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Microsimulation of Artificial Stock Markets Based on Trader Roles

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Abstract

On financial markets trading takes place continuously and market prices are typically formed whenever two traders make an agreement. Most of the artificial markets, however, implement discrete time modelling and try to set the market price at equilibrium, where most demands and supplies can be matched. This paper describes the structural design of an artificial market environment that supports continuous trading and helps to study how different traders affect market dynamics in different situations. We identify different types of traders and describe an architecture based on their role and the market microstructure where they interact. In order to get an accurate representation of the market dynamics we apply a bottom-up microsimulation approach, and further, represent traders by intelligent agents. We start building from a more basic level than current approaches in the sense that we consider continuous order matching mechanisms and implement agents’ behaviour based on their role in the market. For this reason we trace the life-cycle of the orders observing the changes they suffer especially caused by traders’ different decision till they trigger market prices.

1 Introduction

The market price of an asset changes continuously whenever an order is executed. Several traders interact in order to accept, match or place orders based on the trading rules of the market. Investors continuously place orders on the financial market and they expect the best execution of them. A good execution might refer to immediacy, price improvement, low costs, etc. Market places thus, where orders are executed, should provide an environment where investors requirements are satisfied [11, 19]. In order to fulfill requests and achieve smooth trading different markets use different trading mechanisms (order matching mechanism, trading rules, market participants, etc). While several studies ignore the importance and influence of trading mechanisms on price formation the market microstructure literature studies how trading mechanism affects market dynamics [12].

Theoretical models sustain that markets are efficient and ignore the influence of market microstructure on price formation. They consider rational, homogeneous traders, who maximize utility and assume that market prices are random contain all available information and are driven by demand-supply equilibrium. The hypotheses formulated are, however, not supported by empirical and experimental findings, that suggest that traders are ”boundedly rational” and price series contain some empirical patterns. The problem with the theoretical models is that they are normative: they say how traders and markets should behave, not how they really are. In contrast experimental studies are descriptive and aim to study how agents really behave, and how their behaviour influences market prices [8].

A promising way of studying market dynamics is agent based computational economics and microscopic simulation. The idea behind the two approaches is basically the same: analyze how global regularities arise from individual interactions. They study market dynamics via the transparent feature of traders’ behaviour, allow for heterogeneity, bounded rationality, learning, etc. For this reason they implement artificial stock markets where different types of traders commonly represented by software agents interact and evolve with the market[17, 6, 8].

Artificial stock markets are implemented with the aim to study how and why market anomalies do arise, and to study how relaxing ”irrealistic” assumptions on theoretical models influences the findings. Several studies try to create environments that are able to generate empirical patterns observed, in order to find out why they arise. Although explanations exist that
suggest that stylized facts mainly arise from the heterogeneity and bounded-rationality of the agents (e.g. [4]), the models that generate patterns are however far too simple to contain all the influencing factors. It is not clear how the factors that are ignored influence the findings. As it seems impossible to consider all influencing factors, at some level aggregation is required. In order to find out how aggregation can be made so as to contain significant influential factors, a continuous observation of market participants is necessary in various trading environments at individual level.

A common artificial market structure involves constant absolute risk averse (CARA) utility maximizer investors, who submit orders at discrete time step, based on the expected price and utility. They choose between a risky and a riskfree asset. Agents represent usually two type of investors: fundamentalist and technical analysts and the difference in their performance is analyzed. The submitted orders are accumulated and centrally matched at periodic intervals and market price is set based on aggregated demand and supply (e.g.[4, 7, 13, 1]). Artificial stock markets that aim to study market dynamics usually implement in this way simple call-auctions, although most markets are continuous [14, 3].

There are two main characteristics of the existing artificial markets that we would like to emphasize: the aggregated way of price formation mechanism and the used trader types. Automated aggregated order matching does not fully represent market dynamics, only call auctions. Existing implementations mainly consider only investor type of behaviours and categorize them based on their belief regarding future values: they set fundamentalists against technical analysts (who can be further optimists or pessimists) who are all utility maximizers and ignore in some way the role of the traders. We think that the belief regarding stock values influences traders only when they set limit prices, and in reality their motivation for placing orders probably goes behind their belief and has to do with their financial status and role in the market. Simple investors might trade in order to make long-run investment, dealers to provide liquidity, brokers commit themselves to execute orders on behalf of the investors’ and might exert simple order-routing behaviour. Different traders’ role in this way might influence (discounted by their belief, need and preferences) the way they place an order and define an order.

In this paper we describe the architecture of different financial agents based on their role in the market. We use the bottom-up approach applied by the microscopic simulation and agent-based computational methodology. We emphasize the importance of going more into detail when designing artificial stock markets that aim to help us to understand market dynamics. Deepness regards traders role and continuity of price formation. We start with a top-down description of the structure of the financial markets and trace orders in order to identify the aspects that can significantly influence market dynamics.

The rest of the paper is structured as follows. First, in Section 2 we briefly describe existing artificial stock markets. Then, in Section 3 we clarify some commonly used expressions by describing the general structure of stocks markets with special focus on the role of different traders and the price formation procedures. Then, in Section 4 we discuss price formation at high, observable level. In Section 5 we go one step deeper and discuss how orders are determined and changed. This tracing of orders helps us to define the architecture of our artificial market and to determine the different building elements that need to be controlled and implemented. In Section 6 we identify the tasks different traders face by taking a closer view how they handle orders based on their role in the market. Finally we conclude in Section 7.

2 Background: Artificial Stock Markets

Agent-based models offer the possibility to transparently model financial markets and to study in this way the direct effect of agents’ behaviour on the market prices. In order to implement artificial stock markets we need to identify factors that might influence market dynamics. Artificial markets should accurately represent real financial markets as they aim to help to understand price dynamics, and further can serve to make markets more efficient. If it turns out, for example, that in a certain market it is possible to gain superior advantage, because of some characteristics of it (e.g. informational inefficiency) the used structure can suggest which factors should be reconsidered in order to make a market to function more smoothly.

Artificial stock markets that aim to study market dynamics usually implement simple call-auctions, although most markets are continuous [14, 3]. A common artificial market structure involves constant absolute risk averse (CARA) utility maximizer investors, who submit orders at every time step, based on the expected price and utility. The submitted orders are accumulated and centrally matched at periodic intervals. The market price is usually set so as to maximize trading volume: at the intersection
of demand and supply curves [7, 13] or based on excess demand [1] (here no limit price is given). The expected price and dividend are averaged to form the market price over the fractions of trader types in [4].

There are only a few artificial markets that implement continuous trading. Some studies attempt to implement continuity via randomization: for example by matching only orders of two randomly selected traders [10]. One of the most improved models that implements continuous trading is the Santa Fe Artificial Stock Market described in [16]. The trading mechanism used is a continuous double-auction market, where market orders are matched against limit orders by means of centralized limit order books. This structure, however does not consider real behaviour as the influence of agents’ behaviour on order flow is supposed to arrive based on a Poisson distribution.

Most of the existing settings of the artificial markets are able to replicate and thus explain stylized facts with the interaction of adaptive, heterogeneous agents [4]. In [16] is shown that, even under completely random IID order flow, temporal structure in prices can rise and for prices to be effectively random, incoming order flow must be non-random, in just the right way to compensate for the persistence. Further, there is also support found for some theoretical hypotheses: in [2] an attempt is made to formally interpret the efficient market hypothesis and the rational expectation hypothesis as emergent properties and is found that these will hold even if individuals do not believe them. Microeconomic behaviour thus, can be very different from macroeconomic behaviour and this feature places restrictions on inferring individual behaviour from aggregate results [2].

This observation proves the necessity to try to understand economic phenomena by constructive means through agents’ behaviour, such as aimed by the agent-based computational economics (ACE) literature [17, 18]. The studies mentioned above use this approach, they mainly apply, however, aggregate matching of orders, call-market mechanism, and ignore the role of intermediaries. However, most stock markets use continuous trading, and further order matching is not always automated but also involves financial agents (such as brokers, dealers and market makers) and thus price formation depends on their behaviour as well [14, 16]. The question is can the present settings represent continuous markets? Do prices in continuous markets converge to the same market values as prices in call-auctions? Does a continuous market-structure, that applies call-auction at the end of the day, converge to the same price as pure call-markets? This is probably not the case because some structures provide more effective markets; continuous markets contain more information than call markets[12].

Aggregation, randomness and automation is at some level required as there are too many parameters that might influence price dynamics, and in order to analyze their effect we need to treat them in controlled manner. In order to implement an accurate representation of the stock markets and to get valid results we need to study at which level (for which factors) can randomness and aggregation be introduced. For this reason, we aim to start the constructive implementation from the very-bottom. There are two main ”design issues” where we aim to go more into detail related to previous studies: (continuous) order matching and role based trading. Both are related to the price formation mechanism, thus in order to be able to implement them we need to identify parameters that influence price dynamics. For this reason we apply first a top-down approach to identify ”forces” that govern orders which on their turn trigger market prices; and than use the identified parameters to provide a constructive understanding of market dynamics.

3 Market structure

In order to implement artificial stock markets we need to know how real markets function at high level. For this reason we describe here the typical price formation mechanisms and the type of the market participants based on their role and tasks in the market.

3.1 Market participants

We classify different market participants (traders) in two main groups:

- investors and
- financial agents.

Investors are simple traders, who place public orders. Financial agents are traders endowed with special role in the financial market. There are several types of financial agents endowed with different tasks based on the market microstructure where they interact. In the exchange markets typically four types of financial agents interact[14]:

- commission brokers: are employees of member firms, who execute public orders as asked by the brokerage firm
- floor brokers: are independent members who act as brokers for other members (because they are for example too busy)
registered traders or competitive market makers: are allowed to trade for their account, and provide added liquidity.

- specialists: they serve as brokers for matching buy and sell orders, and to handle special limit orders; and further, they need to maintain a fair and orderly market by providing liquidity when the normal flow of orders is not adequate. (They must buy and sell for their own account when public supply or demand is insufficient to provide a continuous, liquid market). Specialists maintain a limit order book, for unexecuted orders and publish their quote (bid-ask spread). This spread is based on the incoming orders, trend, inventory position of the specialist, and position of the limit order book, and indicates thus, in a sense the current market value of this stock. The question is how the specialists use this information to determine the actual numerical value of this spread.

The number of different financial agents and the way they are allowed to trade is given by some market specific regulations. There are markets where stocks have one single specialist assigned (e.g. NYSE) responsible to maintain price continuity, but stocks can have more specialists (e.g. competitive market makers, or dealers on Nasdaq) as well, whose quotes are made available and brokers can chose to trade thus with the dealer who offers the best market.

As the above described classification suggests, financial agents need to conduct basically two tasks:

- execute orders on behalf of the clients: broker specific tasks
- execute orders for own account: dealer specific tasks

Whether these tasks are compulsory or optional and further whether an order represents a public or an internal order determines different agents denomination and role on a certain market. There are some brokers for example who are required to execute orders for customers but cannot keep inventory. Further, specialists must act as brokers and commit themselves to execute orders on others’ behalf and they must act as dealers in order to provide liquidity.

Based on the above mentioned criteria, in the artificial stock market we include two basic types of financial agents whose behaviour might radically differ:

- brokers
- market makers

Brokers are entailed with the basic intermediary task, that is route and execute investors order in the best possible way. Market makers execute some kind of control over market, and their basic task is to ensure liquidity. They display bid and offer prices and are able to buy/sell at publicly quoted prices. Whether a financial agent is allowed to maintain a certain level of inventory and/or to take public orders are additional characteristics which can be further simply set. For example one single market maker (assigned to one type of stock) in the artificial stock market represents a specialist from the NYSE, while more competitive market makers can represent dealers from the Nasdaq.

3.2 Characteristics of stock markets

Investors require the best execution of their orders that can be manifested in price improvement, speed, low costs, etc. The trading environment thus, where traders interact must provide a structure that strives to satisfy investor’s expectations [11, 14, 19].

A good market is characterized by timely and accurate information, liquidity and efficiency. Traders expect to trade at justified price, that reflects the available information (external efficiency), further they require low costs for transaction (internal efficiency). Liquidity refers to the possibility to buy or sell quickly (marketability) and at a known price, that does not substantially differ from previous transactions (price continuity). A market with price continuity further requires depth, which means that numerous potential buyers and sellers are willing to trade at prices below and above the current market price [14].

Markets differ regarding their quality as they try to achieve the required characteristics in different way. There are basically two types of markets: call markets and continuous markets. On call-markets trading occurs at specified times, and a single price is set so that the quantity demand is as close as possible to the quantity supplied. On continuous markets trades can occur at any time the market is open. Intermediaries (market makers, brokers) try to ensure liquidity and price continuity, by trading for their own account if necessary. Although most markets are continuous they also employ a call-market mechanism when uncertainty is large such as such as at open, close or to re-open following a trading halt (possibly caused by the release of some significant new information)[14, 9]. The reason for this is the temporary use of call market mechanism contributes to a more orderly market and less volatility [14].

There are two major trading systems applied on the markets: auction markets and dealer markets. On
auction (price-driven) markets bids and asks are submitted to a central location, where they are matched. On dealer markets individual dealers provide liquidity for investors by buying and selling for themselves. Continuous markets usually combine trading systems, in the sense that they are basically auction markets but if there is not enough activity intermediaries intervene as dealers.

Artificial stock markets usually implement only call markets, although most of the financial markets are continuous.

4 Price formation at high level

Market prices are directly determined by the order matching mechanism of a stock market. Orders represent the trading decision of a trader Figure 1. According to this we split the problem of studying market dynamics into two sub-problems:

- how do orders arise;
- how are the orders matched;

![Figure 1: Price formation at high level](image)

Market participants might be involved both in placing orders and matching them. It is not difficult to observe these actions, what is more problematic is to define what is behind them: when, how and why do participants take these actions, what are the parameters of the orders and how and when do traders update them. How traders solve these problems depends on their role in the market and some individual characteristics.

4.1 Placing orders

Orders are primarily initiated by investors or by financial agents trading for own account. Traders are influenced by several factors before they place an order: such as: goal, belief, financial situation, preferences, stock characteristics. These factors do not directly influence the formed market prices but through the trader behaviour and are reflected in the characteristics of the placed orders.

An order is characterized by the following parameters: the name of the stock to which it refers, the asked or offered volume, the side of the trading action (buy or sell) and a price quote (in case of the limit order). The question is what are the values of these parameters and how do traders set them and why in that way:

- what is the chosen stock and why?
- what is the required volume?
- how do traders set the limit price?

The determination of the parameters describing an order depends on the investors’ internal states and external stimuli and is the result of an intricate decision-problem the investors are faced with. Orders arise thus primarily as the result of the intention or need to change portfolio composition, but they are usually not immediately executed in that form, especially public orders. They are overtaken by brokers and executed or forwarded with some slight modifications.

4.2 Order matching

Orders are continuously placed by simple investors, who entrust their brokers or brokerage firms to execute them, and by brokers acting on behalf of investors or own purposes. Orders go through one or more financial agent who might split and slightly transform them (e.g. price improvement) before they are actually cleared and cause a market price to rise. Market prices in general arise as a result of order matching between some financial agents on the market place. The market price can be the result of a simple order matching of two (partial) orders (e.g. taking the other side of an order like accepting the quoted price of the specialist or market maker) or an aggregated order matching (e.g. equilibrium price of call auctions). Considering the different price formation mechanisms we differentiate two main order-matching procedures: deterministic matching and negotiation.

By deterministic matching we mean a matching method clearly specified by trading rules, such as: automatic matching made through electronic communication networks (e.g. ECN), clearings in the limit order book, accepting monitored quotes of the market makers on the NASDAQ, or call auction structures, where an equilibrium price is defined. Agents enrolled with special role can be part of this matching system: e.g. specialist via limit order book matching or an auctioneer. The market price that results from deterministic matching is more or less determined by a well-specified algorithm that does not depend further on subjective preferences or behavioural factors.
Negotiation aims to improve prices through competition between agents and occurs, for example on the NYSE trading floor between brokers trying to trade between specialists’ bid-ask spread. This method is aimed to assure price continuity. If negotiation is applied the market price depends pretty much on the agents’ subjective price-adaptation mechanism (e.g. price suggested on auction and the value of the new offer if it is not accepted).

A combination of negotiation and deterministic matching, like the Walrasian tatonnement, is possible, where price is adjusted to excess demand/supply till convergence of equilibrium is achieved. This auctioneer method is, for example, applied to determine the gold price in London, but further is not a common method used on exchange markets. On financial markets usually both methods are used, but not in order to determine a single equilibrium price, but rather separately giving rise to several different prices. Several studies consider only auction methods in artificial stock markets and set single market prices by accumulating orders although most of the markets apply continuous trading. We think that aggregation is indeed a useful tool for empirical analyses purposes, however it can be only used to study the dynamics of continuous markets if prices in continuous market converge to the price set by call-auction. Convergence to equilibrium is not guaranteed: market price is trading price in between certain pairs of sellers and buyers rather than an aggregate phenomenon induced by the market supply and demand [20].

5  Price formation in detail

As mentioned earlier the price formation mechanism can be split into two sub-problems: one refers to two order-matching that directly results in market prices, and the second problem concerns the trading decision that initiates an order. This section aims to help us to identify the main decision problems market participants need to face by tracking step by step how orders can trigger market prices (Figure 2).

5.1  The life-cycle of the orders

Suppose Agent_A receives Order_X from Investor_X. The agent can execute this order in several different ways depending on his current status, belief, market situation and role. There are basically three main choices he can do [19]:

1. execute the order or part of it internally (represented by Order_X^I);
2. try to find other agents that are willing to take the other side of the order preferably at an improved price (Order_X^N);
3. submit the order for execution to a "third party": eg. automatic electronic execution or market maker (Order_X^P).

Depending on the routing decision of Agent_A Order_X might be transformed to one or more other orders before final execution. Transformation might be applied to volume and/or price. It is often possible to improve the execution price or to clear first only part of the order, and later the rest at different price and even through different matching mechanism.

The final market price that this order triggers depends on the agent’s routing decision:

1. Agent_A executes the order internally within his own account if, for example, he needs it, or is required to provide liquidity, or received a counter order from another investor or agent.
   - In the most simple case the agent might take the other side of the order for the required volume at the price specified by the investor. Then this price will be the current market price.
   - If the agent received within some time interval another order from another investor he can try to match them. The two orders can be matched only if the price of the buy order is equal or higher than the price of the sell order. The formed market price in this case will be somewhere between the two specified prices and the transaction volume the minimum of them.

The question is what will be the market price if the two quotes are not equal: a fair price at half way in between the two, or a price in favour of one of the parties. The answer depends on agents’ characteristics (such as, decision-making mechanism, transaction price, etc.) and trading rules that apply on the specific market.

If the order is not entirely executed the agent continues the routing-decision for the rest and might clear it by using similar or even different trading-mechanism. Agents are required to improve the price specified by the investor (that is the current market price in case of market order).

Trading rules and market makers’ public bid-ask spreads control and serve as comparative basis for defining price quotes and final agreements. Let us consider bid B as the best bid offered by
2. Some market structures give the opportunity for agents to make agreements with other agents. On the NYSE, for example brokers have the opportunity to improve prices by means of negotiation (double auction) between the specialist’s bid-ask spread \((B, A)\). This stimulates competitiveness and provides liquidity. Suppose, for example that:

- Agent_\text{A} acts on behalf of Investor_\text{X} who sent a buy order: Order_\text{X} at quoted price: \(P_X\) and further
- Agent_\text{B} acts on behalf of Investor_\text{Y} who sent a sell order: Order_\text{Y} at quoted price \(P_Y\)

The agents have the following possibilities if they do not clear the orders internally:

- They both might accept the offer of the market makers if, their price fits the bid ask spread, that is if: \(P_X \geq A\) or \(P_Y \leq B\). if this holds the market price will be \(P = A\) (Order_\text{X}^D) and respectively \(P = B\) (Order_\text{Y}^D).
- Agents however try to improve prices and they can negotiate for this reason between the bid-ask spread: for every \(P_X \geq B\) \((P_Y \leq A)\) is an improvement to trade between \(B\) and \(A\) rather then accept \(B\) \((A)\).

For example, if the specialist is willing to buy for 100 and selling for 101, the \(X\) order has a limit price of 102 and \(Y\) a limit price of 100, \(X\) could accept the specialist price at 101, but he can improve even more this price if he buys at a lower price from \(Y\), and of course \(Y\) prefers to sell at a price higher than the specialist’s bid, thus a deal of 100, 5 or even 100, 2 would be preferable by both parties. The negotiation is going on, till someone accepts the last shouted price/order. The question is how do agents decide which bids/offers to make, and how do they change the value of their bid (e.g. starting from the specialist’s bid and incrementing it with decimals). No matter how the negotiation is solved (double auction, Dutch auction, second price, etc.) if a match is possible the formed market price is \(P \in [A, B]\)

3. If there is no negotiation possible or \(P_X \leq B\) in case of a buy order (or \(P_Y \geq A\) in case of a sell order) the order is delayed or handed on to a superior party (e.g. entered in the specialist’s limit order book for later execution). In this case orders are matched via a well-defined matching algorithm (deterministic order-matching), based on explicitly given price formation rules, such as:

- optimization for trying to find equilibrium (e.g. trading volume maximization on call-
• automatic order matching based on some priority (price, time, volume, etc.)

The market price formed in this way is rather market dependent and objective, while the previous prices depend on the agent’s strategy.

Tracing the way an order makes till it is executed shows that a multitude of factors might influence the value of the formed 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 behaviour. When we implement the artificial stock market we aim to consider these parameters and study whether these influences are significant for the characteristics of the price dynamics.

5.2 Relation between different types of traders

Agents in Figure 2 represent financial agents, and as defined in Section 3.1 we consider them either brokers or market makers (Figure 3). Market makers function on the market itself, brokers however can work also independently and have contact with member brokers from the floor or directly contact market makers if they want to trade. 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 can happen that investors (if for example member firms, or via electronic trading systems) trade directly with the market maker (specialist on NYSE). Brokers on the floor might be allowed to take or not public orders. In a common situation brokers are contacted by investors to execute an order, they further try to trade with other brokers (double-auction on NYSE) or market makers (the specialist on NYSE, and the dealer with the most attractive quote on Nasdaq).

6 Designing artificial stock markets

The design of an artificial market includes the following steps: defining the market structure regarding number, and type of traders, and stocks; the order matching mechanisms and implementing traders. We focus in this section on identifying and describing traders’ behaviour based on the tasks they face as a consequence of their role in the market.

Although traders can have a common structure at high level (in the sense that they all are influenced by some stimuli, make decisions, and place orders [15] they need to execute different role-dependent tasks, and as a consequence they behave in different ways. Simple investors, for example, only reconsider from time to time their portfolio, market makers or specialists must besides provide liquidity, and brokers make commitments to execute orders for investors and should keep a certain level of inventory. It is obvious that prices move as a result of aggregate behaviour of agents playing different roles, it is however not clear how and whether some type of agents have more influence on prices than others. Investors who post orders, for example, could manipulate the outcome more than brokers who execute only orders posted by others, or it can be the case that the way brokers clear the received orders influences the outcome more. Next we describe traders’ typical behaviour with respect to their role.

We classify traders in three main behavioural categories based on their role:

• Investor behaviour
• Broker behaviour
• Market maker behaviour

6.1 Investors’ behaviour

Investors generate orders and send them to brokers. Regardless of their real motivation behind trading they are basically faced with a portfolio management problem. The value of the portfolio depends on the weighted value of each stock. The value of a stock can be objectively determined as the current market price of that stock. Investors however associate a subjective value to the stocks. Investors determine subjective value based on the news they receive, personal attachment to a stock, needs, etc.
this actual subjective value, on the expected future value and further on some external parameters, investors decide to update their portfolio from time to time. They decide in this sense from which stocks, how many shares to have, and which is the value of the specific stocks for them. We can consider the portfolio problem as a transformation problem of the actual portfolio to a new one. A choice for a new portfolio results in placing orders. The order generation involves stock selection, limit price determination, trading volume and trading side determination. Further they might have preferences for a brokerage firm or order execution process [19].

Summarizing, the general behaviour of an investor is composed by the following sub-behaviours:

- monitor market state
- react to needs
- interpret sensed information based on beliefs
- evaluate portfolio based on interpreted information
- update beliefs
- generate orders
- send order to a (specific) broker

6.2 Brokers’ behaviour

Brokers primarily commit themselves to execute orders received from investors. For the moment we ignore how they take care of their inventory, as that task is basically similar to investors’ behaviour. In this sense we can consider these brokers as “order-routing brokers” that need to carry out the following main behaviours in order to implement their task:

1. Monitor market state
2. Receive order related messages
3. Select order and its parameters for execution
4. Forward orders or accept offers

These behaviours suit the general agent framework presented in [5]. The first two tasks refer to the agents’ activity regarding the way they perceive their environment. Decision-making concerns order selection and definition. Order placement or acceptance are the actions through which agents influence their environment. All these behaviours are executed in a cyclic and parallel way (Figure 4). Continuous trading is supported in this way.

The processes on the figure represent the behaviours that brokers’ need to complete in order to fulfill their role. Brokers differ regarding their belief, the way they reconsider their belief, analyze information, select order and trading mechanism, match orders, define negotiation prices. Let us follow a typical order routing behaviour:

**The message receiver behaviour:**

1. broker listens to messages
2. at a certain point he receives a request to execute an order
3. he stores this new order in the order book, puts a time stamp on it, and marks as unexecuted
4. repeats steps 1 . . . 3

**The market monitor behaviour:**

The brokers continuously observe information change on the market. Information that they are interested in concerns:

1. new market prices
2. best bids and offers of market makers and/or on negotiation floor

Of course if brokers do not need to immediately execute orders and they can trade for own account they consider other news as well and can make some kind of analysis based on their belief.

**The decision-making behaviour:**

1. the broker observes that the order book of some type of stock is not empty
2. selects an order for execution based on the trading rules that apply, its belief and current market information. There are several selection scenarios possible; he might select (Section 5):
   - the order with the earliest arrival time (FIFO mechanism), or
   - with the best execution probability (considering current market conditions);
   - aggregate and try to execute more orders at once with similar parameters
3. an order is selected in view of possible trading mechanisms. In a general case the broker has three choices:
   - (a) match orders internally: if for example there are orders in the order book that clear at a price close to the current market price
Continuously Listen to Messages

REQUEST
OrderBook
Receive Message

REPLY
Analyze Information

Belief
Historical Data

Objective data?

Update Belief

INFORM
REQUEST

Parallel Behaviours

Figure 4: The architecture of order-routing brokers

- Continuously Listen to Messages
- REQUEST
- OrderBook
- Receive Message
- REPLY
- Analyze Information
- Belief
- Historical Data
- Objective data?
- Update Belief
- INFORM
- REQUEST

Decision

Matching

OrderBook

Trade

Trading Rules

Select Next Order and Trading Mechanism

Type Mechanism

Type Reply

Match with orders from LOB

Yes

Define new limit price

No

Try to negotiate

Make new price offer?

WaitForReply

Answer

Accept

Submit Order

Publish transaction

Shout

Make Deal

Wait

No

Yes

Decision

Perception

S
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Yes

Wait

No

Submit Order

(b) try to negotiate with other brokers within the market makers’ quoted spread
(c) define a new (improved) limit price for the order based on market conditions in order to submit it to a third party for execution (such as market maker or central matching system)

4. If the broker decides to accept an order or his placed order is accepted, a deal is made and the transaction price of this deal is published as the new market price. If the broker chooses to negotiate he has to make further decisions regarding the offered negotiation price and the increment (decrement) of this. This value depends on the actual quote of the market maker, the offers that other brokers make for negotiation purposes and the initial limit price of the selected order and on the chosen value-adjustment step (value of increase/decrease).

As we can see even the behaviour of simple order routing brokers that interact within the same market structure, might differ at several points. Most studies however ignore the presence of brokers and study only investors’ behaviour and use simple order matching algorithms. We aim to study whether it makes sense to use order-routing brokers, whether the way they select, route and negotiate influences considerably the market dynamics. If it turns out that they do not significantly influence the outcome, they can be replaced indeed by a simple order-matching mechanism and further influence of investors’ behaviour can be studied. Otherwise we have to study the influence of investors and liquidity traders within some assumptions regarding final order matching.

6.2.1 Market makers

Market makers are responsible for the liquidity of some specific stocks. One stock has one market maker on the NYSE (specialist) and more competitive market makers (dealers) on the Nasdaq. Market makers specify the bid/ask spread at which they are willing to trade and accept orders at those quotes, the spread is made public, and thus other market participants can decide if they want to accept it, or which one to accept. Further, limit orders that cannot be cleared within a certain time, or not close to the current market price are submitted to market makers, who store
them in their limit order book and execute later if possible. Figure 5 depicts the typical behaviour of a market maker.

![Diagram of market maker behaviour](image)

Figure 5: The behaviour of market makers

The primary task of market makers is to provide liquidity. For this reason (next to common orders) they overtake orders that could not be executed by brokers and commit themselves to take the other side of a trade if no one wants to. They can do this by changing their bid/ask spread (Figure 5). A changing bid/ask spread can show thus a new state of the limit order book, but also the market makers changing position. Market makers differ in the way they update their quote.

If we consider only the order-routing behaviour of the market maker, the bid/ask spread changes according to the following simple rules. When a new order arrives it is compared to the current bid/ask spread. If it is a buy (sell) order above (below) the current ask (bid) price a deal is made for the possible amount at the outstanding ask (bid) value. If no match is possible or the match is not possible for the whole asked amount, the new order is entered into the limit order book and the new bid - ask spread is calculated as the maximum bid and minimum ask, specifying also the volume available at these quotes. If the new order defines a limit price that is worse than the outstanding bid/ask, than it is simply put into the limit order book. This task is a simple order-matching task, market makers must do more than this to provide liquidity.

The question that we need to study is how do they set the quotes if there are no orders on one of the trading sides? And further, how will they change the bid/ask spread so as to stimulate trading if there were no transactions made for some time?

The three main behaviours presented above are able to represent all type of traders from different markets. Brokers basically are entitled to route and execute orders based on requests. Whether they are allowed to take public orders, trade for own inventory or maintain a certain level of inventory can be specified by input parameters. The market maker behaviour is suitable to represent specialists’ behaviour from the NYSE and dealers behaviour from Nasdaq. If some financial agent is allowed to trade for own account, the investor behaviour is supplied to its basic behaviour.

7 Conclusion and future research

This paper aims to present the architecture of an artificial stock market that considers the microstructure of existing markets. We identify and describe the tasks and choices that different traders face based on their role in the market by tracing orders. We point out the need to consider brokers and their role in price formation mechanism and to have a well-defined microstructure. The designed agent structures can be used both for discrete and continuous trading. As can be seen from the designed architecture even the behaviour of simple order-routing brokers might differ regarding the way they improve prices and try to execute orders.

The question is whether agents’ behaviour has a significant influence on price dynamics. If it turns out that it is not significant their behaviour can be simply replaced by an order-matching algorithm and the influence of investors’ behaviour can be easier observed. However, if it turns out that indeed they play an important role we need to think: how can their behaviour be generalized, automatized in order to be able to analyze the influence of order-placing traders on price dynamics. In this case the control of brokers’ behaviour is necessary when we finally introduce investors and study market dynamics with regard to their behaviour.

By studying market dynamics through traders behaviour we can observe whether some information is considered by agents when taking trading and respectively routing/order matching decision. These experiments can help thus in this way to observe information absorption into prices. We can study through the transparency of the artificial market architecture whether the orders of the investors are executed as expected, and if not we can identify where does the market structure need reconsideration. The efficiency of the markets can be improved in this way.

References


