented at individual level. It is important to mention that the *KapSyn* is the only ASM in which *intra-day* data is generated. The representation of XETRA implies a market structure with auctions opening and closing a trading day, intraday auctions in between if necessary, and continuous sessions in the meantime. *KapSyn* also represents so-called designated sponsors (brokers) who interact on XETRA and NASDAQ.

More than one stock is traded on the *KapSyn*. Investors have actions at their disposal associated to each stock. An action can be placing a buy order, placing a sell order or changing the expected value. With each action a so-called reaction time is associated. The reaction time depends on the expected utility that the action can generate and is lower for higher utilities. At each simulation round an action is selected for execution. Selection depends on the reaction time associated to the actions. Actions with smaller reaction times have a higher probability to be selected.

The findings within the *KapSyn* point out that efficiency of markets (with respect to the transaction costs) depends highly on the microstructure and liquidity of stocks. Results show for example, that NASDAQ is more efficient for mid-size orders, while XETRA is more efficient with respect to the execution of small and block-size trades. The role of designated sponsors is demonstrated in non-liquid markets. The authors also suggest changes to the structure of real markets in order to improve efficiency. They claim that reducing the designated sponsors' maximum spread can increase the market efficiency in XETRA, and an optimum number of six auctions per trading day is proposed to reduce transactions costs in XETRA.

The ASMs described above apply mainly one of the constructive approaches (nonlinear, microscopic, or ACE) to study market dynamics (see Section 2.5 and Table 2.1). The boundaries between the various constructive approaches are, however, too thin, therefore most of the ASMs can be characterized by more than one approach. Accordingly to the approach that is claimed by the authors, a nonlinear dynamics approach is applied in *SSM* and *ABS*, microscopic simulation is the basis behind the *LLS, MDS, OMP* and *CTAM*. Finally, the *ABMI, GASM, SF-ASM* and *BS* as well as the *EGM, EMM, and KapSyn* can be classified as agent-based computational studies, the main structure of the latter three relying strong on the market microstructure literature.

In the next two sections we analyze the design and mechanisms of these artificial stock markets based on the conceptual framework introduced in Chapter 2. First we describe how organizational elements are represented in these models and then we discuss the variety of applied price formation and order execution mechanisms, and the related traders' behavioral representation. The findings within these ASMs related to market dynamics are summarized in Section 3.5. After analyzing these markets in more detail we discuss to what degree they are agent-based, and how they define and represent agents.

3.3   Organizational aspects of Artificial Stock Markets

The most realistic way of modeling a system (in this case a stock market) would be to represent every detail, to precisely implement its whole structure. This representation seems, however, impossible given the variety of complex structures and mechanisms of stock markets and further the presence of several hidden factors and processes that are not (or cannot be) revealed. Further, in order to study the effect of some specific factors on the market dynamics, we need to exclude other ones. For this reason, controlled environments are needed in which factors of influence can be added and modified in a flexible way. The market structure chosen, and the simplifications and approximations made depend of course on the aim of the research. The consequences of the choices made need to be examined however. In this section we summarize what choices are made in the various ASMs regarding the architectural elements of the markets they model. A structured overview of the institutional organization of the studied markets is provided in various tables.

3.3.1   Traded assets

Although hundreds of assets are traded on stock markets, in general ASMs model only few assets. As illustrated by Table 3.1, usually two types of assets are traded on artificial stock markets: one risk-free and one risky stock. Multiple (risky) assets can be traded at the *GASM* and *KapSyn* markets. At the *GASM* market, experiments with two stocks have been conducted, while at *KapSyn* the number of stocks can be as high as 122 in earlier versions, and 50 in newer versions, this quantity being limited by computational implementation. Risk-free assets might represent mutual funds or bonds paying a constant interest rate. In most cases, however, they represent the cash reserve of traders. In some of the models, risk-free assets are not explicitly handled. In these models traders are not concerned with their portfolio or wealth. Implicitly a risk-free asset, namely cash, is always present as prices are expressed in terms of money.

Dividends paid by risky assets are represented in few of the cases only, such as *ABS, LLS, SF-ASM* and *BS*. The dividend process might introduce additional dynamics in the prices. Dividends vary usually on the basis of stochastic processes.

There is a well-determined fundamental value in most of the ASMs. This value typically follows a random IID (independent and identically distributed) process. There are only a few exceptions to stochastic changes. In the BS the fundamental value depends on the current price and the dividend paid. In the *ABS* and *SF-ASM* the dividend paid by the risky stock is compared to the interest rate of the risk-free stock to get its real value. Equal rates mean that the real value equals the current price and dividend. Lower dividend percentage suggests under-valued stock, whereas higher dividend percentage is perceived as an overvaluation of the stock. Interestingly, in *KapSyn* there is no unique fundamental value, but all investors have their own individual belief about it.

	Stocks \ ASM	Traded assets		Fundamental value	Dividend
		risk-free / cash	risky		
1.	SSM	-	1	log follows Wiener process (random IID increments)	-
2.	ABMI	-	1	log random walk	-
3.	ABS	1	1	depends on dividend and risk-free interest rate	stochastic IID
4.	GASM-1	1	1	-	-
	GASM-2	1	N (2)	-	-
	GASM-3	1	N	- closed version: changes at mean-reverting time - open version: constant	-
5.	LLS	1	1	-	stochastic growth
6.	SF-ASM	1	1	depends on price, dividend and risk-free interest rate	AR(1)
7.	BS	1	1	current price + dividend	stochastic IID
8.	MDS	-	1	-	-
9.	OMP	1	1	-	-
10.	CTAM	1	1	random walk	-
11.	EGM	-	1	jumps with some probability	-
12.	EMM	1	1	Poisson jump: ± 1 stochastically	-
13.	KapSyn	1	N<123	individual constant expectation estimates	-

Legend:
"–" – this factor is not represented
"N" – more than one issue represented
"*number*" – number of given factors possible to use in the experiments
"(*number*)" – number of factors actually used in the experiments presented
"IID" – independent and identically distributed
"AR" – autoregressive

Table 3.1: Representation of the stocks traded in the ASMs

3.3.2 Orders

Based on Table 3.2 we can conclude that ASMs usually choose to express trading intentions of traders either by market or by limit orders. These are the most common orders at stock markets as well.

In artificial markets representing call-auctions, the initiated orders are often market orders. In the *SSM* model, orders are in fact not explicitly represented, but only the excess demand. In *GASM, LLS* and *SF-ASM* limit orders are generated. Orders at *LLS* and *SF-ASM* are modeled as demand functions of investors regarding the risky asset in function of the possible stock prices. In this case investors send to the auctioneer a set of price-dependent limit orders.

On continuous markets limit orders or both limit and market orders can be placed. Both limit and market orders are placed in *MDS, OMP, CTAM, EGM* and *EMM*, market orders being matched against the quoted bid and ask, limit orders being entered into a limit order book if they cannot be cleared. Further, limit orders in *OMP* can be turned into market orders. In *EGM* and *EMM* investors' trading intentions are expressed in the form of market orders, and the market maker determines bid and ask quotes with limit prices.

In the *KapSyn* market, limit orders are generated, but traders might also decide to accept quoted orders, which is in fact equivalent to placing a market order. Unexecuted orders at *MDS,OMP,CTAM* and *KapSyn* can be canceled if wished. Orders placed at the *OMP* market can contain thresholds for canceling them, which can be changed with time.

3.3.3 Market participants

In Table 3.3 we summarize the type of the markets participants represented. In the ASMs studied traders typically perform one action: they place orders as the result of some decision (that is mainly utility maximization in every trading round). In this way only investors are represented by these traders. There are several studies in which investors are not modeled individually. Instead, just the orders placed are modeled arriving according to some distribution, such as at *MDS, EGM* and *EMM*. In *SSM* and *ABS* a mass-statistical approach is used. This means that traders are not represented individually, but just masses (groups) of traders with similar strategies. What is under analysis here is the evolution of fractions of traders in various groups. In *ABS*, investors are represented by simple equations that define their trading decisions. Individual investors with their own (sometimes complex) decision-making behavior are simulated in *ABMI, GASM, LLS, SF-ASM, BS, OMP, CTAM* and *KapSyn*.

In ASMs that resemble call-auctions (the first seven in the list), the final order execution is often carried out by an automated execution system, and as a consequence financial agents (such as brokers or market makers) are rarely modeled. Brokers who commit themselves to execute orders for others are not represented in the majority of the studies. In fact, we found one single study, the *KapSyn* where the role of the brokers is recognized and brokers are represented.

In a few studies the behavior of market makers is modeled. In fact there are only three ASMs modeling call auctions (*SSM, ABMI* and *SF-ASM*) and three ASMs based on continuous sessions (*EGM, EMM* and *KapSyn*) in which a market maker is explicitly represented. The way they are modeled ranges from simple price-adjusting equations to sophisticated learning mechanisms. We will discuss their tasks and behavior in more detail in Section 3.4.

	ASM	Market orders	Limit orders
1.	SSM	X	-
2.	ABMI	X	-
3.	ABS	X	-
4.	GASM-1	-	X
	GASM-2	-	X
	GASM-3	-	X
5.	LLS	-	in the form of demand functions
6.	SF-ASM	-	in the form of demand functions
7.	BS	X	-
8.	MDS	X	X
9.	OMP	X	X
10.	CTAM	X	X
11.	EGM	placed by investors	placed by market makers
12.	EMM	placed by investors	placed by market makers
13.	KapSyn	-	X

Legend:
"–" – this factor is not represented
"X" – this factor is represented

Table 3.2: The type of orders in the ASMs

	Participants	Role			Representation investors	
ASM		Investors	Brokers	Market makers	Individual	Group
1.	**SSM**	N	-	1	-	X
2.	**ABMI**	N	-	1	X	-
3.	**ABS**	N	-	-	-	X
4.	**GASM - 1**	N	-	-	X	-
	GASM - 2	N (10030)	-	-	X	-
	GASM - 3	N	-	-	X	-
5.	**LLS**	N	-	-	X	-
6.	**SF-ASM**	25	-	1	X	-
7.	**BS**	500	-	-	X	-
8.	**MDS**	N	-	-	-	X
9.	**OMP**	N	-	-	X	-
10.	**CTAM**	N	-	-	X	-
11.	**EGM**	N	-	1	-	X
12.	**EMM**	N	-	1	-	X
13.	**KapSyn**	N (< 123)	N	N	X	-

Legend:
"–" – this factor is not represented
"X" – this factor is represented
"N" – more than one issue represented
"*number*" – number of given factors possible to use in the experiments
"(*number*)" – number of factors actually used in the experiments presented

Table 3.3: The representation of market participants in the ASMs

Execution mechanism ASM		Trading session		Execution system		
		call	continuous	single price auction	continuous 2-sided auction	hybrid
1.	SSM	X	-	X	-	-
2.	ABMI	X	-	X	-	-
3.	ABS	X	-	X	-	-
4.	GASM-1,2,3	X	-	X	-	-
5.	LLS	X	-	X	-	-
6.	SF-ASM	X	-	X	-	-
7.	BS	X	-	X	-	-
8.	MDS	-	X	-	X	-
9.	OMP	-	X	-	X	-
10.	CTAM	-	X	-	X	-
11.	EGM	-	X	-	X	-
12.	EMM	-	X	-	X	-
13.	KapSyn	X	X	X	X	X

Legend:
"–" – this factor is not represented
"X" – this factor is represented

Table 3.4: Trading sessions and execution systems in the ASMs

3.3.4 Trading sessions

At most of the ASMs **call market sessions** are implemented. Within *SSM, ABMI, ABS, GASM, LLS, SF-ASM* and *BS*, for example, traders or selected groups of traders simultaneously place orders at every discrete point of time that is modeled in the simulation.

There are several ASMs that implement **continuous trading sessions**. On markets with continuous trading sessions, an order can be placed at any time and transactions are made whenever possible. Consequently, traders do not need to make decisions simultaneously. Most ASMs apply however discrete-time simulation (i.e. discrete time intervals, simulation rounds with even time intervals in between) to model markets. In these, typically, the trader whose decision is considered next, is selected from the population by a central mechanism at every simulation round. In *OMP* a randomly selected trader makes a trading decision (place, accept or cancel an order). In the *MDS, EGM* and *EMM* no special implementation is needed, because traders are not focused on individually, but orders arrive one by one under the assumption of random order flow.

At the *KapSyn* stock market continuous time is implemented by using a discrete state space. Transition from one state into another depends on time related parameters. In this framework agents' decision process regarding which action to take next is independent of each other and takes place simultaneously in parallel. A decision process contains the following steps. First, each agent determines a set of alternative actions for each stock. Then, each agent selects one action for each stock. Finally, one action is selected for each agent. All the selections depend on the utility and execution time of the actions. The greater the

expected benefit gained from the action of an agent, the shorter will be the reaction time and the higher the selection probability. After all agents have made their decision with respect to the next action to be carried out, the system executes the action with the shortest reaction time. After an action that is observable by all market participants, i.e. a buy or a sell action, the decision process determining the next action is repeated on the basis of the new market conditions. Therefore, in this case, only one action is executed in a simulation round.

In order to model continuous trading sessions, at *CTAM* discrete-event simulation is applied. In this model traders do not continuously make decisions. Rather, they "sleep" and "wake up" at times defined by previous decisions, that might concern pre-defined time, execution of an order, or reaction to some event. Each operation in the model is performed by the computer in the appropriate time order.

3.3.5   Execution systems

The execution system typically applied during call market sessions in most of the artificial markets is the **single-price auction**. Examples are the *SSM, ABMI, ABS, GASM, LLS, SF-ASM*, and *BS*. In these models traders simultaneously submit orders that are centrally matched at a price at equilibrium.

Besides call-auction type of markets, **continuous-auction** markets are represented in the literature as well. Within most of the ASMs that implement continuous trading sessions price formation is commonly based on automated central execution systems, such as within the *MDS, OMP* and *CTAM*. Traders in these can trade directly with each other, without the intervention of a third party.

Although in real life continuous **quote-driven markets** are very common (Reilly and Brown, 2003; Demarchi and Foucault, 2000), only very few studies try to conduct experiments in such a kind of environment. The difference between continuous auction markets, and continuous quote-driven markets is that in the second one a market maker is responsible for executing orders, traders can trade with each other only with the help of this market maker, and the market maker can or has to take position (i.e. trade for own account) if necessary. We indeed observed ASMs implementing this feature in our literature survey. Artificial markets that represent continuous quote-driven trading are basically inspired by the microstructure literature. Accordingly, within the *EGM, EMM* and *KapSyn* models market makers set bid and ask quotes and execute orders based on their beliefs, position and received orders.

The most detailed, realistic representation of stock exchanges is implemented by the *KapSyn* model. Price formation in this model depends on the microstructure of the stock exchange that is modeled. In this sense the NASDAQ is represented as a dealer (quote-driven) market, where trades are made at the dealers' quoted bid and ask price.

In the KapSyn, **hybrid markets**, namely a representation of the XETRA market structure, are also studied. Transactions on XETRA take place based on the content of the order book, that is at best bid or ask. Further, in special cases (e.g. open, close, extreme price change) auctions can be conducted. The market price determined by the auction is the quoted price at the highest trading volume (Loistl and Vetter, 2000).

3.3.6 Market rules

The protocols in ASMs are confined mainly to the possibility whether to allow or not short selling (i.e. selling shares without possessing them), and to limit the size of the orders. At Santa Fe, for example the maximum number of shares that can be traded is 10, while it is possible to sell short up to 5 shares.

Prices and dividends in the ASMs are always made public without any delay. In case of continuous-auction markets with central automated order execution mechanism, that is at *OMP, MDS* and *CTAM*, the maximum bid and minimum ask quotes from the limit order book are public. AT *KapSyn*, if the XETRA model is selected, the content of the whole limit order book is available to all participants during continuous trading sessions, and the best bid and ask quotes are published during call-auctions. Information reflects only price and volume and does not disclose the identity of the traders.

Several other assumptions are made in the ASMs, such as publicly known forecast functions, agents who have perfect knowledge about market equilibrium equations, prices and fractions of trader types (e.g in the *ABS*). Although information of this type is not available on real markets, it makes artificial markets easier to be validated and makes the dynamics easier to be studied.

3.4 Price formation and the behavioral aspects in ASMs

In this section we focus on the decision problems that traders face, based on their role, as discussed in Section 2.3. We analyze how these issues are represented in the ASMs studied here. The problem we face is that, although the role and the outcome of the actions participants take (orders placed, transactions) are more or less visible on real markets, the details of the strategies, decisions, reasoning behind their actions are not really observable by others. Designers, therefore, have to make a number of assumptions when they represent traders.

3.4.1 The order-placing behavior

The way how various ASMs represent behavioral factors related to placing and determining orders is based on the factors identified in Section 2.3, and is elaborated in more detail in this subsection.

3.4.1.1 Policy statement

The objectives of the investors are summarized in Table 3.5. How they try to realize this depends on the strategy they use: fundamental, technical, random or another strategy. The main **investment objectives** of the modeled investors in ASMs is to get as much profit as possible. At the *SSM, ABMI, ABS, EGM* and *EMM* they aim to achieve this through arbitrage opportunities, i.e. by trading when price does not equal perceived value. At *ABMI* seasonal traders are also represented. Seasonal traders, like farmers, buy during one period and sell during the next one. At *LLS, SF-ASM, BS* and *KapSyn* traders maximize some kind of utility function. Further, traders aim to optimize their portfolio at the *GASM*, to maximize

	ASM	Investment objectives
1.	SSM	maximize profit by arbitrage
2.	ABMI	arbitrage / maximize profit / seasonal need
3.	ABS	maximize profit
4.	GASM-1,2,3	optimize portfolio by maximizing utility / liquidity
5.	LLS	maximize expected utility
6.	SF-ASM	maximize CARA utility
7.	BS	maximize CARA utility
8.	MDS	-
9.	OMP	maximize profit, minimize risk, achieve gain
10.	CTAM	invest / update portfolio
11.	EGM	arbitrage / liquidity
12.	EMM	arbitrage / liquidity
13.	KapSyn	maximize utility and realize benchmark portfolio

Table 3.5: The investment objectives of traders in the ASMs

wealth at *CTAM* and to achieve a personal gain with minimal loss at *OMP*. At *MDS, EGM* and *EMM* investors are not explicitly represented. In these models just the order flows are generated. The type of the orders generated depends on the percentage of specific type of traders (informed, noisily informed, uninformed) in the population. At *KapSyn*, where more assets are traded, participants have an individual benchmark portfolio in mind, which they want to achieve. Regarding the **time-horizon**, the majority of the objectives can be said to be long-term as they remain fixed during the full length of the experiments.

In most of the studies there are no **investment constraint**. In a few ASM' investment constraints are restricted to a finite amount of cash available to the traders, or a fixed number of shares.

Investors' **attitude to risk** is modeled by some ASMs by introducing risk averse traders. They strive to minimize loss within the *OMP* and minimize risk within the *CTAM*. Investors at *SF-ASM, BS* and at the extended *LLS* model in (Zschischang and Lux, 2001) are constant absolute risk-averse (CARA) utility maximizers of wealth, meaning that the risk they take is always a fixed percentage of their wealth. Further, at the *KapSyn* market, risk is measured as the deviation of the actual portfolio from the desired portfolio.

3.4.1.2 Investment strategy

The assumptions the various ASMs make with respect to the hardly observable aspects covering an investors' decision is presented in Table 3.6. Investment strategies are differentiated based on the information that traders exploit to place orders or to **forecast future values**. Investors are classified accordingly as informed or fundamentalist traders, which might be perfectly or noisily informed, technical traders and random traders.

- **Fundamentalists** or informed traders are focused on within *SSM, ABMI, ABS, GASM-3, CTAM, EGM* and *EMM*. Within the *ABS* some of them have a perfect foresight of the next market price, and in the rest of the studies mentioned they know the fundamental value. Noisily informed traders are represented in *SSM, CTAM* and *EGM*. At *SF-ASM* investors compare the dividend payed by the risky stock to the interest rate of the risk-free asset in order to have an indication of the fundamental value. Fundamentalists believe that the risky asset is over-valuated (under-valuated) if it pays more (less) than the risk-free asset. At the KapSyn market all agents have individual expectations regarding the fundamental value of a stock.

- **Technical trading strategies** based on historical data are considered in all ASMs except for the *MDS, EGM* and *EMM* markets. Agents in *SSM* look at price trends, but they additionally might take into account the opinion of other more successful participants. In this ASM the number of traders with different strategies changes over time by means of transition probabilities. The transitions depend on the opinion of other groups, on price trend and profit. Besides trend followers, biased traders are focused on in the *ABS*, who just simply add or subtract a small number from the current price. Trend followers are focused on in the *ABMI* model as well.

  A variety of technical trading strategies is applied in the experiments within *GASM*. These include mean-variance trading, relative chartist trading and mean-reversion, momentum and contrarian trend traders. Mean-variance trading is based on the modern portfolio theory pioneered by Markowitz. Traders using a mean-reversion strategy believe that the price will return to a long-run mean value. Relative chartist traders determine the desired weigh of an asset in their portfolio based on performance measures. Momentum traders think price follows trend: if it is increasing, it will continue to increase, and if it is decreasing, it will continue to decrease. Contrarian traders believe that the price will change trend.

  Investors in the *LLS* model take into account an average of a number of past historical returns, and a random value is added to their demand to account for heterogeneity and noise.

  In addition to fundamental measures, technical measures are used by traders at *SF-ASM* for forecasting future values. Here the traders apply moving average functions for the last few periods in order to try to guess into which direction prices will move.

  In *BS* arbitrarily many forms of forecast functions are generated. These are combinations based on past prices and dividends. In the *OMP* a unique determination of the forecast value is given, where, besides the analysis of historical data, the opinion of other market participants, and the forecasts of the media is taken into account. In this

Strategy ASM		Fundamental	Technical	Random	Other
1.	**SSM**	- informed - noisy	- based on opinion of others and price trend	**-**	**-**
2.	**ABMI**	- informed	- trend followers	-	seasonal
3.	**ABS**	- informed with perfect foresight	- biased - trend follower	**-**	mixed
4.	**GASM-1**	**-**	- based on historical volatility	X	**-**
	GASM-2	**-**	- mean-variance - relative chartist - mean reversion	X	**-**
	GASM-3	X	- momentum (think price follows trend) - contrarian (think price trend will change)	X	**-**
5.	**LLS**	-	- assume that returns in past occur with equal probability	-	-
6.	**SF-ASM**	- expectation based on relation dividend and interest rate	- moving average	**-**	mixed
7.	**BS**	**-**	- evolving, arbitrary complex combinations of historical prices and dividends	**-**	**-**
8.	**MDS**	**-**	**-**	X	**-**
9.	**OMP**	**-**	- trend follower - lookup-table best strategy - trading rectangle	**-**	**-**
10.	**CTAM**	- noisily informed	- polynomial fit past prices - trend follower - mean reverting - daily traders - other	X	mixed
11.	**EGM**	- informed - noisily informed	**-**	X	-
12.	**EMM**	- informed	**-**	X	**-**
13.	**KapSyn**	- individual expectation (optimists / pessimists)	- up to 40 scenarios	-	mixed

Legend:
"–" – this factor is not represented
"X" – this factor is represented

Table 3.6: The investment strategies of traders in the ASMs

ASM traders decide when to trade based on the idea of a trading rectangle. The trading rectangle is determined by the current time, a target price, a stop loss price and a threshold time (investment horizon). When price and time values fall within the range of this rectangle the traders do not feel pressure to trade, but once one of the limits are exceeded they consider to perform an operation. For instance, in case of shares bought, the target price is the price that would push the trader to sell in order to cash the gain, the stop loss price represents the price at which the trader would sell to limit the loss. In the extended version of the *OMP* a specific trader is introduced which searches in a lookup table with historically successful strategies. In *CTAM* traders try to fit a polynomial function to past time series. Within the NatLab platform, that is based on *CTAM*, arbitrary many strategies can be modeled. Experiments presented include, for instance, trend followers, mean reverting traders, daily traders, and traders switching strategies. Further, experiments with humans are conducted to capture their strategies. Finally, up to 40 technical scenarios are possible in *KapSyn*.

- In addition to fundamental and technical trading strategies **random trading strategies** are very common in ASMs. On the one hand, random orders often represent the decision of noise traders. On the other hand, random order generation might also model a variety of trading strategies without paying special attention to the individual behavior of traders. In some cases random traders are needed to provide liquidity in the market. Random orders are generated, for example, within *GASM, MDS, CTAM, EGM* and *EMM*. Random traders can be actually looked upon as "bounded myopic" technicians. Further, expected values are sometimes altered with random values to represent errors and bounded rationality in the forecasts of traders. At the *GASM* market the expected value is calculated based on the current price and a random draw from a Gaussian distribution where the standard deviation is dependent on historical volatility. In this case random traders are used to represent noise traders.

3.4.1.3 Portfolio maintenance

Asset allocation. Since most studies, except *KapSyn* and *GASM*, focus on trading one type of risky asset, the choice for the assets to be included into the portfolio always regards that risky asset. The required weight of the stocks usually depends on the utility function applied. This is the case for example, in the *GASM, SF-ASM, LLS* and the *KapSyn* models. At *GASM-2* the required weight of the assets depends on the strategy and the utility function applied.

Orders. As described in Section 2.3.1.3, based on (Reilly and Brown, 2003), investors primarily place orders as part of a portfolio management process, orders thus being entailed by the difference between required and current portfolio contents. This explicit form of portfolio management is applied at the *GASM* stock market and at the *BS* to determine the size and side of the orders. In general in ASMs there is no explicit modeling of portfolio management, but traders implicitly maintain a portfolio, even if it consists of one stock, and as a consequence the issues mentioned with respect to portfolio management hold for the way the attributes of orders are determined in general. Table 3.7 illustrates this in more detail.

The studies that are not explicitly concerned about the portfolio management problem, determine the orders only as a function of the future expectations of the traders. In the *ABS*,

	ASM	Order size	Order side	Order price
1.	SSM	excess demand functions that depend on the number of individuals in each group: - optimists are buyers - pessimists are sellers		-
2.	ABMI	fixed or changing fraction of wealth bounded by credit limits	- market maker: position - fundamental: arbitrage - technical: sign strategy - seasonal: alternating	-
3.	ABS	forecasts functions as functions of expected forecasts values		
4.	GASM-1	random fraction shares or cash	random	current discounted by random Gaussian
	GASM-2	current-desired (portfolio fraction)	sign size	current discounted by random Gaussian
	GASM -3	fraction of the present amount or cash	- fundamental: arbitrage - technical: depends on price trend - random: equal probability	current discounted by random Gaussian
5.	LLS	demand curves number of shares whished to buy or sell as a function of price		
6.	SF-ASM	demand function based on risk aversion and forecast in function of price		
7.	BS	current-desired (depends on the expected excess return)	sign size	-
8.	MDS	Poisson distribution	equal probability	uniform probability (tick size multiplied by random integers greater than bid (for sells) and less than ask (for buys))
9.	OMP	%wealth based on forecast	based on trading rectangle	weighted combination of opinion, media and past trend
10.	CTAM	- random - %wealth	- sign difference between forecast and current - random - arbitrage	random / current ± tick
11.	EGM	1	random / arbitrage	-
12.	EMM	1	random / arbitrage	-
13.	KapSyn	function return, risk, desired portfolio	relation expected return, interest rate	relation estimate, marginal market price

Table 3.7: Various ways to determine the dimensions of an order in the ASMs

for example, orders are expressed in the form of forecast functions; on the *SF-ASM* and the *LLS* markets the **trading volume** is a demand function based on the traders' forecast as a function of price and risk. Further, the number of shares to trade can be based on forecast and a fraction of the wealth, like in the *OMP* and *CTAM*. Orders are not always explicitly determined. For instance, in *SSM* the excess demands are defined as a function of the number of individuals in each group.

The relation between the forecasted value and the market price can be used to determine the **trading side** of an order. In the most simple case traders decide to sell/buy if the expected price is below/above the current market price. Within *OMP*, traders choose the trading side according to the aforementioned trading rectangle. Further, often stochastic functions are applied to determine the trading side. Buy and sell orders are placed with equal probability in *MDS, EGM* and for random traders in *CTAM*. At *KapSyn* the probability of being selected is related to the expected utility. There, the traders select the order they want to make stochastically based on some utility function and probability distribution.

Regarding the **quoted price** of the limit orders, in the literature the limit price defined by the traders is often the forecasted price of the stock. In reality however, traders do not submit their forecast values, but at a limit price deduced from this value. This feature is taken into account in *CTAM*.

3.4.1.4 Monitoring and adaptation

In general traders monitor the following data in the ASMs: the new market prices, perceived fundamental values, bid and ask quotes when applicable, and the performance of themselves and of others. As mentioned in Section 2.3 monitoring serves and entails **adaptation**.

There are two views with respect to the importance to represent adaptive behavior. According to the first view adaptation is not important. Proponents of this view, like (Gode and Sunder, 1993), argue that ASMs with random traders, also referred to as zero-intelligence traders, can properly model traders' behavior. According to the second view it is important to represent adaptive behavior, because the environment in which traders interact continually changes (prices, news, goal). In some studies, e.g. (LeBaron, 2001), it is claimed, for example, that evolution is the core dynamic at work of agent-based markets. The question is to what degree the traders represented need to be adaptive so as to realistically reflect market dynamics. Do they need to learn, do they need to adapt their strategy in order to be successful and/or to survive?

Adaptive behavior can be realized and represented at various levels. It can range from static functions taking as arguments data from the changing environment, to evolution of a whole set of strategies. Within these we can differentiate the following types of adaptation: random (non-adaptive) behavior, weak adaptation with traders sticking to a static parameterized strategy, adaptation with traders switching their strategy to a new one taken from a fixed set of parameterized strategies, and strong adaptation with an evolving set of strategies. Further, depending on the representation of traders (i.e. cumulative or individual) adaptation can be realized either at group level or at individual level.

- **Random behavior.** (Gode and Sunder, 1993) show that a market with zero-intelligence agents acting randomly can converge to the theoretical equilibrium price in a continuous double auction framework. This view suggests that price is determined by the

market structure rather than by the intelligence of the agents. In order to study the effect of market organization on market dynamics and market quality, one indeed has to be aware of the effect of traders' behavior and traders' interactions. Keeping thus investors' behavior simple helps to understand this relationship. This reasoning is applied at *MDS*.

- **Weak adaptation at group level.** In *EMM* and *EGM* orders are generated based on some stochastic process which do not take changes in the environment into account. Although adaptation in these markets is very weak, it is not completely random, since the type of the orders placed depends on the fundamental value.

- **Adaptive behavior at group level.** In *ABS* and *SSM* a fixed group of strategies is defined. However, the fraction of traders belonging to one of these groups changes over time. In the *ABS*, financial markets are modeled in the form of nonlinear stochastic systems. In this model prices and beliefs co-evolve over time. The fraction of different agent-types changes based on the successfulness of the strategy used. Similarly, in the *SSM*, there is a transition probability associated with the number of different types of traders. In these studies successful strategies have a bigger influence on prices.

- **Adaptive behavior at individual level with a fixed set of strategies.** Recent studies suggest that emergent properties of markets are entailed through interaction of individuals. It is important, thus, to represent these properly. Many studies model investors' behavior at the individual level. The strategy of traders in various ASMs differs given the nature of the approaches applied. Within each ASM only one type of monitoring and adaptation strategy is used which is the same for all the individual traders. As illustrated by Table 3.8, adaptations vary from simple value adjustments to intricate evolution of strategies.

  Most often traders use one single strategy during the full length of a simulation. Traders in *ABMI, GASM, LLS, OMP, EGM* and *KapSyn* apply the forecasting/trading strategy associated to them at the beginning of a simulation. In *OMP* only one type of agent exhibits adaptive behavior. This agent selects its next strategy from a table in which good performing strategies are monitored. In *KapSyn* there is a slight adaptation of beliefs in the sense that technical traders simply correct the expected value of a stock upward or downward. Most traders in *CTAM* use one single strategy as well. In some experiments, however, traders who occasionally switch between two strategies are introduced as well.

- **Adaptive behavior at individual level with evolving strategies.** In *SF-ASM* and *BS* traders can switch strategies if they are not successful enough. At *SF-ASM* each trader has its own set of strategies, from which they choose the most suitable one every trading round. Strategies within a set have in fact the same structure, they differ only with respect to the value of the parameters used.

  There are two commonly used techniques to implement adaptive behavior concerning the evolution of the whole set of strategies: neural networks and evolutionary algorithms. Two of the ASMs presented apply these techniques: the *SF-ASM* and the *BS*.

ASM		Set of strategies		Traders' choice for strategy		
		Fixed	Evolving	Fixed	Switching	Varying across various types
1.	SSM	X	-	-	X	-
2.	ABMI	X	-	X	-	-
3.	ABS	X	-	-	X	-
4.	GASM 1,2,3	X	-	X	-	-
5.	LLS	X	-	X	-	-
6.	SF-ASM	-	X	-	-	X
7.	BS	-	X	-	-	X
8.	MDS	random order flow: can resemble anything				
9.	OMP	X	-	X	-	for the trader with "lookup table" strategy
10.	CTAM	X	-	X	X	-
11.	EGM	X	-	X	-	-
12.	EMM	X	-	for investors	for market maker (reinforcement learning)	
13.	KapSyn	X	-	X	-	-

Legend:
"–" – this factor is not represented
"X" – this factor is represented

Table 3.8: Evolution of strategies in the ASMs

At *SF-ASM* agents have individual sets of strategies, and genetic algorithms are used to evolve such a set over time. Strategies are described by so-called "condition- forecast" rules, where the condition part contains market state indicators (fundamental and technical) and the forecast part contains the forecast parameters of the expectation function (trend, variance). Selection, mutation and crossover are applied to adapt the set of strategies to the changing conditions. At *SF-ASM* agents who learn (i.e. evolve their set of strategies) are selected centrally with some probability every given trading period. Choice for learning is thus globally determined by the system and is not initiated by the trader itself.

In the *BS* model investors try to find the best trading strategies in a so-called business school by means of genetic programming, where forecast functions are learned and adapted to changing conditions. In this ASM agents who are not successful consider the possibility to use another forecasting strategy. They select their new forecasting function from a set of strategies (called the school) which evolves over time. In an evolution phase badly performing strategies are eliminated and give place to new strategies. At *BS* at every trading period in the experiments there is a probability for each trader to go back to learn. This probability depends on the relative net change in wealth (compared to all traders) and on the growth-rate of wealth. Learning means choosing a forecast function (randomly) from the set of functions that would have performed better for the latest given number of periods.

In *BS* it is analyzed whether it makes sense to learn. Findings suggest that learning makes sense since if a successful agent is blocked for some time, his predictions perform poorly later. However, it is observed that if a successful strategy will be used by more traders, after a while it will be no longer successful. This property reflects information dissemination in the time series.

A key-question in implementing evolution in behavior is how to measure the "fitness" of a strategy. A strategy can be said to perform well (given the market conditions) if it is the one which provides the maximum return, wealth, utility, or the minimum forecast error among all strategies used. At *SF-ASM*, the distance of the forecast value from the real outcome indicates the fitness of the forecast function. In the *BS* ASM a ranking measure is provided, upon which traders can measure how good they perform related to the other participants.

3.4.1.5   Time factors

An important aspect that is related to modeling most of the organizational factors discussed so far, is time. Below we give a discussion on how the various dimensions of the time factor are represented in the ASMs. A summary is given in Table 3.9.

- **Time-horizon of the investment objectives:** investment objectives in the ASMs studied generally hold during the whole experiment.

- **Forecast horizon of the investment strategies:** traders usually forecast one period ahead.

- **Past horizon for historical data analysis:** the length of past time period for analysis varies a lot, theoretically any combination is possible. The maximum value used in the selected literature is 420 time steps in the LLS model.

- **Timing of order placement:** as we indicate in the "frequency of order placement" column in the Table 3.9 very often either all traders or a group of randomly selected traders will place an order.

  In almost all call-auction type of markets, namely in *ABMI, ABS, GASM-1, LLS, SF-ASM* and *BS*, all traders simultaneously make a trading decisions. Their decision usually results in placing a new order. In *GASM-2* and *GASM-3* only part of the traders is selected stochastically. Selecting only a fraction of traders is a way to simulate asynchronous behavior, mimicking the fact that they carry out different tasks at the same point in time. This representation implements the property that traders are not confronted with the problem of making trading decisions all the time and whenever others are trading.

  In ASMs that implement continuous trading sessions asynchronous behavior of traders is self-evident. In these models, at every simulation round, usually one order is generated. In case of aggregated representation of investors or their decision (e.g. *MDS, EGM* and *EMM*) this order is stochastically generated. In case of individual representation of traders one of the traders is selected to make a decision. At *OMP* the next investor to make a decision is randomly selected. He decides whether to trade or not based on a threshold and the market state that define the so-called "trading rectangle". At *KapSyn* the next event to be carried out depends on the reaction time of all events prepared by investors. This implementation attempts to represent the fact that market events happen at non-even intervals after each other. Finally, in *CTAM* the time moment for placing an order can be predefined or triggered by some event, such as news or a price change. It is important to note that timing of orders in *CTAM* and *KapSyn* is decentralized (determined by the investors) and not determined centrally by the system. This implementation represents a kind of autonomy of the traders.

- **Waiting patience for the execution of an order:** represents the time for which an order remains valid. In call-auctions, where trading of market order takes place every time period, and investors receive an answer immediately, this factor is not relevant. However, in markets where continuous sessions are represented and/or limit orders are placed, unexecuted orders can be canceled after a while. The waiting time depends, for example, on the threshold within the *OMP*, and is removed or canceled stochastically within the *MDS*.

- **Time for monitoring changes and update:** traders observe the changes in the environment and monitor their performance from time to time. In general, new values are observed every trading round. Performance measures are used in models in which traders change or adapt their strategy. Traders decide mainly stochastically, based on a predefined threshold, linked to a fitness measure, whether to update their strategies. In *SSM* and *ABS* fitness is implicitly taken into account every trading round. For the agents at the *SF-ASM* slow and medium learning periods of 100 and, respectively, 250 time periods are applied. In *BS* this period can take a value up to 20 trading rounds.

Timing ASM	Past	Frequency order placement	Monitoring fitness
1. **SSM**	1	Poisson process	1
2. **ABMI**	N	all simultaneously	-
3. **ABS**	N	all simultaneously	1
4. **GASM-1**	10-150	all simultaneously	-
GASM-2	N	stochastic for random and depends on the reallocation periodicity for technical traders	-
GASM-3	N	2 % simultaneously	-
5. **LLS**	N (10-420)	all simultaneously	-
6. **SF-ASM**	50/100/150	all simultaneously	100 / 250
7. **BS**	N(10)	all simultaneously	1 - 20
8. **MDS**	-	1/unit time	-
9. **OMP**	1-150	1 /simulation turn	-
10. **CTAM**	N	1 at predefined time or as a result of some event	-
11. **EGM**	N	1 stochastic	-
12. **EMM**	1	1 based on Poisson process	-
13. **KapSyn**	N	1 / simulation turn	-

Table 3.9: Choice for time-related factors in the ASMs

3.4.2 Order execution in ASMs

The various way orders are executed and as a result prices are formed on the ASMs studied is summarized in Table 3.10 for single price auctions and in Table 3.11 for continuous trading sessions. In the remainder of this section we elaborate on the different execution mechanisms implemented.

3.4.2.1 Order routing and order execution by brokers in ASMs

In stock markets orders initiated by investors are taken over by brokers for further routing and execution (cf. Section 2.3.2). Although on real markets several brokers interact, with the well-defined role to execute orders on behalf of the investors, they are not represented in the ASMs studied. There is one exception, namely *KapSyn*, which recognizes the importance to include brokers in ASMs. The paper mentions that the authors haver realized this after they consulted financial analysts. The question is in which measure the introduction of brokers in various ASMs influences the market dynamics. We believe they have some influence as they might improve the price of the orders received, encourage trading and as a consequence provide liquidity and further, they might trade for their own account as well.

3.4.2.2 Order execution (by market makers) in ASMs

The main role of the few market makers in the ASMs studied is to monitor the market through quoting bid and ask, and to execute the orders received from investors. Two main

types of execution mechanisms are represented: single price call auctions and continuous quote-driven order executions.

The activity of the market makers to keep their position and their role to provide liquidity for inactive stocks is rarely modeled. One exception is the *KapSyn* market where so called "designated sponsors" interacting on the XETRA representation, can, but are not obliged to, set bid and ask quotes, to increase liquidity when there is only one order standing without a counter order. Further, at *ABMI* the market maker trades based on his position. In this case, however, no special public bid and ask quotes are published, given that all orders are market orders, and price is centrally set according to an automated mechanism. At *EMM*, the position of the market maker influences his decision as well. At other markets liquidity is provided in the sense that market makers are selling and buying for themselves.

- On **call auctions** order execution involve determining a transaction price. In *SSM* the market maker determines changes in price by reacting on imbalances between demand and supply. Similarly, in the *ABMI* the market maker is represented by a simple equation on which price changes are based. At *SF-ASM* orders are aggregated and the market price is defined by a so-called auctioneer, who actually carries out an automated execution of orders.

  In ASMs that implement order-driven call market sessions, the main decision to take is how to define and determine the **equilibrium price**. In *SSM, ABS* and *LLS* the markets price is determined such that supply matches demand. In order to find the equilibrium point, these models assume that the supply and demand functions of the traders are known by the order execution system. At *SF-ASM*, as well as during call auctions at the XETRA version of *KapSyn*, equilibrium is determined at the price at which trading volume is maximized. A new market price is often at the intersection of demand and supply curves (like at *GASM*), while at *BS* price is based on the excess demand/supply discounted with some adjustment value.

- During **continuous sessions** market makers need to match received orders against each other. To this end they determine **bid and ask quotes** that take into account the content of the limit order book. Market makers are represented within *EGM* and *EMM*, where a multi-round Glosten-Milgrom model (see for a description for example (O'Hara, 2002)) is implemented for determining bid-ask spreads. In fact, in the *EGM* the market maker has a price discovery role, he sets the bid and ask quotes based on the market orders received, on his knowledge and assumptions regarding the fundamental value of the traded stock, and on his assumption regarding the proportion of informed traders (who know what the fundamental price is) versus uninformed ones. The electronic market maker in *EMM* sets its bid and ask quotes while striving to maximize its profit given the order imbalance. In these ASMs the behavior of the market makers is **adaptive**. The learning market maker is implemented based on the Glosten-Milgrom model from the market microstructure literature (Glosten and Milgrom, 1985). In EGM the Bayesian learning technique, in EMM reinforcement learning is applied. The market makers at *KapSyn* modify their quotes with respect to the limit order book. They cannot quote however, a price worse than the limit orders in the book.

ASM	The price in single price auctions
SSM	stochastic increase / decrease depending on the excess demand and risk aversion
ABMI	price adjustment by 0.001 * current price based on order imbalance, risk, and the position of the market maker
ABS	supply = demand
GASM 1,2,3	intersection supply and demand curves
LLS	supply = demand
SF-ASM	supply = demand and does not exceed available number of shares
BS	adjustment based on excess demand and speed of adjustment
KapSyn	highest volume that can be traded

Table 3.10: Variations on the market price at single price auctions

ASM	The bid-ask quotes in continuous sessions
MDS	highest buy price and lowest sell price from the limit order book
OMP	highest buy price and lowest sell price from the limit order book
CTAM	highest buy price and lowest sell price from the limit order book
EGM	adapted by means of Bayesian learning based on order flow and probability density estimate of the fundamental value
EMM	adapted by means of Reinforcement learning based on position, order-imbalance and some threshold
KapSyn	based on the content of the limit order book

Table 3.11: Order execution at continuous sessions

In all studies the **timing of the new quotes** is entailed by the arrival of new orders. In *EMM* the electronic market maker reacts when the order imbalance reaches a predefined threshold. Market makers, in general, do not have to change the quotes otherwise since, in the ASMs, they are not required to provide liquidity for non-active stocks. In fact the markets represented do not deal with inactive stocks, except in the XETRA representation within *KapSyn*.

Another task of market makers on continuous markets is **managing the limit order book**. In limit order books (LOB) unexecuted limit orders are stored. LOB's are part of markets with continuous trading sessions that handle limit orders. These are: *MDS, OMP, CTAM*, and the XETRA representation within *KapSyn*. In all these markets management of the LOB means storing limit orders and determining the buy order with highest price and the sell order with lowest price.

While in *EGM, EMM* and *KapSyn* the market microstructure approach is used, the rest of the continuous session-based ASMs apply an automated order matching mechanism.

Execution systems at *MDS, OMP* and *CTAM* represent a **continuous automated order execution mechanism**, where new orders are matched against unexecuted orders that are stored and arranged based on their price in a limit order book. Unexecuted limit orders are sorted (buy orders increasing, sell order descending), new market orders are executed immediately against the sorted book and limit orders are compared to earlier arrived, unexecuted orders in the book. If the quoted price of a sell order is lower than the price of a buy order a transaction is made for the minimum of the quoted amounts. The market price is the quoted price of the order placed earlier, that is the quote. This price formation mechanism implements simple automated order matching but does not reflect more complex order clearance where market makers themselves are involved.

As illustrated by the large scale of design and implementation approaches applied in the ASMs studied here, there are arbitrary many ways to represent traders, to determine a forecasting strategy, to implement adaptive behavior, to construct a portfolio and develop other decision strategies that lead the investors to place certain orders. In addition a variety of order execution and price setting mechanisms are represented. And this is in fact what we expect, given the hardly observable feature of traders' behavior and price formation illustrated with clouds in Figure 2.2. The question remains how the traders' performance, and especially the market dynamics is influenced by these implementation choices.

3.5   Findings of ASMs

Artificial stock markets are primarily designed to help us understand market dynamics. For this reason they mainly focus on the analysis of price or return dynamics within some specific market structure. Several ASMs try to study what kind of structures and behaviors can reproduce time series with characteristics similar to those on real markets. They also consider and test findings of theoretical and empirical models from the literature. In relation to market efficiency some models also study whether there exist strategies that are consistently more successful than others. A final goal is to pinpoint under which conditions the ASMs manage to achieve one or more of these objectives. Some of the results of the ASMs studied are highlighted in Table 3.12.

3.5.1   Evidence for theoretical predictions

Classical theoretical models claim that markets are efficient. In ASMs testing the efficiency of the markets is a central topic. In the studies on ASMs it is usually analyzed whether the price or return series generated are random, or whether some pattern (linear or non-linear correlation) can be observed. There is a discussion going on whether randomness or patterns in the time series say anything about the efficiency of markets, or are sufficient to prove or reject the EMH (see the discussion on the EMH in Section 2.4.4). These tests are also used, to analyze whether price series exhibit realistic properties, found by empirical studies. A more widely accepted way to test (informational) efficiency, is to check whether and in which measure the market price can trace the fundamental value of a stock. This is however, only possible if the fundamental value is known. Further, a persistent long-term success of the same agent or strategy suggests inefficiency of markets.

Depending on the applied organizational and behavioral settings evidence is reported both for classical theory and empirical "stylized facts" .

The efficiency of different market structures is explicitly studied within the *KapSyn* framework. Here it is shown that efficiency depends on the execution systems and the size of the orders, NASDAQ being more attractive for mid-size orders, while XETRA being more efficient for small and block size orders. Further, suggestions are given on how to change the organization of markets in order to improve market efficiency. It seems that limiting auctions to up to 6 per day could improve market efficiency, as it reduces transaction costs.

Evidence for the Efficient Market Hypothesis (EMH) and the related Rational Expectation Hypothesis (REH) is found within the *BS* model. In this market both EMH and REH, are emergent properties. They cannot be rejected at aggregate level for several time series, even if most of the market participants do not believe in them. This finding is in line with the property of the EMH, that markets are efficient if sufficiently many investors believe that they are inefficient, and proves that features at macro level are not necessarily the same as features at micro level. In this study efficiency is tested both by analyzing time series properties, and by analyzing the grade of successfulness of learning traders. It turns out that traders' learning activity "is not entirely futile", as 51% of the searches in the business school leads to more success. However, no strategy is reported using which it would be possible to earn above-average profit, fact that suggests that the given market is efficient.

	ASM	Random series	Patterns / stylized facts	Successful strategies	Definition of efficiency
1.	SSM	+/-	GARCH	-	-
2.	ABMI		trend	+	everyone breaks even
3.	ABS	-	- chaotic cycles - fat tails - volatility clusters	-	stable prices?
4.	GASM 1	- for large number of traders	- for small number of traders	-	IID series
	GASM 2	-	- mean-reversion - fat tails - volatility clusters	mean-reversion	-
	GASM 3	-	- mean-reversion - fat tails - volatility clusters -	depends on market conditions	-
5.	LLS	+	- bubbles and crashes if only short-term trends focused	-	random walk
6.	SF-ASM	-	- fat tails - volatility clusters - correlation volume volatility	-	rational expectation equilibrium
7.	BS	+	-	-	IID series
8.	MDS	-	- fat tails - volatility clusters - autocorrelation volume	-	prices instantly and correctly adjust to reflect new information
9.	OMP	-	- fat tails - volatility clusters	- lookup-table strategy	-
10.	CTAM	-	- bubbles and crashes	- depends on the presence of fluctuations	-
11.	EGM	-	- fat tails	-	market maker able to learn fundamental value
12.	EMM	-	-	-	market maker able to learn real value + liquid market with low spread
13.	KapSyn	-	-	-	low transaction costs

Legend:
"–" – this property is not observed or it is not focused
"X" – this property is observed

Table 3.12: Findings of ASMs

In the simplified *ABMI* investment model, where interacting investors have credit limits, the market tends to a point where everything is in equilibrium, i.e the wealth of traders breaks even. If, additionally, seasonal traders are involved in the same model, the market gets more efficient if trend followers learn the pattern entailed by seasonal traders. Also, the experiments within the *ABS* lead to dynamics close to equilibrium. The case with slowly learning traders at *SF-ASM* approximates the equilibrium point predicted by the rational expectations hypothesis. Finally, by making the simulation scenarios more complicated, time series properties become random at the extended *LLS* market.

At *EGM* and *EMM*, informational efficiency on the markets is tested by looking whether market makers can trace the fundamental value. At *EMM* the market maker can approximate the fundamental value better over time, if he applies reinforcement learning. In moderately noisy environments reinforcement strategies converge successfully to optimal analytical strategies. At *EGM* the market maker successfully tracks the fundamental value as well by applying Bayesian learning, even if only half of the traders is perfectly informed. In this model negative autocorrelation can be observed for high frequency data. However, autocorrelation of raw returns decays rapidly and there are no arbitrage opportunities for low frequency data, indicating randomness and efficiency of the market.

In *ABMI* it is shown how the demands of the investors create inefficiencies. If the traders have a credit limit and change the scale of investment based on their wealth and credit limit, the market tends toward a point where everything is efficient. This point is noisy, there are fluctuations around it, but each agents' wealth stays more or less fixed. When a large number of different strategies is additionally introduced efficiency takes a long time to establish and markets become chaotic and volatile fast afterwards because of the dynamics stemming from the interaction between the different strategies.

3.5.2 Patterns in price series

Many ASMs find evidence for stylized facts, this feature being mainly entailed by interactions between heterogeneous agents. Fat tails and volatility clusters are observed within *ABS, GASM, SF-ASM, MDS* and *OMP*. Fat tails and negative autocorrelation of returns at one lag are reported in *EGM*. In addition, within *SF-ASM* a correlation between the trading volume and volatility is found. In *ABS* chaotic cycles are observed. Bubbles and crashes occur within *LLS* and *CTAM*. In *LLS* these occur if only short-term trend strategies are applied by the investors. However these disappear as soon as traders holding shares as a constant faction of wealth are introduced which will dominate the market. In *CTAM* bubbles and crashes are caused by a tiny fraction of trend followers. Further, a reversion to mean is reported in the study on the *GASM* market. At *ABMI* patterns are entailed by the position and risk aversion of market maker, who needs to get rid of her position.

In some of the ASMs successful trading strategies are discovered. Trend followers in the *ABMI*, as well as the lookup table strategy in *OMP*, mean-reversion traders at the *GASM* market, and fast learning technical traders at *SF-ASM* can systematically dominate the market, meaning that the market is not efficient in these cases. In *CTAM* the short range mean reverting behavior is the winning strategy in a market with no periodic daily trend. In case of periodic fluctuations risk-averse trend followers are the most successful. Further, market settings exist within *MDS* that reproduce linear time series, where patterns approach a linear

function for large granularity. In some of the studies that reject linear predictability, evidence for non-linear effects is found. This is the situation in the *ABS* and in some other ASMs discussed in (LeBaron et al., 1999). Further, although in general (for 85%) price series within the *BS* are random, in a few cases nonlinear signals are discovered in this model as well. Linear and non-linear features of price series reject the random walk property.

Findings of experiments within ASMs confirm the fact that the market mechanism chosen matters. Therefore, many authors claim that evidence for stylized facts is crucial, because realistic models are needed for studying market dynamics and for drawing realistic conclusions.

3.6 To what degree are the ASMs agent-based? - a discussion

Taking as a starting point the various definitions on agents and autonomy, presented earlier in this chapter, in this section we attempt to determine to what degree the ASMs presented above are agent-based. To this end we analyze what is meant or might be meant by "agent" in the various models and we discuss whether these can be looked upon as autonomous and/or intelligent.

In general, in the ASMs studied, all investors or order generating processes that represent investors' decision can be viewed or implemented as agents. Further, market makers or processes of price formation can also be considered as agents.

With respect to the grade of autonomy, all individual components can be considered as being autonomous in a sense. However, most of the traders do not decide themselves whether they will trade in the next trading cycle or simulation round or not. Instead, they are selected globally by the system (see Table 3.13). The few ASMs in which timing of decision-making is internal to the traders are the *GASM-2, GASM-3, CTAM* and *KapSyn*. *GASM-3*, however, does not really differ from a global selection mechanism, since in this case the internal value refers to a probability of trading which is the same for all the traders. In *GASM-2* technical traders have an individual "reallocation periodicity" value that states the period after which traders' might reallocate the composition of their portfolio. In *CTAM* traders react to some events or wait for a while before they analyze the market conditions. These values differ for the various traders and can vary over time. Finally, in *KapSyn* a reaction (or execution) time is associated to each individually planned action as a function of their utility. Concluding, we can consider trader representations in these three markets as exhibiting some kind of autonomy.

As far as "intelligent agents" are concerned, most traders are flexible but only a few of them realize flexible behavior by means of "artificial intelligence" capabilities. In a sense all traders (except completely random ones) are responsive, as they react to changes in their environment. Further, all investors are goal-directed, except for cases in which decisions are represented by random order flows. Finally, social behavior, i.e. interaction in ASMs is self-evident as participants need to trade with each other. Social behavior in a larger sense, e.g. to consider other traders' opinions is also considered in a few models, like the *OMP*. However traders do not "collaborate".

	ASM	Nr. traders who take decision /trade simultaneously.	Selection trader to make decision	Can decide not to trade	Do not decide every round\\
1.	SSM	aggregated order flow representation (no individual trading)			
2.	ABMI	all	all	+	-
3.	ABS	aggregated order flow representation (no individual trading)			
4.	GASM-1	all	all	+	-
	GASM-2	depends on individual parameters of traders		+	- stochastic for random traders. - reallocation periodicity for chartists
	GASM-3	2%	everyone trades with 0.02 probability	+	-
5.	LLS	all	all	+	-
6.	SF-ASM	all	all	+	-
7.	BS	all	all	+	-
8.	MDS	only order flow is modeled			
9.	OMP	1	Random	+	-
10.	CTAM	1 (or more ?)	initiated by the traders themselves	+	+
11.	EGM	1	stochastic order flow	+	-
12.	EMM	1	Poisson process	+	+
13.	KapSyn	- decision made by all simultaneously - order placed by 1	stochastic higher probability for actions with lower execution time (reaction time)	different reaction time associated to actions	

Table 3.13: Traders' grade of autonomy in the ASMs

Reactive behavior often is reflected only in the fact that traders take a decision based on new market data, such as market prices or a new fundamental value. As illustrated by Table 3.8 reactive behavior by means of changing the trading or forecasting strategy is specific only to the traders within *SSM, ABS, SF-ASM, BS* and *OMP*. Further, learning techniques are applied on the market makers' side within the *EGM* and *EMM*. Among these, in *EGM* Bayesian learning, while in *SF-ASM, BS* and *EMM* artificial intelligence based techniques are applied, namely genetic algorithms (GA), genetic programming (GP), and reinforcement learning.

3.7   Summary

The main topic of this chapter is a survey on agent-based artificial stock markets. Therefore, in the first part of this chapter, we made an attempt to give a universally accepted definition of the notion agent-based artificial stock markets. However, this turned out to be no easy task, given that there is no general agreement on the definition of the composing terms, and in particular on the concept of agent. For AI researchers agents are intelligent autonomous software entities endowed with AI adaptation techniques. For some people, however, agents might mean just simple representations of forecast functions of a trader in form of an equation. According to this discussion one might view an ABASM as any market model in which prices are formed endogenously as a result of participants' interaction and in which the representation of participants varies form simple equations of forecast functions to intricate software components endowed with human-like artificial-intelligence based adaptive behavior.

In the second part of this chapter we looked at several ASMs and analyzed how they cover the important organizational and behavioral aspects of stock markets, as presented in Chapter 2. Based on the comparison we deduce the following main conclusions:

1. usually only **investor type** of traders are represented, and the represented market makers generally carry out only automated order matching or price adjustment;

2. the importance to represent and study **continuous trading sessions** is recognized by more and more researchers;

3. **autonomous asynchronous behavior** of traders is rarely represented, traders being centrally coordinated;

4. all ASMs apply discrete time simulation; only one study applies event-driven simulation;

5. there are **arbitrary many ways** to represent the hardly observable aspects of price formation and trading behavior;

6. **market settings** such as market structure, trading strategies (i.e. how hardly observable aspects are represented) as well as **the number of traders** influences a lot the dynamics of markets and the properties of the resulting time series.

As far as the traders' role is concerned, most ASMs focus on representing the investor type of behavior. Only *KapSyn* includes brokers, and only a few markets include market makers whose behavior resembles a somewhat more complex decision-making process than automated order matching or price determination (e.g. the *EGM* and *EMM*). In reality, however, the behavior of brokers and market makers directly affects price formation. The need to represent market participants with different roles is pointed out in (Loistl and Vetter, 2000).

In many ASMs all traders place orders at discrete points in time. Orders are then aggregated and the new price is determined at some equilibrium point. The way orders are executed in these structures resembles call auctions. This way of modeling it is thus useful to study the dynamics of single price call auctions. However, call auctions are not representative, since, as observed in (Smith et al., 2002; Demarchi and Foucault, 2000; Reilly and Brown, 2003) and (Raberto and Cincotti, 2005), on most of the markets continuous trading sessions dominate.

In line with the above observation more and more studies on ASMs recognize the importance to model continuous trading sessions. The need to study continuous trading is reflected in the *KapSyn, MDS* and *CTAM* models described in (Loistl and Vetter, 2000; Smith et al., 2002) and (Shatner et al., 2000). These markets try to implement continuous order matching and even asynchronous decision-making. Most of the studies do this, however, by applying discrete time simulation and arrange trading in trading rounds. In *KapSyn*, for example, continuous sessions are imitated by selecting one agent from the crowd whose decision is carried out next. At every simulation round however, all agents make decisions simultaneously, which in not the case in continuous markets. Here the decision of the traders that are not selected is ignored, and in the next trading round, everyone has to reconsider his decision taking into account the new state of the market triggered by the decision of the selected trader. In reality all decisions are executed if possible, whether they were made simultaneously or not. Furthermore, decisions are usually not taken simultaneously, and do not wait for others' actions to be executed: someone can launch an action, before the decision of another agent is completely carried out, causing a new market event.

A more realistic attempt at a continuous trading model is the *CTAM* presented in (Shatner et al., 2000) where traders do not take decisions continuously but "sleep" after actions and "wake up" at predefined times, or as a result of events. Other studies model continuity and asynchronous behavior by randomly (e.g. *GASM-1*) or stochastically (e.g. *KapSyn*), selecting one trader whose decision is carried out, and automatically matching new orders with pending ones if possible.

The problem with centrally and randomly selecting agents whose actions will be carried out, is that, in this way, agents are no longer autonomous regarding their actions and, as mentioned above, it might also happen that the decisions of some traders are not taken into account (e.g. in (Loistl and Vetter, 2000)). Representations of traders in ASMs illustrate passive agents, while agents on the market are autonomous and decide themselves whether they want their decision to be carried out or not. Autonomous behavior can only be accomplished if the agents themselves decide when they want to trade as is the case in real markets.

A vast number of trading strategies in a broad range of market organizations is illustrated by the ASMs presented. Besides the strategies implemented in the ASM literature several others are described by empirical and behavioral studies, and many more exist in reality, a large part of which being not even observable or revealed. This variety has motivated us to design a framework that accommodates this diversity as well as the as yet mainly neglected microstructural features, such as continuous trading, asynchronous behavior and autonomous behavior, and the representation of brokers. Therefore, based on the list of critical factors and on the results (pointing both at possibilities as well as shortcomings) of the analysis of current artificial stock markets we have developed a framework that provides a tool for representing several types of markets and an arbitrary number of trading strategies. We present this environment in the following chapter.

Chapter 4

The ABSTRACTE framework

In Chapter 2 we presented a broad range of market organizations based on a framework that was built up in terms of carefully determined discriminating notions, such as the role of market participants, trading sessions, and execution mechanisms. We also elaborated on the hardly observable processes behind price formation and the hardly observable considerations behind the behavior of traders. Then, in Chapter 3 we presented a number of artificial stock markets (ASMs). We analyzed how these are organized, and how they deal with the hardly observable aspects. We compared these ASMs based on the relevant organizational and behavioral aspects proposed in Chapter 2. As concluded, in reality there is a vast number of markets the organization of which varies along a broad range, and there are numerous variants of price formation mechanisms and traders' behavior. In the ASMs encountered we observe only a very restricted choice from this implementation space, they focus mainly on a very specific static market structure and specific representations of traders' behavior. Moreover, ASMs rarely represent common features, such as continuous trading and asynchronous, autonomous behavior. These observations have motivated us to provide an agent-based artificial trading environment that can incorporate more varying and representative aspects of markets and behaviors.

In this chapter we introduce and describe a modular agent-based trading environment: ABSTRACTE, an "Agent-Based Simulation of Trading Roles in an Asynchronous Continuous Trading Environment". As illustrated by its name, the most specific features of this trading environment are the agent-based approach, the special attention paid to represent various trading roles, asynchronous behavior of participants, continuity and modularity. The ABSTRACTE is not one single artificial stock market, but an environment, a modular tool for representing and studying several types of markets and an arbitrary number of trading strategies. ABSTRACTE is designed with the aim to improve the study and understanding of market dynamics.

We start the description by giving a motivation for designing this specific environment. Then, we present its structure, and we describe its organizational and behavioral aspects based on the list introduced in Chapter 2. After that, we give high level implementation details, primarily to illustrate and underpin the mechanism and the features of ABSTRACTE. In addition, we illustrate the possibility to experiment with various market structures and

strategies on top of the framework. We provide an evaluation of the proposed environment through illustrating how various price formation mechanisms and trading strategies can be configured on top of it, and how earlier models of these particular market structures can be replicated. We conclude the chapter by summarizing the added value of the ABSTRACTE environment.

Preliminary parts of this chapter have been published previously. Asynchronous, continuous-time simulation, and the representation of traders based on their role has been focused on in (Boer and Kaymak, 2003; Boer, de Bruin and Kaymak, 2004), modularity and design details have been described first in (Boer, Polman, de Bruin and Kaymak, 2004; Boer et al., 2005*a*).

4.1   Motivation

The nature of the ABSTRACTE environment stems from our aspiration to take into account the microstructural features of markets, and to abstract from specific individual strategies and price formation mechanisms, allowing for the flexible representation of various strategies. By designing and developing such an environment, we aim to achieve multiple objectives. First of all, we would like to experiment with common and/or rarely studied market types and behaviors, such as continuous trading sessions, brokers, market maker-based price settings, autonomously and asynchronously acting agents. Secondly, we aim to replicate, test and validate some of the existing artificial markets within it. In this way, the introduced environment can help us to study whether findings of experiments within different market models can globally explain some market dynamics.

In this section we aim to motivate why there is a need for the ABSTRACTE trading environment and why we have chosen for specific properties and methodologies (such as modularity and the agent-based computational approach) for designing and developing it. We answer three main question in relation to this environment:

1. Why are we focusing on a trading *environment* instead of a single, specific ASM?

2. Why do we need an *additional ASM* at all if so many variants exist?

3. Why do we choose *the agent-based computational approach* from the variety of approaches that exist?

Despite the large amount of research on modeling stock markets, market dynamics are still poorly understood. The difficulty to understand market dynamics is underpinned by the contradictory and controversial findings of theory and empirical studies. As discussed in Chapter 2 and Chapter 3 the hardly observable aspects of price formation mechanisms and market participants' behavior are the main reasons behind contradictory findings, since everyone makes a different assumption on these. The arbitrary many ways to deal with the hardly observable aspects has given rise to an increasing number of ASM variants. The variety of stock markets and ASMs, on the one hand, motivates us to develop ABSTRACTE as a trading environment. On the other hand, our particular view on what is important to represent and our understanding of the workings of stock markets, motivates us to include within ABSTRACTE aspects that are not generally covered by existing ASMs.

The many forms of real markets, the varying aspects of market organizations, and the various interpretations and assumptions regarding hardly observable aspects are the main reasons why we do not intend to focus on one specific market, but to develop an *environment* instead. ABSTRACTE is a trading environment in the sense that it does not contain concrete implementations of the hardly observable aspects but empty placeholders instead to allow for experiments with multiple market organizations and arbitrary many trading strategies. A trading environment built in this way makes modeling more efficient in the sense that special purpose ASMs do not need to be built from scratch but can be realized by just filling in the empty placeholders. We cannot claim of course that the environment can support modeling of every market structure and every possible trading behavior. In some cases it might need some adaptation or extension in order to allow for additional aspects.

The reason for developing *"a new ASM"* in our case is to support the following common and rarely modeled aspects of stock markets:

- continuous trading sessions;

- hybrid trading sessions;

- market participants with different roles within the market;

- broker's behavior;

- market maker's bid-ask quoting strategies;

- autonomous behavior of participants.

We focus on simulating continuous trading sessions since these are very common on stock markets and the importance to study them is recognized by more and more studies (see Chapter 3). We provide the possibility to conduct call sessions as well because, as we mentioned earlier in this thesis, there is a common tendency towards market organizations with continuous trading sessions combined with call sessions during opening and closing of the market.

As concluded from the comparative study provided in the previous chapter the participants most often focused on are the investors. In ABSTRACTE we would like to take a broader perspective and focus on the effect of the different roles of market participants on dynamics. Accordingly we would like to provide a deeper focus on the market maker's behavior and to conduct experiments with negotiating brokers as well. Market makers modeled in ASMs often carry out automated execution of orders, specific behavior of market makers being mainly ignored. Exceptions are ASMs based on the market microstructure literature. Within ABSTRACTE we aim to allow for the representation of various bid-ask quoting strategies because these may have a decisive influence on prices.

Finally, we pay importance to support autonomous behavior of traders. In the majority of ASMs traders are not autonomous in the sense that they are centrally selected, and thus often they are not able to autonomously control the decision when to place orders.

The aim to mimic this autonomous behavior is one of the main reasons for applying the *agent-based methodology* in order to develop ABSTRACTE. An additional reason is that, despite the fact that there is no common agreement on the definition of "autonomous agents", we can benefit from the standardization efforts made in this area. For instance, we base the

implementation of the trading environment on JADE a framework to develop multi-agent systems (described in (Bellifemine et al., 2003)), which is compatible with the standard proposed by FIPA (the Foundation for Intelligent Physical Agents), "an IEEE Computer Society standards organization that promotes agent-based technology and the interoperability of its standards with other technologies" (FIPA, 2007).

Further, *agent-based computational economics approaches* apply the bottom-up approach for modeling economic systems. Accordingly they make it possible to study market dynamics as emergent properties of individual agent interactions. An agent-based approach provides more flexibility than standard discrete event simulations. By flexibility we refer here to the possibility to gradually include parameters the effect of which can be studied. Further, the computational aspect of the approach enables us to observe explicitly the agents' decision behind their trading behavior as well as the effect of these decisions on prices. Moreover, agent-based approaches provide the option to easily connect to learning algorithms.

In this section we motivated why we propose the ABSTRACTE trading environment. In the remainder of this chapter we describe its structure and provide some design and implementation details. When designing the framework, we pay special attention to the representation of the common features of stock markets like continuous trading sessions. However, we intend to incorporate specific properties of stock markets and the structure of ASMs from the literature as well in order to be able to replicate and test their results.

4.2 The structure of the trading environment

Trading in a market is organized around three main components: the instruments that are traded, the market participants who trade and the institutional structure behind price formation. The institutional structure, i.e. the market microstructure, directly drives the price formation mechanism and determines the type of a market. Instruments, like stocks, are issued by certain companies, and represent ownership in that company. The value of instruments depends therefore on the performance of the company. Being the object of exchange however, instruments are more or less part of the market where they are traded. The price of instruments, is thus, influenced by a multitude of factors, such as issuer specific news, the market organization, and the decisions of market participants. As elaborated in Section 2.2.3 we differentiate two types of market participants: financial traders and investors. Financial traders, on the one hand, have specific well-defined roles on the market. They are further classified as brokers and market makers, based on their role. Investors, on the other hand, are not an internal part of a market organization. They observe markets, make trading decisions, and send their orders to financial traders interacting on markets.

According to the discussion above, the framework consists of three main components (Figure 4.1):

- the marketplace;
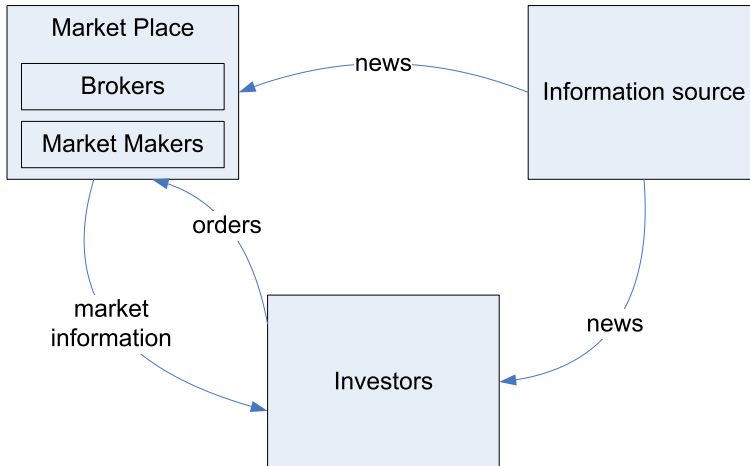
- the set of investors;

- an information source.

Figure 4.1: The components of the framework.

The marketplace models the institutional structure behind price formation, and includes financial traders as subcomponents such as market makers and brokers. In addition, market specific features of stocks (such as name, tick size) that can be traded on a specific market are defined within this component. The existence of brokers and market makers, and their behavior is strongly related to the market organization under study. They have special roles and tasks, determined by the market rules of specific markets.

Given that investors, as defined, do not have a special role within markets, they are represented separately. This implementation makes it easier in the future to let them trade in multiple markets if wished so.

The information source component is introduced to implement the possibility of information coming from the issuer. It is designed with the aim to generate news related to the stocks traded on the market, such as dividends and information regarding the fundamental value.

At a high level of abstraction, the following relationships exist between these components. From time to time the information source component generates news about a stock. News is sent to specific market participants. Investors receive news from the market place and news related to the value of the stock, and generate orders. They send these orders for execution to certain brokers or market makers on the marketplace. The process of sending and executing orders depends on the specific execution system that is applied and on the strategy of the financial traders involved.

Given the highly varying market organizations and the hardly observable aspects of price formation and trading strategies, we do not focus on designing a specific market structure, but strive to design a modular trading environment. Through this modularity we want to support the possibility to run experiments with various market types and trading strategies. In this sense the components are **skeletons**. They are designed to incorporate the generic

aspects of a certain trader or process, without specifying details on the hardly observable and varying aspects. To incorporate the latter aspects the framework contains **empty place-holders**. Empty placeholders can be filled with arbitrary strategies and are thus, part of the skeletons. With the help of these placeholders it is possible to implement properties of stock markets that have not been focused on yet, as well as to incorporate the structure of other ASMs in order to replicate and test their results. We provide within the framework some "pre-fills" of placeholders implementing common behavior encountered in ASMs or in stock markets.

We elaborate on the detailed design and implementation aspects of the components and the relations between them in the next three sections. The presentation of the environment is organized along the list of organizational and behavioral factors we set up in Chapter 2. First, we describe how we represent organizational aspects. Then, we discuss how we deal with the hardly observable and varying features. Finally, implementation related details are presented.

4.3 Organizational aspects

In this section we discuss how the organizational aspects discussed in Section 2.2 are represented in the environment. Behavioral aspects are focused on in the next section.

- **Traded instruments**

  Like the majority of the ASMs, for the time being, we focus on experiments where one risky stock is traded. Cash supplies are available to express the risk free choice of traders. The information source component that represents the issuer can generate dividends and fundamental values if required, and inform traders about the new values. The fundamental value of a stock, and, as a consequence, the way it varies is a hardly observable aspect of real markets. In order to adequately model this reality there is a need for flexibility in the models regarding this issue. Therefore, the algorithms behind news generation can be varied and extended within the framework.

- **Orders**

  Both limit and market orders can be placed by traders acting within the framework. Orders are described by a stock name, size, side and quoted price. Additionally, each order has a time-stamp attached to it that indicates the time at which it was placed.

- **Market participants**

  In contrast to the artificial stock markets from the literature, featuring only investors and sometimes market makers, in this environment brokers are represented as well. The presence of brokers is required, for example, in markets where continuous double-auctions can be conducted, like the NYSE. If necessary, brokers can be excluded from experiments. This is, for instance, necessary when replicating experiments of ASMs that do not implement them.

In the ABSTRACTE, there is at least one market maker assigned to each stock. The primary task of this market maker is to take and execute orders of other market participants. Order execution depends on the execution mechanism applied. Depending on the organization represented the market maker might also need to determine bid and ask quotes in reaction to orders or inactivity. The environment is designed in such a way that, if wished, more market makers can take responsibility for the same stock. This structure reflects competitive dealer-markets. However, we do not study these type of markets in this thesis.

The detailed generic behavior of the market participants is discussed in the next section.

- **Trading sessions**

  Continuous trading sessions are very common on stock markets (Harris, 2003; Demarchi and Foucault, 2000), and although they are rarely encountered in earlier ASMs their importance is being recognized within more and more studies. Given the popularity of continuous sessions we focus on designing and developing a continuous trading mechanism. However, since many artificial markets implement call auctions, we also incorporate call type trading session within the framework.

  It is up to the user to decide with which form to experiment. If continuous trading sessions are applied, orders can be continuously placed by investors, and trades are arranged whenever possible. If call sessions are used, orders can be placed only at designated times. Traders are notified whenever a call session opens and ends. Orders placed during call sessions are aggregated and trading is arranged based on the execution system applied.

- **Execution systems**

  The execution systems that we primarily focus on are continuous quote-driven systems. On these type of markets bid and ask quotes are placed by market makers. The way bid-ask quotes are ultimately determined is market and market maker dependent. The decisions behind this process are in general hardly observable. Therefore, we design and implement empty placeholders using which the experimenter can specify this hardly observable aspect. Thus, experiments with different continuous execution systems can be conducted within the framework, as specified by the implemented and configured bid-ask quoting strategy of the market makers.

  In order to provide the possibility to study auction-based markets, and to replicate experiments of the common single price call auction form ASMs, a framework for auction-based execution mechanisms is also incorporated into the environment. The way trades are arranged and prices are ultimately determined is again hardly observable in practice, and moreover varies from market to market. Therefore, we do not choose for a specific, predetermined execution mechanism, but provide the framework only. Empty placeholders give the user the possibility to experiment with various strategies.

  In addition, we support the representation of persistent double auctions, a mechanism applied, for example, on the NYSE. During a persistent double auction brokers can negotiate between the quoted bid and ask prices of the market maker (see Section 2.2.5).

- **Market rules and regulations**

  Rules describe the type of the trading session, and determine details of the specific execution mechanism applied within the framework. In general, based on the specified market type, they might refer to the tick size, the upper and lower limit of a bid-ask spread, the number of call auctions that should be conducted, the time interval between two call-auctions, the specification of events that can trigger call-auctions on hybrid markets (e.g. the intensity of change in prices), the (simulated) length of a trading day, etc.

  Regarding a-priori information, it is possible to simulate the publication of historical price series, the bid-ask quotes of the market maker, and news provided by the information source component, for example concerning the fundamental value. News is available for participants that subscribed to receive it. The limit-order-book is theoretically closed. However, depending on the market-maker's bid-ask quoting strategy the best ask and offer might be visible being identical to the quotes. In the future, we might consider experimenting with open book trading as well.

  Post-trade information regarding the transactions, can be made public to all the participants. The identity of the traders participating in transactions is registered for statistical reasons, but it can be hidden from other participants if wished so.

4.4 Behavioral aspects

In the previous section we focused on the organizational aspects of the markets that are represented within our simulation environment. In this section we focus on the hardly observable aspects of the markets and describe the design bed of price formation mechanisms and traders. We base the description on the behavioral factors given in Section 2.3 and reported in (Boer et al., 2005*b*).

In order to allow for a flexible representation of the price formation mechanisms and for experiments with different trading strategies, the framework incorporates only skeletons for the three trader types, i.e. market makers, brokers and investors. Skeletons only specify the basic structure and generic behavior of the traders. On top of the skeletons traders' specific behaviors (strategies) can be implemented. Since we have chosen for an artificial agent-based implementation of the traders, we illustrate them by focusing on their environment-sensing, decision-making and acting behavior (see (Russell and Norvig, 2003)).

4.4.1 Order-placing behavior

Orders are primarily initiated by investors as a result of some portfolio management process. Investors carry out the following generic behavior:

- they sense their environment;

- they interpret the sensed information and make trading decisions that result in orders;

- they ask a financial agent to execute the orders generated.

The process and reasoning behind trading decisions is however a hardly observable aspect of investors' behavior.

Accordingly, we represent the behavior leading to a trading decision of investors as a black box (Figure 4.2). This box can be filled in with any strategy. The investor component of the environment is designed in a way to reflect the generic behavior. Arbitrary order-placing strategies can be configured to fill in the black box part of it.
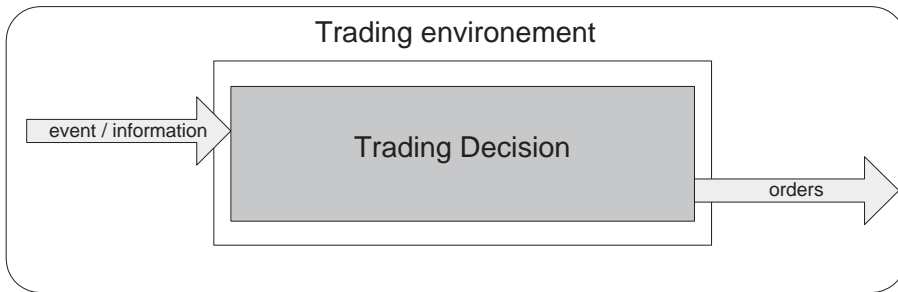

Figure 4.2: The generic behavior of investors.

As suggested by the literature on behavioral finance, illustrated by the various ASM implementations, and discussed by Boer et al. (2005*b*), arbitrary many strategies might exist behind trading decisions. In general, as theory describes, trading decisions are driven by portfolio management processes (Reilly and Brown, 2003). Accordingly, trading decisions are based on the individual investment strategies that try to meet the particular policy statement guidelines, and reflect the portfolio construction and maintenance decision of the investors resulting in orders.

Given that the strategy behind the trading decision is varying and unknown, in the skeleton we need to allow for various possibilities.

Two main questions arise in relation to designing trading behaviors:

- how to trigger a trading decision?

- when to trigger a trading decision?

An investor considers to make a new trading decision in the following situations:

- the order he placed is filled;

- a market event happens: a transaction is made, the market price changes, or the bid-ask quote changes;

- news arrives related to the fundamental value or dividends;

- a time horizon is reached (e.g. the holding period of a given portfolio).

In case the investor applies a portfolio management process, a trading decision might imply reevaluation and reallocation of his portfolio.

The trading decision results in a set of orders. This set can be empty, meaning that the investor doesn't want to place any new order. Given that we focus on one type of stock for the time being, in the experiments conducted, investors decide to place either one single order (possibly for more than 1 share) or no order at all.

The environment contains only the skeleton, which provides the generic investor-type of behavior. It does not include a specific trading strategy, but an empty placeholder on top of which different strategies can be implemented. In this way experiments with arbitrary types of investors can be conducted in a flexible way. Various investors can be set to behave, for example, like the traders at SantaFe (LeBaron, 2002), KapSyn (Loistl and Vetter, 2000) or at a sort of "business school" (Chen and Yeh, 2001) trying to maximize a specific utility function, or to use arbitrage opportunities like traders in other markets (e.g.; Das (2003), Chen et al. (2001)). Further, if required they could generate orders with random values like the traders in (Shatner et al., 2000; Chan and Shelton, 2001) or (Das, 2003), trade a predefined fraction of their portfolio (Raberto et al., 2001; Shatner et al., 2000) and use a variety of fundamental and/or technical strategies to forecast future values. Thus, an investor component in the framework is characterized by the particular strategy applied to make trading decisions.

4.4.2 Order execution

4.4.2.1 Order execution by brokers

Brokers on financial markets are primarily entitled to execute orders on behalf of investors. In this respect they are mediators. Of special interest is their role in persistent double-auctions because in that case negotiation is involved. Similar to the investors' skeleton, the design of the brokers within the framework involves just their generic behavior, the chosen strategies behind the decision problems being at the users' freedom.

As discussed in Section 2.3.2 and illustrated by Figure 4.3, the common mediator behavior of brokers consists of the following main tasks:

- sense their environment,

- receive orders from investors,

- decide how and in which order to execute the trading instructions received;

- arrange transactions and report on them.

The main decision problem brokers are faced with is thus how to fill the received orders. This problem is illustrated by the first black box on Figure 4.3. There are various scenarios possible. The number of possibilities is limited by market rules.

If a broker can handle more than one order at a time he needs to decide which of the orders to process next. A broker might, for example:

- select the order with the earliest arrival time (FIFO mechanism); or

- select the order with the best execution probability (considering current market conditions); or
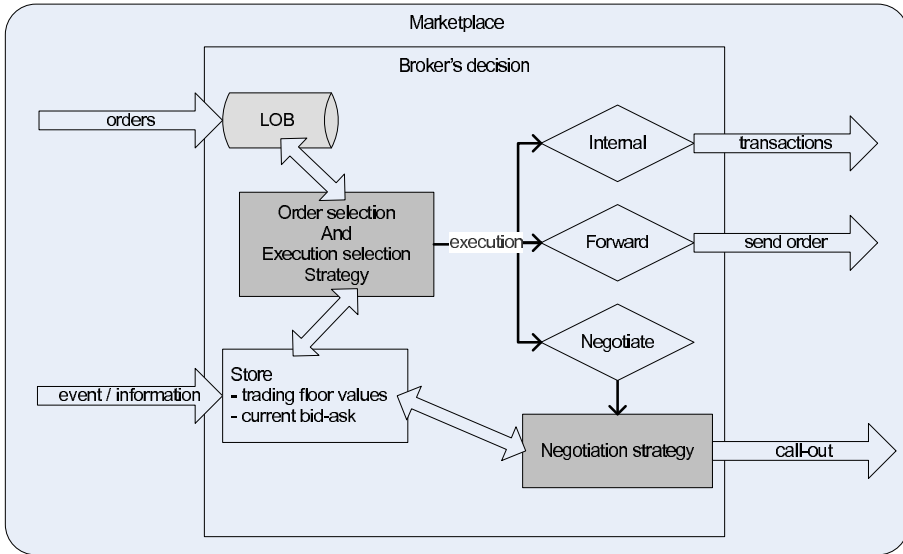
Figure 4.3: The generic behavior of brokers.

- aggregate and try to execute more orders with similar parameters at once.

The choice which order to select depends on the possible trading mechanisms that are applied on the market in which the broker interacts. Theoretically a broker has three ways to carry out a trading instruction:

- match orders internally: if, for example, there are other earlier received orders in the order book (LOB) of the broker that clear at a price close to the current market price;

- try to negotiate with other brokers within the market makers' quoted spread, for instance, through persistent double auction, like at NYSE (represented by the black box entitled "negotiation strategy" on Figure 4.3);

- submit the (improved) order to a third party (such as a market maker or a central matching system) for execution.

Brokers are allowed to negotiate with each other only within the specified bid/ask spread. It does not make sense to negotiate outside it, as then it would be more profitable for one of the parties to trade with the market maker. Brokers might apply a variety of negotiation strategies. The decision they take during the negotiation strategy results either in a new quote or the acceptance of a quote made by another market participant. A number of decisions need to be taken if brokers choose to negotiate, such as the negotiation price offered, the changes applied to the negotiation price, and the time-length for trying to negotiate an item. These values might depend on the actual quote of the market maker, the offers that other brokers make for negotiation purposes, the initial limit price of the selected order, etc. If the broker

decides to accept a bid or offer, or if his quote is accepted, a transaction price is determined, a deal is made and the transaction price of this deal is published as the new market price.

The strategy applied by a broker to select and execute orders can be influenced by his inventory, either because he doesn't want to invest, or because in certain markets constraints are put on the level of inventory that brokers are allowed to keep.

The way brokers analyze information, and interpret it to select and execute orders, or to define a negotiation strategy are hardly observable aspects and can take arbitrarily many forms, properties illustrated by black boxes in Figure 4.3. We build the architecture of the brokers in such a way as to allow for implementation and experiments with different strategies. Since it is not clear how in reality brokers solve all the decision problems that they face, we have to experiment with a number of possible solutions. Allowing for different strategies enables us to study how the brokers' success and the market dynamics depends on the strategy applied. Hence, again the framework contains the skeleton that provides the implementation of the generic behavior of broker-agents leaving a concrete strategy implementation for negotiation, and for order selection and execution as an empty placeholder to be filled in by the user.

4.4.2.2   Order execution and the role of market makers on continuous markets

Market makers are financial agents on continuous markets with the specific role to provide liquidity for the stocks they are responsible for. Accordingly, when designing the behavior of market makers we focus on representing this particular feature. According to the generic behavior of market makers described in Section 2.3.3, and illustrated in Figure 4.4, the tasks that market makers need to repeatedly carry out, is to:

- perceive the environment;

- determine bid and ask quotes;

- receive orders and execute them against the quoted bid-ask values if possible;

- enter unfilled orders into the limit order book.

The question and the main decision problem market makers are faced with, is:

- *when* to change the bid-ask quotes; and

- *how* to determine them in order to reflect market conditions and to provide liquidity?

The strategy that governs the market makers' decision depends on the market organization where they interact, but also on individual and situational characteristics. In principle, they reconsider the bid and ask quotes in two main situations:

- whenever new orders arrive; or

- whenever they perceive that the stock they are responsible for is not liquid enough, which is reflected for example by the fact that no orders arrive for a while.
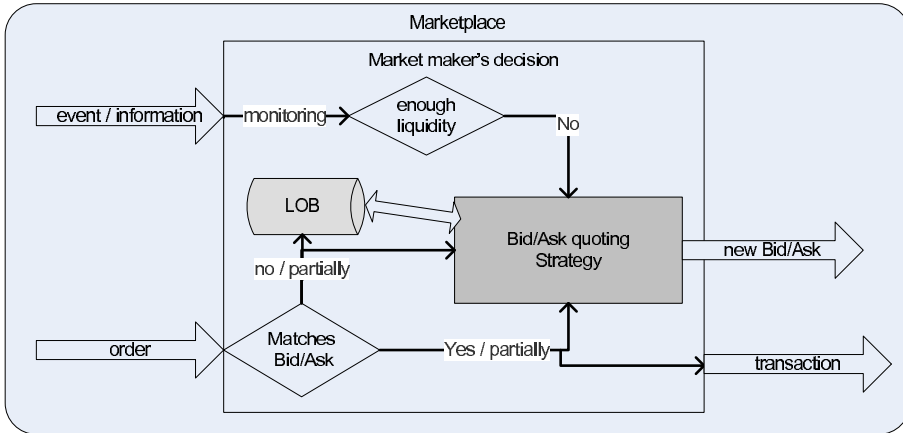
Figure 4.4: The behavior of market makers.

Additionally, other considerations, like their belief that current quotes do not reflect market conditions, can lead market makers to revise the bid and ask.

Market makers apply various strategies to set their bid and ask quotes. In order to allow for experiments with multiple market maker types, the skeleton of the market makers again does not provide a concrete solution to this decision problem, but an empty placeholder to be extended with user-defined strategies. Experiments with several market making algorithms can be conducted and compared in this way, such as bid-ask determination based on Bayesian learning as implemented by (Das, 2003), or based on position imbalance and a threshold like in (Chan and Shelton, 2001), or simply based on the content of the limit order book, like in KapSyn (Loistl and Vetter, 2000) or in continuous automated auctions. In fact order execution on automated continuous markets can be considered as a special bid-ask quoting strategy of a market maker.

4.4.2.3 Automated and equilibrium-based execution of orders

As we mentioned before, our primary aim is to represent continuous trading sessions. However, since call sessions occur as well in real life, and since many market models focus on call sessions, we emulate these type of markets as well.

In this last short section, we focus on the way equilibrium prices can be determined during call auctions. In the framework we allow this task to be carried out by market makers as well as a specific *auctioneer behavior*. Based on the study in Chapter 2 we define the generic auctioneer behavior of market maker as consisting of the following steps (Figure 4.5):

- collect orders during a call;

- determine the new equilibrium price based on the received orders;

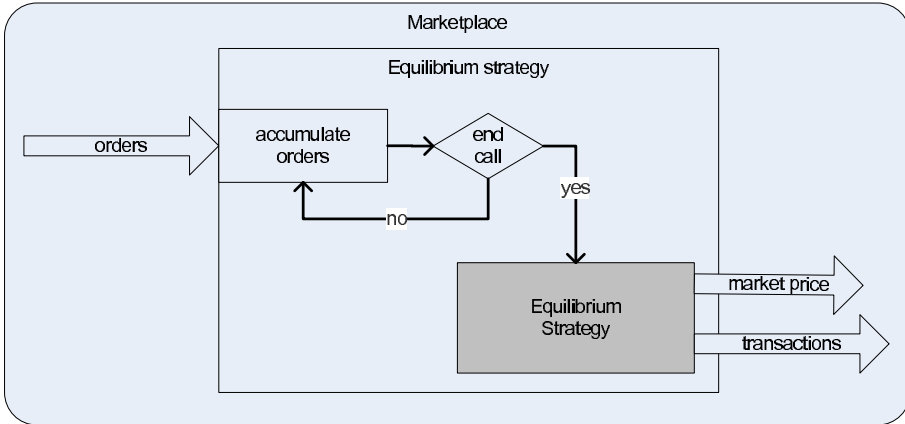- execute the orders that fit this price.

Figure 4.5: Price formation at equilibrium.

The strategy used for determining the equilibrium price varies from market to market. Often, it is not clear how it is solved in real markets. In the framework therefore, we again provide an empty placeholder for it, and we let implementations plugged in by users determine the final strategy. Consequently, experiments with several different strategies can be conducted, that can be, for example, the supply and demand intersection as implemented by Raberto et al. (2001) or Brock and Hommes (1998), the strategy based on excess demand like in (Chen and Yeh, 2001), or at highest volume, as determined in (Loistl and Vetter, 2000).

4.5 Implementing the ABSTRACTE environment

Note that the generic structure of market participants, described in the previous sections reflects the wide, system theoretic view of Russell and Norvig (2003), and the formalized view of Wooldridge (1999) on agents. Traders continuously sense their environment, make decisions based on some internal state, and act upon their environment. This view on market participants and the reasons described in Section 4.1 motivated us to use an agent-based framework to implement the trading environment.

In this section we give a backstage view on the introduced environment. First, we briefly present the agent-based environment in which ABSTRACTE is implemented and explain the basic notions used in it. These notions are important, as we often refer to them when describing our environment. Then, we describe how various components, especially agents, are implemented within ABSTRACTE, and how they interact. Finally, we illustrate the modularity of the environment by showing how a variety of strategies can be incorporated and configured on top of it in a flexible way.

4.5.1 The JADE environment

The agent-based environment on which ABSTRACTE is built on is JADE 3.4. JADE - Java Agent DEvelopment Framework is a framework to develop multi-agent systems in compliance with the FIPA specifications, an accepted standard definition of agent-based environments (Bellifemine et al., 2003; FIPA, 2007; Bellifemine et al., 2005).
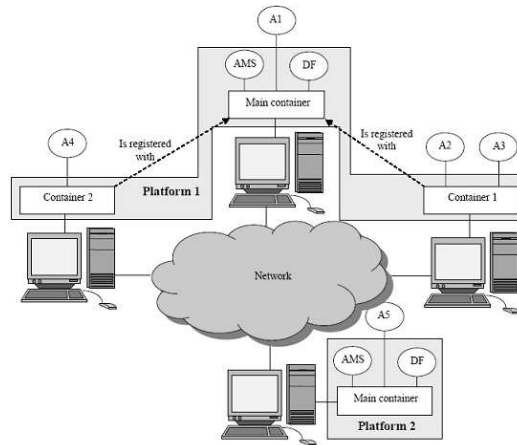

Figure 4.6: An example of JADE containers and platforms (Caire, 2003)[pg.05]

4.5.1.1 Containers and Platforms

Each running instance of the JADE runtime environment is called a **container**. A container can host several agents. A set of containers can form a **platform**. A single special **main container** must always be active in each platform. The first container to start in a platform must always be the main container. All other containers in this platform must be so-called normal (i.e. non-main) containers. Normal containers must register with the main container. In order to be able to do this the address of the main container (host and port) must be known to them.

In a network more main containers can be started. Every main container is part of a different platform to which new normal containers can possibly register. Figure 4.6 illustrates the above concepts through a sample scenario showing two JADE platforms composed of 3 and 1 container respectively. Agents A2 and A3 are on the same container. Agents A1 and
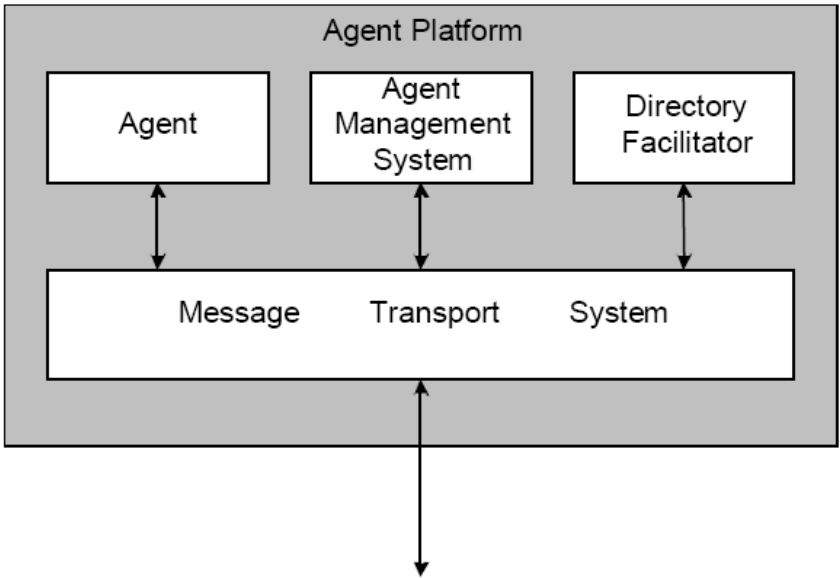
Figure 4.7: Reference architecture of a FIPA agent platform (Bellifemine et al., 2005)[pg.7]

A2 host on different containers, but the same platform, while agents A4 and A5 are part or different platforms.

JADE agents are identified by a unique name. Provided they know each others name, they can communicate transparently regardless of their actual location.

4.5.1.2 AMS and DF

On each main container two special agents are located, which are automatically started when the main container is launched (Figure 4.7):

- the **AMS** (Agent Management System) and

- the **DF** (Directory Facilitator).

The AMS provides a naming service. It ensures that each agent in the platform has a unique name. Further, it represents the authority in the platform: for instance it can create and kill agents on remote containers. The DF provides a Yellow Pages service, i.e. it registers the services that the various agents offer. Agents are allowed to publish one or more services in the DF. Through the DF an agent can find other agents which provide the services

he requires. Messages are exchanged through the Message Transport System, also called Agent Communication Channel (ACC). This software component controls all exchange of messages within the platform, also allowing messages to and from remote platforms.

4.5.1.3   Agents and Behaviors

In JADE, each agent is identified by an agent identifier, called **AID**. An AID object includes a globally unique name for each agent. The globally unique name consists of the agent's name and the name of the platform in which the agent lives. Within a platform agent names must be unique.

The job an agent has to do is typically carried out within behaviors. A **behavior** represents a task that an agent can carry out. In order to make an agent execute the task implemented by a behavior object it is sufficient to add the behavior to the agent. Behaviors can be added to an agent when it starts and within other behaviors.

An agent can execute several behaviors concurrently. Scheduling behaviors is not preemptive but cooperative. Therefore, it is the programmer who needs to define when an agent switches from the execution of a behavior to the execution of the next one.

Behaviors in JADE embed a status and execute different operations depending on that status. They complete when a given condition is met. There are some specific behaviors implemented in JADE, such as the one-shot behavior and the cyclic behavior. One-shot behaviors are executed only once. Cyclic behaviors are executed cyclically, they never complete.

Further, JADE provides the possibility of combining simple behaviors together to create complex behaviors. Complex behaviors include:

- Sequential behaviors; and

- Parallel behaviors.

Complex behaviors consist of sub-behaviors. As their name indicates, the sub-behaviors of a sequential behavior are executed in sequential order, while the sub-behaviors of a parallel behavior are executed concurrently. A complex behavior completes when all sub-behaviors are completed.

4.5.1.4   Agent communication

JADE agents communicate through asynchronous message passing. Each agent has a sort of mailbox (the agent message queue) where the JADE runtime posts messages sent by other agents. Whenever a message is posted in the message queue the receiving agent is notified. Processing messages from the message queue is the programmer's task. If and when the agent actually picks up the message from the message queue to process it is completely up to the programmer.

Messages exchanged by JADE agents must have a predefined format. The format used by JADE is the ACL (Agent Communication Language) language defined by the FIPA. This format comprises a number of fields, in particular:

- The sender of the message in the form of an AID.

- The AID's constituting the list of receivers.

- The communicative intention also called the performative. The performative indicates what the sender intends to achieve by sending the message. The performative can be:

    - REQUEST, if the sender wants the receiver to perform an action,

    - INFORM, if the sender wants the receiver to become aware of something,

    - QUERY_IF, if the sender wants to know whether or not a given condition holds,

    - CFP call for proposal,

    - PROPOSE, ACCEPT_PROPOSAL, REJECT_PROPOSAL, if the sender and receiver are engaged in a negotiation, and more.

- The content. This is in fact the actual information included in the message. It can describe the action to be performed in a REQUEST message, the information that the sender wants to disclose in an INFORM message, etc..

- The content language. The language of the content indicates the syntax used to express the content. In order to understand each other, both the sender and the receiver must be able to encode/parse expressions compliant to this syntax.

- The ontology. The ontology is the vocabulary of the symbols used in the content and their meaning. In order to communicate effectively the sender and the receiver must ascribe the same meaning to the same symbols for the communication.

- Control fields. Control fields are used to control concurrent conversations and to specify timeouts. Control fields might specify a conversation-id, or a requested keyword with which someone should reply to a given message. A conversation-id control field is used, for example, to give a unique identifier to the message. The sender of the message then expects an answer with the same conversation-id. Further, a sender might also fill in a keyword for a reply-with control field. In this case he considers an answer to this message a message with the same keyword in an in-reply-to control field. Finally, the reply-by control field informs the receiver of the message about the time until which the sender waits for an answer.

4.5.2   The architecture of the ABSTRACTE environment

The ABSTRACTE trading environment consists of two main applications, that are run separately on the same platform:

- the marketplace and

- the investorbuilder.

The *marketplace* is the component that models the market organization. This is the place where transactions take place and prices are formed. The marketplace application has to be started first, because this runs the main container. Market makers and broker agents host on this main container.

The *information source component* described in Section 4.2 is included into the marketplace application as well. In this way we can avoid some time-synchronization problems.

The *investorbuilder* application is created with the aim to host the investors. Investors, being not internal to a market, are implemented in a way to run separately from the marketplace itself. More than one investor-builder application can be running to interact with the same marketplace, making it possible to run the ABSTRACTE in a distributed way. When an investorbuilder application is launched, a new JADE container is created. This container is linked to the specified marketplace, that is already running.

4.5.2.1   The agents

Agents in the ABSTRACTE environment are all extensions of JADE agents. The JADE Agent class is the common superclass for user defined software agents. It provides methods to perform basic agent tasks, such as message passing, life cycle support including starting, suspending and killing an agent, and scheduling and execution of multiple concurrent activities.

We distinguish two classes of agents interacting within the marketplace and the investorbuilder applications:

- trader agents, and

- manager agents.

Trader agents represent the market participants. They all have a portfolio: the amount of cash that they have, and a list of stocks that they possess, the quantity for each of them, and, optionally, a value attached to each stock. Manager agents are introduced to control the market environment. They carry out tasks like keeping track of the time, creating and managing a given list of traders, generating information, diffusing information, acting as an intermediator between agents being hosted on the same or on different containers.

Taking into account the classification from Section 2.2.3 based on the role of market participants we implement three different trader agents:

- the *Investor*,

- the *Broker*, and

- the *MarketMaker*.

Among these trader agents the *Investor* is part of the investorbuilder application, while the rest is part of the marketplace.

In addition, there are a number of manager type of agents implemented, namely:

- the *InvestorManager*.

- the *MarketManager*,

- the *AgentManager*,

- the *NegotiationManager*,

- the *NewsManager*,

- the *TimeManager*.

The *InvestorManager* is part of the investorbuilder application, and the rest is introduced to manage the marketplace. Next we elaborate on the behavior of each of these agents one by one.

4.5.2.2 Trader agents

Trader agents are implementations of the *skeletons* presented in the previous sections. Thus, they do not contain a concrete implementation of a specific trading strategy, but *empty place-holders* to allow for experiments with varying strategies, as discussed in Section 4.4. Running samples of agents are therefore composed from two parts: a generic part that implements the skeleton, and a varying part that substitutes the empty placeholder.

In order to let strategies vary among traders, we apply the "strategy behavioral pattern" as described by Gamma et al. (1997) and Freeman et al. (2004). User-defined strategies are encapsulated in strategy classes, extending an abstract strategy class that is the aforementioned empty placeholder in the skeletons. Strategies and their attributes have to be declared and described in structured files (XML-files).

The main task of trader agents (i.e. market makers, brokers and investors) is executed through a main behavior. The main behavior of each agent is a cyclic listening behavior through which they continuously sense their environment. In addition every agent carries out role-dependent behavior. The role-dependent behavior of each agent is primarily event-driven and depends on the agents' specific settings.

- **The Investor**

    Investor agents implement the skeleton of investors described in Section 4.4. Their main behavior (*InvestorBehavior*) is to continuously listen to new information (see Figure 4.8). They perceive and interpret the news received based on their individual settings and strategy. Investor agents consider to place orders when news arrives, when they get notified of the execution of an earlier placed order, or a given time has elapsed. In all these cases the *OrderPlacingBehavior* is started. The way an *Investor* agent interprets the information received and the way he decides what kind of order to place, if at all, is not hard-coded within the ABSTRACTE but an empty placeholder indicates where that decision should be made. The empty placeholder is modeled by the *AbstractOrderQuotingStrategy*. The actual decision of an agent during a simulation depends on the concrete strategy applied on top of this placeholder. The generated orders are sent for execution to a market maker or a given broker.

    Investor agents as described above are implemented in a way to represent individual investors. Within ABSTRACTE it is also possible to run investors who continuously generate orders, ignoring answers to their order. This latter variant represents a group of investors, and can be useful if, for example we are not interested in individual investors' performance.
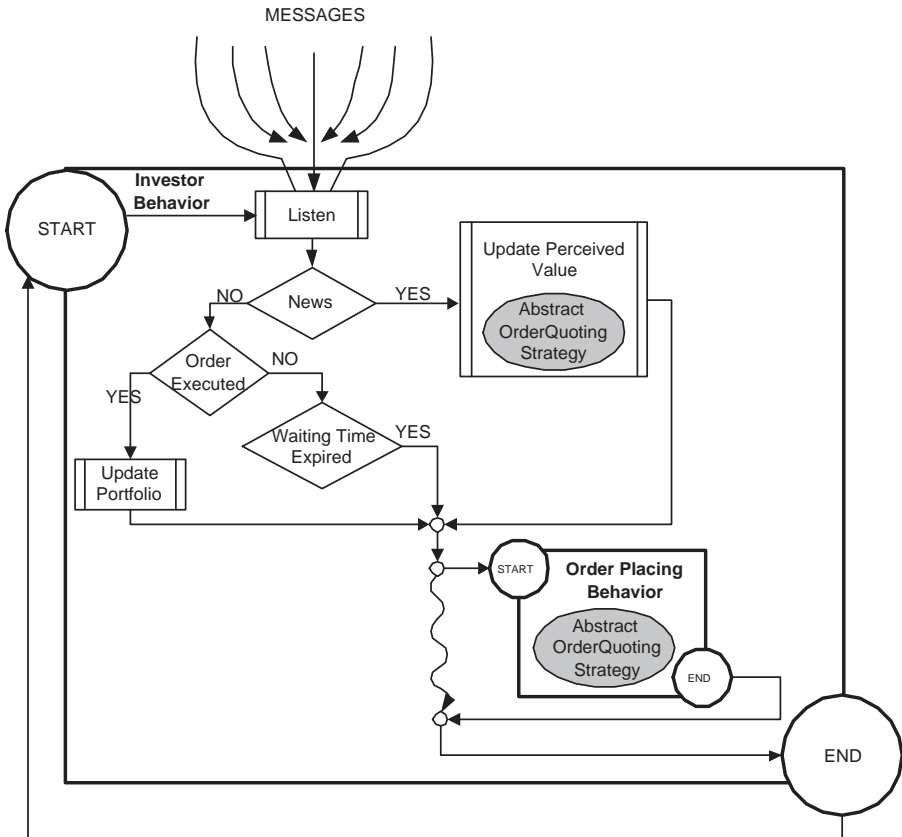
Figure 4.8: The behavior of an Investor agent

- **The Broker**

The *Broker* agent implements the brokers' skeleton described in Section 4.4. The main behavior of the *Broker* is the *BrokerBehavior*. This behavior continuously listens to messages and receives orders from the investors. New orders are put into an order book. If the order book is not empty the broker tries to fulfill the orders from it. The execution of orders is the task realized within the *TradingBehavior* of the Broker depicted by Figure 4.9. Brokers first determine the order that they will execute next. The selection of the order depends on the selection mechanism of brokers and on the current market conditions. For a flexible representation of brokers' behavior this process should thus not be hard-coded but represented by an empty placeholder.

If Broker agents are part of a market where the persistent double auction mechanism is applied (like on NYSE), they can try to negotiate. Negotiation is allowed only for prices between the bid-ask spread. Buy orders with a price that is lower than the bid and sell orders with a limit price higher than the ask are forwarded to the *MarketMaker*.

If negotiation is possible, the *NegotiationBehavior* is started. The design of this behavior is depicted by Figure 4.10. The aim of this task is to execute the selected order at an improved price. Within this the broker decides about the new price he would like to execute the order. He then compares his offer with the proposals (call outs) that are on the market. If the call out on the counter trading side suits his value he accepts it. It is the task of the *AcceptCallOutBehavior* to communicate the broker's decision towards the trading floor. The broker waits for a confirmation of transaction or refusal of his acceptance by invoking the *WaitForAnswerBehavior*. This behavior can end by either an answer or the expiration of the time the agent is willing to wait for an answer.

If the broker does not like the call out that would clear his order he tries to call out a better price than the call out that is on the same trading side (buy or sell) as his order. If he succeeds in this the *SendNewCallOutBehavior* is carried out to communicate the intention to other brokers via the trading floor. The broker waits again a given time for a reaction from other participants with the help of the *WaitForAnswerBehavior*.

In case the broker gets a positive answer to his call out a transaction takes place and the broker updates accordingly his order book and portfolio. This task is solved by the *HandleTransactionBehavior*. If the call out of the broker is overbidden he tries to determine a new call out. If he does not succeed to execute the order within a given time, the order will be sent to the market maker.

Just like the determination of an order for execution from a given order book, the determination of a call out prices is a process that is hardly observable and can take many forms depending on broker's preferences. Therefore, both the selection of an order and the determination of a new call out should be represented in a flexible way. This is possible again with hard coding only empty placeholders for these processes.

The *Broker* agent in the current version of the ABSTRACTE is not modular yet. The reason behind this is that we have not been interested in conducting experiments with brokers for the purpose of this thesis. Therefore, we have not implemented this type of trader agent yet for some time but have kept an earlier version of it. In this version the selection of orders is made according to the "first in first out" (FIFO) protocol. Further,
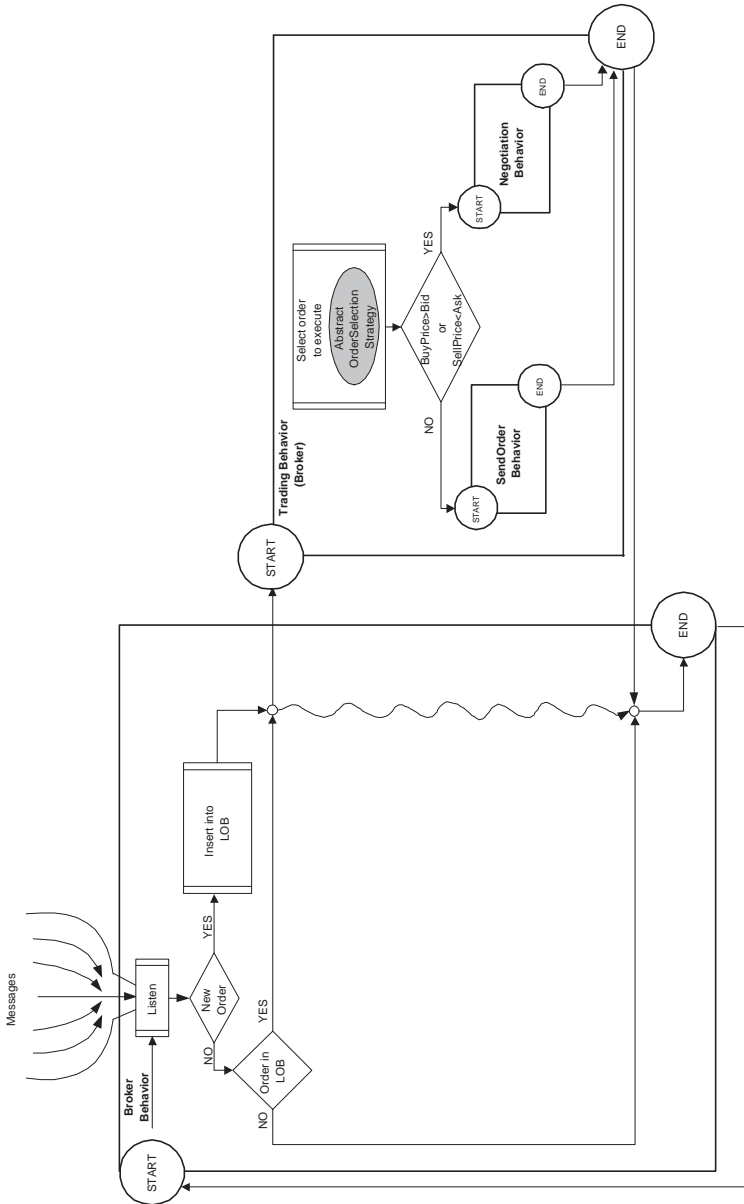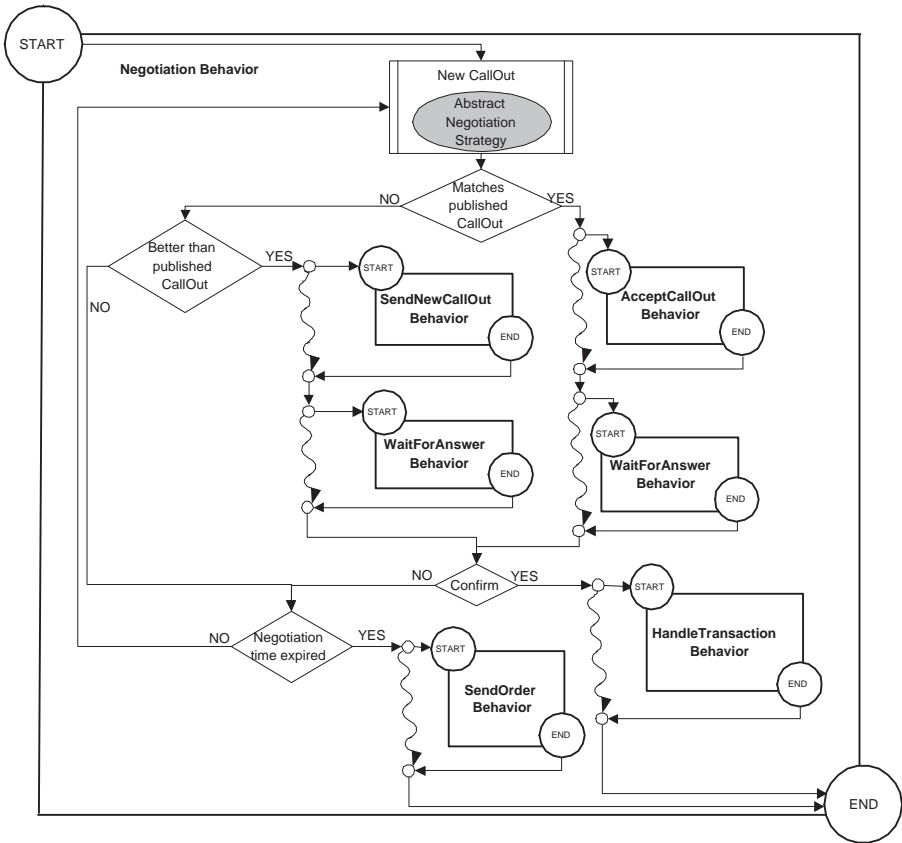
Figure 4.9: The behavior of a Broker agent

Figure 4.10: A possible negotiation process of a Broker agent

determination of a new call out is by a stepwise increase/decrease as a function of the limit price of the order to be executed, the bid and ask quotes, and the outstanding last call outs.

- **The MarketMaker**

  The *MarketMaker* implements the skeleton of the market maker as described in Section 4.4. Market maker agents are the first trader agents that are started. There is at least one market maker in every simulation. Automated execution systems can be modeled by a market maker as well. The specific execution mechanism will then fill in the empty placeholder.

  There are two different main behaviors implemented for the MarketMaker: the *MarketMakerBehavior*, and the *AuctioneerBehavior*. Which of them will be carried out depends on the trading session modeled. During continuous sessions the $MarketMakerBehavior$ is started, on call sessions the $AuctioneerBehavior$ is carried out.

  In Figure 4.11 the $AuctioneerBehavior$ is depicted. The main task within this behavior is to wait for "call" signs. The market maker accumulates within this behavior the orders sent by investors. He stops accumulating orders at the end of a call. Then, he tries to arrange trades based on the applied execution system. The actual execution system fills in the empty placeholder modeled by the *AbstractAuctioneerStrategy* sustained for this reason in the skeleton of the market maker. The market maker publishes all the possible trades and notifies the involved traders about the transactions.
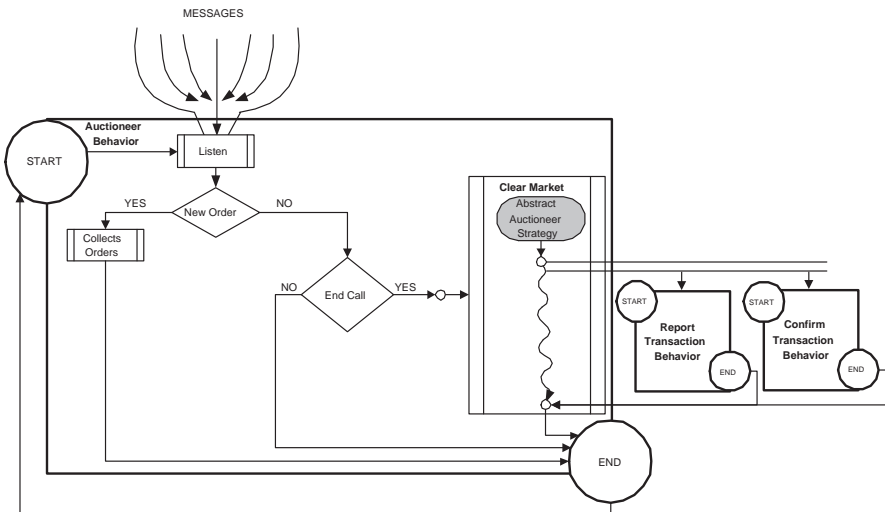

Figure 4.11: Order processing by MarketMaker during call sessions

Figure 4.12 illustrates the order processing behavior of the market maker in continuous markets. In this case the main behavior of the market maker is the *MarketMakerBehavior* which is again cyclic. This behavior is started after the bid and ask quotes are initialized. The value of these depends on the applied bid-ask quoting strategy to be filled in on an empty placeholder, determined during configuration time. After initialization the $MarketMakerBehavior$ starts to receive and handle orders. When a new order is arrived, the *OrderMatchingBehavior* is started. This behavior tries to match the order with the currently standing quote on the appropriate side: sell orders with bid quotes, and buy orders with ask quotes.

If the order can be traded with the quote, the *MakeDealBehavior* of the market maker is started, as a sub-behavior of the *OrderMatchingBehavior*. The task of this sub-behavior is to fill the order with the quote. As soon as the transaction is made, two sub-behaviors are added to this latter behavior, that are executed in parallel way (indicated with parallel lines in the figure). The *PublishTransactionBehavior* is used to report the transaction, while the task of the *ConfirmTransactionBehavior* is to notify the agents involved in the trading arrangement that their order has been filled. This behavior sends the details of the arrangement to the initiators of the orders. Finally, it is the task of the *MakeDealBehavior* to update the content of the limit order book. This is necessary if, for example, the quotes used for arranging a trade, represented orders from the limit order book. This task is completed by the *UpdateLOBBehavior*.

When the *MakeDealBehavior* ends, the *UpdateBidAskBehavior* is activated as a sub-behavior of the *OrderMatchingBehavior*. This behavior takes care to determine the new bid and ask quotes. As the way bid and ask quotes are determined is a hardly observable aspect of real markets, and there are many possibilities to determine them, this mechanism is not hard-coded but represented by an empty placeholder that is implemented by the *AbstractBidAskQuotingStrategy* class. Notice that a similar arrangement is implemented in the *UpdateLOBBehavior* discussed earlier, as this behavior is hardly observable in reality as well, and it might be realized and implemented in different ways.

If only part of the order could be filled, the *OrderMatchingBehavior* is restarted. If the received order doesn't match the quote on the appropriate side, it is inserted into the limit order book and the *UpdateLOBBehavior* is started. Similar to the situation after transactions, after the modification of the LOB, the MarketMaker revisits its *UpdateBidAskBehavior* in order to adapt bid and ask quotes to the changing situation. In order to ensure liquidity the market maker also considers adapting bid and ask quotes if no orders arrive for a while. In such a case again, the *UpdateBidAskBehavior* is started, which applies the specified extension of the *AbstractBidAskQuotingStrategy*.

Figure 4.12: Order processing by MarketMaker on continuous quote-driven markets

4.5.2.3 Manager agents

- **The InvestorManager**

  The $InvestorManager$ agent is part of the investor-builder application. It is responsible for managing a list of investors. Its main role is to solve the interaction between a marketplace and the investors it manages within this investor-builder application.

- **The MarketManager**

  The $MarketManager$ agent is the main authority that controls the market. It is the agent that takes care to open and close the market. It is responsible for the relation between the marketplace and the investor-builder applications. It receives requests of $InvestorManager$ agents who act on behalf of investors who want to join the market. Furthermore, it notifies the agents if the market needs to be closed.

- **The AgentManager**

  The AgentManager agent has control over the agents that represent financial traders. Its main task is to manage a list of various MarketMaker agents and a list of different BrokerAgents. It is the agent who creates the financial agents, and through which the created agents can be notified about events related to market organization, such as opening or closing of a market.

- **The NegotiationManager**

  The $NegotiationManager$ agent represents the negotiation floor where $Broker$ agents negotiate. Negotiation floors are the places where continuous double auctions are conducted. This agent controls negotiations, playing a sort of intermediary role between brokers. It publishes bids and offers, if those are better then previous call-outs, and rejects quotes placed earlier that are overbidden. Finally, it takes care to conduct and publish transactions if an agreement has been made (see Figure 4.13).

- **The TimeManager** The *TimeManager* agent keeps track of time. It notifies other agents when a call auction starts and ends.

- **The NewsManager**

  The *NewsManager* represents the information-source component. This agent is started immediately after launching the marketplace, and it generates fundamental value related information. Agents interested in new fundamental values need to subscribe to a "news-list". The NewsManager agent sends new information to all agents who require it (i.e. are subscribed). Currently this agent is part of the marketplace application. We plan to implement the information source component as a separate application in the future so that it can represent information external to the market and can have influence on multiple markets.
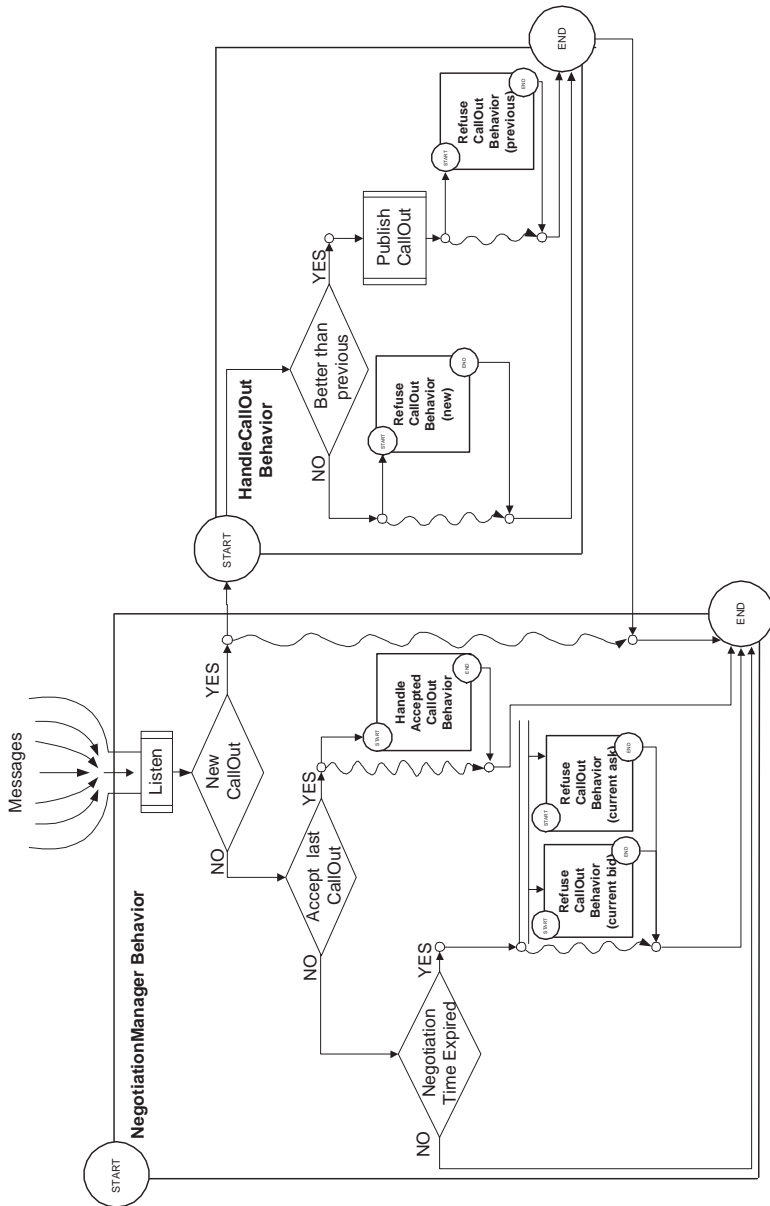
Figure 4.13: Processes on the trading floor where negotiation takes place

4.5.3 Agent interactions in ABSTRACTE

In this section we illustrate how agents within ABSTRACTE interact with each other. Describing all details behind communication and all relations between agents goes beyond the scope of this thesis. Here we aim to provide an overview on how communication takes place. For this reason, we first depict the main relationships between the various agents. Then, we describe how messages are exchanged between some of the agents. Finally, we illustrate the content of messages through two examples.

4.5.3.1 Relationships between the agents

The most important relationships that hold between the various agents is depicted by Figure 4.14. The *MarketManager* agent is in the midpoint of this figure, illustrating its central role. The *MarketMaker* agent creates the *AgentManager* agent, who in its turn, creates and manages the required financial trader agents, namely the *MarketMaker* agents and the Broker agents. The *AgentManager* also creates the *NegotiationManager* with the help of which broker agents can negotiate.
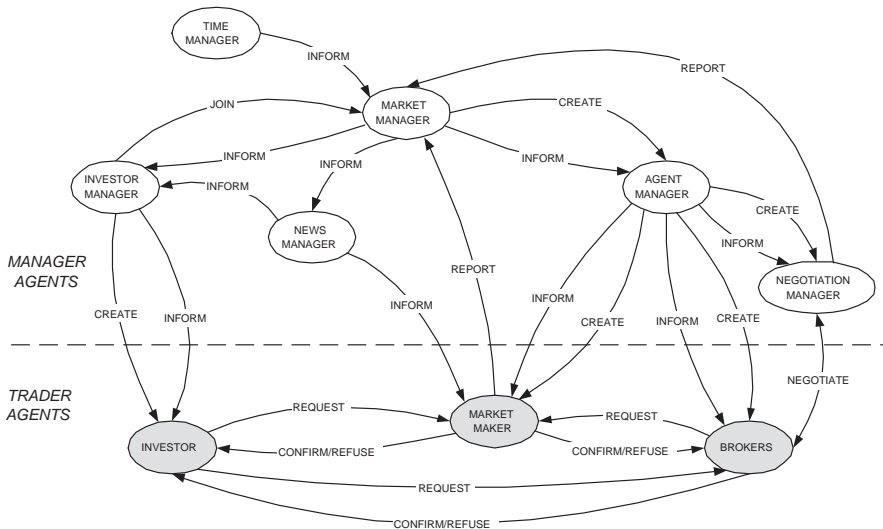

Figure 4.14: The relation between the agents in ABSTRACTE

When an investorbuilder application is launched, a newly created *InvestorManager* joins the marketplace and creates the required *Investor* agents. Investors send order requests to the *MarketMaker* agents and the *Broker* agents. Those in turn, confirm or refuse the execution of the requested order.

The *MarketMaker* agents publish trading arrangements reporting to the *MarketManager*. The *MarketManager* forwards the information towards all interested *InvestorManagers*.

The *NewsManager* agent generates fundamental value related news, and sends this information to agents (e.g. *InvestorManager* agents) who are subscribed to the news list. It also notifies the market makers that there is news. The *TimeManager* informs the *Market-Manager* about the development of the time when relevant events need to be planned, such as a call that should begin or end, or when it is time to close the market. The *AgentManager*, *InvestorManager* and *NewsManager* is notified by the *MarketManager* about these events. The other agents are notified by the manager agent that created them.
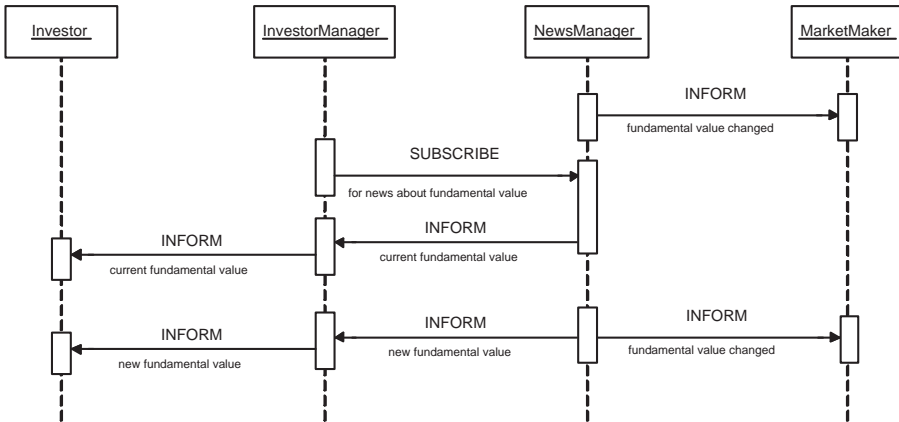

Figure 4.15: The dissemination of fundamental information

4.5.3.2 Message flows

In this subsection we illustrate how some of the agents communicate with each other.

The dissemination of the fundamental value. Figure 4.15 depicts how information regarding the fundamental is sent towards market participants. Agents who are willing to receive this information should subscribe for news at the *NewsManager*. If required by the model, the *NewsManager* agent can notify the market makers any time the fundamental value changes. After an *InvestorManager* agent is created, he subscribes to the *NewsManager* to receive fundamental information. The *NewsManager* confirms the subscription by sending the current fundamental value to the market maker. *InvestorManagers* forward the information to the informed traders on the market.

The dissemination of market information. Investors receive fundamental information from the *NewsManager* and market information from the *MarketManager*. As Figure 4.16 illustrates whenever the market price or the bid-ask quote changes on the market, the *MarketMaker* agent informs the *MarketManager*, which in turn informs *InvestorManagers*. *InvestorManagers* publish the information on a "blackboard" so that all investors that they manage have access to this publicly available set of information.
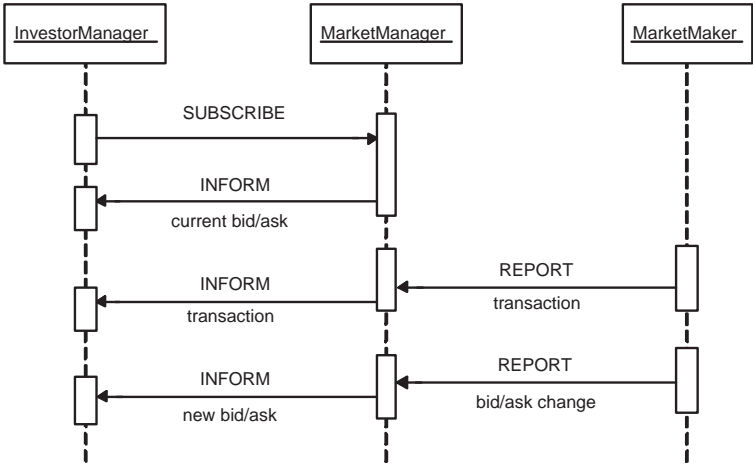

Figure 4.16: The dissemination of market information

The communication process of brokers. Figure 4.17 depicts how brokers communicate with the *NegotiationManager* when they try to negotiate. They call out bids and offers for this reason and send the call-out to the *NegotiationManager*. Call-outs are refused if better bids or offers are made by other agents, or if they are not valid, when placed (i.e. they are at a worse price than outstanding call-outs). Call-outs can be accepted by other brokers who think the bid or offer is advantageous to them. All bids and offers are controlled by the *NegotiationManager*, who acts as an intermediary between brokers, and takes care of the transactions. When a Broker accepts a call-out or his call-out is accepted, the *NegotiationManager* confirms the details of the trading arrangement to the involved brokers, and reports the transaction to the *MarketManager*. If the broker cannot fulfill an order received by an investor at a price between the bid-ask spread, he forwards the request to the *MarketMaker*, who will take care of the order and communicate itself with the *Broker* who initiated the order from then on.
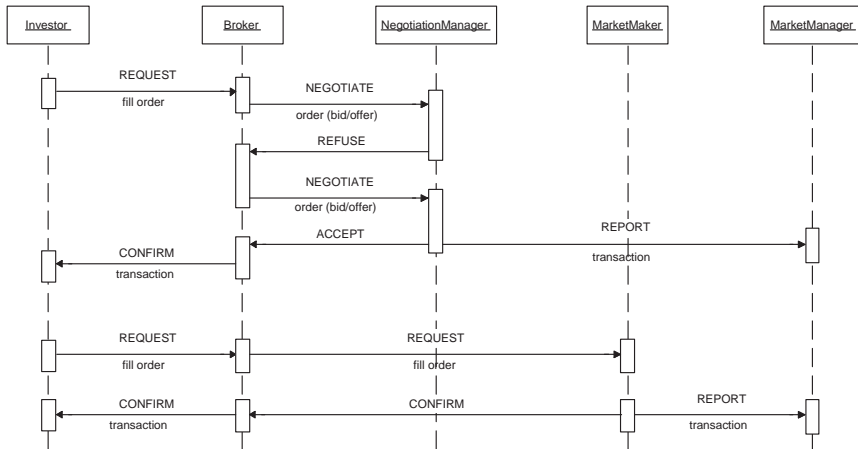
Figure 4.17: Communication process of a Broker agent

4.5.3.3 Messages

As pointed out in Section 4.5.1.4 the format of messages exchanged between JADE agents is based on the ACL language defined by FIPA. We illustrate this format through two examples. The first example is a request sent by an investor to a market maker to execute a given order. The second example contains the reply of the market maker to this request.

Sample buy-order   The message that expresses an order placed by an investor has the following form:

```
(REQUEST
   :sender
      (agent-identifier
          :name                      Investor1_mycomputer@mycomputer:1099/JADE
          :addresses                 (sequence http://mycomputer:7778/acc
                                     http://mycomputer:1931/acc )
          :X-JADE-agent-classname    investorbuilder.agents.investors.Investor)
   :receiver
      (set ( agent-identifier
          :name                      MarketMaker_mycomputer@mycomputer:1099/JADE ))
   :content
      "(action (agent-identifier
          :name                      Investor1_mycomputer@mycomputer:1099/JADE
          :addresses                 (sequence http://mycomputer:7778/acc
                                     http://mycomputer:1931/acc )
          (FILLORDER
             :TRADER                 Investor1_mycomputer
             :ORDER (ORDER
                 :ORDERID            "3"
                 :STOCK (STOCK
                     :NAME           ABC
                     :AMOUNT         100
                     :PRICE          76.10)
                 :SIDE               BUY)
             :TIMESTAMP              1155853195968)))"
   :language fipa-sl
   :ontology Market_ontology )
```

The message begins with a communicative intention, also called performative. The communicative intention of the investor is a "REQUEST", expressing that the investor requires the market maker to perform an action. The intention is followed by information about the sender. This information includes the unique name of the investor, the address where it hosts together with its communication channels, and the name of the class this agent is an instance of. Each sender needs to indicate to whom he wants to send the message, therefore, the message also contains the unique name of the receiver. This is the part from which the agent communication channel (ACC) can find out to which agent to route the message.

Next, the content of the message is specified. Since the performative is a request, the content needs to be a description of an action. For an action, the name and address of the agent who initiated the task is again given. Then, the real content follows. In this sample, the action that the investor wants to be carried out is the execution of an order. The "FILLORDER" action contains data about the agent's identity who places this order, the details of the order and the time at which the order is placed. Each order of an agent has a unique identifier. An order is given for a certain stock and quantity. In the sample above, the limit price is also specified, for market orders this value is set to 0. Finally, the trading side is given, in this case being a buy order.

The syntax of this content corresponds to the so-called fipa-sl language. The symbols used in the content need to correspond to a predefined vocabulary (i.e. ontology). The FILLORDER, ORDER and STOCK objects must, therefore, be predefined and added to the ontology used. The vocabulary of the ABSTRACTE is determined by the Market_ontology class. FILLORDER needs to extend the JADE Action class.

Sample confirmed transaction   The second example contains the answer of the market maker to the investor's request. In this case the market maker confirms a partial fulfillment of an order.

```
(CONFIRM
   :sender
      (agent-identifier
         :name                    MarketMaker_mycomputer@mycomputer:1099/JADE
         :addresses               (sequence http://mycomputer:7778/acc
                                  http://mycomputer:1931/acc )
         :X-JADE-agent-classname  marketplace.agents.marketmakers.MarketMaker )
   :receiver
      (set ( agent-identifier
         :name                    Investor1_mycomputer@mycomputer:1099/JADE ) )
   :content
      "((TRANSACTION
            (STOCK
                  :NAME      ABC
                  :AMOUNT    80
                  :PRICE     75.96)
            (SIGNATURE
                  :BUYER      Investor1_mycomputer
                  :SELLER     MarketMaker_mycomputer
                  :PLACE      MarketMaker
                  :TIMESTAMP  1155853195968)))"
   :in-reply-to   "3"
   :language      fipa-sl
   :ontology      Market_ontology )
```

123

This message looks very similar to the previous one. It contains similar fields, the sender being now the market maker and the receiver the investor. The content in this case is not an action, but a predicate. The type of the content depends on the performative, which is here "CONFIRM", a reply. The TRANSACTION and SIGNATURE structures again need to be defined as part of the Market_ontology. There is one additional field compared to the previously presented example. The "in-reply-to" field contains the identifier of the order which has been executed. If an investor has sent more orders, he will know, by looking at this attribute, for which of his orders he has obtained an answer.

4.5.4 Implementing ASMs and traders on top of the trading environment

So far we have described the ABSTRACTE trading environment based on the framework proposed in Chapter 2 which allows the experimenter to implement his own choice of important structural and dynamical aspects of stock markets and artificial stock markets. In this section we present how these various market structures and strategies can be configured in a flexible way on top of the proposed trading environment. ABSTRACTE is not a specific stand alone ASM, but just the skeletal structure of a trading environment. Within this environment the structural place of the varying organizational aspects and strategies is well-defined by means of strategy patterns (empty placeholders). Their content however is not specified. In order to be able to conduct experiments, organizational aspects and strategies have to be configured on top of the framework by completing and giving meaning to these empty placeholders. New strategies can be created by extending the empty placeholders and can be configured in a flexible way, without a need to change the framework. The various strategies can have a different number and type of parameters.

Figure 4.18 illustrates how an agent is configured. The components *The Skeleton of an Agent*, *Agent Manager*, and *Configuration* are part of the trading environment. The representation of the various strategies does not have to be part of the framework itself. They just have to be designed and implemented taking into account the strategy patterns (empty-placeholders) within the agents' skeleton. A configuration part is used to specify which implementations of a certain strategy exist, and where can they be found. Here the strategies and the related parameters can be registered and initialized uniformly based on a predefined descriptive structure.

In case someone would like to experiment with a new strategy the following steps need to be taken:

- implement the new strategy on top of the strategy pattern, i.e. by taking into account the properties of the empty placeholder in place of which this strategy will be applied;

- register the new strategy (i.e. describe its name, location and parameters) within the configuration component that belongs to the application or within a similar configuration file;

- specify which configuration files should be read for the experiment that is planned, specify the participants and the assigned strategy for each of them.
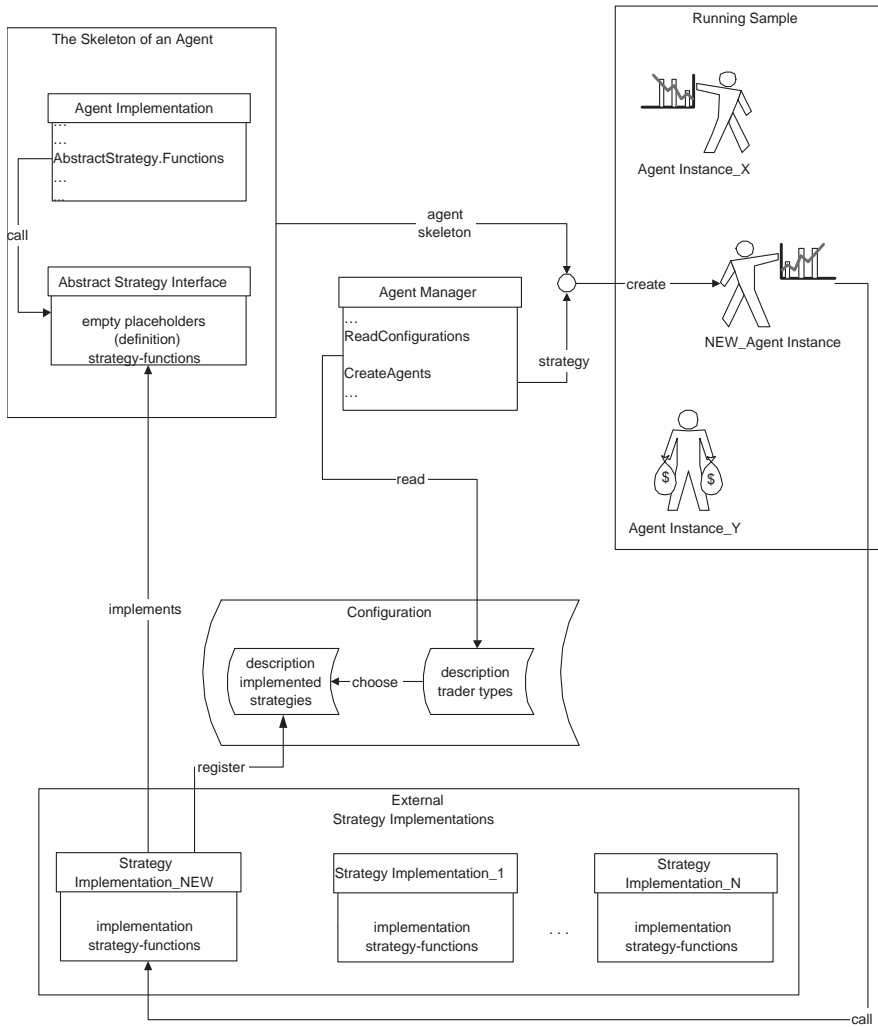
Figure 4.18: Sample skeleton with implemented strategies.

At configuration time the concrete strategy that is specified in the used configuration file is linked to the skeleton. Consequently, during the simulation run the appropriate strategy will fill in the empty placeholder.

4.6 Evaluation

The aim of this section is to illustrate the modularity of the ABSTRACTE trading environment, namely to indicate to what extent it is able to support experiments with various market organizations and market participants. For this reason, we present experiments with two artificial stock markets implemented on top of the ABSTRACTE. These ASMs implement in different ways the hardly observable aspects behind the price formation and the trading behavior of participants. They differ mainly with respect to the trading session applied and the execution system used, and with respect to the strategy behind the market maker's decisions.

In this section we describe these experiments and compare their dynamics and results. Through the experiments, we aim to test the adequacy of the trading environment, that is to test whether it functions correctly, i.e. as expected. It should be noted however that, since the ABSTRACTE is an environment to support the design of multiple market organizations and trading strategies, its correctness can only be evaluated in relation to the markets that are simulated. Next, we say a few words about evaluation in general and then we present the experiments.

4.6.1 Validation, verification and testing

By evaluation of the ABSTRACTE environment we mean "testing its accuracy" in relation to the markets that are simulated. It is important to distinguish between validation of a model, verification of a model, and testing a model.

In order to understand this terminology we adopt the definitions by Balci (1998)[336]:

- "*Model verification* is substantiating that the model is transformed from one form into another, as intended, with sufficient accuracy. Model verification deals with building the model *right*."

- "*Model validation* is substantiating that within its domain of applicability, the model behaves with satisfactory accuracy consistent with the study objectives. Model validation deals with building the *right* model."

- "*Model testing* is ascertaining whether inaccuracies or errors exist in the model. In model testing, the model is subjected to test data or test cases to determine if it functions properly. (...) [T]esting is conducted to perform either validation or verification or both. Some tests are devised to evaluate the behavioral accuracy (i.e, validity) of the model, and some tests are intended to judge the accuracy of model transformation into one form or another (verification)."

Evaluation of the ABSTRACTE environment is two-fold. We want "to build the right model" when representing reality, i.e. real markets. And, in case of replicating existing models, we want to build the represented market model right. While validation against

reality is very difficult if part of reality is hardly observable, verification against an already built model is easier. It can be compared, for example, whether both models generate the same output given the same input, if it is about deterministic environments. Otherwise, in stochastic environments the statistical properties of the results should be similar. If not, at least one of the implementations is not correct. Verification difficulties often arise from the fact that the details and/or settings of the model that one wants to replicate are not completely disclosed.

The difficulty to verify and validate market models arises from the complexity of the reality that they model, and from the hardly observable aspects that are part of this reality. Market environments contain many parameters that can influence the market dynamics, and many aspects of real markets are hardly observable if at all. Consequently, simplifications and abstractions are needed in models, and assumptions cannot be avoided. The main question that market modelers face is: how is it possible to test whether a model appropriately reflects and explains reality if parts of this reality are not observable?

A number of questions arise in relation to this issue:

- In which measure should a model reflect reality?

- In which measure should a model reflect reality so as to give new insights into its dynamics?

- When can we say that its accuracy is satisfactory, consistent with the study objectives?

- How can we judge whether it is consistent with the objectives if parts of the modeled system are not observable?

- Is the model's explanatory or predictive power more important than its conformance to reality?

- What is the trade-off between realistic features of a model and its explanatory power?

In order to analyze to what degree a model conforms to reality, calibration can be applied (testing, fitting real data to the model) and experimental results concerning traders' behavior can be implemented (LeBaron, 2006). Given that part of reality is not observable, calibration in ASMs is often possible only with respect to the statistical properties of empirical data, and not the data itself.

In order to test the accuracy of the ABSTRACTE environment and the ASMs on top of it, we first conduct functional *testing*. Functional testing is applied by providing inputs (test data) to the model and evaluating the corresponding outputs (Balci, 1998). Then, we analyze the properties of the time-series generated. We compare the results to predictions of theoretical models, findings of empirical studies, and experimental studies carried out with ASMs based on similar market organization. We mainly look whether the ASMs are efficient, in the sense that we investigate whether time series are random, and whether some persistent patterns can be observed.

4.6.2 Experimental settings

The ASMs presented here are very simple models. When deciding about the organizational and behavioral aspects of these ASMs we have chosen for simple representations. The reason is that the aim of this chapter is to illustrate the modularity of the introduced environment. In this section, therefore, we do not aim to study and give new insights into market dynamics, but we want to test and show the accuracy of the proposed environment. Simple models suffice for this reason. A case study designed for studying market dynamics in a specific ASM (which is again configured on top of the ABSTRACTE) is presented in Chapter 5.

4.6.2.1 The ASMs studied

In order to illustrate the modularity of the ABSTRACTE environment we consider an ASM with continuous trading sessions and an ASM with call trading sessions see (Table 4.1). By definition the behavior of the market makers in these trading sessions is also different. The two models focused on are:

1. the Roll market model; and

2. a call auction model.

The first ASM we have conducted experiments with, is based on the model introduced by Roll, as described in (Campbell et al., 1997). The reason why we have chosen for this model, is that it is analytically tractable. This means that the properties of the generated price series can be analytically deduced and compared to the properties of the simulated results. Consequently, we can use this model to evaluate the environment.

As a second case a simple call auction type of market is represented. In this model price is formed at discrete points in time, as opposed to continuous trading. Through this example we aim to show that within our environment experiments with call-auctions can be conducted as well. This suggests that experiments of other ASMs from the literature featuring call sessions can be replicated.

Table 4.1: The illustrated market models

Model	Organizational aspects			Behavioral aspects	
	Order	Trading Session	Execution System	Order Placement Strategy Investor	Order Execution Strategy Market Maker
Roll	market	continuous	quote-driven	random	fundamental value $\pm$ spread
Call	limit	call	price-driven	random	intersection supply-demand

4.6.2.2 Organizational aspects

- **Stocks, orders, quotes and market participants**

    In all experiments described here, one risky stock is traded, and sufficient cash supplies are available. In the first ASM, fundamental values are generated.

    A single, representative investor agent is used to model many investors[1]. Investors place market orders in the first model, in the second model they place limit orders.

---

[1]In Chapter 5 we present a case study in which more investors are individually represented.

In both implementations a market maker is responsible for the liquidity of the stocks and the execution of orders. In the first model, that is quote-driven, bids and offers are quoted by the market maker.

- **Trading sessions and execution systems**

We present experiments both in continuous and call trading sessions. In the first model trading sessions are continuous and the execution system is quote-driven, while in the second one call auctions are modeled.

By focusing on continuous markets we aim to show that our trading environment is designed in a way to allow for experiments with these common, but rarely represented trading sessions. As mentioned before, the experiment with call auctions is presented to illustrate the possibility to configure multiple market structures within the introduced environment, and the possibility to replicate experiments of ASMs from the literature.

4.6.2.3 Price formation and behavioral aspects

- **Order placing by investors**

In line with the purpose of this section, the investors' trading strategy is similar in both models. Investor agents continuously place orders, their common investment strategy being in all cases random order generation. In case of the second model in which limit orders are generated, the limit price is pseudo-randomly generated, from a normal distribution around the last market price with a given standard deviation (that is usually set to 1). The side of an order is generated with an equal probability to be buy or sell. In the first experiment, the volume of orders and the quoted bid-ask volumes are set to 1 unit. In the second experiment, the number of shares offered or asked is a multiple of 100 and below 10000.

- **Price formation and the order execution behavior of the market makers**

While the order placing behavior of investors is similar, the order execution strategy of market makers differs within the two models. The market maker applies specific bid-ask quoting strategies during continuous sessions, and determines prices at equilibrium in the call auctions.

Market makers set the market price based on the orders they receive and the particular strategies implemented and plugged in on top of their skeleton. At the beginning of the experiments, there is an initial market price (P_0) given, set to 100.00. In case of the continuous market model, the market price is formed at the bid or ask quote of the market maker, depending on whether a sell or a buy order was matched against it. In case of the call model, the market prices are determined at equilibrium at the end of each call. The equilibrium point is at the intersection of supply and demand curves so as to maximize the trading volume.

4.6.2.4 Simulation runs

Within each market model we have conducted several rounds of experiments. For continuous market settings rounds were specified in terms of real time length, while for the call market settings in terms of the number of call auctions, a call lasting for varying time length in the different experiments. In case of continuous settings, rounds lasted for 5, 10, 15, 30 and 60 minutes in real time, while in call settings 1000 calls have been made, a call lasting for 1, 5 and 10 seconds respectively in real time through the different experiments.

The results turned out to be stable over time, in the sense that the dynamics were similar regardless of the length of the experiments. In call markets, given the preselected number of call auctions, 1000 market prices have been determined. The size of the time series generated in the continuous models varies from around 1500 (in 5-minute experiments) to around 30000 (in 1-hour experiments). In general 300-500 transactions have been carried out during a minute.

The number of transactions carried out depends on the computational speed of the computer used. It also depends on the time it takes the investor to place new orders. Further, it depends on the market structure, on the time it takes the market maker to handle orders, to set new bid and ask quotes in case of continuous markets, and to determine the equilibrium price in case of call markets. Given that the behavior of market maker is computationally more intricate than the investors' behavior, we delayed the investors' decision with 0.1 seconds in the continuous setting, i.e. we allowed them to place new orders only every 0.1 seconds. In doing so, we tried to avoid to overload the market makers with orders.

4.6.3 The Roll model

4.6.3.1 Model specific settings

The Roll model is a continuous quote-driven ASM. The market maker sets the bid and ask quotes at equal distance from the fundamental value (FV) he perceives. Accordingly, the bid price is set to $FV - s/2$, and the ask price to $FV + s/2$, where s is called the spread value. Investors are represented by a single investor agent, who continuously places market orders of size 1, with equal probability regarding the trading side. Market prices result from matching the orders to the quotes of the market maker.

We have conducted experiments with two different settings regarding the fundamental value:

1. a simple Roll model, with constant fundamental value; and

2. a general Roll model, with changing fundamental value.

In the first, simple Roll model, the fundamental value is fixed and does not change during the experiments. In the second, more general variant, the fundamental value changes randomly following a normal distribution with mean 100.00 and deviation 1.00. The market maker senses the changes regarding the fundamental value and adapts the bid-ask quotes accordingly. FV is, in both the simple Roll model and the general Roll model, initialized to 100.00, and the spread varies across experiments, taking a value of 0.50; 1.00 and 2.00.

4.6.3.2 Evaluation and results

In the analytical model of Roll that we aim to replicate, the bid-ask spread has an impact on the time series properties of the returns; a negative serial correlation arises. The explanation in the simplest case is that, if the fundamental price does not change, the bid and ask quotes will not change either, and as a consequence the measure of change between two consecutive market prices is either 0, or the spread, or the negative spread (0, s, or $-s$). As the bid and ask prices are fixed, there are never two consecutive increases or decreases in the price. It can be established analytically that the value of the correlation is independent of the spread and equals -0.50. It can further be shown that the general Roll model with changing fundamental value leads to similar properties. That is, even if the fundamental price changes, the serial correlation of returns is non positive, under the assumption that changes in the fundamental are serially uncorrelated and independent of the probability of the order side generated (Campbell et al., 1997).

Functional tests   A primary verification that we have conducted regarding the correctness of the implementation and the adequacy of the framework was functional testing. During testing we have inspected the generated orders and time series with respect to changes in prices and the autocorrelation of returns at lag 1.

- First, we have inspected the *consecutive changes in prices*. It turned out that indeed the return series based on the difference between the values of the transaction series contain only values of 0, s, and $-s$. In this sense the implementation is thus analytically correct.

- Then, based on the theoretical findings with respect to the Roll model, we analyzed the *autocorrelation of returns* generated by the experiments we have conducted with the implemented version of the Roll model. We have found that, indeed, in all the experiments the autocorrelation at lag 1 is close to -0.5 in case of the simple Roll model with constant fundamental value (see Table 4.2). More specifically, the value of autocorrelation is independent of the value of the spread, which we set to 0.50, 1.00 and 2.00 respectively. Further, the autocorrelation is negative, and even quite close to -0.5 in experiments conducted with changing fundamental values as well (see Table 4.3).

From functional testing we can conclude, that the findings with respect to price changes and autocorrelation are in accordance with the analytical predictions. This suggests that the environment functions correctly if we place the implementation of the Roll model as a form of bid-ask quoting strategy on top of it. We can thus state that we have built "the model right".

Other time series properties   So far, we have seen that the autocorrelation of return series at lag 1 is negative in Roll models. This finding is due to the impact of the bid-ask spread on the time series properties. There are other interesting properties of financial times series published in literature both in relation to the Roll model, as well as other theoretical, empirical and experimental findings. From all these we analyze the distribution of return series and we look whether volatility clusters are present.

Table 4.2: Roll model with constant fundamental value. AC stands for 'autocorrelation at lag 1'.

s	Length Experiments (minutes)	Nr. Transac-tions	AC Price	AC Return	AC Squared Return	Skewness Return Series	Kurtosis Return Series	Roll Measure
	5	2165	-0.03	-0.51	0.00	0.00	1.95	0.51
	10	4458	-0.03	-0.53	0.03	0.00	1.94	0.52
0.5	15	6735	-0.01	-0.51	0.01	0.00	1.98	0.51
	30	13887	0.00	-0.50	0.00	0.00	2.01	0.50
	60	26669	-0.01	-0.50	0.00	0.00	1.99	0.50
	5	2386	0.02	-0.50	0.03	0.00	2.04	0.99
	10	4649	0.02	-0.50	0.02	0.00	2.03	1.00
1.0	15	7389	0.01	-0.49	0.00	0.00	2.03	0.99
	30	13836	0.00	-0.49	-0.02	0.00	1.99	1.00
	60	28602	0.00	-0.51	0.01	0.00	2.00	1.01
	5	2179	-0.02	-0.53	0.05	0.00	1.96	2.08
	10	4331	-0.01	-0.51	0.01	0.00	1.98	2.03
2.0	15	6762	0.01	-0.50	0.00	0.00	2.02	1.98
	30	13689	0.01	-0.49	0.00	0.00	2.02	1.98
	60	27373	0.01	-0.50	0.01	0.00	2.01	1.99

Table 4.3: Roll model with changing fundamental value and spread $s = 1$.

s	Length Experiments (minutes)	Nr. Transac-tions	AC Price	AC Return	AC Squared Return	Skewness Return Series	Kurtosis Return Series	Roll Measure
	5	2320	0.02	-0.48	0.26	-0.04	2.86	2.22
	10	5136	0.00	-0.49	0.23	0.01	2.90	2.22
1.0	15	6573	-0.01	-0.52	0.28	0.00	3.04	2.28
	30	14193	0.01	-0.50	0.23	0.00	2.95	2.22
	60	26410	0.01	-0.50	0.24	0.01	2.95	2.22

- *Distribution*

  It is interesting to observe that the kurtosis of the returns is close to 3 in the experiments in which the fundamental value is changing. The skewness is close to 0 in all experiments (see Table 4.3). These values suggest that returns are almost normally distributed, which is also demonstrated by Figure 4.19. One of the reasons behind this phenomenon is probably the fact that the fundamental values, on which the bid and ask quotes are based, are generated randomly from a normal distribution.

- *Volatility clusters*

  It can be observed that the autocorrelation of the squared returns is close to 0.2 in the experiments where the fundamental value changes. Similar results are found by Alexander (2001, pg67) for empirical data. The explanation given for this phenomenon is that autocorrelation of squared returns could be the implication of volatility clusters. By analyzing the return series generated by our model, it seems indeed that returns of the same absolute size are generally not isolated, but occur in clusters of small size.

  Volatility clusters observed in the general model are possibly there by construction. The fundamental value is generated from a normal distribution, fundamental values are thus, in general close to the mean, and the price changes are relatively small. Every now and then the fundamental value might be chosen further away from the
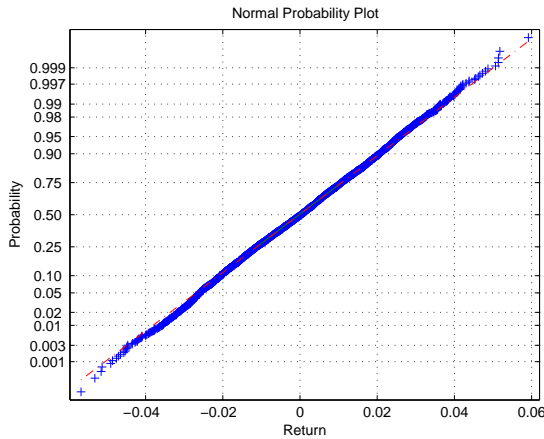
Figure 4.19: Example: normal probability plot of returns in the general Roll model.

mean, causing a higher return in absolute measure. If this is the case, most probably the next fundamental value will be again close to the mean, causing again a big relative change in prices, and thus autocorrelation of returns.

The accuracy of the Roll measure   Roll has also developed the so-called Roll measure to estimate the spread when quoted data are not available ($s = 2 * \sqrt[2]{-Cov\left[\Delta P_{t-1}, \Delta P_t\right]}$). Regarding the Roll measure we found that in the simple model, the estimated spread indeed equals the quoted spread, that is 0.5, 1, and 2 respectively. However, in the general model, this is not the case, the estimated spread being more than twice higher than the real spread, which is 1. The reason behind this phenomenon is that the estimated spread is deduced from the transactions. Transaction prices are quoted prices, quoted prices are determined in function of fundamental value. Transactions thus, depend in this case on a changing fundamental value. As the fundamental value changes every time, bid and ask quotes change continuously, and, thus, there is always a difference between the execution price of two consecutive transactions. The Roll estimate of the spread is thus, not an accurate measure of the transactions costs in this setting. This result is in accordance with empirical findings from the literature.

4.6.3.3   Discussion

In this subsection we have validated and verified the ABSTRACTE environment with the Roll model on top of it. Concluding, we can say that the joint test of the environment and the market maker's Roll model-based strategy proves their accuracy. We have additionally analyzed time series properties, and tested the accuracy of the Roll measure, and our findings

turned out to be in accordance with empirical findings from the literature.

About the efficiency of this market we can say that it is efficient by construction. Fundamental values are known, and they are immediately incorporated into the market prices as they change, because the market maker determines the price of bids and offers based on them. Although the assumptions of the model are not realistic, it illustrates that random walk and stylized facts do not exclude each other, i.e. volatility clusters might occur even ina random environment.

4.6.4 The call market model

4.6.4.1 Model specific settings

The second market structure represented is a call-market. In this case, an investor agent again represents the investors, and continuously generates random limit orders around the last market price. Market prices are set by the market maker, who collects during each call the orders sent by the investors and determines prices at the intersection of supply and demand curves so as to maximize trading volume.

4.6.4.2 Evaluation and results

Functional test   In order to test whether the environment with the single price call auction on top of it functions correctly, we have conducted again functional tests. During these tests we have looked at sample data from randomly selected call sessions, and checked whether market prices are set at equilibrium, and trading volume is maximized. The analysis suggests that the equilibrium algorithm of the market maker within the ABSTRACTE environment works correctly as expected.

Time series properties   In contrast to the Roll model in which some "regular" properties could have been observed, in call auctions with prices set at equilibrium from randomly generated orders, price series exhibit the "random walk" property (Table 4.4). In this model, there is a strong serial autocorrelation of prices, that follows from the fact that investors generate random orders around the last market price.

Further, the change in volume is negatively autocorrelated indicating that increases (decreases) in transaction volume are most often followed by decreases (increases) in it. This phenomenon, as well as the values of the rest of the statistical data suggests that prices determined in this way follow a random walk (Figure 4.20). This is to be expected, as orders are randomly generated, too.

Table 4.4: Experimental results in the call market model.

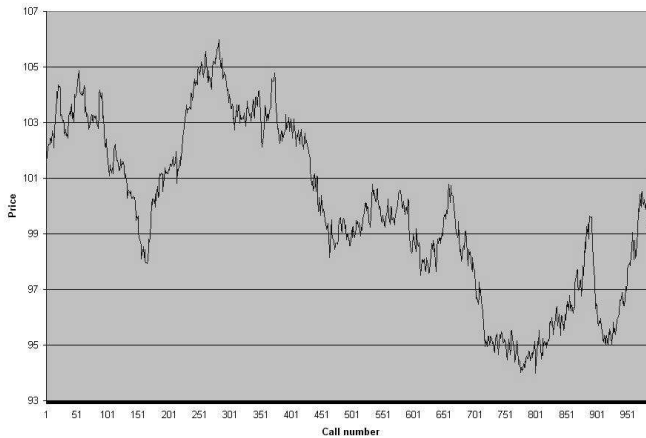| Length call (seconds)	Orders Executed/ Call	Average Volume/ Transaction	AC Price	AC Return	AC Squared Return	Skewness Return Series	Kurtosis Return Series	AC Volume	AC Change in Volume
1	22	6851	0.998	0.00	0.01	0.10	3.38	-0.02	-0.52
5	120	38670	0.997	0.03	-0.01	-0.15	3.12	0.03	-0.47
10	240	75451	0.998	0.03	0.06	0.02	2.89	-0.02	-0.51

Figure 4.20: Example: Price dynamics over call sessions, a session lasting 1 second.

The results seem to be independent of the length of calls, except for the transaction volume of course, given that during longer transactions more orders are received and matched. Given the computationally complex task of the market maker compared to the behavior of investors, we have analyzed whether there is a delay between placing and processing orders, and it turned out that this problem does not exist: orders are always processed immediately by the market maker.

The market models presented above are aimed to illustrate the flexibility stemming from the modularity of the ABSTRACTE trading environment, showing the possibility to represent multiple market structures with the help of it. Many other strategies can be represented in ABSTRACTE.

Comparing the results obtained by experimenting within different market settings one can conclude, that as expected, market organizations influence to a high degree market dynamics. The question is what these dynamics are, and how they differ once we introduce more precise market settings that represent real markets more realistically and in more detail.

We would like to emphasize that in this chapter we aimed to present the trading environment that we have designed and developed, and illustrate what it can offer as compared to ASMs in the literature. As a consequence, for the purpose of this chapter we do not focus here on more intricate experiments. However, our long term aim with the trading environment, as pointed out by the way it is designed, is to conduct experiments in more realistic,

and thus, more intricate, market settings.

In the next chapter we analyze market dynamics within a more complex market model, namely an extended version of the Glosten and Milgrom information model. To round off this chapter we discuss the added value of the ABSTRACTE environment.

4.7 The added value of the ABSTRACTE environment

In this chapter we have described the ABSTRACTE trading environment, the design of which is based on the conceptual framework proposed in Chapter 2 and on the analysis of ASMs in Chapter 3. The question we aim to answer in this section is, what the added value is of the environment presented here. Some of the properties of the ABSTRACTE are also characteristics of other ASMs. In ABSTRACTE we aim to keep the good aspects of existing ASMs (like the agent-based approach) and we try to repair the shortcomings that we sense. The main properties that we discuss can be deduced from the description of the environment given previously in this chapter and from the case studies presented above. Moreover, they are further emphasized by the case study presented in the next chapter.

- **Agent-based approach**

  The main approach applied to design and implement the ABSTRACTE environment is the agent-based computational (ACE) approach. We have chosen for the ACE approach because in this way emergent properties of market dynamics from individual interactions can be studied. Agent-based systems are accurate tools to study complex dynamic systems, like stock markets. Within agent-based computational economics (ACE), artificial stock markets (ASM) are studied extensively to assess how global regularities arise from individual interactions of market participants (Tesfatsion, 2001). Usually, individuals are represented by (software) agents interacting in an artificial environment. By using agents for studying market dynamics, heterogeneous, boundedly rational, and adaptive behavior of market participants can be represented and its impact on market dynamics can be assessed.

- **Special attention paid to various trader-roles**

  Unlike most ASMs which mainly focus only on investors, or even just provide an order generation mechanism, we differentiate market participants' behavior based on their role in the market. Within ABSTRACTE specific behavior of various market participants is provided and skeletons are designed for three types of participants: investors, brokers, and market makers. Market makers can further exhibit either price quoting (dealer) or auctioneer behavior, depending on the market where they interact.

- **Emphasis on continuous trading sessions**

  Within ABSTRACTE we primarily aim to focus on studying market dynamics in continuous trading sessions. The most common ASMs in the early literature represented single-price call auctions. In single-price call auctions orders are aggregated at discrete points in time and market price is set at equilibrium (see Chapter 3). In these, at each trading round (i.e. call) the investors are asked to submit their orders, and the market price is determined by aggregating supply and demand (e.g. (Marsili, 2001;

Challet et al., 2005; Brock and Hommes, 1997; LeBaron, 2002; Raberto et al., 2001)). Although ASMs that study single-price call auctions are encountered regularly in literature, in real financial markets continuous trading sessions and quote-driven execution mechanisms are more common (Demarchi and Foucault, 2000; Harris, 2003). This has prompted some groups to look beyond the call market structure, and study markets with continuous trading sessions. Examples of such models have been described in (Loistl and Vetter, 2000; Chan and Shelton, 2001; Smith et al., 2002; Shatner et al., 2000). We also follow this trend. Remark however, that, as shown in the previous section, ABSTRACTE supports experiments with call auctions as well.

- **Continuous-time simulation**

  The majority of the market models that implement continuous trading sessions apply discrete-time simulation to model trading and price formation. In (Loistl and Vetter, 2000) and (Raberto et al., 2001) continuous sessions are modeled by centrally selecting the trader whose decision is carried out during the next trading session. Another approach is proposed in (Shatner et al., 2000), where traders "sleep" after actions, and "wake up" at predefined times, or as a result of certain events.

  At a high level of abstraction, the discrete-time models of financial markets are turn-based games, in which the market participants take turns to execute their actions. The specific characteristics of the simulation models determine how the players take turns and how they arrive at their decisions. Players remain passive in the market until it is their turn (i.e. they are selected) to take decisions and perform actions. This means that while a trader is selected, the environment is frozen. In reality, however, the environment can change while participants make decisions.

  In ABSTRACTE continuous trading sessions are implemented using continuous-time simulation. Continuity is modeled by concurrent execution of agent actions (in Java threads) which interact by asynchronous message passing. This implies that the trading environment is continuous and dynamic, and as a consequence, a number of traders can simultaneously be active, carrying out various tasks.

- **Autonomous, active traders**

  In the majority of the ASMs traders whose decision will be taken into account are centrally selected, often at random. In contrast to most of the ASMs in the literature, in the ABSTRACTE framework traders are not centrally selected, but are individual, autonomous elements. They decide when to place an order. Autonomy results from the agent-based implementation that we have chosen.

- **Concurrent, asynchronous behavior of agents**

  Autonomous representation and continuous time simulation of traders implies asynchronous execution of tasks, i.e. traders may be carrying out different tasks at the same moment. Figure 4.21 gives insight into the workings of the ABSTRACTE in a certain time interval. It illustrates the behavior of different traders who are acting asynchronously just as on the real markets. Various brokers conduct different (sometimes even parallel) tasks at the same simulation moment. At time $T1$ for example $Broker\_A$ has no jobs, he is just waiting for new messages or analyzing the market, $Broker\_B$

is busy with deciding which order to execute, while $Broker\_C$ tries to negotiate. In the meantime $Broker\_D$ receives a new order from an investor, besides selecting an order for execution.

As the figure illustrates tasks might start at varying points in time for the various agents and might be under execution for shorter or longer periods. The duration of negotiations for example depends on whether there are counterparties at that time on the negotiation floor or not, and on the grace period of a specific agent waiting for answers.

- **Modularity**

  One of the most important features of ABSTRACTE that makes it so specific, is its modularity. The environment is modular with respect to

  - the execution system applied; and
  - the traders' strategies.

  Modularity means that various market structures and arbitrary many types of strategies can be implemented on top of the proposed environment. ABSTRACTE allows for this in an easy and flexible way. This kind of representation enables the user to model many market structures and gives the freedom to implement any kind of available or presumed trading strategy. In the future modularity can be extended to other elements, like news formation, for instance.

  We do not claim that the ABSTRACTE environment is fully generic. Indeed, we are trying to incorporate more and more structures and strategies. Although, incorporating a new aspect, and even a new strategy might require modification and adaptation of the environment, those adaptations will improve the model, and make it more valuable.

- **ABSTRACTE is a distributed system**

  Although we didn't make use of this aspect in this thesis, another specific feature of ABSTRACTE is the fact that it is a distributed system. This means that markets and investors can be started and run as stand alone applications. This property enables the user to run experiments with investors who trade on multiple markets.

4.8   Summary

In this chapter we have introduced and described the ABSTRACTE flexible agent-based trading environment that is able to capture varying features of stock markets in order to study market dynamics, incorporating features that are rarely represented in other ASMs. Additionally, we have shown through simple examples how various market organizations and strategies can be configured and studied within the environment. In order to be able to provide an acceptably accurate explanation and analysis of the workings of a financial market, several features should be represented. This is why we have chosen for an agent-based micro-simulation approach based on market microstructure literature. In order to allow for the representation of diffuse assumptions regarding the workings of financial markets we did
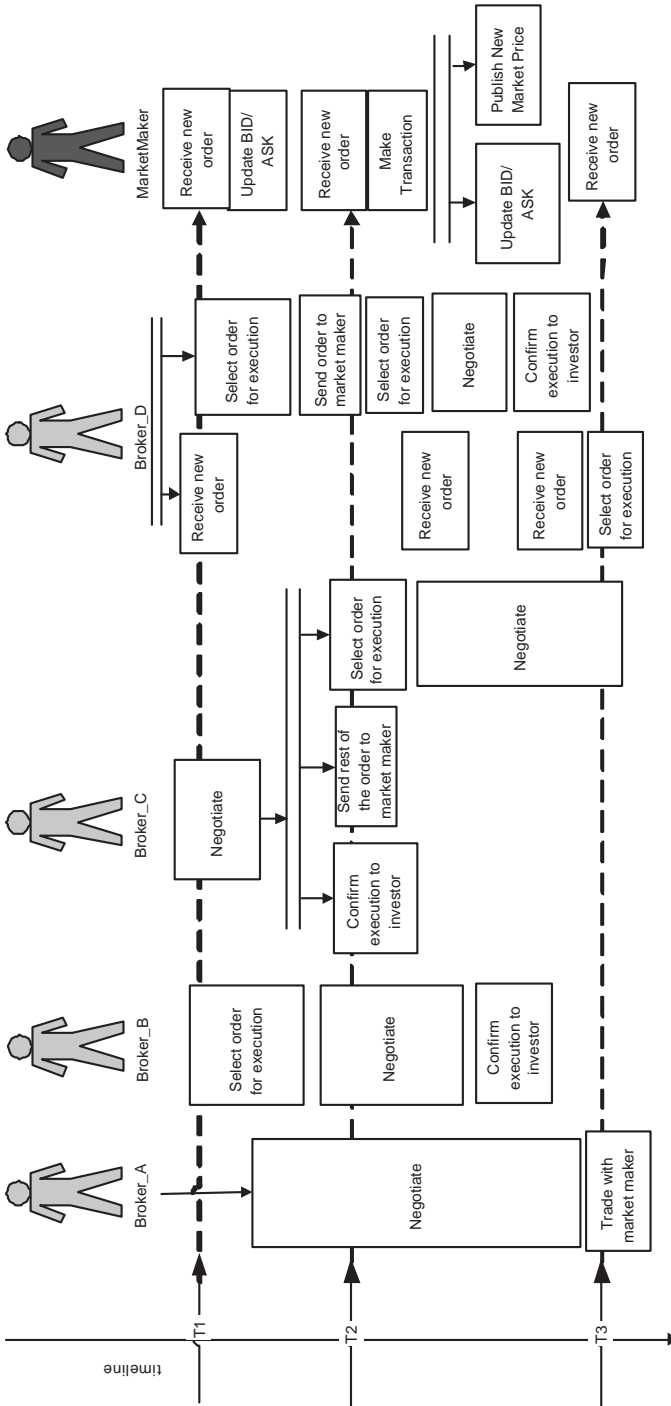
Figure 4.21: A view into asynchronous trading behavior

not choose for a certain market mechanism, but for a framework on top of which experiments with arbitrary many types of trading strategies in various trading environments can be conducted and compared. During the design of the framework, we have striven to address the perceived shortcomings of ASMs in the literature, discussed in Chapter 3. Consequently, the framework allows for continuous trading, asynchronous and autonomous decision-making and considers the different roles traders have to fulfill in the market. In addition to capturing rarely considered features of stock markets, the introduced ABSTRACTE trading environment allows for testing of previous findings in the literature; for studying how different market structures with the joint influence of various types of agents affect market characteristics; and for analyzing whether a certain behavior can be more successful than others in certain environments. Further, it allows for studying which features of the market prices are due to learning, adaptation and which are coming from the structure of the market itself. All these studies serve to test the quality of markets having different structures and might indicate changes that need to be made in order to improve market quality.

Chapter 5

The Continuous-Time Extended Glosten and Milgrom Model

In this chapter we aim to evaluate the ABSTRACTE environment with a new model on top of it. For this reason we replicate and extend the experiments of an ASM in which continuous trading sessions are represented. In contrast to the ASM studied the implementation of which is based on a turn-based mechanism, we focus on continuous-time simulation. The extension amounts to addressing the question to what degree the models developed in turn-based simulations are extensible to continuous, asynchronous simulations. Since most financial markets are continuous with asynchronously interacting traders, while its agent-based models are often turn-based, this is an important question to address in order to assess the limitations of the current modeling practice.

The research presented in this chapter is based on the learning market maker from Das (2005). This model extends the Glosten and Milgrom (1985) information-based model, which was proposed to show the influence of informational asymmetry on the bid-ask spread in financial markets. We consider an information-based model, since they provide insights into the adjustment process of prices that we are interested in (O'Hara, 2002).

In this chapter we combine the learning market maker, which Das describes in a turn-based model, with investors that interact asynchronously and autonomously. We implement the model on top of the ABSTRACTE environment described in Chapter 4 that applies continuous-time simulation instead of discrete-time simulation. We study the characteristics of the market prices that arise in continuous, asynchronous simulation, and compare it to the characteristics of the prices in the turn-based implementation. Further, we elaborate on the additional considerations that are needed in order to extend the turn-based model into a continuous, asynchronous model. Part of this chapter has been published in (Boer et al., 2007).

5.1 The extended Glosten and Milgrom model

The organization of the artificial market that we use in order to study market dynamics is based on an extended version of the information-based Glosten and Milgrom model proposed in Das (2005) (hereafter EGM). The Glosten and Milgrom (1985) model was proposed to show the influence of informational asymmetry on the bid-ask spread. In the Glosten and Milgrom model, the market maker tries to discover the fundamental value of a stock by means of Bayesian learning. He determines the bid and ask quotes based on his expectation of the real value, the order flow, taking into account his prior knowledge regarding the ratio of informed and uninformed traders. In Das (2003) and Das (2005) a nonparametric density estimation technique is proposed for maintaining a probability distribution over a range of expected true values. The market-maker uses these probability estimates to set bid and ask prices. Discrete time simulation is applied in this extended model, as well as a probabilistic representation of the order flow. In this section, we describe the characteristics of the EGM market. We first discuss the organizational aspects, and then we elaborate on the behavioral aspects of this market model based on the framework for a taxonomy of stock markets proposed in Chapter 2, and on the framework for a taxonomy of artificial stock markets in Chapter 3.

5.1.1 Organizational aspects

In both the original Glosten and Milgrom (1985) model and the extended EGM version described by Das (2003, 2005) trading sessions are continuous and the execution system is quote-driven. There is one stock traded. One market maker and multiple investors are represented.

The stock does not pay dividends. It is assumed that the stock has an underlying fundamental value, which is generated exogenously to the market.

The underlying *fundamental value* of the stock at time t is V^t (rounded to cents). V^t follows a jump process, being constant most of the time, and changing occasionally.

Trading is organized in trading rounds (turns) as a sequence of bilateral trading opportunities. Each trading opportunity involves a single potential investor who is selected at random from an unchanging pool of potential traders. The selected trader can buy at the offer, sell at the bid, or choose not to trade (Lyons, 2001). The market maker is responsible for the liquidity of the stock and the execution of orders at the current bid or ask price. He sets bid and ask prices as a function of the order flow and the market information he possesses. All orders are assumed to be market orders of one unit.

The market maker does not know the fundamental value, but, in order to ensure an efficient market, he tries to capture it by maintaining a probability density estimate (PDE) over a range of expected true values. The probability estimates are initialized according to the normal distribution. The initial bid and ask prices are calculated from this initial PDE and a priori expectations of the market maker. After initialization trading rounds start. A round consists of the following steps:

1. The probability is evaluated for a jump in the fundamental value, and the jump is carried out if it is the case.

2. An investor(type) is selected randomly from the pool to place an order.

3. A $Buy, Sell$, or $No\ order$ is sent by the selected trader to the market maker.

4. The market maker processes the order and carries out the transaction if it is the case.

5. The market maker updates his probability density estimate of possible fundamental values.

6. The market maker updates the bid and ask prices (P_B and P_A).

We elaborate now on these steps. First we discuss how the fundamental value is modified. We focus on the investors' behavior in relation to the second and third steps. The market maker's behavior is discussed in relation to the rest of the actions.

5.1.2 The fundamental value

In the EGM model a jump in the fundamental value occurs with some probability (0.001 in the experiments) at every trading period, that is at every discrete point in time. The jump process is modeled as a random process following $V^{t+1} = V^t + \tilde{\omega}(0, \sigma)$, where $\tilde{\omega}(0, \sigma)$ represents a sample from a normal distribution with mean zero and variance σ^2.

5.1.3 The investors' behavior

Investors are differentiated based on the information they receive regarding the fundamental value. There are two types of investors:

- informed traders and

- uninformed traders.

The informed traders are further classified as

- perfectly informed or

- noisily informed.

Perfectly informed traders observe the correct fundamental value (V^t), while noisily informed investors observe a distorted fundamental value $W^t = V^t + \tilde{\psi}(0, \sigma_W)$. Here, $\tilde{\psi}(0, \sigma_W)$ represents a sample from a normal distribution with mean zero and variance σ_W^2. Finally, uninformed traders do not know what the underlying fundamental value is, and they trade randomly.

Informed traders decide whether to trade or not, based on their observation of the fundamental value. An informed trader will buy if the fundamental value that he observes is higher than the market maker's ask price, i.e. if $V^t > P_A^t$ in the case of perfectly informed traders, and $W^t > P_A^t$ in the case of noisily informed traders. He will sell if the fundamental value that he observes is below the bid price, i.e. if $V^t < P_B^t$ or $W^t < P_B^t$. He will place no order if the observed fundamental value is within the bid-ask spread, i.e. $P_B^t \leq V^t \leq P_A^t$ or $P_B^t \leq W^t \leq P_A^t$). Uninformed traders place buy and sell orders with equal probability ($\eta \leq 0.5$). They can also decide not to place orders with probability $1 - 2\eta$.

5.1.4 The behavior of the market-maker

After an investor has been selected, and has placed an order, it is the market maker's task to carry out the rest of the actions (steps 4 to 6) within a trading round. On his turn, the market maker needs to carry out the following tasks:

1. receive and execute orders;

2. update the probability density estimate (PDE) based on the received orders;

3. adjust the bid and ask quotes according to the changes in the PDE.

5.1.4.1 The information set of the market maker

The market maker executes sell orders at the current bid price (P_B) and buy orders at the current ask price (P_A). The private information regarding the fundamental value is revealed implicitly by the type of the orders submitted by the (informed) traders. Information regarding the fundamental value of the stock diffuses from the informed traders to the market maker in this way. A series of sell orders might indicate that the fundamental value is lower than the current bid price, and a series of buy orders might indicate that the fundamental value is higher than the current ask price. However, the market maker will have to take into account the noise incorporated by the orders of the noisily informed traders, and the noise implied by the orders submitted by the uninformed traders.

Figure 5.1 illustrates the process of information diffusion in the model. The market maker aims to set bid and ask prices to capture the underlying fundamental value of the stock. The fundamental value is known only by the (perfectly) informed investors, and is not known by the market maker. The main task of the market maker is to learn this value. As mentioned above, he tries to do this by maintaining a set of possible true values with probability estimates attached to each of them (see Section 5.1.4.2).

The range of possible values, the corresponding probabilities, and the learning process of the market maker is based on a set of current and a priori known information. Current information refers to the actual order placed, and a notification when a change in the fundamental value occurs. The a priori information set of the market-maker contains:

- the fraction of informed traders (α) and uninformed traders ($1 - \alpha$) in the market;

- the probability for an uninformed trader to trade (η);

- the initial fundamental value V_0;

- the distribution function of the jump process ($\tilde{\omega}(0, \sigma)$);

- the distribution function of the noise process ($\tilde{\psi}(0, \sigma_W)$).
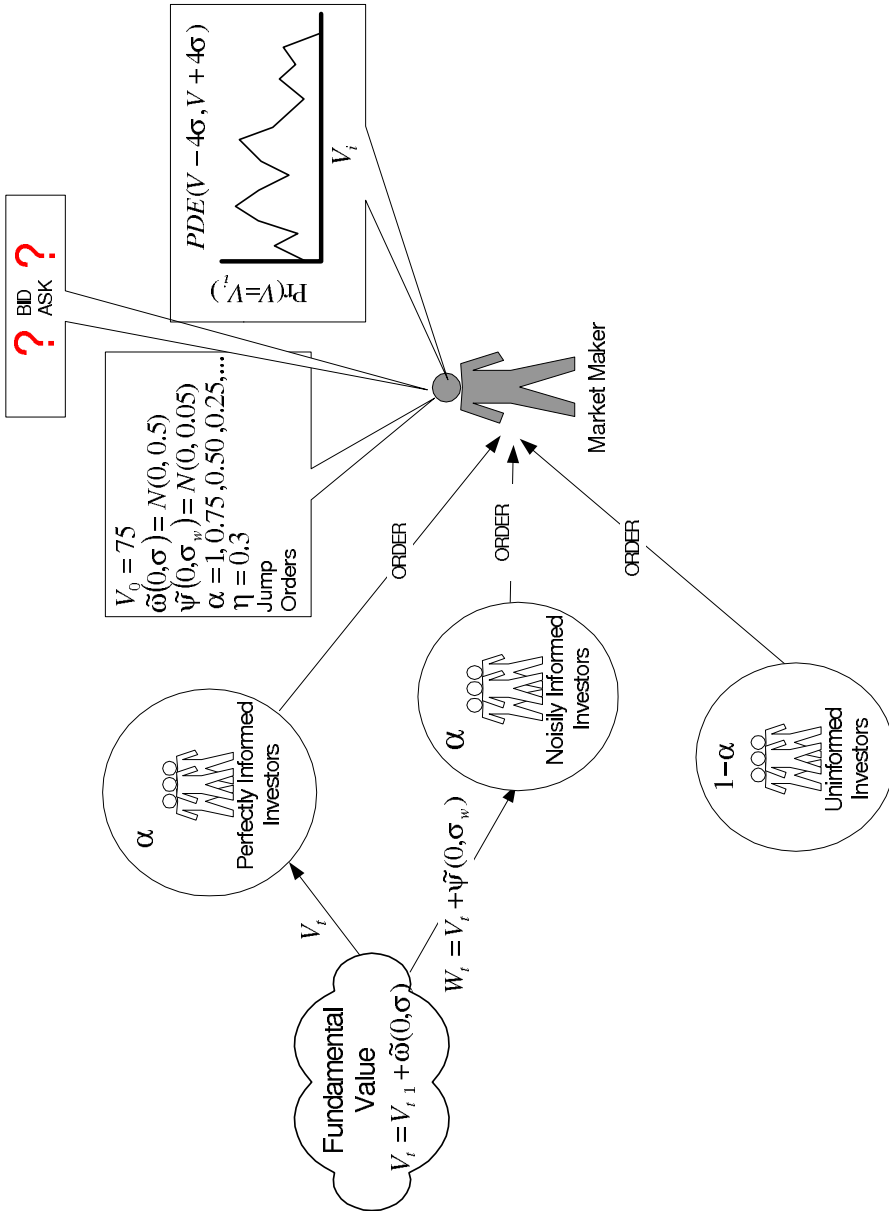
Figure 5.1: Information diffusion in the EGM model.

5.1.4.2 The probability density estimate

The range of possible values maintained by the market maker to estimate the fundamental value, as proposed by Das (2005) varies from

$$V_{min} = V_0 - 4\sigma$$

to

$$V_{max} = V_0 + 4\sigma - 1.$$

The values are given in cents, in intervals of one cent. The market maker keeps a probability density estimate (PDE) over the whole range of possible values determined in this way.

Whenever a jump in the fundamental value occurs, the range of possible values is re-centered. That is, after each jump the market maker sets V_0 to the current expected value, and the range of possible values is reset at 4σ distance from the new V_0.

Initialization. At the beginning of the simulation, and after a jump in the fundamental value, the probabilities are initialized to follow a normal distribution within the given range of possible values. Accordingly:

$$\Pr(V = V_i) = \int_{V_i}^{V_i+1} \mathcal{N}(0, 4\sigma)dx; \text{ where } i \in \{V_0 - 4\sigma, ..., V_0 + 4\sigma - 1\} \quad (5.1)$$

Here, $\mathcal{N}$ is the normal density function in x with mean zero and standard deviation 4σ. The array is kept in a normalized state at all times, so the entire probability mass for V lies within it. The probabilities are updated whenever a new order arrives.

Updating the PDE. When an order arrives, the market maker updates the probabilities for V_i by scaling the distribution, based on the type of the order. The new probabilities at time *t+1*, $\Pr(V = V_i^{t+1})$ will be set to the current probabilities given that the corresponding order arrived $\Pr(V = V_i^t|Order)$. The values are updated using Bayes' Rule according to the following generalized equation:

$$\Pr(V = V_i|Order) = \frac{\Pr(Order|V = V_i) * \Pr(V = V_i)}{\Pr(Order)}, \quad (5.2)$$

where the *Order* can be:

- *Buy*,
- *Sell*, or
- *No order*.

The prior value probabilities $\Pr(V = V_i)$ refer to the current probability estimates. $\Pr(Order)$ represents the prior probability of a certain type of order, while $\Pr(Order|V = V_i)$ is the conditional probability of a certain type of order. The prior probability of an order

is the cumulated conditional probability of that action weighted by the probability estimate of the given values.

$$\Pr(Order) = \sum_{V_i=V_{\min}}^{V_{\max}} \left(\Pr(Order|V = V_i) \Pr(V = V_i) \right), \qquad (5.3)$$

The conditional probability of placing a certain order depends on the fraction and type of the investors involved. In general:

$$\Pr(Order|V = V_i) = (1 - \alpha) \Pr(Order\ from\ uninformed\ investors|V = V_i) + \\ + \alpha \Pr(Order\ from\ informed\ investors|V = V_i) \qquad (5.4)$$

The model assumes that in case of uninformed traders the probabilities are known and these are independent of the current market situation. Accordingly,

$$\left. \begin{array}{l} \Pr(Buy\ from\ uninformed\ investors|V = V_i) \\ \Pr(Sell\ from\ uninformed\ investors|V = V_i) \end{array} \right\} = \eta \qquad (5.5)$$

Consequently,

$$\Pr(No\ Order\ from\ uninformed\ investors|V = V_i) = 1 - 2\eta$$

Let us now elaborate on how the conditional probabilities of the various order types can be computed for the informed investors.

The conditional probability of orders with perfectly informed traders In a market with perfectly informed traders, the probability for a sell order or a buy order depends on the fraction of various traders and the probability they will trade. Accordingly, the market maker bases his estimates on the expectation that (rational) informed traders will always buy if the perceived fundamental value is above the ask price, they will always sell if the perceived value is below the bid price, and they will not trade otherwise. Then,

$$\Pr(Sell|V = V_i) = \begin{cases} (1 - \alpha)\eta + \alpha, & if\ V_i < P_B \\ (1 - \alpha)\eta, & if\ V_i \geq P_B; \end{cases} \qquad (5.6)$$

$$\Pr(Buy|V = V_i) = \begin{cases} (1 - \alpha)\eta, & if V_i \leq P_A \\ (1 - \alpha)\eta + \alpha, & if\ V_i > P_A \end{cases} \qquad (5.7)$$

In addition to receiving buy or sell orders, it is also possible that the market maker does not get any orders at a certain turn. The prior probability for no order $P_{No\ order}$ is equal to $1 - (P_{Sell} + P_{Buy})$. The fact that there are no (informed) traders who want to trade, given the current bid and ask prices and the current fundamental value, suggests that the bid and ask prices are currently set around the fundamental value. By adjusting the estimated probabilities, the market maker can make the bid-ask spread smaller, in order to ensure market liquidity and to encourage trading.

If the market contains perfectly informed traders, the following updates are being made in order to determine the new probability estimates of not receiving any order:

$$\Pr(No\ order|V = V_i) = \begin{cases} (1 - \alpha)(1 - 2\eta),\ if\ V_i < P_B \\ (1 - \alpha)(1 - 2\eta) + \alpha,\ if\ P_B \leq V_i \leq P_A) \\ (1 - \alpha)(1 - 2\eta),\ if\ V_i > P_A \end{cases} \tag{5.8}$$

These equations capture the property that the probability that uninformed traders place no orders does not depend on the true value of the stock. Informed traders on the other hand, do not place orders if the true value is within the bid-ask range.

The conditional probability of orders with noisily informed traders. If the market maker has to deal with noisily informed traders instead of perfectly informed ones, the noise is incorporated into the updates. Accordingly, the probabilities for sell, buy, and no orders are determined by the following equations:

$$\Pr(Sell|V = V_i) = (1 - \alpha)\eta + \alpha \Pr(V_i + \tilde{\psi}(0, \sigma_W) < P_B) \tag{5.9}$$

$$\Pr(Buy|V = V_i) = (1 - \alpha)\eta + \alpha \Pr(V_i + \tilde{\psi}(0, \sigma_W) > P_A) \tag{5.10}$$

$$\Pr(No\ order|V = V_i) = (1 - \alpha)(1 - 2\eta) + \\ + \alpha \Pr(P_B \leq V_i + \tilde{\psi}(0, \sigma_W) \leq P_A) \tag{5.11}$$

The second term in (5.9) reflects the probability that a noisily informed trader sells if the observed fundamental value, including the noise is below the current bid price P_B. This means that the trader will submit a sell order also if the noise in the noisily informed trader's observation is smaller than the difference between the bid price and the fundamental value. Although a perfectly informed trader would not sell in this case, the additional noise can cause a noisily informed trader to make different decisions. Similarly, a noisily informed trader will place a buy order if the observed fundamental value, including the noise is greater than the current ask price P_A. Finally, a noisily informed trader, will not place orders, if the perceived fundamental value, including the noise falls in the interval between the bid and ask values.

The various conditional probabilities for each possible order and investor type are summarized in Table 5.1. According to (5.2), after all current probabilities have been updated by being multiplied with the corresponding conditional probabilities, the new probability estimates are scaled with the factor in (5.3).

Illustration of the conditional probabilities and PDE updates Figure 5.2 illustrates possible updates of the probability density estimate (upper part) after the receival of an order, and the conditional probabilities (lower part) used to update the estimates. In the sample 50% of the traders are perfectly (a) and, respectively, noisily (b) informed ($\alpha = 0.5$) and the probability for uninformed traders to place buy orders and respectively sell orders is set to 0.3 ($\eta = 0.3$). Further, the standard deviation of the noise that alters the fundamental value

Table 5.1: Summary of the probabilities that various investors place a certain type of order as a function of the current market situation.

Order type	Condition values	Uninformed investors	Perfectly informed	Noisily informed
Sell	$V_i < P_B$ $P_B \le V_i$	$(1-\alpha)\eta$	α 0	$\alpha \Pr(V_i + \tilde{\psi}(0, \sigma_W) < P_B)$
Buy	$V_i \le P_A$ $P_A < V_i$	$(1-\alpha)\eta$	0 α	$\alpha \Pr(V_i + \tilde{\psi}(0, \sigma_W) > P_A)$
No order	$V_i < P_B$ $P_B \le V_i \le P_A$ $P_A < V_i$	$(1-\alpha)(1-2\eta)$	0 α 0	$\alpha \Pr(P_B \le V_i + \tilde{\psi}(0, \sigma_W) \le P_A)$

is 5 cents ($\sigma_W = 0.05$). The cross signs on the x-axis represent the bid and ask values before the receival of an order. Diamonds represent new bid and ask values, that are set based on the new probability updates. The learning process to update the bid and ask values is described in Section 5.1.4.3.

Figure 5.2 (a) depicts the PDE updates and the corresponding conditional probabilities, in case of receiving a buy order from a pool with perfectly informed investors. The figure reflects that a buy order is perceived by the market maker as an indication that the stock is undervalued, and, as a consequence the new probabilities for the values above the current ask will be increased, and the new probabilities for the possible values below the current ask will be decreased. Given that the conditional probabilities are the same for the values on the same side of the ask, probability values are multiplied with the same factor on the same side of the ask. The PDE's are then discounted with the a priori probability of placing a buy order (see (5.3)).

The updates with noisily informed traders result in a similar density function as for the scenario with perfectly informed traders. The new density function is however, smoother, given the uncertainty caused by the noise added to the fundamental value (Figure 5.2 (b)).

Please note that receiving a sell order would lead to density functions that are symmetric to the ones resulted after receiving a buy order. The case of no orders leads to different results. If the selected investor decides not to place any order (Figure 5.3) the market maker believes that he managed to capture the bid and ask values. Consequently, he increases the probabilities for the values in between the bid and ask, and lowers the probabilities for the rest of the values.

Recall, that, after the arrival of an order the market maker adjusts his current probabilities for the whole range of possible fundamental values (between V_{min} and V_{max}) in an attempt to track the actual fundamental value. Figure 5.4 shows the evolution of the market maker's probability density estimate when receiving three consecutive buy orders in market runs with different rates of perfectly informed (a, b, c) and noisily informed (d, e, f) traders. Each plot represents one trade event and one update round including the normalization of the probabilities. "NDF" refers to the normal density function, which is valid at the initialization step or at the moment a jump in the fundamental value occurred, because in that case the market maker's probability estimate has just been initialized or re-centered.
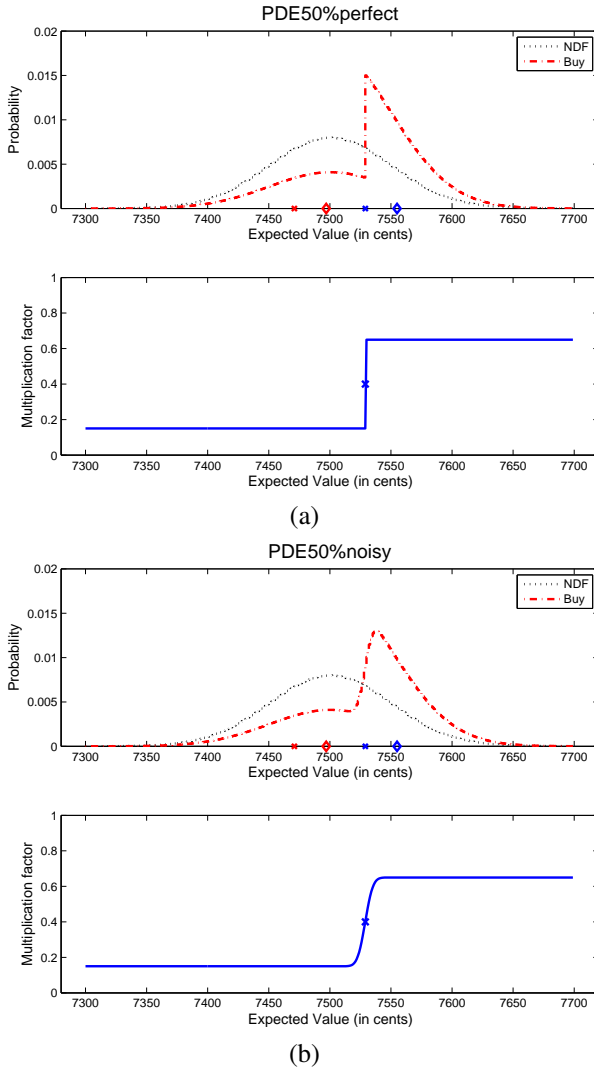
Figure 5.2: Sample probability density update after receiving a buy order when 50% of the traders are perfectly (a), or noisily (b) informed.
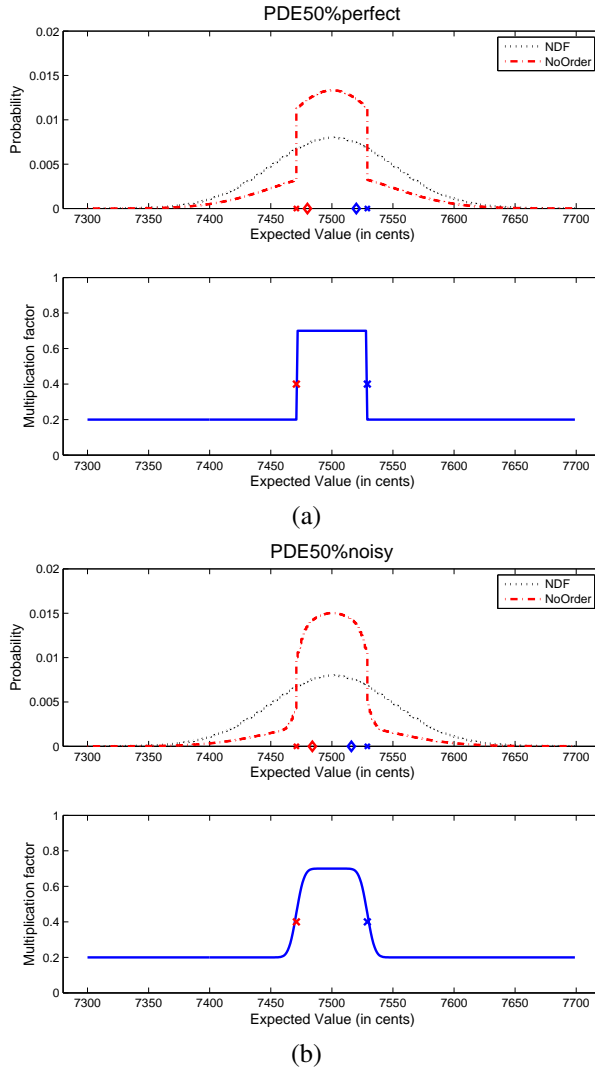
Figure 5.3: Sample probability density update after perceiving no order when 50% of the traders are perfectly (a), or noisily (b) informed.
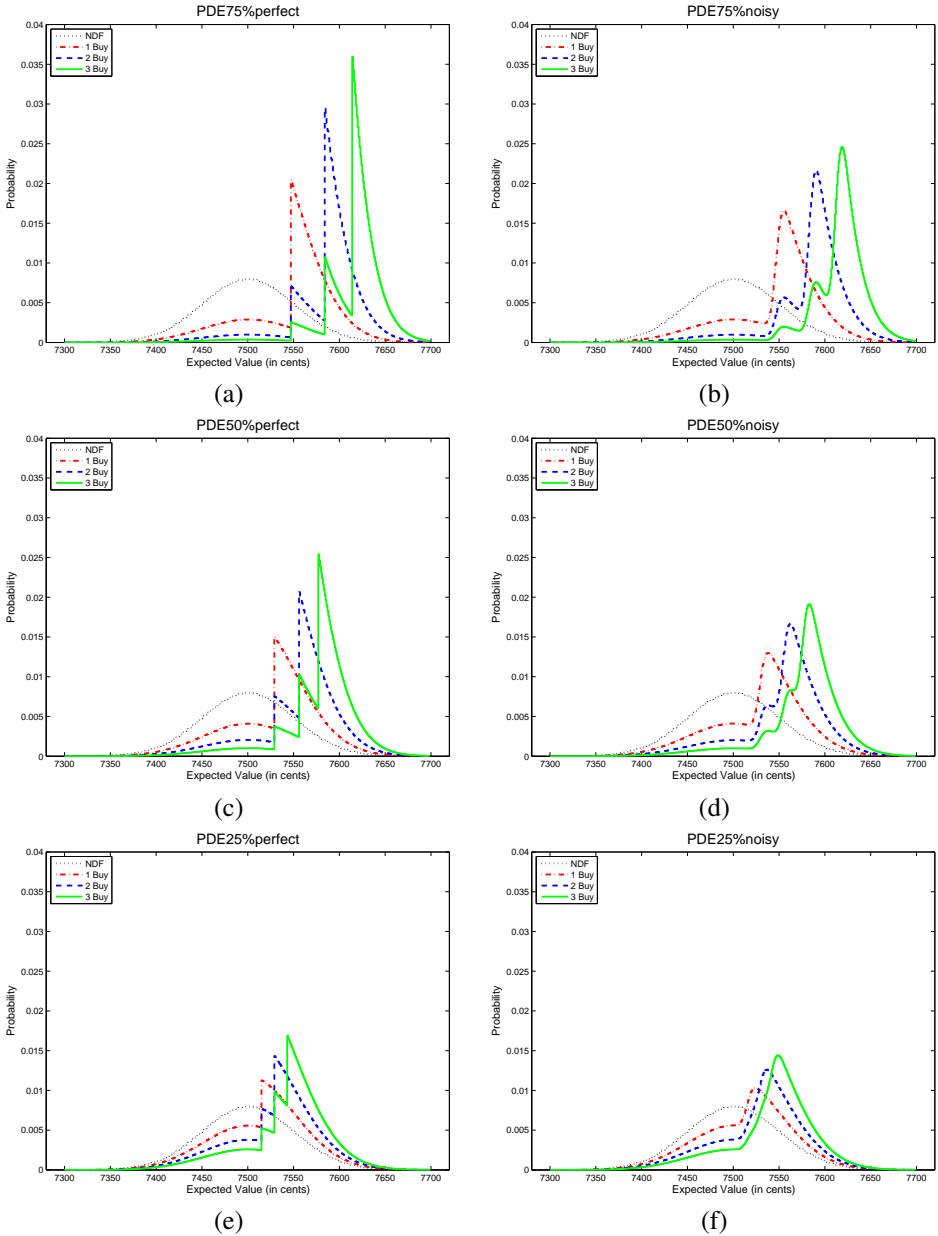
Figure 5.4: The path of evolution of the probability density estimate of the market maker, when receiving three consecutive buy orders, with different fractions of perfectly informed (a,c,e), and noisily informed (b,d,f) traders

Table 5.2: Numerical sample of the conditional probabilities in case of perfectly informed traders.

Parameters		Buy		Sell		No Order	
α	η	$V_i \leq P_A$ $(1-\alpha)\eta$	$P_A < V_i$ $(1-\alpha)\eta$ $+\alpha$	$V_i < P_B$ $(1-\alpha)\eta$ $+\alpha$	$P_B \leq V_i$ $(1-\alpha)\eta$	$V_i < P_B, P_A < V_i$ $(1-\alpha)(1-2\eta)$	$P_B \leq V_i \leq P_A$ $(1-\alpha)(1-2\eta)$ $+\alpha$
1	0.3	0	1	1	0	0	1
0.75	0.3	0.075	0.825	0.825	0.075	0.1	0.85
0.5	0.3	0.15	0.65	0.65	0.15	0.2	0.7
0.25	0.3	0.225	0.475	0.475	0.225	0.3	0.55

As Figure 5.4 illustrates, as a result of receiving a series of buy orders, most of the mass has been shifted to the right a couple of times, resulting in upwards shifts of the probabilities over a smaller range. The peaks in upward shifts are at the current ask value. This is a natural consequence of the fact that, a buy order indicates that the stock is undervalued. Thus, the probability that the current value is higher than the current ask value is increased. Accordingly, all values (in the range of possible values) above the current ask are multiplied with a factor greater than one, and the ones below the ask are multiplied with a factor less than one.

Note again, that, with noisily informed traders (Figure 5.4(b)(d) and (f)), the updating algorithm results in a much smoother probability distribution than with perfectly informed traders. This happens because the noise is taken into account when updating the probability values (see the last column of Table 5.1).

It can be also observed, that the higher the rate of informed traders the higher the peaks, because the probability that the orders are placed by informed traders is higher (see Table 5.2). Further, the higher the rate of informed traders the more to the right are the shifts in the density estimates. This results from the fact that with a higher percentage of informed traders the Bayesian learning method applied results in more extreme bid and ask values, i.e. values that are further away from the mean (see the details of calculating the bid and ask in Section 5.1.4.3).

A series of sell orders leads to symmetric results. They shift the mass of probabilities to the left with peaks around the bid value. Further, receiving no orders results in higher probabilities in between the bid and ask values. Mixed signals of buy, sell and no orders cause thus, shifts, and peaks in the density estimate (see for example Figure 5.5), depending on the sequence of the orders received. After updating the probability density estimates the market maker is ready to incorporate the new information into the new bid and ask values.

5.1.4.3 Adjusting the bid and ask quotes

The market maker tries to set the bid and ask prices such that these reflect the fundamental value of the stock. As he does not know this value, the new bid and ask prices will be based on the expected value given the adjusted probability density estimate after arrival of an order.
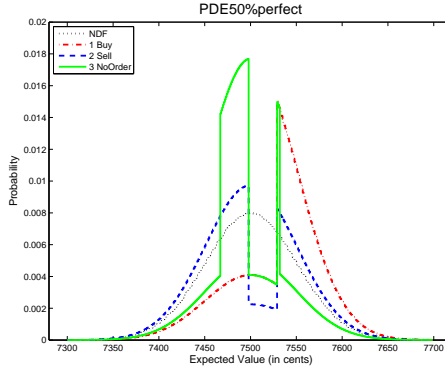
Figure 5.5: Sample probability density update after receiving a series of buy, sell and no order, when 50% of the traders are perfectly informed.

The bid price is set to the expectation of the true value given the probability that a sell order will arrive. Similarly the ask price is set to the expectation of the true value given the probability that a buy order arrives. In other words,

$$P_B = E[V|Sell], \tag{5.12}$$

$$P_A = E[V|Buy]. \tag{5.13}$$

By definition, in order to estimate the expectation of the underlying value, it is necessary to compute the conditional probability that the true price equals a certain value ($V = x, x \geq 0$) given that a particular type of order is received. For market sell orders the expectation then becomes:

$$E[V|Sell] = \int_0^\infty V Pr(V = x|Sell)dx \tag{5.14}$$

For market buy orders the expectation can be written as:

$$E[V|Buy] = \int_0^\infty V Pr(V = x|Buy)dx \tag{5.15}$$

Given the $[V_{min}, V_{max}]$ range of possible values, (5.14) and (5.15) can be refined to:

$$P_B = \sum_{V_i=V_{\min}}^{V_{\max}} V_i(\Pr(V = V_i|Sell)) \tag{5.16}$$

$$P_A = \sum_{V_i=V_{\min}}^{V_{\max}} V_i(\Pr(V = V_i|Buy)) \tag{5.17}$$

When trying to solve these equations, they turn out to be more complicated than observed at first sight. The definition is circular, since the bid price depends on the bid price, and the

ask price on the ask price. This is because, as elaborated in (5.6) - (5.11) the conditional probabilities of sell orders are bid price dependent, and the conditional probabilities of buy orders are ask price dependent (see also Table 5.1). In case of perfectly informed traders, for instance, different expressions have to be substituted for values below and above bid in case of sell orders, and for values below and above ask in case of buy orders. Consequently, (5.16) and (5.17) should be refined as:

$$P_B = \frac{1}{P_{Sell}} (\sum_{V_i=V_{\min}}^{P_B-1} V_i \Pr(Sell|V = V_i) \Pr(V = V_i)$$

$$+ \sum_{V_i=P_B}^{V_{\max}} V_i \Pr(Sell|V = V_i) \Pr(V = V_i)), \qquad (5.18)$$

$$P_A = \frac{1}{P_{Buy}} (\sum_{V_i=V_{\min}}^{P_A} V_i \Pr(\text{Buy}|V = V_i) \Pr(V = V_i)$$

$$+ \sum_{V_i=P_A}^{V_{\max}} V_i \Pr(\text{Buy}|V = V_i) \Pr(V = V_i)), \qquad (5.19)$$

where P_{Sell} is the a priori probability of a sell order, and P_{Buy} is the a priori probability of a buy order. These values are determined by the equations (5.6) and (5.7). Now, (5.6) - (5.11) can be easily substituted into the right hand side to get the final expressions.

So, we get fixed point equations: bid is calculated as a function of bid (P_B), and ask is calculated as a function of ask (P_A). Furthermore, the bid price is primarily driven by sell orders, while the ask price is primarily driven by buy orders; and at a first sight, none of the quotes depends directly on the probability that no orders arrive. In fact, both sell and buy orders, as well as no order placements, will influence both the bid and ask values, as the effect of these situations is incorporated in the update of PDE (see (5.2)).

In order to solve the fixed point equations we follow the approach taken in (Das, 2005) taking into account that $P_B \le E[V] \le P_A$. The bid price is computed by repeatedly computing the right hand side of (5.18), thus cycling from E[V] downwards until the absolute difference between the left and right hand sides of the equation stops decreasing. Similarly, the bid price is computed by cycling from E[V] upwards until the difference between the left and right hand sides of the equation stops decreasing. The fixed point real-valued solution is then chosen as the one closest to the integral value at which the distance between the two sides of the equation is minimized.

So far, we have described the EGM model based on (Das, 2003, 2005). Next, we discuss how this model can be replicated on top of the ABSTRACTE environment. There are two important differences between the implementation properties of the EGM model as described by Das, and the properties of ABSTRACTE. First of all, the former applies discrete time simulation, while the latter is based on continuous time simulation. Further, in the original EGM model individual investors are not focused on, to be more precise, they are

centrally selected to decide when to trade. In contrast, as emphasized in Chapter 4, within ABSTRACTE it is possible to represent, individual, autonomously acting investors.

In the remainder of this chapter we analyze whether and how experiments within the EGM model can be replicated on top of ABSTRACTE in a continuous time setting. We consider two main cases, which differ primarily with respect to the autonomy of the investors. First, we try to replicate EGM and focus on centrally selected traders. Then we elaborate on autonomously interacting traders.

5.2   The case of centrally selected investors

In order to validate and verify the EGM market as implemented within ABSTRACTE we have first carried out experiments with orders arriving as assumed in (Das, 2003, 2005). That is, orders arrive one by one, and the type of the trader who places the order is stochastically determined based on the given fraction of informed and uninformed traders (α). This feature is implemented by modeling one single representative trader. Every time this trader considers placing an order he first of all decides whether he will act as an informed or an uninformed trader.

The time line of events in the replicated EGM market model (further referred to as CEGM) that corresponds to this description, is as follows:

1. The market maker initializes the bid and ask prices (P_B and P_A). These are made public to all participants.

2. The representative trader determines stochastically whether the next order will represent a decision of an informed trader or the decision of an uninformed trader.

3. Depending on the selected type of trader a $Buy, Sell$, or $No\ order$ is generated and sent to the market maker.

4. The market maker processes the order, carries out the transaction if needed, and updates the PDE, P_B and P_A.

5. If there is a transaction the market maker confirms the transaction to the trader involved.

6. The market maker publishes the new P_B and P_A.

7. Steps 2 to 6 are repeated.

Please note, that this time line of events does not involve the jump process for the fundamental value. In contrast to the original EGM model, the news source within ABSTRACTE is independent of the market. In the original EGM at every trading round, first the probability of a jump in the fundamental value is evaluated and investors are selected to trade afterwards. In our implementation the jump can occur at any time, independently of the actual step that is carried out by the market participant in action. When a change in the fundamental value occurs, the new value is made public, and thus, informed investors can take into account the new value instead of the old one in their decisions. The effects of having an independent news source will be discussed later in this chapter.

5.2.1 Experimental settings

The experimental settings correspond to the ones from Das (2005), unless we specify otherwise. The numerical values given in this section are used in most of the experiments. The choice for the specific values is motivated in Section 5.4. There, we also discuss outcomes with other (more extreme) settings, and we elaborate on the sensitivity of the results on the values chosen.

Fundamental value related settings.

- The initial value (V_0) is 7500 cents.

- The standard deviation (σ) of the jump process is 50 cents.

- In the discrete time simulation of the EGM model changes occur with some probability at every discrete time step (trading round). Because the probability of a jump is very low (1 in 1000) the underlying fundamental value of the risky asset is constant for most of the time and changes occur occasionally at various moments. In order to model the jump process in the continuous setting, we draw the time of the next jump randomly from a uniform distribution in a given interval. Given the stochastic feature of the two types of jump processes, both frequent and rare jumps can occur in both of the simulations. Accordingly, the slight difference in the frequency of jumps does not affect the outcomes. What is more important is the property that the size and direction of the jumps is based on the same probability function. In our experiments the fundamental value jumps at periods drown randomly from a uniform distribution every 30 to 60 seconds in real time.

- The noise process has a mean of 0 and a standard deviation of 5 cents.

Investor related settings.

- The fraction of perfectly informed traders (α) varies across the experiments, taking the values of 0.75, 0.5 and 0.25. (In (Das, 2005) mainly experiments with 0.5 are focused on).

- The probability (η) that uninformed traders place a buy order (and, respectively, sell order) is set to 0.3. Consequently, the probability that uninformed traders do not trade is 0.4.

- All investors place market orders for one quantity of the risky stock. The investors do not withdraw their order once it is submitted.

Market maker related settings.

- The market maker knows the fraction of uninformed traders and the probability with which they trade.

- The market maker also knows whether informed traders are perfectly informed or noisily informed, and the noise distribution.

In the original EGM, experiments are reported taking 50000 trading rounds. Given the continuous time feature of the environment that we use, in our case we need to let the simulations run for a certain time. We have chosen to run the experiments for 10 minutes in real time. The number of trading rounds, updates in the bid and ask quotes, and the number of transactions conducted within this time depends on the performance of the computer and on the settings of specific models. In the experiments that we present here this time period leads to an average of 40000 adjustments made in the quotes. What in fact is more important with respect to the stability of the results is the fact that the price discovery process of the market maker is similar between two jumps of the fundamental value.

5.2.2 Experimental results

Figure 5.6 shows how the market maker sets his bid-ask spread trying to follow a given profile of fundamental value. The fraction of informed traders is set to 0.75 in (a) and (d), 0.5 in (b) and (e), and 0.25 in (c) and (f). The figures on the left hand side show the result of a typical experiment for perfectly informed traders, while the experiments on the right hand side are conducted with the presence of noisily informed traders. At first sight there is no remarkable difference between the various outcomes. It seems that the market maker is able to learn the underlying fundamental value of the asset fairly quickly from the trades of the informed traders. Sometimes however, the market makers seems to slightly over- or underestimate the fundamental value estimated by receiving orders from noisily informed traders.

In order to be able to compare the outcomes we need to take a closer look to the results. Figure 5.7 illustrates segments from the experiments with 3 consecutive jumps, and Figure 5.8 is a snapshot taken immediately before and after a jump.

From these figures we can conclude that, when the fraction of perfectly informed traders is high (0.75) the market maker is able to learn the underlying fundamental value quickly. This is to be expected, since the market maker learns primarily from the trades of the informed traders. In scenarios with a higher level of noise (higher rate of uninformed traders, or informed investors receive noisy value) the market maker needs in general more time to learn the fundamental value. Note the increased uncertainty after news arrives in the market, i.e after a jump in the fundamental value. The bid-ask spread is initially large, but the spread is reduced gradually as time passes. The learning progresses fairly regularly, and the prices evolve without much fluctuation. This indicates stable learning on the part of the market maker.

The market maker becomes thus, more insecure after the arrival of news in a market with a higher level of noise. He still manages, however, to learn the fundamental value most of the time. Sometimes however, the market maker can make small mistakes. In case of experiments with 50% and 25% noisily informed traders, for instance, the market maker slightly overestimates or underestimates the fundamental value. By taking a closer look at the detailed numbers behind the figure we discovered that the explanation for this phenomenon can be found in the probability density updates. Bid and ask values become two consecutive values after a while, and their cumulated probability becomes a value above 0.9. The rest of the possible values is estimated to have a probability below 0.1, most of them below 1.E-8. Independently of the side of the arrived orders, when these values close to 0 are
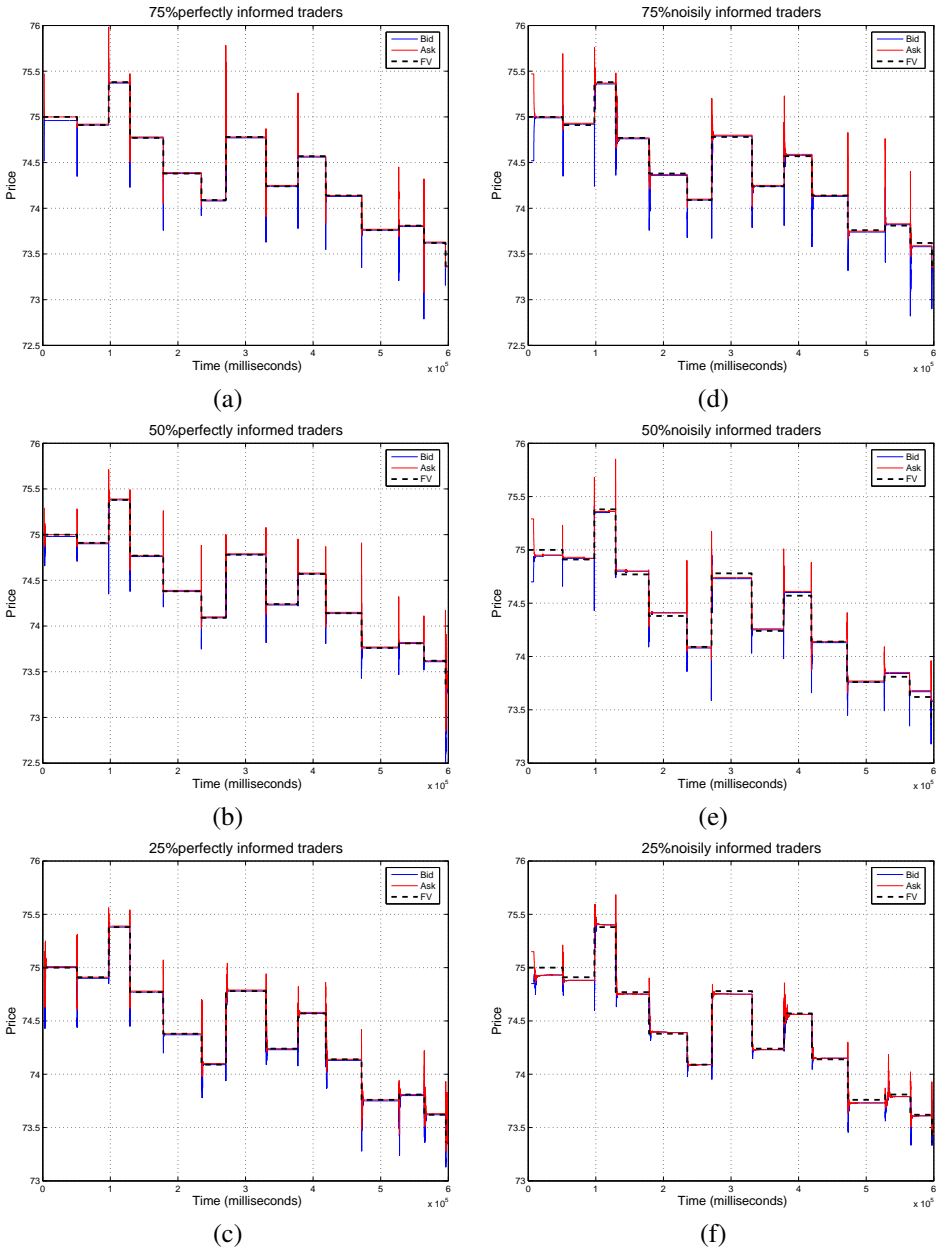
Figure 5.6: The learning behavior of the market maker in case of central selection.
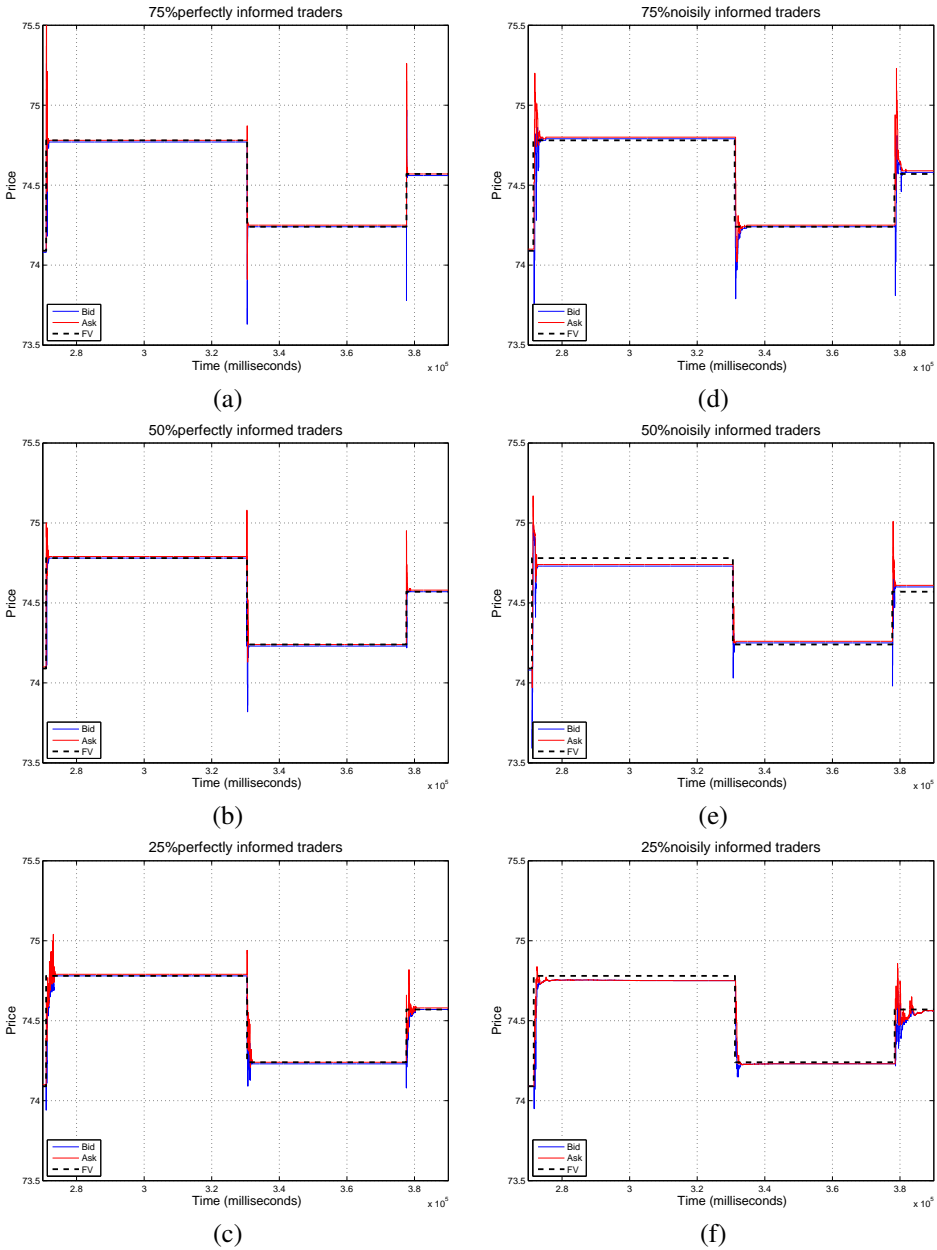
Figure 5.7: The learning behavior of the market maker in case of central selection, closer view at a simulation run.
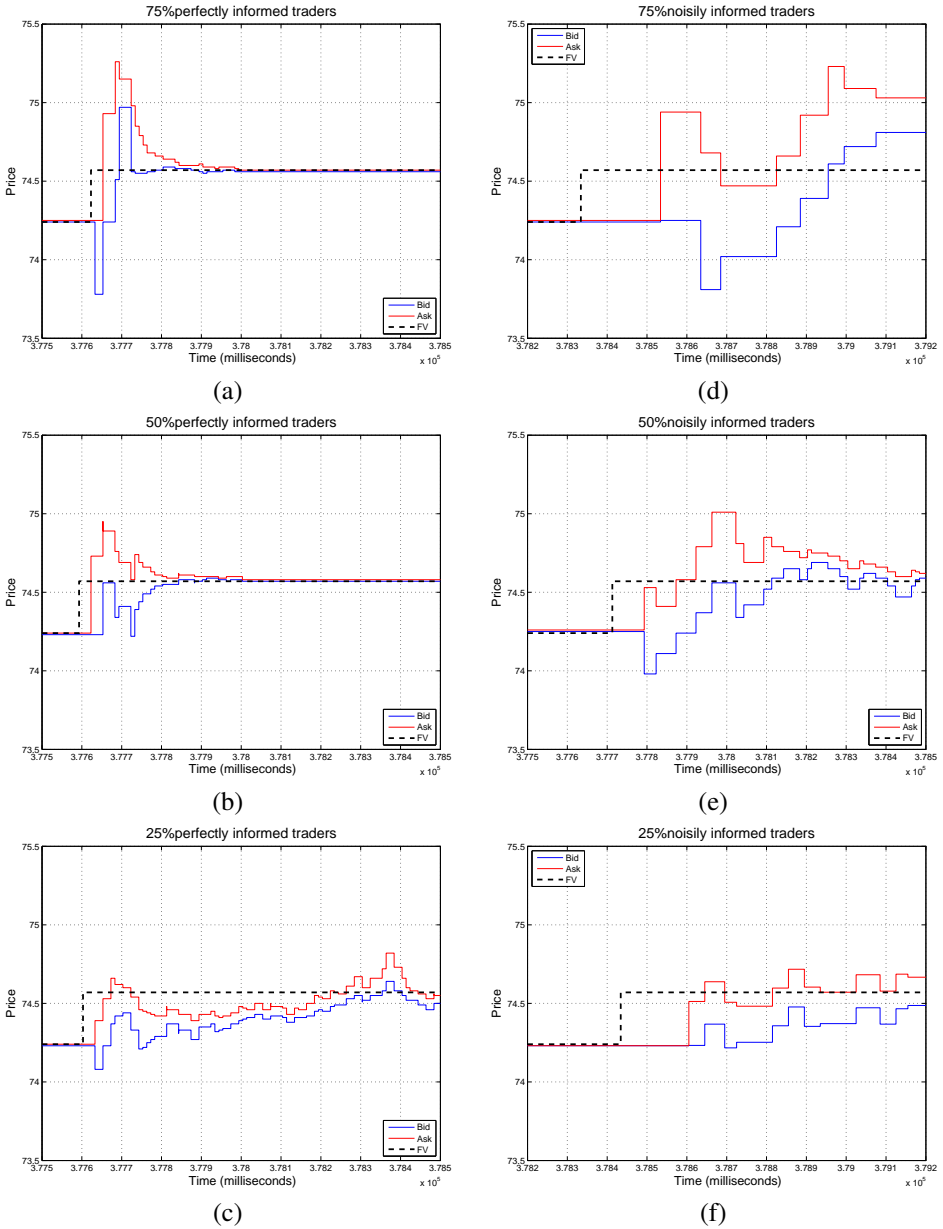
Figure 5.8: The learning behavior of the market maker in case of central selection, immediately before and after a jump.

multiplied, they do not change much, but stay in the neighborhood of 0. As a consequence bid and ask remain the same. A possible solution to this problem would be to re-center the interval of possible values and set up a new normal PDE in cases like this. In Das (2005) experiments with larger spread values are run. Larger spreads could also solve the problem in some of the cases, the results depend however, on the size of the noise.

When studying carefully the segments on Figure 5.8, a slight delay can be observed in the reaction of the market maker to the change in the fundamental value. This feature is the consequence of the continuous time implementation and the fact that the news source that generates the fundamental value is a component running independently. On its turn, the timing of the adjustment in the bid ask spread depends on the time of receiving an order, and on the timing of the orders placed by the selected investor who might have decided to place a new order just before being informed about the new true value. Consequences and (side)effects of the continuous time implementation are elaborated on in Section 5.4.

5.3   The case of autonomous traders

In the experiments presented in Section 5.2 central selection of the type of investors is implemented by modeling one single representative investor who decides at each trade on the type of trader that he simulates. In this section we focus on experiments with autonomous, individual investors. A comparison of central, turn-based selection of investors, and autonomous representation of individual investors is illustrated by Figure 5.9. In turn-based selection there is always only one investor who is selected, and is required to make a decision. The decision of the selected investor is always known by the market maker, even if it leads to no orders. Central selection entails that traders cannot place orders whenever they want to, but only when they are selected to do so. Autonomous investors decide themselves when to trade, and their decision is taken into account at all times. The autonomy of investors entails simultaneous or asynchronous behavior. That is, the investors might react simultaneously to some information (e.g both Investor 1 and Investor 2 react at the same time to B6 and A6 on the figure), but they might also be carrying out different tasks, at the same moment (e.g. between the first and the second change in the bid and ask values). One of the agents, for example, might just listen to news, while another one is analyzing the market, and a third one is waiting for his order to be executed, and all this as a consequence of their autonomy, being not coordinated by some central system.

Given the autonomous feature of investors it is not possible to provide a unique time line of events within the new, *autonomous, continuous time* (ACTEGM) *model*. We can provide only an independent description of the behavior of the various market participants. The behavior of the investors and the behavior of the market maker corresponds to the description given in Chapter 4.
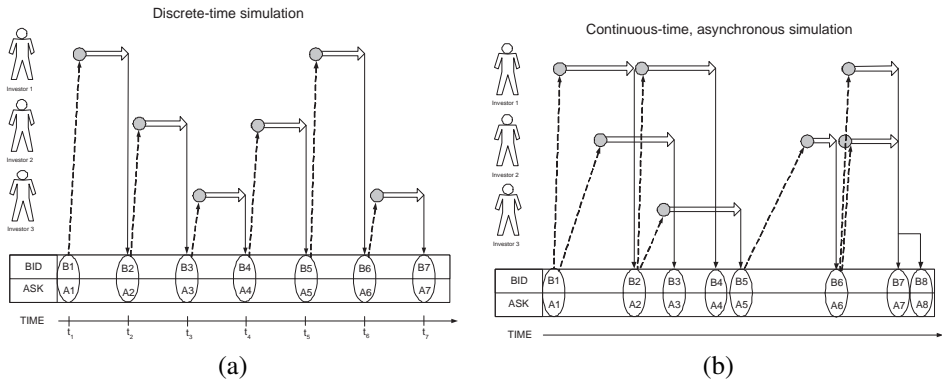
Figure 5.9: Turn-based selection of investors vs. autonomous behavior of investors.

The time line of an investor's behavior.

1. Listen to news and/or confirmation of placed orders.

2. Perceive and interpret the available information.

3. If there are no pending orders sent already, place an order depending on the individual belief and decision-making mechanism.

The time line of the market maker's behavior. The behavior of the market maker is the same as in the CEGM market, with centrally selected investors.

1. The market maker initializes the bid and ask prices (P_B and P_A). These are made public to all participants.

2. The market maker waits for messages, processes the message, carries out the transaction if an order is involved, updates the PDE, P_B and P_A.

3. If there is a transaction the market maker confirms the transaction to the trader involved.

4. The market maker publishes the new P_B and P_A.

5. The market maker processes the next message.

In this section we analyze the performance of the market maker in tracking the fundamental value in the asynchronous, continuous time simulation with autonomous, individual investors. We examine whether the market maker is able to react timely to changes in the fundamental value and whether the fundamental value is correctly reflected in the market prices. Das (2005) has shown this to be the case in the discrete-time model. Our results in the turn-based Section 5.2 model with central selection also confirm this conclusion.

5.3.1 Experimental settings

The experimental settings are similar to the settings used to conduct experiments with centrally selected investors, described in Section 5.2. In this way we can compare the results and analyze the effects of autonomous traders. The individual, autonomous, representation of the investors entails however, the specification of additional attributes. The attributes include the number of traders for each type of trader, and timing aspects, such as the time horizon of the investors, and the no order condition of the market maker.

The number of investors. Given the individual, autonomous representation of the investors in our implementation, the number of each type of investor needs to be specified to each fraction applied. While a small number of investors might be not representative, a lot of traders could overload the market maker with orders, if they place orders faster than the market maker can handle them. In order to avoid this situation, in the first place we conduct experiments with the minimum number of investors necessary: three informed – one uninformed for $\alpha = 0.75$, one informed – one uninformed for $\alpha = 0.5$, and one informed – three uninformed for $\alpha = 0.25$. Later on, in Section 5.4, we also study the implications of considering more interacting investors.

The "no order" condition In turn-based models, in each period, there is either zero or one order to be processed placed by a single (selected) investor. The market maker knows in this way at each moment whether a decision has been made. He thus, is implicitly informed also about the fact that someone decides not to place an order. In order to keep this property, in the autonomous, continuous case we let the investors send explicit "No order" messages to the market maker when they decide not to trade. Informing the market maker that someone does not wish to place an order is not realistic, however. In reality, investors do not communicate such decisions, they communicate only when they decide to place a buy or sell order. Therefore, later on in this chapter, in Section 5.4, we also discuss the consequences of not notifying the market maker about the "no order" decisions.

Timing aspects. In the discrete implementation, investors decide whether to trade or not only when they are selected by the central simulation manager. The situation is similar in a continuous setting with a central selection mechanism. In a continuous setting with individual, autonomous investors, investors decide to trade or not whenever they think it is worthwhile to do so. In such a setting quite some events can take place in the market while an investor is waiting for the execution of his order. The fundamental value can change for example, or market conditions can change as a result of executing orders of other traders. If an investor has no orders placed, because it was not worthwhile for him to do so, he could analyze the possibility to trade again immediately, or he could wait for a while first and reconsider after waiting the possibility to trade again after some time period as market conditions (like bid and ask values) might have changed. For how long an investor waits before examining the market conditions again depends on his *time horizon*. In our experiments, investors analyze market conditions either when news arrives or, when their order is executed, or when their individual time horizon "expires". If not specified otherwise, we set the time horizon of investors to 0, meaning that they consider placing an order whenever they get the chance.

5.3.2   Experimental results

Figure 5.10 illustrates that, the market maker is able to learn the fundamental value most of the times in a setting with autonomous investors as well. However, fluctuations (uncertainty) after a jump occur more often and are longer visible in general, than in the case of centrally selected investors. In the segments provided in Figure 5.11 and Figure 5.12 this property is more visible.

   An interesting feature that we observe is that the market maker seems to be more uncertain when working with 75% informed traders as opposed to 50% or 25% informed traders. In the market with 50% informed traders, the uncertainty can be exclusively ascribed to the presence of the uninformed trader. In Figure 5.12 (a) and (d) a kind of overreaction can be observed. After the fundamental value jumps, the market maker's bid and ask prices begin to fluctuate with a decreasing amplitude, before approximating the desired value. This phenomenon can be attributed to the larger amount of informed traders in the market with 75% perfectly informed traders. Here, three informed and one uninformed investors are interacting, as opposed to one informed and one uninformed trader in the experiments with 50% informed traders. All informed traders respond immediately to the change in the fundamen-
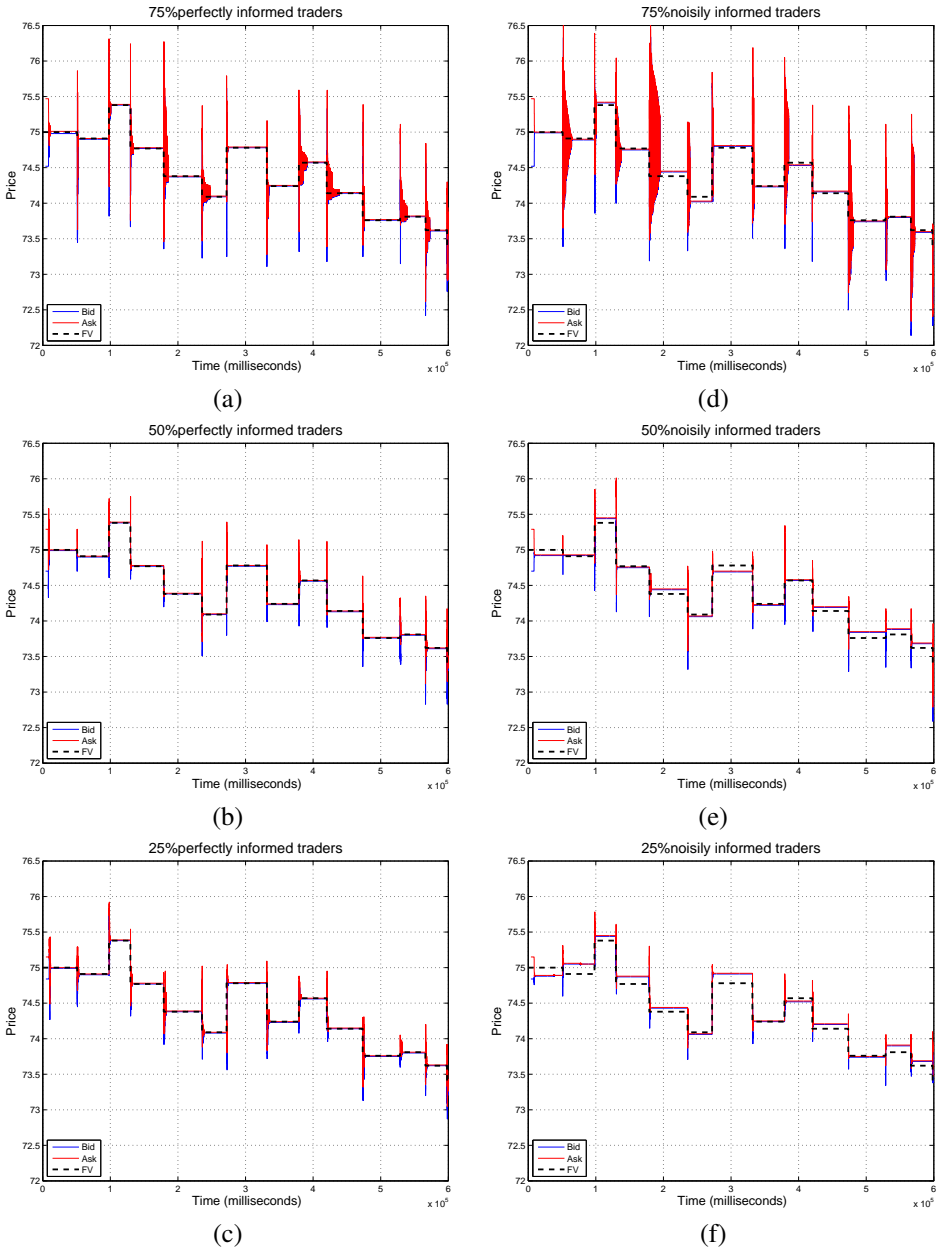
Figure 5.10: The learning behavior of the market maker in case of autonomous investors.
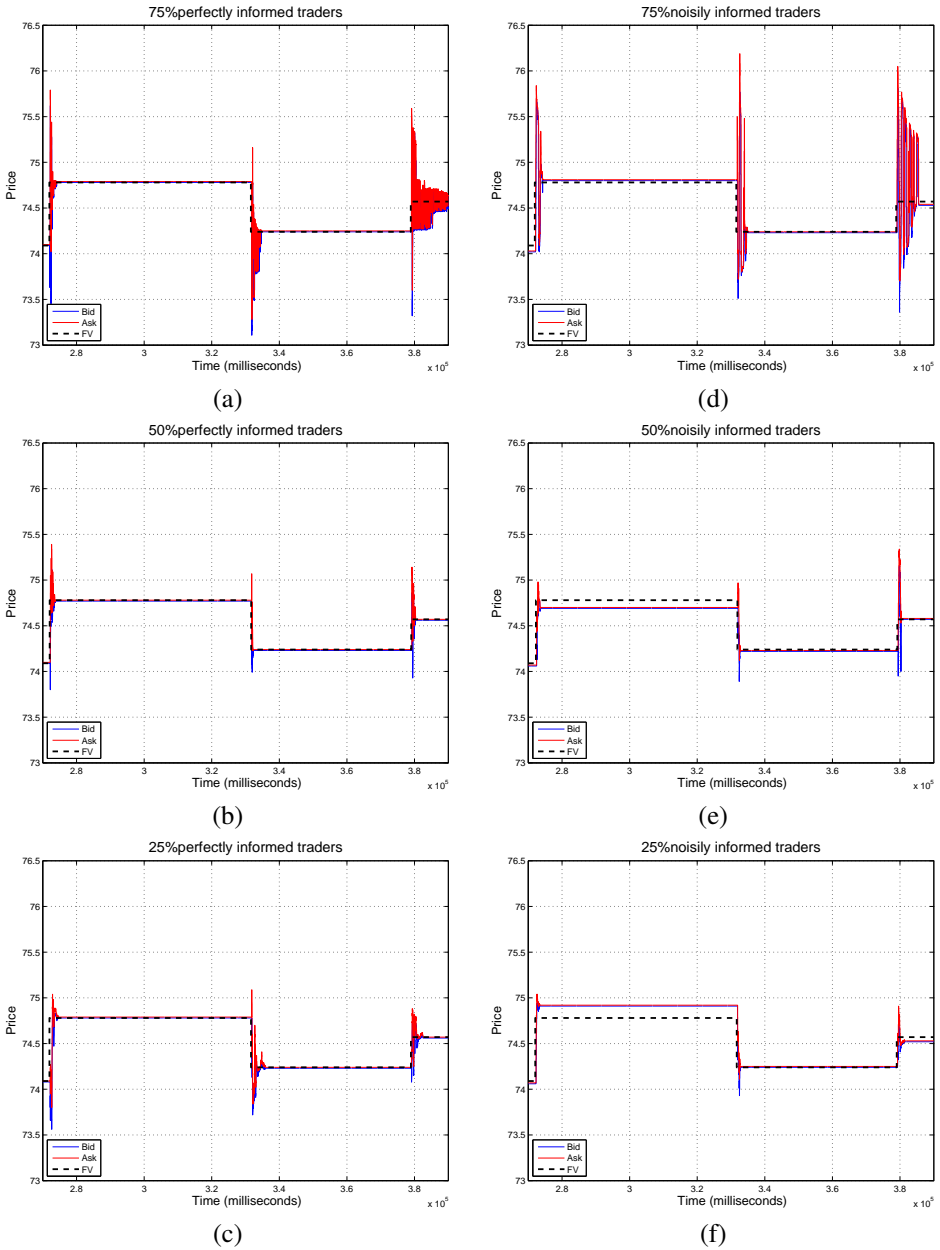
Figure 5.11: A segment from the learning behavior of the market maker in case of autonomous investors.
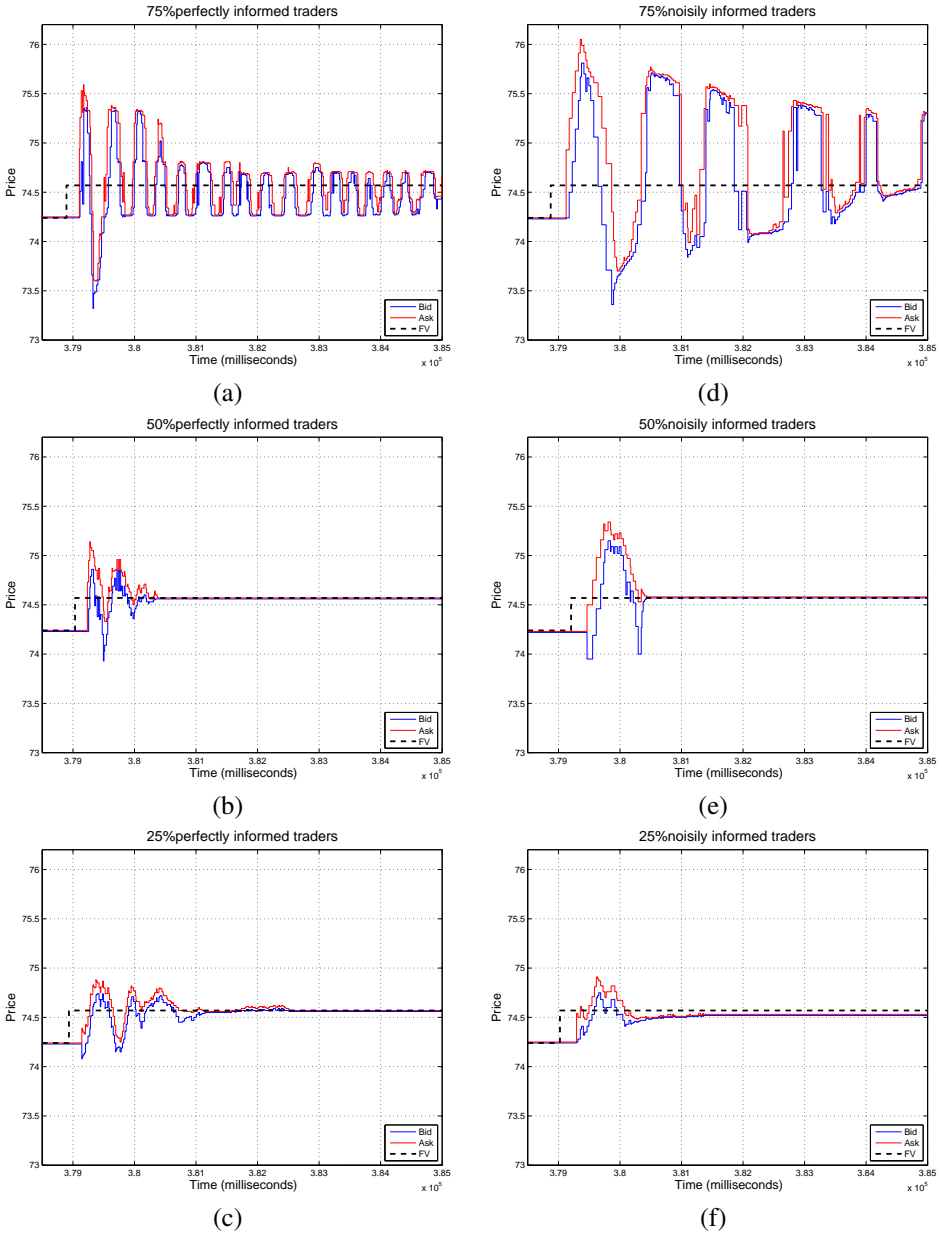
Figure 5.12: The learning behavior of the market maker immediately before and after a jump in the fundamental value in case of autonomous investors.

tal value by placing the same kind of order, thus causing the peaks in the resulting bid and ask prices.

Note that the repeated peaks are not visible in Figure 5.8(a) and (d), viz. the model with central selection. Although, in case of central selection, the market maker is also uncertain about the correct bid-ask prices after a jump in the fundamental value, the market maker quickly learns the new fundamental value, especially when the fraction of informed traders in the market is high. There are no other large oscillations.

The diverging results in the price discovery process of the market maker in the two models presented can be attributed to the autonomous, individual representation of investors. In the next section we elaborate on some of the consequences discussed so far and we analyze what kind of other consequences autonomous representation and continuous time simulation can cause.

5.4   Discussion

In this section we aim to analyze how the various implementations and extensions of the EGM model perform, and what the effect on the market dynamics is of making the model and the settings more realistic. In relation to this we elaborate on the differences between the dynamics of the turn-based, continuous time model with central coordination of investors, and the dynamics of the continuous time model with autonomous traders. We focus especially on the following questions.

- In which case do the various models give the most appropriate results?

- Which model and setting is closer to reality?

- What happens when trying to make them more realistic?

5.4.1   How realistic are the models?

The EGM model seems to be appropriate to learn the fundamental value of a stock known and diffused by informed traders. The question is however, how the results can be related to the dynamics of real stock markets. It must be admitted that the model contains several unrealistic elements.

1. In the turn-based models (EGM and CEGM) investors are controlled, in the sense that they are not allowed to trade whenever they want to, but only when they are **centrally selected** to do so.

2. In the ACTEGM model **the number of investors is relatively low**.

3. In all models **the market maker knows** whenever investors make a decision, thus also **when investors decide not to trade**.

4. In all models all investors plan only **one time horizon ahead.**

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5. In all models **the market maker knows information that is not available in reality**. We refer here to the time of change in the fundamental value, the rate of informed and uninformed traders, and the frequency with which uninformed traders place an order.

6. In all models there is a **well-defined fundamental value**.

In this chapter we aim to focus mainly on the first three items and on the consequences of allowing a more realistic representation of these aspects. We will also indicate briefly how some of the other "unrealistic" elements could be eliminated.

5.4.2 The effects of individual, autonomous representation

In the ACTEGM model we tried to eliminate the first unrealistic element. In the experiments presented in Section 5.3 we have avoided central selection, and represented individual, autonomous investors. In this way the EGM model became closer to the behavior of human traders. It has also caused however, diverging results that are mainly manifested in the fluctuating bid and ask values. In Section 5.3.2 we already gave a brief indication of the reasons behind this phenomenon. In this section we elaborate on this and give an indication on how the problems can be repaired.

(Simultaneous) reactions of informed traders to changes in the fundamental value. In the continuous model, in which investors are represented as individuals and exhibit autonomous, asynchronous behavior, every trader has the opportunity to submit an order whenever the trader determines it is worthwhile to do so. This feature implies that if more investors interact on the market, it can happen that some of them decide to place orders at the same time. For example, when all informed traders observe the same jump in the fundamental value, and it is worthwhile to submit an order, they will all do so. Given that the market maker is able to process only one order at a time, this homogeneous, (close to) simultaneous decision will result in a queue of orders. If there are more informed traders in the market, there is also a larger queue.

Consider, for example, the experiments with 75% perfectly informed traders in Figure 5.12(a). Here, the number of informed investors is three as opposed to one single informed investor in the experiments with 50% (b) or with 25% (c) informed traders. The difference thus, between these experiments, is not only the fraction of the uninformed investors. The number of informed players in the market is also different. The question is now, whether the observed fluctuations are caused only by the random trader, or whether the number of informed investors (in absolute terms, and hence not in terms of the fraction) also plays a role. In order to answer this question, we take a closer look at the 75% case. Further, in Section 5.4.3 we analyze situations with populations of multiple informed traders.

Figure 5.13 shows a part of the simulation run with four traders three of which are perfectly informed. In the upper panel the bid and ask prices, and the fundamental vale are displayed immediately before and after a jump in the fundamental value. On the second panel from above, the orders are displayed at the time these are processed by the market maker. This panel is aimed to illustrate how orders trigger the changes in the bid and ask values shown in the upper panel. The third panel illustrates the (same) orders at the moment
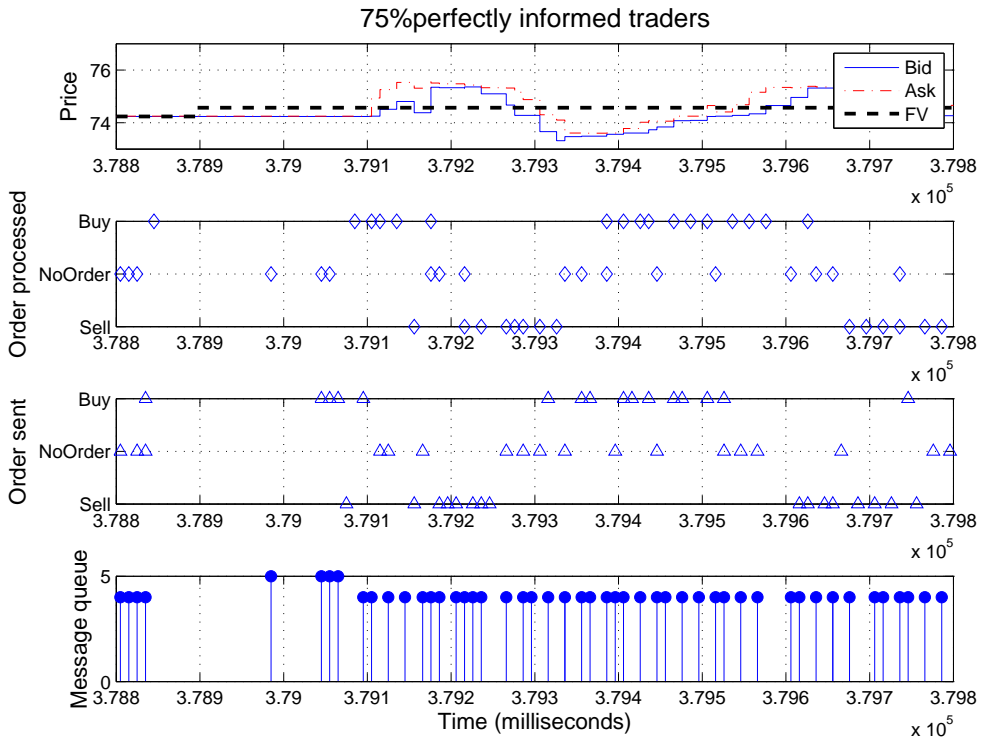
Figure 5.13: Market prices, orders processed, orders sent, and the pending message queue over time, in a market with four traders, of which three are perfectly informed.

they have been placed by the investors. In the lower panel the number of pending messages are shown at the time when the market maker processes a message.

Overshoots and herd-like behavior. In this figure the reason for fluctuations becomes more pronounced. Since all informed traders submit an order of the same type, each individual order pushes the market maker's bid and ask prices in the same direction, causing a strong movement in one direction. As soon as these orders are processed, the bid and ask prices are typically over- or underestimating the fundamental value. Given that the informed traders know the actual fundamental value and see the results of this overreaction, they will again submit an order, driving the prices back in the direction of the fundamental value and even further away in the other direction. This process may be repeated several times until the market maker sets his bid and ask prices around the fundamental value.

The speed of information diffusion. In Figure 5.13 the speed of information diffusion can be followed as well. As can be observed, the change in the fundamental value is not immediately reflected in the prices. This market is thus inefficient for a moment. The delay in the price adjustment process of the market maker is caused by the presence of unprocessed

orders at the time of the jump. As there are already some orders that wait for execution when the fundamental value changes, it might take the market maker some time to realize that the fundamental value has changed. The delay in information diffusion is also caused by the fact that there is some time spent between the moment an investor places an order (thus also an order from an informed investor through the orders of which information diffuses), and the moment the market maker executes the order.

At time 379100 the market maker begins to process a series of buy orders sent by investors before this time, when the stock was overvalued. The market maker manages to capture the fundamental value through the first adjustment, however, he continues to increase the quotes as he thinks that follow up orders are reactions to new quotes. Those have been sent however before the adjustment.

Timing aspects. Another consequence of the autonomous representation of the investors is the delayed reaction of the market maker to the change in the fundamental value. Although the fundamental value changes at time 378900 the market maker reacts to this change only at 379100, because he gets the message about the change only then. At this point the message queue drops to four elements, so the change in the fundamental value is now investigated. The market maker, as well as the investors, is notified however, about the change immediately. This can be seen from the correct reaction of investors and the increased message queue. Informed investors send buy orders as soon as they sense that the stock is mispriced. The message queue increases to 5 elements (just) before time 379000, the 5ht element being the sign that there is a change in the fundamental value. The market maker processes sequentially first however the messages that are waiting in the queue. These ones became outdated though at the moment of jump.

The following additional timing issues can cause the model to not behave as expected.

- From an investor's point of view the fundamental value might change between the time he placed an order and before the time this order is processed by the market maker.

- The market maker might be notified later than the investors about the change in the fundamental value.

- Both the investors and the market maker might show a delayed reaction to changes if at that time they are carrying out another task.

Most of these timing issues might be considered as realistic. For instance, in reality it might happen as well that someone receives important news after placing an order. If so, he might cancel the order he placed in case that this order does not conform anymore to the news and is not executed yet. In the model this behavior could be modeled by introducing cancel type of messages and giving them higher priority then request messages. The market maker's delayed reaction to news about a change in the fundamental value could also be solved by giving higher importance to the news message than the request messages.
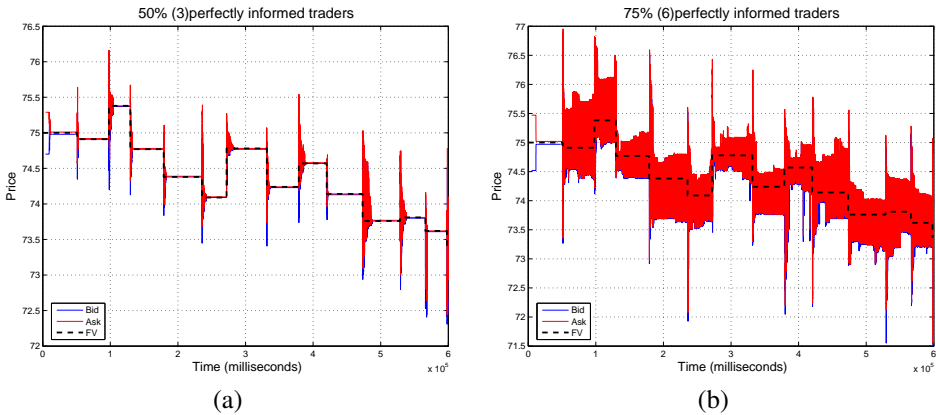
Figure 5.14: Performance with increasing number of investors if 3 out of 6 (a) and 6 of 8 (b) traders are perfectly informed.

5.4.3 The effects of increasing the number of investors

The autonomous, individual representation of investors thus causes herd-like behavior in case more than one informed trader interacts on the market, who immediately react to a change in the fundamental value. Herd-like behavior in turn results in overshoots in the price discovery process of the market maker. In the original Das (2005) model and in the CEGM turn-based model, this effect is not present, because only one trader can submit an order at a time, and thus, when the next trader enters the market, he observes the new bid and ask prices, in which the new information is already (partly) processed.

In the experiments with autonomous traders presented so far, the number of traders is kept relatively small, while in the models in Glosten and Milgrom (1985) and Das (2005) the number of traders is not relevant (only the fractions of various types of traders matter). This has to do with the typical feature that in the original models investors are either not represented individually (so, just the order flow is generated) or one single investor is centrally selected to trade at each trading period.

In this section we analyze what happens when we increase the size of the trading crowd. Figure 5.14 illustrates experiments in which the size of the population has been doubled in case of 75% perfectly informed traders, and tripled in case of 50% perfectly informed investors. As we have expected, in simulations with an increased number of informed traders the market maker performs worse, and the order queues cause larger peaks in the bid and ask prices, than in simulations with less investors. While the market maker was able to quickly learn the fundamental value when trading against 1 informed and 1 uninformed trader, it takes him more time to correctly adjust the bid and ask prices when trading with 3 informed and 3 uninformed traders, or he does not succeed in adjusting at all.

When a queue of pending orders arises, the market maker will aim to handle the orders one by one. Market orders that need to wait for other orders to be executed before they are handled will not be cleared at the price they have been placed for. The market maker, how-

ever, processes all the orders as if they would have been placed one after each other, taking into account the effects of the transactions resulting from the earlier arrived orders. This implies that the amplitude of fluctuations increases with an increasing number of informed investors. The question is how to deal with this herd-like behavior of traders.

5.4.4   Adjusting the model to the herd like behavior

How can we avoid to misinform the market maker while maintaining the autonomy of the investors, and the continuous time evolution of the market? The solution that we propose is to let the investors send limit orders instead of market orders. The market maker then would execute only the orders that correspond to the current bid or ask, and ignore and reject the other ones. In this way the investors will not mislead the market maker, and moreover, the investors' orders will not be executed at an inconvenient price. Note, that this approach does not require modifications to the learning algorithm of the market maker.

In order to apply this approach the limit prices need to be determined. The limit price could be set to the actual bid or ask values for instance. However, this setting would cause many unnecessary communication between the investors and the market maker as it would lead to many useless messages. In order to avoid overloading in the communication process, the investors could also set the price at the fundamental value that they know, since this is the ultimate price at which they would trade, excluding the transaction costs. This means that an investor will sell at the current bid as long as it is higher than the current fundamental value (plus the transaction costs) and an investor will buy at the current ask, as long as it is lower that the current fundamental value (minus the transaction costs). As transaction costs are ignored for the purpose of this thesis, we set the limit prices to the fundamental value plus one cent for sell orders, and the fundamental value minus one cent for buy orders. Trading at the fundamental value of course immediately reveals the true value of the stock to the market maker. Given, however, the nature of the learning algorithm that is based on the order side and not on information in the limit prices we do not have to be concerned about this problem. Accordingly, we choose to set the price quotes at the fundamental value plus-minus one cent.

In Figure 5.15 the results of applying this setting are illustrated for the case of 75% informed investors. On the left hand side simulations with perfectly informed traders, on the right hand side simulations with noisily informed traders are presented. Panels (a) and (d) show the results during the whole simulation run. Panels (b) to (d) represent segments from the simulation. As it can be noticed, the limit orders have successfully eliminated the fluctuations observed in Figure 5.10 (a) and (d).

Alternative approaches   Another way to deal with the queues caused by the autonomous behavior and homogeneous setting of informed traders is to introduce more variation in the order placement behavior of the traders. Introducing different reaction times for the investors, for example, would reduce the size of the queue that arises when a change in the fundamental value of the risky asset occurs. Different reaction times are realistic parameters, they could be the result of different news-sources, location or time needed to analyze the news.

Although at first sight the queue of messages makes the model perform worse than in the case of turn-based models, it reveals in fact valuable information from which the mar-
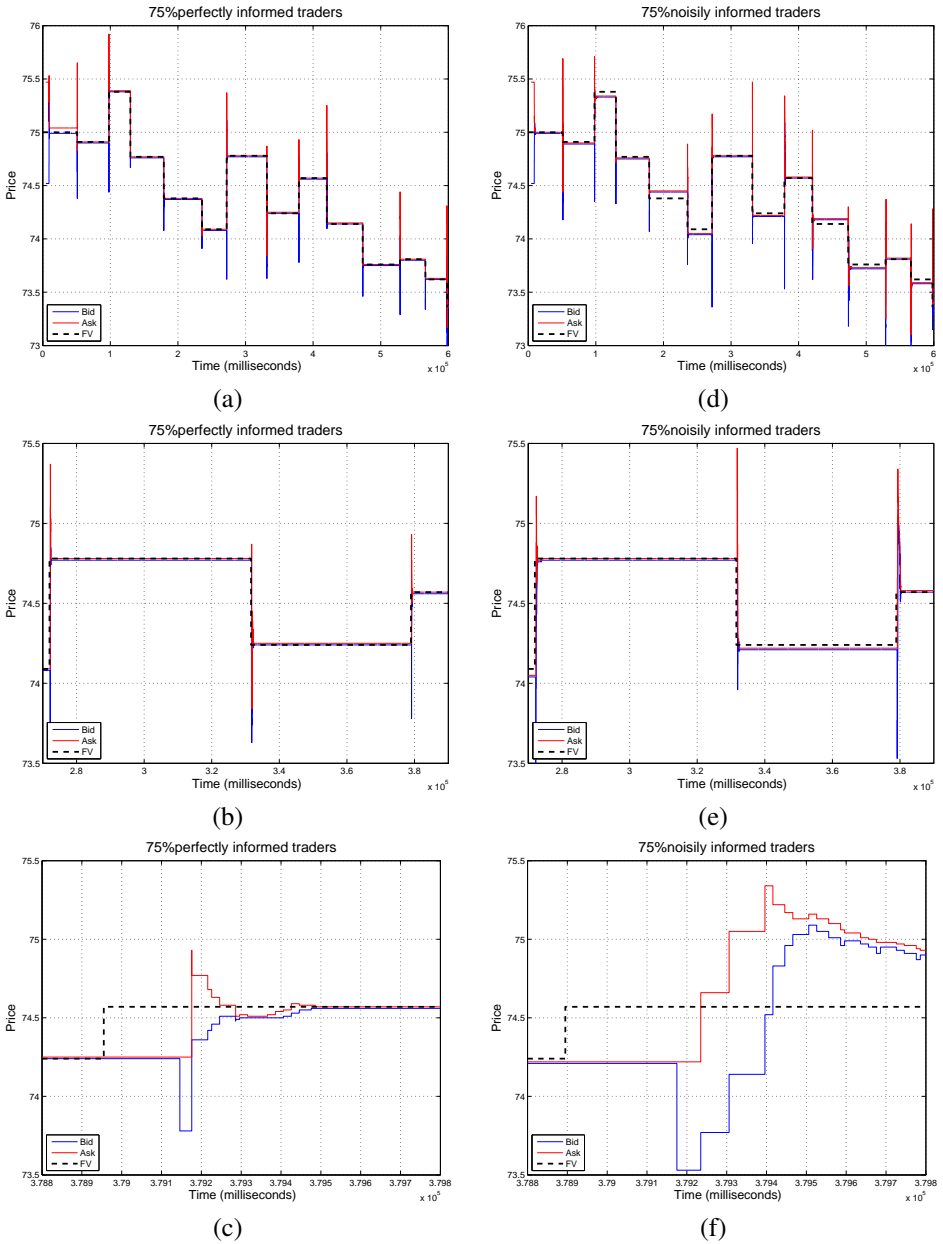
Figure 5.15: The learning behavior of the market maker in case of 75% autonomous investors who send limit orders.

ket maker could learn. In order to improve the learning algorithm, thus, the market making algorithm could be adjusted to handle trading crowds, by eventually learning from this specific situation (see for example (Koornneef, 2006) for a solution). The queue might indicate for instance, the number of informed traders, or a change in the fundamental value. The market maker could try to avoid overreaction by, for example, modifying his expectations more smoothly, when he observes a queue of orders on the same trading side. He could also temporarily modify the parameter indicating the fraction of informed traders when using the learning algorithms, assuming that the queue consists mainly of the orders of informed traders who react to mispriced stocks. Further, the market maker could learn the fraction of informed traders, information that is given in advance in the current model. This would make the model more realistic, as in reality the market maker does not know this fraction. In our future research we intend to investigate these extensions to the learning behavior of the market maker.

5.4.5 Effects of the no order condition

Once again, in the experiments presented up to now we let the investors send explicit "No order" messages to the market maker, when they decided not to trade. We have chosen for this solution, in order to keep the model as close to the replicated EGM as possible. This way of trading is not realistic however, as in reality investors do not inform the market maker that they do not want to trade. In order to make our model more realistic, in the experiments described in this section we have modified the investors' behavior, so that they do not notify the market maker about their "no order" decision. Next, we analyze the consequences of this modification.

Defining the market maker's no order condition.   In the turn-based EGM model it does not make a difference whether investors send an explicit no order message or not, because the market maker will interpret a turn with no outcome as a no order. In the discrete situation, the "no order condition" occurs when a buy or sell order is not placed in a trading round. During continuous simulation, however, there are no trading rounds, and orders are not placed at fixed times. If an investor decides to not to place any orders, because for him it is not worthwhile to do so, he could reconsider the possibility to trade again after a while, as market conditions (like bid and ask values) might change after a while. In the experiments presented here, we set the time horizon of the investors to 20 milliseconds. The investors analyze thus, every 20 milliseconds the market conditions again (unless they receive news in the meantime), in case they decide not to place an order.

This setting raises the following question: how long should a silent (no order) period last before the market maker decides that investors do not want to place orders because the fundamental value is captured?

For experimental purposes the time horizon of investors is constant and homogeneous. Moreover, the chosen value might not be optimal. The time horizon of investors is highly heterogeneous in reality and might vary from stock to stock, further it might change over time. In order to obtain an optimal performance of the model the time horizon (even if it is the same for all investors) and the no order condition should be properly determined. In order to determine properly for how long investors should wait for a change in the environment to
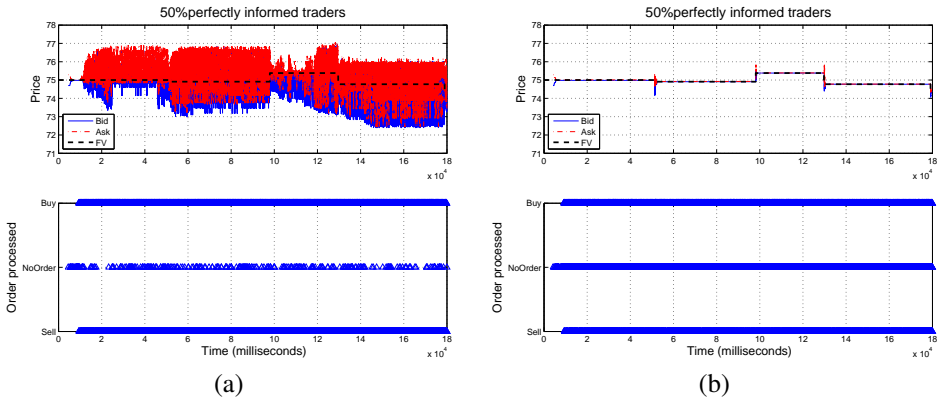
Figure 5.16: Market prices in a market with 50% of perfectly informed traders, no order condition of 50 (a) and 5 (b) milliseconds.

reconsider their decision, and to determine the no-order condition for the market maker the performance of the application should be analyzed. One of the values that could be looked at is how often bid and ask values change in the central selection case. Another aspect is how long it takes to get an answer to an order, and the frequency with which investors place no orders in the ACTEGM model with no order messages. Further, it should be taken into account, that all these values depend on the number of traders and the computational performance of the computer used to run the experiments. In the thesis we do not aim to analyze this problem, although we will illustrate the consequences of choosing different values.

Sensitivity to the no order condition. Figure 5.4.5 illustrates experiments with a relatively high and a relatively low value for the no order condition. In the first case the market maker counts every 50 millisecond period of silence as a no order condition, while in the second case this value is set to 5 milliseconds. These settings involve that the market maker will apply more often the "no order" condition in the latter case, than in the first case (see the lower panels). As it can be observed the speed of adjustment depends on this value. The smaller the value of the no order condition, the faster the convergence of the bid and ask values to the fundamental value. It should be mentioned further, that the speed of adjustment depends in addition on the number of traders, on the time horizon value of the traders, and on the performance of the computer used to run the experiments

5.4.6 Other unrealistic aspects

Although the ACTEGM model contains more realistic elements than the EGM and CEGM model, there still are many aspects that do not cover real behavior or market structure. As we mentioned in Section 5.4.1 in reality the fundamental value is not crisp, the market maker knows neither the rate of informed and uninformed traders, neither the level of noise in

the information set of the investors. We already suggested that the unrealistic assumptions regarding the knowledge of some of these elements could be avoided in the autonomous case by trying to learn these values from the queue of orders.

Finally, we should remark that the continuous time implementation, the independent representation of the news source, and the individual, autonomous representation of investors imply various timing issues leading to results that diverge from the results generated by the original EGM model. These are, at one hand realistic and interesting, on the other hand they might cause more complex behavior, and thus they should be taken into account when analyzing market dynamics.

5.5   Conclusion

In this chapter we have replicated the extended EGM model described in (Das, 2003, 2005) in the continuous time ABSTRACTE environment. The original model is implemented by applying discrete time simulation. In contrast the ABSTRACTE environment is based on continuous time simulation. The difference in the flow of time entails that time related aspects should be carefully chosen, and should be taken into account when analyzing experimental results within ABSTRACTE. We have presented two specific cases with respect to the investors' behavior. In CEGM centrally selected investors are mimicked. This selection does not require an individual representation of traders, and is in accordance with the description given by Das. The difference between the original model and our model is, that the fundamental value is represented independently.

The central selection of traders is not realistic however, and therefore, in the second case, in the ACTEGM model we have relaxed this assumption, and have focused on autonomous, individual representation of traders. In Section 5.3, we have pointed out that continuous implementation of markets and an individual, autonomous representation of traders carrying out tasks asynchronously requires specification of additional parameters. For example, attention should be paid to the number of different types of investors in addition to their fraction, and to the no order condition. Individual, autonomous behavior of the traders can influence market dynamics in an interesting way. In general it can cause the model perform worse through the herd-like behavior. These effects can be eliminated however, by slightly changing the market structure, i.e. letting the investors place limit orders instead of market orders. Further, herd like behavior might also reveal valuable information about the fundamental value.

The results of our experiments point out that continuous simulation of continuous markets, and individual asynchronous representation of traders' behavior influence the dynamics of the model. Given that most financial markets apply continuous trading sessions, these features should thus be taken into account during modeling.

It might seem that the asynchronous, continuous-time framework just makes the dynamics, and the interpretation of the results, more intricate. It has, however, several advantages compared to the original model. While in the original framework, no attention is paid to the way orders are generated, in the model presented in this thesis there is special attention paid to the behavior of individual investors. Investors in the continuous setting are more realisti-

cally represented, being able to make decisions autonomously. Further, the agents may have more information available in the continuous-time framework, for example, by interpreting order queues. We expect that this additional information would enable the market maker to learn several quantities that would be unknown to him on actual markets (such as the fraction of informed traders and the distribution of the jump process).

Chapter 6

Conclusions and future research

The research goal that we have stated in this thesis was to help the study and understanding of market dynamics. As various, often evolving, market organizations exist, we did not choose for one specific market to study, but we strived to allow for the representation of multiple markets. In a similar way, we have focused on traders' variable behavior. In this chapter we aim to give an overview and evaluate to what degree we managed to achieve the research objective and answer the research questions formulated in Chapter 1. We will also give hints for future research.

6.1   Evaluation objective

In the introduction of the thesis we have stated the following research objective:

Contribute to the study and understanding of market dynamics by providing a computational agent-based continuous-time simulation approach that supports a flexible representation of stock market organizations and traders' variable behavior.

In relation to our research objective we have formulated a number of research questions. The first amongst these focused on the structure and functioning of real markets:

Research Question 1.
Which are the relevant common and variable aspects of stock markets that should be taken into account when studying them?

Chapter 2 has been devoted to this question. In order to be able to answer it we have studied the market microstructure literature. As a result, we have proposed a **conceptual framework** that contains various aspects, dimensions along which the various market organizations and individual traders can be differentiated.

When trying to answer Research Question 1 we have differentiated two type of aspects:

- organizational aspects, i.e. static aspects that are well-defined, and

- behavioral aspects, i.e. dynamic aspects containing elements that are hardly observable

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We distinguished the following **organizational aspects**:

1. traded instruments

2. orders and quotes

3. market participants

4. trading sessions

5. execution systems

6. market rules

The hardly observable, dynamic aspects are mainly price formation related. In the price formation mechanism often a market participant is involved. Therefore, we have categorized this aspect as being behavioral.

We have formulated the **behavioral aspects** in terms of the role of the market participant concerned. We have analyzed the generic behavior of three groups of market participants: investors, brokers and market makers. Further, we have tried to identify hardly observable, and varying aspects that differentiate individual traders from each other within each group. As a result, we proposed the following aspects for the three trader types.

Aspects that differentiate investors are: investment objectives, investment constraints, attitude to risk, investment strategy, portfolio maintenance, monitoring, and time issues. It is however, difficult to give a generic representation in such a detail, as these aspects are correlated, and actions related to them are not executed sequentially. All these aspects influence however the order investors place at the end of their decision process. So, they can be included in one way or another in the investors' order placing strategy; and investors can be simply looked upon as traders who generate orders.

The main aspect that differentiates **investors** is, thus:

- the order generation mechanism.

Aspects that differentiate **brokers** are:

- order selection mechanisms;

- order execution mechanisms;

- negotiation strategies;

- strategies to determine transaction prices.

Aspects that differentiate **market makers** are:

- order execution mechanisms;

- determination and timing of quotes;

- handling the limit order book.

The way we described trader roles turned out to be advantageous in two ways at least. Firstly, it can be easily translated to the perception-decision-action architecture of agents. Secondly, the generic, specific and hardly observable components, can be captured in a straightforward way by designing the agents as consisting of skeletons and empty place-holders for the various existing or presumed behavioral strategy patterns.

Chapter 2 ends with an overview of approaches used to study market dynamics. The primary aim of this overview is to analyze how the various approaches deal with the hardly observable aspects (i.e. how they model them and what they assume about them), and what these approaches assume or conclude about the market dynamics. The analysis points out that assumptions regarding price formation vary along a large scale, from matching two orders and simple linear equations to complex, nonlinear equilibrium models, and intricate behavior of market makers. Further, the assumptions regarding traders' behavior varies from homogeneous rational traders with fixed trading strategies to heterogeneous, boundedly rational traders with evolving strategies, and arbitrary many other possibilities and combinations of strategies.

After being able to describe the structure and workings of real markets, we turned our focus to artificial stock markets. Accordingly, Chapter 3 dealt with:

Research Question 2.

To what degree do ASMs from literature reflect the workings of real markets and how do they deal with the common and variable aspects of real stock markets?

In order to answer this question we analyzed a number of ASMs from the literature, and compared their structure, and traders' representation to the workings of real markets. We did this on basis of the framework of organizational and behavioral aspects proposed in Chapter 2. The analysis resulted in a conceptual framework for a taxonomy of ASMs that extends the conceptual framework for describing stock markets with design and implementation aspects. This taxonomy can be used as a map, a sort of checklist based on which additional ASMs can be analyzed.

One of the conclusions of this synthesis, and the answer to the research question, is that although many ASMs focus on call-auctions, the importance to study continuous trading sessions is more and more recognized. When implementing continuous trading sessions, however, mainly discrete-time simulation is applied, not continuous-time simulation. When analyzing the type of traders in various ASMs with respect to their role in the market, we can conclude that investor traders are most often focused on. The role of market makers is seen as important only in a few cases, and brokers' behavior is ignored. Further, traders are generally implemented as a crowd, and their behavior is often centrally controlled. Individual, autonomous traders are rarely modeled.

Based on the analysis of the workings of real markets and on the synthesis on ASMs we proposed the ABSTRACTE trading environment in Chapter 4. The contents of this chapter forms the answer to:

Research Question 3.

How can we design and develop a modular, flexible agent-based environment using which one can study both the common and the varying, hardly observable features of stock markets, as well as their aspects that have been rarely or not represented in existing ASMs?

As suggested by our answer to Research Question 3 the environment is agent-based,

and is designed with the purpose to deal with the varying and hardly observable aspects of real markets, with the relevant factors that can be found in existing ASMs, as well as the aspects ignored by the ASMs studied. Accordingly, the main properties that we have striven to achieve, and which finally drove the design process of the trading environment were:

- continuous trading sessions;

- continuous-time simulation;

- individual trader representation;

- autonomous, asynchronous (not controlled, always simultaneous or sequential) behavior of traders;

- modularity as regards trading strategies and price formation mechanisms.

The approach we took was to build the environment based on the static, well-defined organizational aspects and the generic behavioral aspects discovered in Chapter 2. In the implementation these are the only hard-coded parts. For the varying, hardly observable aspects we used only empty placeholders that can be filled in with arbitrary many solutions in a flexible way.

We provide a number of variants to fill in the empty placeholders on top of the skeletons, and in the second part of Chapter 4 we illustrate how the environment can support multiple market organizations and behavioral implementations. By using, simple and analytical case studies we have been able to gain confidence about the correct functioning of the environment with the implemented ASMs on top of it.

While in Chapter 4 only simple ASMs are studied to illustrate the modularity of the AB-STRACTE environment, in Chapter 5 a more detailed study of the dynamics of a specific market is presented and discussed. The case study concerns the continuous-time, asynchronous implementation of the extended Glosten and Milgrom model from Das (2005) with autonomous, individually represented investors. This representation helps us to give a fist answer to the last research question, namely:

Research Question 4.

What is the added value of the proposed environment as compared to existing ASMs, and how can it improve the understanding of market dynamics?

The results of the experiments show that there are some important differences in the nature of available information between turn-based models and continuous-time, autonomous, asynchronous agent-based models like ABSTRACTE. On the one hand, much information is available to the agents in turn-based models, since each agent can observe the consequences of the previous decisions (e.g. prices that have been formed as a result of other agents' trading decisions). In continuous, asynchronous models, there is uncertainty regarding this information, because the agents take decisions based on available information at some point in time, but the market state may change between the placement of an order and its execution. On the other hand, additional information might be revealed in the continuous, asynchronous models, which is not available in turn-based models. For example, a sudden increase in the number of entries in the order book might entail information that can be acted upon, while it is not available in turn-based models.

In the end, the answer to the last research question, Research Question 4, can be derived from both Chapter 4 and Chapter 5. What makes the ABSTRACTE environment specific, is the fact that it is based on continuous-time simulation and on an individual representation of various market participants, without putting constraints on the representation of hardly observable and varying aspects, namely the price formation mechanism and trader's specific behavior. The most important value of the ABSTRACTE environment lies in its modularity, i.e. in the fact that experiments with various market structures and with arbitrary many trading strategies can be run on top of it. Since, only a few strategy implementations are provided at the time being, to fill in the empty placeholders, replication of some specific ASMs or market structure might require adaptation of the environment. We expect however, that this will not take too much effort, and the grade of adaptation required will be reduced over time.

Given the above answers to the research questions, and the argumentations behind them, we can state that we have managed to achieve the stated research objective, namely to aid the understanding of market dynamics. The approaches and frameworks proposed in this thesis will help the study of market dynamics in multiple ways. The conceptual framework can be used to compare properties of real and artificial stock markets, and can serve as a guideline to design new ASMs. The ABSTRACTE trading environment is a test bed of ASMs, and a tool to implement new ASMs. In this way the environment can help us to study, understand and compare market dynamics within new and existing ASMs. Results might suggest how certain market organizations should be changed or improved to improve market quality.

6.2   Future research

Research in the field of market dynamics can be conducted in many directions, due to the fact that market dynamics are still difficult to understand, and that many varying market organizations, and hardly observable aspects of price formation and traders' behavior exist. Based on the contents of this thesis we suggest future research in three main directions: the conceptual framework, the trading environment, and the specific ASM studied in this thesis.

The conceptual framework proposed can be used as a guideline to design new ASMs. Further, it is a framework that helps to structure existing literature, i.e. to classify, compare various ASMs and to analyze how given ASMs conform to reality. In the thesis, we have compared only a limited number of ASMs, this list can be extended at any time. Further, the framework could be extended or modified if necessary, to include other important aspects that differentiate stock markets.

The ABSTRACTE trading environment itself can be further developed in many directions. For example, multiple stocks could be considered, and investors could be modeled as portfolio managers in multiple stocks. In relation to this more market makers could operate on the same market. Then, the news generation process could be separated, and should be made modular to support other forms of news generation, and fundamental value evolution. Further, the behavior of brokers could be focused on, for instance market dynamics could be studied and compared with brokers in double auction vs. dynamics of markets without double auction. The environment can additionally be used to compare dynamics of various market structures, like call vs. continuous trading sessions, and to study the relation to the empirical and experimental literature. Another challenging application of the environment is

to run it in a distributed way. It would be interesting to conduct research with more types of markets running simultaneously trading in similar stocks, and observe the behavior of traders who exploit differences in pricing. Finally, the set of provided strategies to fill in the empty placeholders could be extended with learning strategies applying computational intelligence approaches, for instance.

In relation to the specific ASM studied within the ABSTRACTE, i.e. the continuous-time implementation of the extended Glosten and Milgrom model, we propose additional experiments, extensions, modifications, and analysis to better understand the dynamics of the model, and the relation between the aspects that drive the dynamics. A more detailed statistical analysis could be conducted for example, to further test the efficiency of the market. The performance of various investors, and the performance of the market maker could be analyzed for this reason. Then, the behavior of the market maker could be improved, as suggested, to learn from the order queue. In this way, some unrealistic assumptions of the model could be dropped, like the knowledge related to the rate of informed and uninformed traders. These adaptations would make the model more realistic, and would lead to a higher degree of efficiency. Experiments with a higher number of individual traders would make the results more valuable as well. There are several other interesting situations to experiment with in both the discrete-time and the continuous-time framework. It would be interesting, for example, to vary the jump process and investigate the market maker's learning behavior under different circumstances. Large jumps could be introduced for this purpose, or historical time series could be used to model the jump process. Another challenging task is to adapt the learning algorithm of the market maker in order to account for both perfectly informed and noisily informed traders.

Samenvatting
(Summary in Dutch)

Over de dynamiek van financiële markten wordt een uitgebreide discussie gevoerd door onderzoekers en financiële experts, die proberen te begrijpen en te verklaren hoe financile markten opereren. De ingewikkelde dynamiek van markten en allerlei moeilijk waar te nemen aspekten ervan, zoals de besluiten die ten grondslag liggen aan de prijsformatie mechanismes, of ook de motivatie van investeerders voor hun akties op de markt leiden tot uiteenlopende verklaringen. De verscheidenheid van aannames binnen de verschillende benaderingen heeft geleid tot controversile, elkaar tegensprekende beschrijvingen van de dynamiek van markten, hetgeen aangeeft dat de werking van markten tot op heden slecht begrepen wordt.

In hun poging om een beter begrip te verkrijgen van de dynamiek van markten, worden in studies op het terrein van de op agent technologie gebaseerde computationele economie markten gerepresenteerd vanuit een bottom up benadering. In het algemeen kunnen deze op agent technologie gebaseerde modellen van aandelenmarkten gekarakteriseerd worden als modellen waarin agenten om beurten geselekteerd worden door een centrale instantie, waarbij ze een enkelvoudige handeling verrichten. Dat wil zeggen, er wordt om beurten handel gedreven op diskrete tijdstippen, een vooraf vastgelegd repertoire van handelsalternatieven wordt gemodelleerd, en de handelaars zijn niet autonoom maar nemen alleen dan een besluit om al of niet te handelen als ze daartoe geselekteerd worden.

Het doel van dit proefschrift is een bijdrage te leveren aan het inzicht in de dynamiek van markten door middel van een uitbreiding van de op agent technologie gebaseerde invalshoek. Om ons doel te bereiken stellen we een omgeving voor, die modulair is, gebaseerd op continue tijd en gebruik maakt van agenten, waarbij de deelnemers aan de markt individueel en autonoom gemodelleerd worden. Om zo'n omgeving te kunnen ontwikkelen maken we allereerst een analyse en een vergelijking van aandelenmarkten uit de praktijk en artificile aandelenmarkten ("artificial stock market"s of ASM's). Deze analyse is het uitgangspunt voor twee conceptuele raamwerken: een om aandelenmarkten uit de realiteit te beschrijven en de andere voor artificile.

Voor het conceptuele raamwerk waarmee we aandelenmarkten uit de praktijk beschrijven nemen we de literatuur over de microstruktuur van markten als uitgangspunt. Binnen dit raamwerk worden de organisatie van markten en de deelnemers daaraan onderscheiden langs twee assen, te weten organisatorisch en in termen van gedrag. Organisatorische aspekten refereren aan statische, welgedefinieerde elementen, zoals de verhandelde instrumenten,

het type orders, het type uitvoeringssysteem en de sessies waarin handel gedreven wordt. Gedragsmatige aspecten zijn dynamisch en bevatten elementen die nauwelijks waar te nemen vallen. We concentreren ons op het gedrag van drie groepen participanten in de markt: investeerders, effectenmakelaars en 'market makers', zoals de hoekman op de Amsterdamse Effectenbeurs. We beschrijven het generiek gedrag van elk type deelnemer. Daarnaast proberen we de nauwelijks waarneembare en variërende elementen te bepalen waardoor individuele deelnemers binnen dezelfde groep zich van elkaar onderscheiden. Om te analyseren in hoeverre de ASM's uit de literatuur de mechanismes van markten uit de praktijk modelleren, en hoe ze omgaan met de gemeenschappelijke alsook varirende aspecten van aandelenmarkten uit de praktijk, bestuderen we een aantal ASM's uit de literatuur, vergelijken we de struktuur ervan en hoe handelaren gerepresenteerd worden, met de gang van zaken in de werkelijke wereld. Deze analyse levert een taxonomie van ASM's op waarbij we het conceptuele raamwerk van de aandelenmarkten uit de praktijk uitbreiden met ontwerp- en implementatieaspekten. Deze taxonomie kan gebruikt worden als een routebeschrijving, een soort check list waarop een vergelijking van additionele ASM's gebaseerd kan worden.

We nemen de analyse van de mechanismes van markten in de praktijk en de synthese over ASM's als uitgangspunt voor onze bijdrage: de ABSTRACTE omgeving (Agent-Based Simulation of Trading Roles in an Asynchronous Continuous Trading Environment). Deze omgeving maakt gebruik van agenten, en is ontworpen met het doel onderzoek te verrichten naar de variërende en moeilijk waar te nemen aspecten van markten in de praktijk, alsmede de relevante factoren die we kunnen vinden in bestaande ASM's, alsook de aspecten die daar achterwege gelaten zijn. Derhalve zijn de belangrijkste eigenschappen die we willen implementeren, en die de drijvende kracht vormen achter het ontwerpproces van deze marktomgeving de volgende: de mogelijkheid om continu handel te drijven, simulatie in continue tijd, individuele representatie van de deelnemers, autonoom en asynchroon (niet van buiten af bestuurd, niet alles tegelijkertijd of strikt sequentiël) gedrag van de deelnemers, en modulariteit wat betreft handelsstrategien en het prijsvormingsmechanisme.

Ons idee is om de omgeving te bouwen, gebaseerd op de statische, welgedefinieerde organisatorische aspecten, met daarnaast alleen de generieke aspecten van het gedrag. In de implementatie zijn dit de uitgeprogrammeerde onderdelen. Voor elk van de varirende, nauwelijks waarneembare aspecten gebruiken we een lege mal, die op een flexibele manier gevuld kan worden met een willekeurig aantal oplossingen.

In dit proefschrift beschrijven we een aantal varianten waarmee deze lege mallen ingevuld kunnen worden, en we laten zien op welke manier de omgeving gebruikt kan worden om een aantal marktorganisaties en voorbeelden van gedrag te beschrijven. We gaan uit van eenvoudige en analytische case studies en dit stelt ons in staat om vertrouwen te verkrijgen wat betreft het korrekt funktioneren van de omgeving met de gemplementeerde ASM's daaraan toegevoegd.

In dit proefschrift presenteren we daarnaast een gedetailleerde studie van de mechanismes in een specifieke markt. Deze case study behandelt de asynchrone implementatie in continue tijd van het uitgebreide Glosten en Milgrom model met autonome, individueel gemodelleerde investeerders. De resultaten tonen aan dat er een aantal belangrijke verschillen aan te geven zijn in de aard van de beschikbare informatie tussen op beurten gebaseerde modellen versus autonome, asynchrone, op agenten gebaseerde modellen met continue tijd zoals ABSTRACTE. Enerzijds is er veel informatie beschikbaar voor de agen-

ten in modellen die op beurten gebaseerd zijn, omdat iedere agent de gevolgen kan waarnemen van eerdere beslissingen (bij voorbeeld prijzen die het resultaat zijn van de beslissingen van andere agenten). In continue, asynchrone modellen bestaat onzekerheid omtrent deze informatie, omdat de agenten hun beslissingen baseren op de informatie die beschikbaar is op een bepaald ogenblik in de tijd, terwijl de toestand van de markt kan veranderen tussen het ogenblik waarop de order geplaatst werd en waarop die uitgevoerd wordt. Anderzijds, in continue, asynchrone modellen kan informatie beschikbaar komen, die niet beschikbaar is in modellen die op beurten gebaseerd zijn. Zo kan bij voorbeeld een plotselinge toename van orders informatie in zich bergen waarop gehandeld kan worden, terwijl die niet beschikbaar is in modellen die op beurten gebaseerd zijn.

De specifieke aspekten van de ABSTRACTE omgeving zijn dat de simulatie gebaseerd is op continue tijd en dat de diverse deelnemers aan de markt individueel gemodelleerd worden, terwijl er geen beperkingen zijn op hoe de varirende en nauwelijks waarneembare aspekten gerepresenteerd worden, te weten het mechanisme dat de prijs bepaalt, en het specifieke gedrag van de deelnemers. De belangrijkste waarde van de ABSTRACTE omgeving is gelegen in haar modulariteit, waarmee bedoeld wordt dat de omgeving als basis gebruikt kan worden voor experimenten met allerlei marktstrukturen en een willekeurig aantal handelsstrategien.

De benaderingen en raamwerken die in dit proefschrift voorgesteld worden kunnen op vele manieren bijdragen aan de studie van de dynamiek van markten. Het conceptuele raamwerk kan ingezet worden om eigenschappen van zowel aandelenmarkten uit de praktijk als kunstmatige te vergelijken, en kan ook dienen als richtlijn bij het ontwerpen van nieuwe ASM's. Met de ABSTRACTE omgeving kunnen ASM's zowel bestudeerd als nieuw ontworpen worden. In deze zin is de omgeving van nut om de dynamiek van markten te bestuderen, te begrijpen en te vergelijken, zowel middels nieuwe als bestaande ASM's. De hieruit voortkomende inzichten kunnen aanbevelingen opleveren over hoe bepaalde marktorganisaties veranderd of verbeterd zouden kunnen worden teneinde hun kwaliteit te verhogen.

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Katalin Boer-Sorbán was born in Miercurea-Ciuc, Romania, on 1 June, 1976. She completed her secondary education witch specialization informatics at Márton Áron High School, in Miercurea-Ciuc. In 1994 she started her higher education at Babeş-Bolyai University, Faculty of Mathematics and Computer Science, Cluj-Napoca, Romania. She received her B.Sc. degree in Computer Science, in 1998, and her M.Sc. degree with major in Information Systems, specialization Database Management, in 1999. During her studies, Katalin obtained fellowships at the Budapest University of Technology, and the Eötvös Lóránd University, Budapest, Hungary within the Central European Exchange Program for University Studies (CEEPUS).

In 2000, Katalin has joined the Computer Science group at the Econometric Institute of the Erasmus School of Economics at Erasmus University Rotterdam, The Netherlands. Here, first, she carried out research in the area of biometric authentication methods. Then, in 2002 she became a Ph.D. candidate in the area of agent-based simulation of financial markets. She has presented parts of her Ph.D. research at several international conferences and workshops. A version of Chapter 5 of this thesis is published in the Computational Intelligence journal. During her Ph.D. studies Katalin has been involved in teaching Bachelor and Master courses at Erasmus School of Economics, and at the Business Administration Program, at Rotterdam School of Management. As per 2008, Katalin, is affiliated with the Econometric Institute of the Erasmus School of Economics as an assistant professor.

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Agent-Based Simulation of Financial Markets
A Modular, Continuous-Time Approach

The dynamics of financial markets is subject of much debate among researchers and financial experts trying to understand and explain how financial markets work and traders behave. Diversified explanations result from the complexity of markets, and the hardly observable aspects of price formation mechanisms and of participants' motivation behind trading decisions. In an attempt to provide a better understanding of market dynamics, studies in the realm of agent-based computational economics represent markets from bottom-up. The aim of this thesis is to contribute to the understanding of market dynamics by extending the agent-based computational approach. In order to achieve our goal we propose a modular, continuous-time, agent-based trading environment, with individual, autonomous representation of market participants. In order to be able to develop such an environment we first analyze and compare real and artificial stock markets (ASMs). Based on this analysis we propose a conceptual framework to describe real markets. By enriching the framework with design and implementation issues we get a multi-dimensional taxonomy of artificial stock markets. ABSTRACTE, the proposed modular environment is an operational form of these frameworks. ABSTRACTE is aimed to embed the common aspects of real markets that exhibit big variations and are rarely represented in artificial stock markets. This environment provides the user with a flexible mechanism to implement many of the varying and hardly observable aspects of stock markets and traders' behavior. In this way it can contribute to the understanding of market dynamics as it can be used both as a test bed to replicate and evaluate existing market models, and to compare dynamics of multiple ASMs, as well as a tool to conduct experiments with new models and traders.

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