

Fast Agent-Based Simulation Framework of Limit Order Books with Applications to Pro-Rata Markets and the Study of Latency Effects

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Abstract

We introduce a new software toolbox, called Multi-Agent eXchange Environment (MAXE), for agent-based simulation of limit order books. Offering both efficient C++ implementations and Python APIs, it allows the user to simulate large-scale agent-based market models while providing user-friendliness for rapid prototyping. Furthermore, it benefits from a versatile message-driven architecture that offers the flexibility to simulate a range of different (easily customisable) market rules and to study the effect of auxiliary factors, such as delays, on the market dynamics.

Showcasing its utility for research, we employ our simulator to investigate the influence the choice of the matching algorithm has on the behaviour of artificial trader agents in a zero-intelligence model. In addition, we investigate the role of the order processing delay in normal trading on an exchange and in the scenario of a significant price change. Our results include the findings that (i) the variance of the bid-ask spread exhibits a behavior similar to resonance of a damped harmonic oscillator with respect to the processing delay and that (ii) the delay markedly affects the impact a large trade has on the limit order book.

1 Motivation

Complementing the classical methods of statistical analysis and mathematical modelling, agent-based modelling (ABM) of financial markets has recently been gaining traction [11, 9, 6, 3]. In particular, applications of this paradigm to market microstructure [1] have attracted increasing attention. To name but a few, they include the study of statistical properties of limit order books [2], (non-)strategic behavior of a collective of traders [7] when modelled via the flow of their orders, as well as research into market bubbles and crashes [12]. With the ever-increasing importance of automated trading in finance and the rising popularity of artificial intelligence in academic and industrial research, the importance of the ABM approach in the study of electronic markets is likely to grow further.

The diversity of use cases of ABM in finance and economics is reflected by the recent proliferation of a variety of software tools tailored to the particularities of their respective applications, as can be seen in the aforementioned sources. What is missing is an efficient code base implementing a general, all-encompassing multi-agent exchange framework that can be easily adapted to simulate scalable ABMs based on any particular exchange as a special case. Among many other conceivable use cases, such a software environment could serve as a flexible toolbox allowing its users to investigate a range of research questions. Such could include, but are not limited to, the following:

- The impact of different matching algorithms on the (learned) behaviour and revenues of (adaptive) trader agents inhabiting a given limit order book (LOB);
- The amount of strategic decision making required to explain some of the important statistical properties of these LOBs;
- The response of strategic trader agent behavior to a change in the rules of the order matching, as well as to changing infrastructural effects such as communication delays.
- Conversely, the impact of different learning behaviors of the trading agents on the ensuing market dynamics.

To address the need for such a toolbox, we introduce a Multi-Agent eXchange Environment (MAXE), a general code environment for the simulation of agent-based models of electronic exchanges and other financial markets. For the sake of generality, its architecture is based around a generic messaging interface that can be instantiated to reflect the rules and protocols of a wide range of existing exchanges. For convenience, MAXE also provides a Python API to facilitate rapid prototyping of artificial agents. However, since the meaningfulness of ABMs often rests on the capability to simulate large multi-agent populations of market participants, the core of the implementation was written in C++, with an eye for computational and memory efficiency, as well as for support of native multi-threading. To support model calibration as well as studies of agent

behavior on historical market data, our toolbox also integrates market replay capabilities, in addition to support of pure ABM systems.

The remainder of this paper is structured as follows: After placing our toolbox into the context of previous, related simulator packages in Sec. 2, Sec. 3 proceeds with introducing the architecture of MAXE. We present different use cases of our framework. Sec. 4 illustrates an application of our simulation toolbox to agent-based modelling of pro-rata markets. Sec. 5 contains an illustration of a simple study of the effects of communication delays. Concluding remarks can be found in Sec. 6.

2 Related Work

Beyond simple market replay approaches, there still is a need for publicly available ABM software sufficiently generic to be capable of simulating the markets at scale. Our toolbox was designed to meet this demand. The most closely related toolboxes we are aware of include Adaptive Modeler [5], Swarm [17], and ABIDES [4]. In what is to follow, we briefly summarise the features of these packages in relation to ours.

Adaptive Modeler [5] is a “freemium” specialized market simulator first released in 2003 and still maintained. At the core of the software is a virtual market featuring a predefined set of classes of agents that may be further adjusted by the user by changing various parameters such as the population sizes, agent wealth, or class mutation probability. Once an environment consisting of traders and traded assets is specified, the user may start the simulation whilst keeping track of outputs such as the event log, quotes, or various economic statistics. All of these functionalities are – or can easily be – implemented in MAXE as well. In addition however, MAXE also allows the creation of completely customised agents with arbitrary behavior and simulate them on an arbitrary timescale, as the unit time step is not bound to any physical measure of time and can thus be chosen to represent an arbitrarily small fraction of a second.

Swarm [17] is an open-source ABM package for simulating the interaction of agents and their emergent collective behaviour. First released in 1999, it remains maintained today. Whilst not directly designed for financial modelling, it has been used to create the Santa Fe Artificial Stock Market [13] that, for the first time, reproduced a number of stylized facts about the behaviour of traders and further emphasized the importance of modelling of financial markets. Unlike swarm, MAXE comes with an incorporated time-tracking unit that takes care of the delivery of messages between the agents involved and the advancement of simulation time. This allows for a transparent unified channel of inter-agent communication, enabling simple scheduling

of agent tasks (as outlined in an example in Fig. 1) and greatly simplifying output generation and debugging.

ABIDES [4] is the newest open source market modelling tool. Released as recently as 2019, it was specifically designed for LOB simulation. Aimed to closely resemble NASDAQ by implementing the NASDAQ ITCH and OUCH messaging protocols it hopes to offer itself as a tool for facilitation of AI research on the exchange. Just as MAXE, ABIDES allows users to implement their own agents in Python. However, since MAXE also allows specification in C++ we expect that MAXE has an edge in terms of the execution efficiency and scalability. Moreover, MAXE, being based on a compiled binary core interacting directly with the operating system allows for multi-threaded execution of simulations, which becomes an advantage when simulating a range of similar simulations differing only in a number of input parameters. Apart from that, MAXE comes with the implicit support for the trading at multiple exchanges at once and for limit order books matched with different matching algorithms, in particular pro-rata matching. MAXE is also highly modular due to the option to develop a database of agents first, and then configure a set of simulations via an XML configuration file.

3 Architecture

MAXE is based on a message-driven, incremental protocol. Its core logic steps forward time and delivers messages. As such, it could also be utilised for modelling many multi-agent systems – not just financial exchanges. However, our focus throughout this document remains on applications to exchange trading.

Every relevant entity of a trading system one would wish to model (e.g. exchanges, traders, news outlets or social media) can be implemented as an agent. This is different to the usual approach to agent-based modelling of exchanges where at the centre of the simulation is the exchange concerned and the communication protocol between the entities of the trading system is made to resemble the one of the real exchange, often to ease the transition of any models developed there into production environments. As it is the case with any common implementation of message-driven frameworks, agents taking part in the simulation remain dormant at any point in simulation time unless they have been delivered a message. When a message is due to be delivered, the simulation time freezes as all agents that have been delivered at least one message begin to take turns to deal with their inbox. Each agent is given an unlimited amount of execution time to process the messages they have been delivered and to send messages on their own. Messages can be dispatched either immediately (i.e. with zero delay) or scheduled

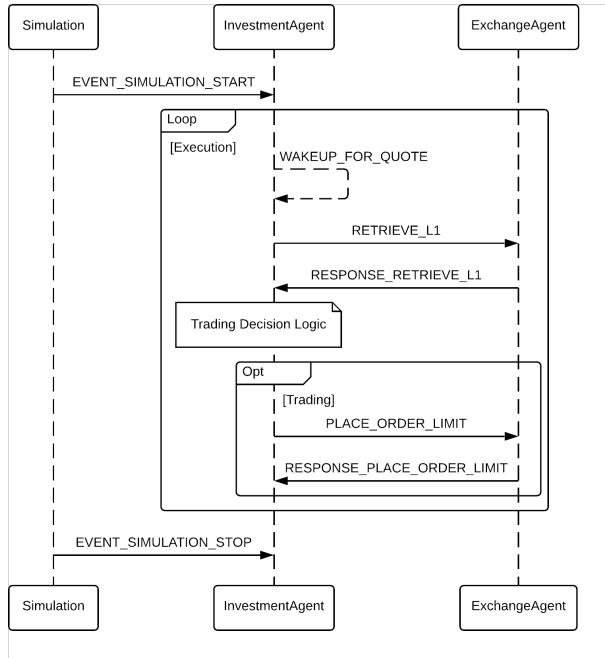


Figure 1: A sequence diagram of an example communication between a trading agent, exchange agent, and the simulation environment.

to be delivered later in the future by specifying a non-negative delay which can be used to model latency for example.

At the beginning of a simulation, each agent is delivered a message that allows them to take initial actions and possibly schedule a wake-up in the future by addressing a message to themselves. At the end of the simulation, a message of similar nature is sent out to all agents to allow them to process and save any data they might have been gathering up to that point for further analysis outside the simulation environment. Fig. 1 shows an example communication of an agent that trades based on regular L1 quote data from the exchange.

Aside from its core, MAXE also contains a small initial repository of common agents that can be expanded upon by its users. This initial repository includes an exchange agent that can operate a number of different matching mechanism, as well as a collection of zero-intelligence and other simple agents. An overview of the top level of the hierarchy of available agents is depicted in Fig. 2. Further details on the various agents can be found in the code repository [14].

For simplicity and in order to facilitate convenient prototyping of trading system models, MAXE has been built with an interactive console interface and designed to read the simulation configurations from a hand-editable XML file. Once a simulation is running, it is up to the user to record any information of interest, although a few agents have been supplied to allow

for monitoring of the most common events and statistics. Furthermore, despite the overall emphasis on the performance of the simulator, MAXE comes with a Python interface, further allowing for fast prototyping and the use of common scientific packages available in that language.

4 Pro-rata over-offering as a result of naive learning

Different exchanges employ different matching rules. One of the most popular matching logic is *price-time priority* which has been intensively studied (see e.g. [1]). Another important matching logic is *pro-rata* (see e.g. [8]). In pro-rata markets, at a given price level, orders are not executed in chronological order as in price-time priority, but in proportion of their size on the price level. Previous research into pro-rata markets [8] showed that traders develop the tendency to over-offer the volume they are willing to buy or sell in order to guarantee or speed up the execution of the quantity they actually intend to trade.

4.1 The Model

To demonstrate the flexibility of our simulator, we present a naive learning model for traders' behaviors and show that the trading agents also develop such tendency after learning and interacting on an artificial exchange. These trading agents make zero-intelligence economic decisions about the price of the asset they wish to acquire or sell similar to the setting in [7] and then use an order placement strategy based on the moving average of order-to-trade volume ratios.

The aforementioned model is implemented as follows: We introduce an *exchange agent*, dedicated to managing a limit order book matched with a pure pro-rata algorithm [10]. We then add a population of *trading agents (traders)*, which, for ease of illustration, are homogeneous and very simple: Each trader places orders at time points distributed according to a Poisson process of rate r_p . Each order is then either immediately marketable with probability f_m , or non-marketable and will hence enter the limit order book at $B + \Delta P$, where B denotes the current best price of the resting queue and ΔP is uniformly distributed on an interval of fixed length that is a parameter of the simulation. If the current order is filled before a new order is scheduled to arrive (i.e. before the end of its *maximum lifetime* T_m , which is precisely the inter-arrival time of the order arrival Poisson process and is thus exponentially distributed with the rate r_p independently of all other maximum lifetimes), a new order is immediately dispatched. Each trader is only allowed to have one outstanding order, and, if the current order is not yet filled at the time another order of the same agent is due to

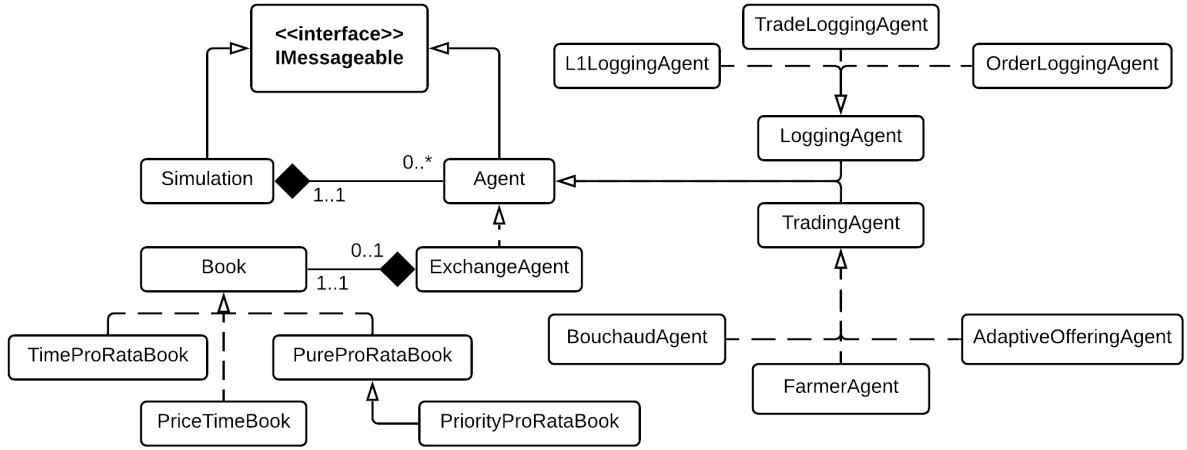


Figure 2: The class diagram of the Simulation-Agent hierarchy of the simulator.

arrive, the remaining volume of the current order is cancelled. Either of the events, firstly, that the particular realised maximum lifetime t_m of the given order has elapsed or, secondly, that the order has been filled, marks the end of the actual *realised lifetime* t_r (note $t_r \in (0, t_m]$).

For each order they place, agents desire to trade a fixed volume v_0 before the end of the order's maximum lifetime. The maximum lifetime (or, indirectly, r_p) then represents the maximum permitted simulation time within which the agent tries to trade v_0 . It can be interpreted as the urgency of the need to trade v_0 . Due to the nature of pro-rata matching, only a fraction of the outstanding order might be filled before the time is up, and hence the agent will instead place an order of volume v_{offered} .

The trader thus interacts with the environment of the market by placing its orders, of which there is exactly one active at a time, and cancelling them if they remain unfilled for what it deems is "too long". As mentioned above, the time of order placement, the type of the order (i.e. whether it is a market order or a not immediately marketable limit order), the price at which the order is placed by the trader, and the order maximum lifetime (i.e. the sense of what is "too long") are all determined at random.

Thus, the actions (in game-theoretic sense) of the agents are the choices of quantities v_{offered} , and the objective of the agent is to learn to offer the quantity v_{offered} such that the quantity executed in T_m units is as close to v_0 as possible.

Hence the essence of its learning can be characterized by defining its history of observations to be the record of fractions of order volumes executed and the respective realised lifetimes of the respective orders as a function of tick distance at which the order was placed

$F_{\text{fill}}(\Delta p)$.

Suppose that an order is being placed and its volume v_{offered} needs to be decided. Let Δp be the particular randomly generated tick distance and let $n = n(\Delta p) \geq 0$ be the number of limit orders previously placed at the tick distance Δp from the best price at the time they were being placed. Then the agent needs to choose the action $v_{\text{offered}}^{(\Delta p, n+1)}$ and $F_{\text{fill}}(\Delta p)$ is simply

$$F_{\text{fill}}(\Delta p) := \begin{pmatrix} f_{\text{fill}}^{(\Delta p, 1)} & t_r^{(\Delta p, 1)} \\ f_{\text{fill}}^{(\Delta p, 2)} & t_r^{(\Delta p, 2)} \\ \vdots & \vdots \\ f_{\text{fill}}^{(\Delta p, n)} & t_r^{(\Delta p, n)} \end{pmatrix} \quad (1)$$

where $t_r^{(\Delta p, n)}$ is the realised lifetime of the order $(\Delta p, n)$ and

$$f_{\text{fill}}^{(\Delta p, i)} := \frac{v_{\text{executed}}^{(\Delta p, i)}}{v_{\text{offered}}}$$

Here $v_{\text{executed}}^{(\Delta p, i)}$ is the volume of order $(\Delta p, i)$ that was executed during its realised lifetime in the book and $v_{\text{offered}}^{(\Delta p, i)}$ is the volume that was placed into the book. The action of the agent is v_{offered} and the policy given the history of observations is

$$v_{\text{offered}} = \frac{\sum_{k=(n-K) \wedge 1}^n f_{\text{fill}}^{(\Delta p, k)} t_r^{(\Delta p, k)}}{\sum_{k=(n-K) \wedge 1}^n t_r^{(\Delta p, k)}}$$

where \wedge denotes the minimum of the values on either side and K the size of the window for the moving average.

4.2 The Findings

Every run of the simulation lasted for $10^4 r_p$ time units and the simulation was run 100 times. At the end of each simulation, we recorded the final v_{offered} for each agent. If for some values of Δp there had been no orders placed by the agent, we did not record anything. We show the *mean over-offering tendency* (computed as the mean of recorded values and expressed as the multiple of v_0 to be offered with the intention of filling v_0 within the order lifetime) in Fig. 3. In the sense of order flow into the exchange, increasing the number of agents in the simulation environment simply corresponds to increasing the order arrival rate, and since we give this example for demonstration purposes only, we settled for an agent population of 100 and treated it as a constant.

Using this model, we aimed to confirm the over-offering characteristic for pro-rata-matched LOBs reported by [16], demonstrating that:

- (i) a significant proportion of orders of any lots would end up being cancelled before being fully filled,
- (ii) traders would have the tendency to over-offer, with the tendency increasing with increasing values of Δp in a positive neighborhood of 0.

We stress that our main purpose was to demonstrate the flexibility of MAXE in a simple case study rather than to venture into a rigorous study of trader over-offering in pro-rata markets.

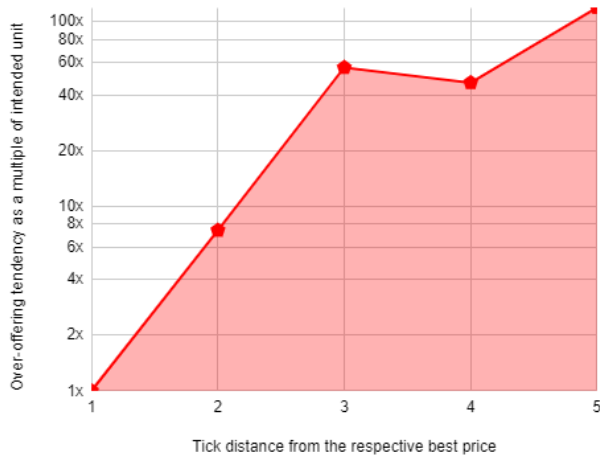


Figure 3: The over-offering tendency of the naive learning agents in the set-up given.

The fraction of all orders placed by agents in our model that ended up being cancelled by the agents that placed them before they were filled varied between 80 and 95%, suggesting a result similar to the one in [8]. The mean over-offering tendency also seems to have varied with the tick distance of the order placement price from the respective best price as depicted in Fig. 3,

which is consistent with the intuition. Further naive experimentation with the relevant parameters hinted that the mean over-offering tendency might be independent of the size of the window for the moving average (K), of the mean maximal order lifetime ($\frac{1}{r_p}$), and the proportion of marketable orders entering the exchange (f_m).

5 The role of processing delay

To demonstrate MAXE’s ability to simulate some aspects of “market physics”, we utilised it to examine the effect processing or communication delays have on various statistics of the market dynamics following a large trade.

5.1 The Model

The core of the model consists of one exchange agent with a modifiable choice of matching algorithm and a population of zero-intelligence trading agents interacting with the exchange. The exchange agent maintains the limit order book and executes orders submitted by the trading agents. At the beginning of the simulation, the LOB contains two small orders, one on each side of the book with the initial bid-ask spread S_0 , to serve as the indicators of the opening prices for further trading.

Following the start of the simulation, traders place orders and are given a fixed period of time to reconstruct the LOB to match the empirical average shape from [2] by placing orders in a manner described below. In the simulation runs focused on statistics not related to the study of impactful trades, the remaining time is used to measure those. The other type of simulations experiences an impact agent entering the exchange and making an impactful trade, following which more statistics are computed. The simulation runs over a fixed time horizon of $40000t_p$, chosen by experimentation focused on the setup appearing to have dealt with the largest of the trades used in our experiment.

The behaviour of our trading agent is similar to the behaviour presented in [2] that has been previously shown to be able to reconstruct the LOB’s shape to be resembling the one of real LOBs of highly liquid stocks on the Paris Bourse. The behavior presented in [2] is further adjusted by some features of the behaviour presented in [7], which has been shown to be able to explain some of the dynamic properties of the LOB, including the variance of the bid-ask spread. For a detailed specification of the agents’ behaviour we refer the reader to [14].

According to the L1 information available to the trader at the time it is making the decision (which may be outdated due to the communication delay between the

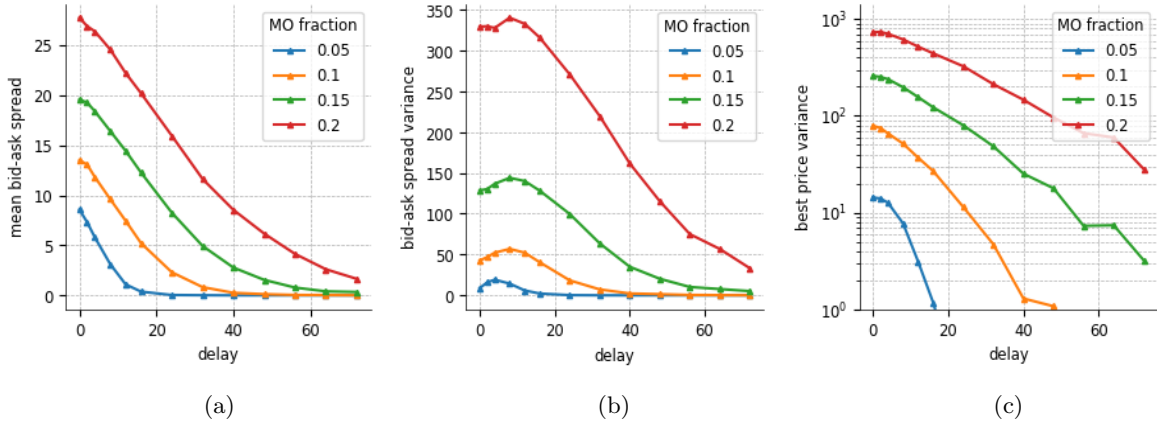


Figure 4: Statistics of the simulation L1 data plotted against d (in multiples of t_p) for different values of f_m .

trader and the exchange), each trader places both market and not immediately marketable limit orders according to a Poisson process with rate r_p , with the fraction of the market orders f_m being a parameter of the simulation. The simulation was run for values of f_m ranging from 5 to 20%.

Each order has lifetime distributed according to the exponential distribution with mean t_l that was a parameter of the simulation. The simulation was run for values of t_l from 200- to 3200-times $t_p = \frac{1}{r_p}$. Thus, the stream of the cancellation orders can be thought of as a marked Poisson process with rate $r_c = \frac{1}{t_c}$ and where the marking probability is inversely proportional to the number of orders in the LOB. The price of the order is drawn from the empirical power-law distribution relative to the best price at the time of observation.

We define the *processing delay* d , or simply *delay* to be the duration between the time the information about the state of the limit order book is produced for trading agents and the time when the exchange processes the agent's order against the LOB. This time includes the two-way latency between the agent and the exchange, the time it takes the exchange to process the queue of incoming orders, and decision time on the trader's side. Furthermore, taking the zero-intelligence approach to model the trading and the limit order book as a whole, the processing delay can also be thought of as encapsulating the time it takes the trader to decide whether and how to trade and possibly evaluating their strategy given the information becoming available during that time, and we shall use this fact when interpreting our findings.

We also define *greed* g to be the size of a large market order expressed as a fraction of the total volume (i.e., considering the volume of all price levels) in the queue it is meant to be executed against.

5.2 Findings

When simulating, we treated the placement frequency r_p as fixed and looked at the effects of the other two time-based parameters, r_c and d , relative to it. The observed effects turned out to be independent of the matching algorithm used. Perhaps somewhat more surprisingly, the cancellation rate r_c appeared not to have had any effect on the statistics considered (see below).

Notation: If Q is the quantity we are observing, let $e[Q]$ denote the empirical simulation-time-weighted mean of Q and $v[Q]$ the empirical simulation-time-weighted variance of Q .

Bid-ask spread

We found that the mean bid-ask spread $e[S]$ increased linearly with the fraction of market orders f_m (with a hint of convexity), decreased with d , and appeared to converge to the bid-ask spread of the initial setup S_0 , coming within a few ticks distance of S_0 for all sufficiently large delays d . The relationship between the parameters involved is depicted in Fig. 4a and fitted ($R^2 = 0.90$)

$$e[S] \approx S_0 + s_0 f_m e^{-s_1 d}.$$

This was in approximate agreement with the relationship for $e[S]$ as a function of f_m provided in [7] which considers the price-time matching logic.

The variance of the spread $v[S]$ gave an appearance qualitatively resembling the amplitude of oscillations of a simple driven damped oscillator with respect to the processing delay (d being the frequency in this analogy, see Fig. 4b), with the resonance delay d_0 constant with respect to all free parameters of the simulation.

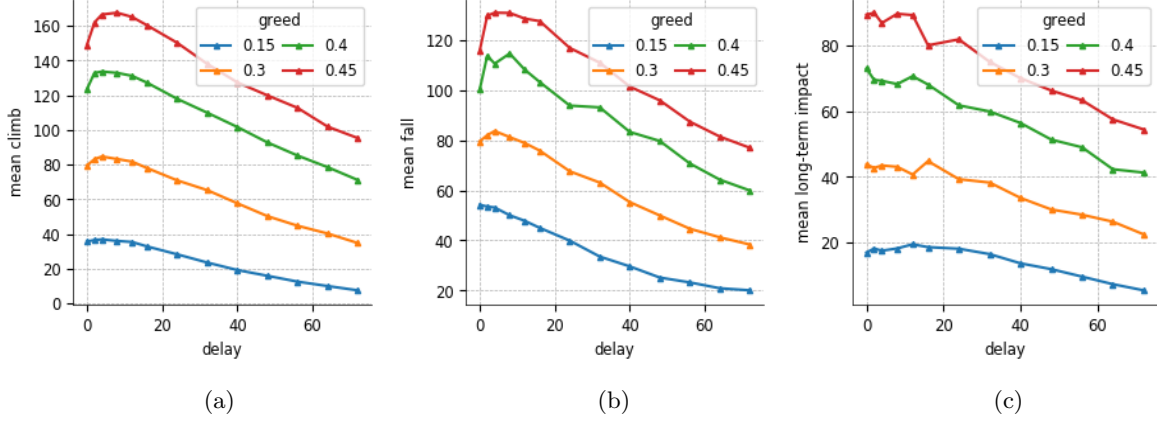


Figure 5: Absolute mean climb, mean fall, and mean long-term impact (in price ticks) plotted against the processing delay d (in multiples of t_p) for fixed values of f_m and varying values of greed g .

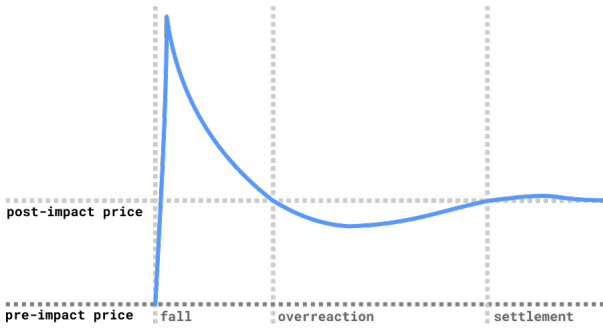


Figure 6: Shown is the shape of the average best price evolution after suffering a large aggressing trade.

Variance of the best price

The time-weighted variance of the best bid and ask prices (simply the “best” price $B(t)$ at time t as the behavior is the same for both sides of the queue, see Fig. 4c) appeared to monotonously decrease with increasing d and, to increase exponentially with increasing f_m , coming to a negligible distance from 0 for sufficiently large values of the delay d .

Shape of the average impact scenario

Turning our attention to the scenario of an impactful trade occurring at time t_I , we define the climb C to be the immediate increase in the best price B following a large (10-100x the size of average market order) trade against the respective order queue. We further define F to be the difference between the highest and the lowest point the best price attains after t_I , and I to be the long term impact of the trade, i.e. the difference between the equilibrium best price prior to the impactful trade and the equilibrium price to which the best price “settles” long after t_I . We expressed the volume of the large trade considered as a fraction of the volume available on the respective order queue at the time the trade is

executed and denote it by g .

We have found empirically that, irrespective of the volume of the large trade affecting the best price, $e[B](t)$ seemed to exhibit the same feature of going through the phases of *fall*, *overreaction*, and *settlement* (see Fig. 6). The climb in the best price itself occurred almost instantly after t_I in the vast majority of cases, with the exception when a delayed limit order unaware of the sudden price movement significantly improved the new best price but was quickly eliminated by newly incoming marketable orders. The first phase, *fall*, exhibited a steep best price fall towards the future equilibrium and its steepness decreased with increasing latency d . The fall was succeeded by something that could be described as an *overreaction*, a phase during which the best price dived further below the future equilibrium price and hit the absolute minimum at the time at which the bid-ask spread was also minimal. The best bid and ask prices then diverged again towards their new equilibrium in the *settlement* phase.

The identification of such patterns has the potential of being of practical utility. They might endow us with a method for predicting the price at which the best price will settle after a large trade given the information about the long-term variance of and current information about the values of the bid-ask spread.

The large trade scenario

We observed that both $e[C]$ and $e[F]$ decreased linearly for large delays and small delays with small values of g (Fig. 5a and Fig. 5b). In addition, large values of g seemed to allow the climb and fall to peak at a specific small delay.

The long-term impact appeared to be mostly linear with d with the downwards slope decreasing with the increasing values of greed, increases linearly with f_m (Fig. 5c). Furthermore, it did not seem to exhibit the

same peak as climb and fall do, demonstrating that these two compensated for each other in the long run. Furthermore, the logarithm of the long term impact increased proportionally to the volume traded, in keeping with the results presented in [15].

We shall say that the best price has reached *stability* if the moving average with a fixed window of size w falls within the distance of $\sqrt{\frac{v[B]}{w}}$.

Whilst we found significant evidence that the impact of a large trade on the best price depends on the greed parameters, perhaps surprisingly, the mean and variance of the time did not seem to exhibit any notable dependence on the level of greed, i.e. the best price appears to converge to stability in time independent of the size of the large trade nor the share of the marketable orders f_m (Fig. 7b).

Further evidence of such behavior was found when producing the results depicted in Fig. 7c. Here, we looked at the proportion of the runs of the simulation in which the price fulfilled the post-impact stability criterion given above before the simulation was terminated. As can be seen from the plot, simulation runs for higher values of the parameter f_m would see the price succeed to become stabilised in the time horizon of the simulation more often than for the lower values, but the greed parameter had again little to no effect on the proportion of the runs that would become stabilised for varying values of d . This is further supported by setting a time limit on convergence in the distant future from the impactful trade and measuring the convergence success rate, defined as the proportion of the simulation runs that succeeded in converging before that time (see Fig. 7c).

6 Conclusions

We have introduced a new multi-agent simulation framework for financial market microstructure, called the Multi-Agent eXchange Environment (MAXE). There are a number of distinctive advantages MAXE offers over alternative simulation frameworks such as ABIDES [4]. Most notably our framework is fast and flexible; it allows to model different matching rules and can model latency.

We have also demonstrated its potency for research into market dynamics. In particular, we used MAXE to conduct a simple empirical study highlighting an over-offering characteristic in pro-rata markets ensuing from agents that adapt their strategies with a simple moving-average learning approach. Furthermore, we utilised MAXE to showcase a mini study of the impact the delay in processing order has on a few LOB statistics and on the behaviour of the best prices after a large trade is registered with the exchange.

In conclusion, MAXE offers a general and efficient simulation environment that can be easily employed for research into properties of various markets or as a benchmark environment for agent-based testing of trading strategies.

Expanding on our illustrative case studies would be interesting in particular, given the dearth of studies utilising ABM in the context of pro-rata matching rules. We hope such research would be greatly aided by our MAXE package, providing a standardised, scalable and easily customisable toolbox to support this kind of research.

7 Access and Documentation

The simulator is available on GitHub [14] under the MIT License. Documentation and the QuickStart Guide can be found on the GitHub pages under the doc folder.

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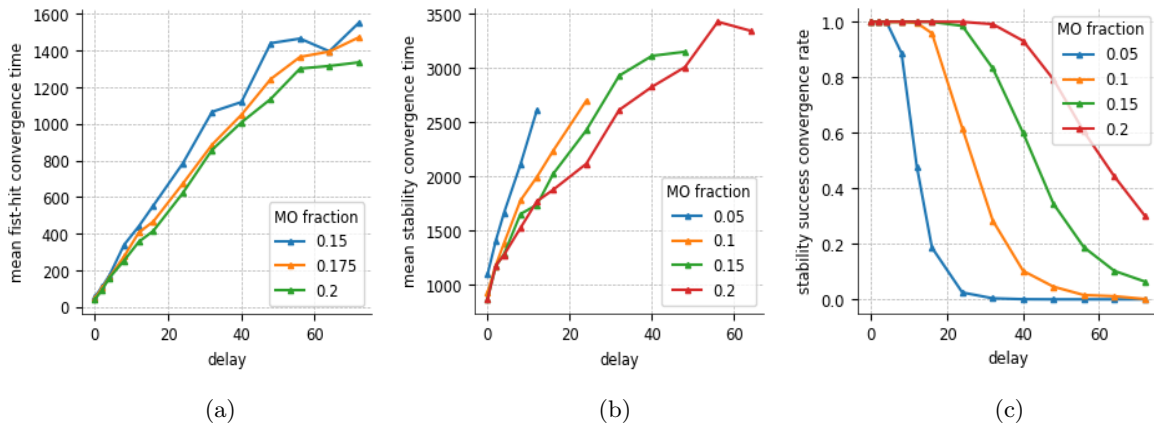


Figure 7: Convergence statistics shown against d (as a multiple of t_p) for different values of f_m . The time is also expressed as a multiple of the mean order placement rate r_p .

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