J Econ Interact Coord (2010) 5:155–167
DOI 10.1007/s11403-010-0069-3

REGULAR ARTICLE

Determining the optimal market structure using near-zero intelligence traders

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Received: 2 October 2009 / Accepted: 20 July 2010 / Published online: 31 July 2010

Abstract We evaluate an agent-based model featuring near-zero-intelligence traders operating in a call market with a wide range of trading rules governing the determination of prices, which orders are executed as well as a range of parameters regarding market intervention by specialists and the presence of informed traders. We optimize these trading rules using a population-based incremental learning algorithm seeking to maximize the trading volume. Our results suggest markets should choose a large tick size and ensure only a small fraction of traders are informed about the order book. The effect of trading rules regarding the determination of prices, priority rules, and specialist intervention, we find to have an ambiguous effect on the outcome.

Keywords Optimal market structure · Agent-based modeling · Call market · Zero-intelligence

1 Introduction

Market microstructure theory as used in conventional finance suggests that the trading rules applied by a market affect the prices at which trades occur, see O'Hara (1995) and Madhavan (2000) for an overview. This influence on prices should then also be visible in the statistical properties of returns such as their distribution and autocorrelations. In the highly structured models of market microstructure theory it is, however, difficult to

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evaluate a wide range of trading rules in a single model. Furthermore, the behavioral assumptions in those models make it difficult to assess the impact the changed trading rules have on the outcome, relative to behavioral influences.

In order to overcome these difficulties we develop an agent-based model in which traders use a very simple trading algorithm that does not assume rational behavior or any other optimizing rule. Such zero-intelligence (ZI) traders have been first introduced in Gode and Sunder (1993) with the explicit aim to investigate the importance of the trading rules for the outcomes of trading. Strategic behavior has been considered to be a dominant influence factor for the market dynamics in previous research. However, Gode and Sunder (1993) find that many of the major properties of double auction and call markets including the high allocative efficiency are primarily derived from the constraints imposed by the market mechanism, independent of traders' behavior. The zero intelligence approach has been widely applied in simulations of financial markets, particularly for the analysis of the stylized facts see Paczuski et al. (1997); Maslov (2000); Challet and Stinchcombe (2001); Krause (2006); Ladley and Schenk-Hoppe (2009); Othman (2008) and Li and Krause (2009). In Cliff and Bruten (2001) such traders have also been used to determine the optimal type of auction markets. The use of appropriate automatons would allow us to focus on the influence the market structure, i.e. set of trading rules, has on the outcomes; in Li and Krause (2009), models with near ZI traders do provide good return properties. Thus, we continue to follow the framework developed in Li and Krause (2009) in this paper.

With traders essentially behaving randomly, applying only minimal restrictions, we are able to investigate a wide range of trading rules commonly found in financial markets, e.g. the tick size, degree of intervention by specialists, priority rules, and market transparency, and conduct research into the design of call markets to obtain the optimal combination of these trading rules.

Thus far only very limited attention has been paid to the optimization of financial markets in the agent-based literature. Most notably Cliff and Bruten (2001) and Cliff (2003) investigate optimization of a real-valued parameter set for adaptation in trading using Genetic Algorithms (GA), an adaptive heuristic search algorithm with the evolutionary ideas of natural selection and genetic recombination. It is shown that a good result is reported with random initial values using GA together with an appropriate objective function. In addition, a recently developed framework of optimization, the population-based incremental learning (PBIL) has been widely applied. It is a type of evolutionary algorithm in which the genotype of the whole population is evolved rather than individual chromosomes. This algorithm, proposed by Baluja (1994), has been found to be simpler and to achieve better results than the standard genetic algorithm in many circumstances, e.g. Baluja (1995). Therefore, in this paper, we apply the PBIL as the optimization algorithm.

Using the results obtained from this research it is possible to derive recommendations to exchanges, regulators on establishing the optimal market structure, for securities issuers to choose the best exchange for their listing and for investors to choose the most suitable exchange for trading.

We continue in Sect. 2 by introducing our model as well as the trading rules considered. Section 3 then discusses the results of our computer experiments and Sect. 4 concludes the findings.

2 Description of the market

2.1 The behavior of traders

We investigate a market in which a fixed number of N traders trade a single asset in a call market. At any time each trader is either a buyer or seller of the asset and submits buy orders $B_i, i = 1, \ldots, N$ such that at time t the limit price is taken from a log-normal distribution:

$$\ln B_i^t \sim N\left(\ln \bar{P}_t + \mu_{\text{buy}}, \sigma_{\text{buy}}^2\right), \tag{1}$$

where $\bar{P}_t$ is the long-term fundamental value in time period t, which we here assume to be equal to the initial price P_0.[1] μ_{buy} denotes the average amount by which the bid price exceeds the fundamental value, and σ_{buy}^2 represents the variance of bid prices around the mean. With $\mu_{\text{buy}} < 0$ the limit bid price will on average be below the fundamental value, although traders may well submit orders with limit prices above the fundamental value given the random nature of the limit price in our model. We might interpret this either as uncertainty about the fundamental value to which traders pay limited attention, different opinions about the true fundamental value or the fact that many traders will ignore the fundamental value to a large degree in their decision-making. While experiments have shown that the exact specification of the decision-making process is not affecting results, we require a minimal amount of information which traders use as a common anchor for their decision; this is necessary to avoid the limit prices and thereby transaction prices to evolve such that an infinitely large bubble emerges. This constraint on the behavior of traders thus implicitly acts as a budget constraint as too large limit prices are not permitted and similarly too small limit prices will not be observed, acting as a minimum size requirement for entering the market.

If we denote by $\widehat{P}_i^{t-1}$ the price at which a trader bought the asset the last time, the limit price of a sell order is chosen according to

$$\ln S_i^t \sim N\left(\ln \widehat{P}_i^{t-1} + \mu_{\text{sell}}, \sigma_{\text{sell}}^2\right), \tag{2}$$

in which μ_{sell} denotes the average amount by which the ask price exceeds the price previously paid by the trader, and σ_{sell}^2 represents the variance of ask prices. A trader will only be able to sell those shares he actually holds, i.e. we do not allow for any short sales, thereby acting implicitly as a budget constraint on the behavior of traders.

The order size for a sell order will always be equal to the number of shares held. The order size for buy orders Q_i^t is a random variable with

$$\ln Q_i^t \sim iidN\left(\mu_{\text{size}}, \sigma_{\text{size}}^2\right), \tag{3}$$

[1] We could also introduce a positive long-term trend of the fundamental value without changing the results of our model.

where μ_{size} denotes the average of the order size, and σ^2_{size} is the variance of the order size.

An order remains in the order book until it is filled or canceled; for partially filled orders the remainder of the order remains in the order book. An order not filled after T_i^t time steps is canceled, where

$$\ln T_i^t \sim iidN\left(\tau, \sigma_\tau^2\right), \tag{4}$$

in which τ is the average time of order remains in the order book, and σ_τ^2 denotes the variance of this time.

The canceled order is replaced by a new order taken from the following distributions:

$$\begin{aligned} \ln B_i^t &\sim N\left(\ln \bar{P}_t + \mu_{\text{buy}}, \sigma^2_{\text{buy}}\right), \\ \ln S_i^t &\sim N\left(\ln P_i^{t-1} + \mu_{\text{sell}}, \sigma^2_{\text{sell}}\right), \end{aligned} \tag{5}$$

where P_i^t denotes the market price at time t.

Whether a trader is a buyer or a seller is determined as follows: if his last transaction was to buy the asset he becomes a seller and if his last transaction was to sell the asset he becomes a buyer. A change from buyer to seller or vice versa only occurs if he has no order remaining in the order book. In the initialization of the experiments buyers and sellers are determined randomly.

2.2 Determination of transaction prices

Following the price formation approach applied in Gode and Sunder (1993) and Cliff and Bruten (2001), the transaction price is determined where the demand and supply curves intersect, i.e., the price at the maximal trading volume is chosen as the trading price. In this market, limit orders with the highest bid prices are first traded and cleared in the market; oppositely, the cheapest sell orders are traded with priority. If we find that there are multiple prices at which the trading volume shows the same maximal value, we employ trading rules to determine which of the prices will be chosen. Any imbalances between buy and sell orders at the transaction price will lead to the need for rationing; how this rationing of buy or sell orders is conducted will depend on the trading rules as outlined below.

In contrast to the models in Gode and Sunder (1993) and Cliff and Bruten (2001), however, we do not use a continuous double auction market but rather a call market in which orders of traders batched. We batch all orders in each time step, where a time step consists of the submission and revision of orders as well as the batching of orders, the determination of the transaction price and execution of the trades.

2.3 Trading rules considered

2.3.1 Tick size

In the market we are able to vary a wide range of trading rules. We will firstly investigate different *tick sizes*, i.e. minimum differences between prices at which orders can be submitted. The tick size has several impacts during trading. As it represents the cost of getting inside other competitors quote, the tick size affects the motivation of submitting limit orders. In addition, the tick size has an impact on the spreads. As reported in many empirical investigations, e.g. Goldstein and Kavajecz (2000) and Jones and Lipson (2001) amongst others, the bid-ask spread declined dramatically by about 25% with the reduction of tick size from 1/8 to 1/16 dollar on the New York Stock Exchange (NYSE). In order to make limit prices to comply to the tick size, we will lower any limit price of buy orders as determined in (1) and (5) to the next permissible price and similarly raise the limit price of sell orders determined by (2) and (5) to the next permissible price.

2.3.2 Priority rules

Secondly, different *priority rules* are employed to determine the rationing of orders in the case of an imbalance between buy and sell orders at the transaction price, see Schwartz (1988) and Domowitz (1993) for an overview of the different priority rules found in several markets. The enforcement of priority rules, as the primary difference between market structures, is another important design feature of trading systems. We use in particular *time priority*, which is the most commonly used rule. It adheres to the principle of first-come first-served, and ensures that orders submitted earlier will be filled first; *reverse time priority* in which orders submitted later will receive priority to be filled; another frequently used rule to promote traders to place larger orders is *size priority* in which larger orders receive priority; *random selection* in which the orders to be filled are selected randomly and with *pro-rata selection*, a common practice on many financial markets such as the Stock Exchange of Hong Kong, the old Toronto Stock Exchange and the batch systems, in which all orders get filled partially to the same fraction.

2.3.3 Multiple prices

Thirdly, for the case of *multiple prices* at which the trading volume is maximal we determine the transaction price to be either the price closest to the previous price, the price furthest from the previous price, the highest price, the lowest price, the price with the minimum order imbalance (the absolute value of the difference between the volume of buy and sell orders at the transaction price), the price with maximum order imbalance or a randomly selected price.

2.3.4 Market transparency

Fourthly, we also consider *market transparency*, which is defined by O'Hara (1995) as "the ability of market participants to observe the information in the trading process". In this context, information refers to knowledge about the prices, the size and direction of orders, and the identities of market participants. In a transparent market, traders are able to have access to information on the order book and react to any orders submitted by other traders. This could reduce the magnitude of adverse-selection problems. Hence transparency is expected to increase profit for traders. Pagano and Rell (1996) show that transparency does reduce the trading costs incurred by uninformed traders in theory. Empirically, Koedijk et al. (1999) discover that the pre-trade transparency can narrow the spread. However, one can argue that transparency can make it difficult to supply liquidity to large traders, who may be reluctant to submit limit orders, since the disclosure may convey information which makes the price moves against the trader's position.

In order to replicate this aspect of the market we assume that a fraction γ of the traders has access to the order book and can observe the potential transaction price as well as the ensuing order imbalance if the trades were to happen instantly. They use this information to revise their own order size according to the size of the order imbalance δ. For a buy and sell order, respectively, we set:

$$\begin{aligned} \widehat{Q}_i^t &= Q_i^t - \alpha\delta, \\ \widehat{Q}_i^t &= Q_i^t + \alpha\delta, \end{aligned} \tag{6}$$

where α represents the fraction of the order size revised, Q_i^t is the order size before revision, and $\widehat{Q}_i^t$ is the order size after revision. This revised size is then used to determine the transaction price.

2.3.5 Specialist intervention

As a final aspect we consider the *intervention of a specialist* into the trading process. A specialist would intervene or influence the prices such that he is prepared to trade a fraction θ of the order imbalance at any time in the market to provide additional liquidity. To achieve this he will submit an order of the appropriate size with a limit price of

$$\widehat{\widehat{P}}^t = P^t - \lambda I^t, \tag{7}$$

where I^t denotes the inventory of the specialist, i.e. the number of shares held by him, λ is the price adjustment of the specialist. Such a linear relationship between the price quoted and inventory has been established in the inventory-based models of market-making, see e.g. Stoll (1978); Ho and Stoll (1980) or Ho and Stoll (1983), although other mechanisms have been proposed in the literature, e.g. in Hakansson et al. (1985).

In line with the behavior of the other traders, we do not assume that the specialist is employing a sophisticated optimization procedure but merely applies a different behavioral rule than other traders. The linear adjustment rule from (7) as proposed for pure dealer markets does not allow for any strategic interactions of specialists with limit order traders, nor does the price setting ensure that the order imbalance is actually reduced by a fraction θ. Furthermore, we assume that the specialist only submits either a bid or an ask price, depending on which side the order imbalance occurs. In that sense the specialist we introduce here is not directly comparable to those in pure dealer markets but more like those of the specialists of the NYSE who only intervene actively by taking positions in cases of market imbalances, e.g. a significantly larger amount of buy than sell orders (or vice versa) within a given period of time, a comparable situation to the order imbalances in our model.

2.4 Optimization of market structures

The methodology used to optimize the market structure is a computer experiment in which trading is simulated over a given number of time periods with a given market structure. The optimization of the trading rules is conducted evolutionary by population-based incremental learning (PBIL), using the trading volume as our performance function. The PBIL, described by Baluja (1994), is "a method of combining genetic algorithms and competitive learning for function optimization."

2.4.1 Genetic algorithm

Genetic algorithms (GA), developed in Holland (1975), are automated optimization algorithms based upon the principles of natural selection and genetic recombination. GAs maintain a group of potential solutions to the objective function being optimized, a so called "population", constructed randomly for the initial generation. Each population member is referred to be a chromosome, represented by a string of binary alphabet. In each generation, the fitness of each chromosome or potential solution is estimated, i.e. it is measured how well each solution optimizes the objective function. The better fitted sets are selected as "parents" and randomly paired to create a new optimal set as the next generation with the reproduction process of crossover and mutation. Since parents with higher fitness are more likely to pass their characteristics on to the child, the average fitness would increase. Therefore, the potential solutions in the last generation are expected to be the best solutions found for the optimization.

Although GAs have been applied successfully in financial market research, see Cliff and Bruten (2001) and Cliff (2003), many issues, such as efficient problem representation and adequate scaling of functions to make sure the good genes pass down to the next generation, need to be solved. Among a fixed number of generations, it is very difficult for the GA to return the optimal solution due to the randomized searching, and the inability of comparing the often very small difference between good and optimal solutions.

2.4.2 Population-based incremental learning

In analogy to GAs, the population-based incremental learning (PBIL) algorithm maintains a population of potential solutions evolving over a number of generations.

However, the PBIL attempts to create a probability vector, measuring the probability of each bit position having a “1” in a binary solution string, to define a population of a genetic algorithm. Instead of transforming each individual into a probability vector used for generating populations and recombination, the probability vector is moved towards the vector that shows the best performance in a similar manner to a competitive learning process. The probability vector π_t is updated based on the following rule

$$\pi_t = (1 - \eta)\pi_{t-1} + \eta\widehat{v} \tag{8}$$

where $\widehat{v}$ represents the best solution in the current generation selected according to the fitness function of the optimization and η the learning rate. This algorithm is capable to maintain diversity in search as the same probability vector could generate distinct populations.

In Baluja (1994), the author compares the empirical performance of a standard genetic algorithm to a simple PBIL, and shows that the PBIL is capable to attain the results more accurately and faster than a standard GA. As a combination of genetic algorithms and competitive learning it makes PBIL an successful and efficient search mechanism employed in such complex optimization problems as the one presented in this paper.

To employ the PBIL algorithm, we first create a probability vector specifying the probability of each bit having the value one. All initial values for the PBIL process are determined randomly, i.e. the initial probability of each bit is 0.5. With the probability vector thus determined, a population will be produced from this vector according to those probabilities. In each generation we determine the fitness of each potential solution and the best solution in the current generation is selected and used to update the probability vector for the subsequent generation using (8).

In each time step we determine 100 different parameter constellations using π_t and then determine the best performing parameter constellation from these 100 different market simulations, giving $\widehat{v}$.

Each trading rule is coded into a vector v, where the precision of the continuous variables α, λ, γ, θ is such that each variable is divided into 17 bits each, the tick size t into 20 bits, and the discrete variables (priority rules, multiple prices) are coded such that all rules are covered.

We let this process continue until no changes to $\widehat{v}$ are found, thus the probabilities in π_t are 1 or 0, giving an identical result for all 100 parameter constellations. Therefore, the resulting market structure established by the last remaining set in the process is then the optimal market structure.

3 Results of computer experiments

3.1 Parameter constellations considered

We consider a market with 100 traders, which consist of 50 buyers and 50 sellers for the first round. The order book contains the traders’ ID number, whether they are buying or selling, their limit price, order size, order submission time and length until the order is to be revised. The initial order book is constructed randomly using the

Table 1 Parameter values considered in the computer experiment

Parameter	Description	Value
μ_{buy}	Average of the bid price exceeding the fundamental value	-0.1
μ_{sell}	Average of the ask price exceeding the fundamental value	0.1
σ_{buy}	Standard deviation of the bid price	0.3
σ_{sell}	Standard deviation of the ask price	0.3
τ	The average time of order remains in the order book	1+ln100
σ_τ	Standard deviation of order remaining time	1
μ_{size}	The average of order sizes	1
σ_{size}	Standard deviation of order sizes	1
μ	Trend line of the price	0
t	Tick size	[0,10]*
α	Fraction of the order size revised	[0,1]*
λ	Price adjustment of specialist	[0,1]*
γ	Fraction of informed traders	[0,1]*
θ	Fraction of the order imbalance traded by specialist	[0,1]*

* Denotes the parameter range used in PBIL optimization

parameter settings described in Table 1 and the initial price P_0 set at 100. We assume that the trading price equals the previous price if there is no trading.

Each simulation is run for 6,000 time steps, where the first 1,000 data points are eliminated from our investigation to exclude any effects from the initial values. The PBIL optimization is conducted using a population size of 100 over 200 generations with a learning rate of 0.2.

3.2 Evaluation of computer experiments

The results achieved by PBIL are returned fast. Convergence of results was achieved after 120 generations. Table 2 summarizes the final trading rules from 25 different experiments, as well as the final value of the trading volume.

3.2.1 Tick size

Surprisingly, the mean of the optimal tick size from the simulation is 8.4132, which is significantly higher than the tick size of one-sixteenth dollar previously applied on the NYSE. Therefore, instead of reducing tick size in the financial market, it is suggested to be increased to maximize the trading volume. This result is consistent with that of Ladley and Schenk-Hoppe (2009) and Goldstein and Kavajecz (2000) who find that the trading volume at the best quotes would be reduced with a decreased tick size. Based on our results, the optimal tick size fluctuates between the minimum value of 6.1879 and the maximum value of 9.7025. Though the trading volume is optimized with the higher tick size, other measures of market performance,

Table 2 Parameter values of the last generation for each PBIL simulation

	Volume	Fraction specialist	Fraction revised	Price adjustment	Fraction informed	Tick size	Multi-price rule	Priority rule
	12.5690	0.2639	0.8999	0.5771	0.0267	6.1879	Lowest price	Size
	12.0790	0.7757	0.8985	0.4442	0.0307	8.0028	Min imbalance	Time
	13.2540	0.8612	0.9986	0.2916	0.0404	9.4567	Max imbalance	Random
	12.0984	0.2271	0.9900	0.2569	0.0300	6.6144	Random	Time
	12.0270	0.9108	0.9424	0.8028	0.0283	9.5384	Max imbalance	Random
	14.7564	0.5887	0.9660	0.2840	0.0320	8.8631	Max imbalance	Reverse time
	12.8730	0.4049	0.9921	0.9086	0.0318	9.6212	Max imbalance	Random
	12.5890	0.4559	0.9133	0.2560	0.0260	9.6552	Max imbalance	Random
	13.0720	0.5554	0.9265	0.1179	0.0327	8.9203	Max imbalance	Reverse time
	12.0740	0.4154	0.9268	0.0940	0.0252	6.8608	Random	Time
	12.5950	0.0275	0.6816	0.3850	0.0269	9.7025	Max imbalance	Size
	14.3010	0.0465	0.9733	0.2201	0.0348	9.4339	Max imbalance	Random
	17.5570	0.8664	0.9537	0.7514	0.0310	8.8434	Max imbalance	Reverse time
	12.7040	0.5234	0.9652	0.6741	0.0290	9.5309	Max imbalance	Random
	14.0100	0.5955	0.9452	0.9679	0.0337	9.4818	Max imbalance	Random
	13.0380	0.5814	0.9868	0.7080	0.0275	8.6728	Min imbalance	Size
	14.1760	0.1994	0.9438	0.4343	0.0283	7.6688	Min imbalance	Reverse time
	12.4816	0.8069	0.9673	0.8138	0.0331	6.4099	Random	Reverse time
	13.2921	0.3910	0.8839	0.1276	0.0274	9.5178	Max imbalance	Random
	12.0490	0.6776	0.7568	0.4497	0.0437	8.2702	Min imbalance	Random
	12.1490	0.4431	0.8665	0.1094	0.0364	9.5007	Max imbalance	Random
	12.1720	0.5647	0.9575	0.2577	0.0327	6.7222	Random	Time
	11.7910	0.1006	0.8929	0.1187	0.0274	7.6487	Min imbalance	Reverse time
	11.9160	0.2958	0.9294	0.8174	0.0171	6.4354	Random	Reverse time
	13.3860	0.6079	0.8504	0.4415	0.0258	8.7692	Max imbalance	Reverse time
Mean	13.0004	0.4875	0.9203	0.4524	0.0303	8.4132	Max imbalance*	Random*
SD	11.2510	0.2548	0.0732	0.2801	0.0053	1.2316		

* The mode is shown instead of the mean for priority rules and multi-price rules

such as the bid-ask spread, liquidity provision and volatility, could be affected differently.

3.2.2 Priority rules and multiple prices

From the computer experiments, we could not observe a specific priority rule and multi-price rule that optimize the trading volume. Particularly, all the different priority rules, except for the rule of pro-rata, could be applied to maximize the trading volume. The multi-price rules that choosing the price either closest or farthest to the previous price, and selecting the highest price could not be used to achieve the optimum result. And, the most frequently obtained multi-price rule is the one to choose the price at which the order imbalance is maximal. In addition, we find a relationship between the tick size and the multiple price rule. When the maximum imbalance rule is found to optimize the trading volume, the optimal tick size is large at approximately 9.5; with the multiple price rule that price with minimum order imbalance is selected, the optimal tick size will decrease to the range of 7.5 to 8.5; and it further decreases with the multiple price rule that prices are randomly selected. This result indicates a trade-off between the size of the bid-ask spread and the multi-price rule that would become relevant should the bid-ask spread be used as an alternative or additional performance indicator for the market.

3.2.3 Transparency

In respect of market transparency, the optimal market structure indicates that a small fraction of only 3.03%, on average, of market traders should be able to access information on the order book and react to any ensuing order imbalance if the trades were to happen immediately. The parameter value, with a dispersion of 0.53%, as shown in Table 2, does not change much from the mean in different simulations. Moreover, these informed traders are allowed to revise their own order size with the adjustment of an average fraction, 92.03% of the order imbalance, with a standard deviation of 7.32%.

3.2.4 Specialist intervention

Similar to the priority rules, it is difficult to identify a particular optimum fraction of the order imbalance traded by the specialist to reach the optimum trading volume. The mean value of the results from 25 simulation is 48.75%. However, it varies in a wide range from 2.75% up to 91.08%. The transaction price submitted by the specialist is formed using (7), where λ is averaged at 0.4524, again with a broad range between 0.0940 and 0.9679. Thus, we could not determine the importance of inventory held by the specialist for the consideration of his price setting based on the results.

3.3 Summary of results

The main results of our optimization can be summarized as follows. In order to achieve the maximal trading volume, the stock exchange should implement a large tick size of approximately 8.5%, allow only a small proportion (about 3%) of traders access to information in the order book. The use of priority rules and multi-price rules does not show any relationship to the trading volume; the extend of specialist intervention is also ambiguous. We can therefore conclude that the main effect on trading volume arises from the tick size and access to the order book.

4 Conclusion

In this paper we investigate the combination of a wide range of trading rules that maximize the trading volume by employing population-based incremental learning (PBIL) in call markets, including tick size, priority rules, multi-price rule, intervention of a specialist and transparency. In order to eliminate the influence of complex trader behavior we use an agent-based model in which traders behave nearly randomly, such that any properties arising can be attributed to the impact of the trading rules directly.

Conducting such an analysis we find a quick convergence of the trading rules towards their optimal combination. The results indicate that the optimal tick size is significantly higher than the one previously applied on the NYSE and most of the priority rules and multiple rules could be applied to maximize the trading volume. For the market transparency, a very small portion of traders should obtain information about the order book. Finally, as the result for the extend of specialist intervention varies in a wide range, it is hard to identify a particular optimal value to achieve the maximum trading volume. These results have direct consequences for the optimal design of financial markets in terms of maximization of trading volume, and thus might inform any market reforms considered by stock, bond or derivatives markets.

In future research the proposed framework can easily be extended to include other objective functions, like minimizing volatility, maximizing share value, or maximizing the trading profits to small traders, in particular using multi-objective optimization. This allows us to determine the most appropriate sets of rules a market should consider without facing the need to balance the different interests at this stage.

Acknowledgments We would like to thank the anonymous referees and the editor for their helpful comments throughout the review process.

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