The Spoofing Resistance of Frequent Call Markets

Buhong Liu
King's College London
London, UK
buhong.liu@kcl.ac.uk

Maria Polukarov
King's College London
London, UK
maria.polukarov@kcl.ac.uk

Carmine Ventre
King's College London
London, UK
carmine.ventre@kcl.ac.uk

Lingbo Li
Turing Intelligence Technology
London, UK
lingbo@turintech.ai

Leslie Kanthan
Turing Intelligence Technology
London, UK
leslie@turintech.ai

Fan Wu
Turing Intelligence Technology
London, UK
fan@turintech.ai

Michail Basios
Turing Intelligence Technology
London, UK
mike@turintech.ai

ABSTRACT

We study the effects of spoofing attacks on frequent call markets (FCMs). Spoofing—a strategic manipulation to mislead market participants by creating spurious limit orders—could harm the market efficiency and has been declared illegal in many countries. However, this practice is still very common, which inspired extensive research on measuring, detecting and curbing such manipulation in the popular market model of continuous double auctions (CDAs). In this paper, we extend this research to frequent call markets and use agent-based modelling to simulate spoofing in this context. Specifically, we apply empirical game-theoretic analysis (EGTA) to compute equilibria of agent-based markets, and demonstrate that while spoofing may be profitable in both market models, it has less impact on FCMs as opposed to CDAs. Finally, we explore several FCM mechanism designs to help to curb this type of market manipulation even further.

KEYWORDS

Market Microstructure; Market Trading Mechanisms; Call Markets

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1 INTRODUCTION

In order-driven markets, the market data reveals the universal beliefs on the market and is a key information source for traders. If the market data, including the best ask and bid price and their sizes, are manipulated, other participants could be misled and suffer from potential loss. It is believed that market manipulation can harm market liquidity [6, 7], reduce market efficiency [19] and raise spreads and volatility [32].

Spoofing is a simple and popular market manipulation method which can be defined as "strategically placing and canceling orders in order to move prices and trade later in the opposite direction" [32]. Spoofing is illegal in many countries [11, 13]. For example, the Dodd-Frank Wall Street Reform and Consumer Protection Act made spoofing illegal in 2010 in U.S. However, spoofing is still common in financial markets, for example, JP Morgan Chase was fined by U.S. regulators in 2020 for price manipulation in precious metal and treasury bill markets [32]. The impact of spoofing on participants and markets is then an important research question in the context of market mechanism design.

Continuous-time double auctions (CDAs) are a very popular trading mechanism applied in modern order-driven exchanges. In a CDA market, the order submissions and order withdrawals are processed serially [3]. However, CDA markets are believed to lead to the latency arms race problem because traders could have huge benefits if they have only tiny access-time advantages over others [3, 21]. The frequent call market, where orders arriving during the clearing interval are accumulated and processed in batch at the end of the interval, is taken as the alternative mechanism addressing the latency arms race problem [3, 25]. In this paper, we aim to investigate the impact of spoofing on frequent call markets (FCMs).

We adopt the agent-based method to model the market and simulate the interaction amongst strategic agents and between agents and the market. We consider three types of strategic agents: one group generate their bidding or asking price, i.e., the strategy, only based on their valuation, the second group also take historical information into consideration, and the last group play a spoofing strategy. We then apply empirical game-theoretic analysis (EGTA) [31] to account for the strategic response of agents to market rules and each other's actions. EGTA helps to find equilibrium states of such agent-based markets and we compare a set of market metrics for agents and markets before and after introducing spoofing. We also compare the impact on FCMs to the impact on CDA markets to examine whether FCMs curb this kind of manipulation. Furthermore, we explore additional designs of FCMs which might decrease the risk of spoofing. To the best of our knowledge, this is the first attempt to analyse the impact of spoofing on frequent call markets.

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The paper is organized as follows: Section 2 overviews the literature on this topic. Section 3 describes the research design and experimental setting. The main empirical results and their analysis are shown in Section 4. The last section summarises our findings.

2 RELATED WORK

We have seen much research on spoofing and price manipulation in order-driven markets. Related research mainly lies in five fields: empirical study of behavior and performance of spoofing traders, the impact of spoofing on markets, the study of spoofing strategies, detecting or predicting spoofers and the mechanism design to mitigate spoofing in markets. Lee et al. [11] study behavior and performance of spoofing traders in Korea Exchange. Lin et al [13] examines the market manipuulation in Singapore Exchange. Mendonca et al [17] conduct an empirical study on the spoofing in the Brazilian capital market. Williams et al [32] claim that spoofing would raise the spread and market volatility. The harm to market liquidity caused by spoofing is also supported by the research of Comerton, Forde and Cumming [6, 7]. Pirrong believes that spoofing also reduces market efficiency [19]. Cartea et al [4] put forward an optimal spoofing strategy based on imbalance in volumes. Tao et al [22] also study the optimal spoofing strategy in high-frequency trading and in turn detect any spoofing in the market. Martìnez-Miranda et al study a model used to predict active spoofing [16]. Wang and Wellman [30] apply an adversarial learning framework to detect spoofing. Moreover, Wang et al [29] adopt agent-based modeling to demonstrate the effectiveness of spoofing in CDA markets. They follow the same framework to investigate the mechanism to mitigate spoofing [28] and trading strategies in the face of spoofing [27].

We simulate the market via agent-based models and explore the behavior at equilibrium. Agent-based markets have been studied in the literature, especially to compare different trading mechanisms. Lettau [12] construct a simple market where two kinds of assets are being traded, a risk-free bond paying zero interest and a risky asset. This market is extended to the Santa Fe Stock Market [1], where agents can buy and sell risk-free and risky assets in a discrete-time fashion. Much follow-up research are conducted in the Santa Fe Market [8, 10, 18].

The auction style is an essential issue in the market design. Most markets adopt the continuous double auction (CDA) while the frequent call markets attracted much attention afterwards because of their advantages over the CDA markets [2, 3, 23]. The design of agents has started from the Zero-Intelligence (ZI) agents designed by Gode and Sunder [9]. ZI agents have no intelligence and take decisions randomly. Cliff introduces bounded rationality to ZI agents [5, 18]. Brinkman et al. [2] construct a strategy space described by the minimum and the maximum shaded surplus from the trade.

To solve equilibrium state of the market, Wellman [31] develops the framework for empirical game-theoretic analysis (EGTA), which is a method to find an approximate equilibrium via simulations. A large number of systematic simulations are required by EGTA method and some sample profiles corresponding payoffs are used to construct a normal-from game. We have seen EGTA method widely adopted in research on financial markets [15, 20, 24, 26, 29]. Robustness of this technique has recently been studied in [14].

3 EXPERIMENTAL SETUP

In this work, we employ a parameterised single-asset financial market model inspired by previous research [2, 15, 29] which is believed to capture the qualitative phenomena found in real financial markets [2]. We adopt the agent-based modeling method to study the complex system and solve the equilibrium strategies using EGTA. The surplus of agents will be explored based on equilibrium strategies. We will compare the agents' performance and market measures with and without spoofing.

3.1 Market Model

We assume a single-asset market filled with N strategic agents, who can submit limit orders, cancel existing orders or take no action following their assigned strategies. We consider a finite and discrete trading horizon T. At each time step t, each agent will decide whether to enter the market—this is controlled by a Poisson process with arrival rate λ. Upon entering the market, an agent observes current and historical level 1 market data, including the best bid and ask price. It plays the role of a buyer or a seller uniformly at random. Before placing new orders, agents will cancel all existing orders. The size of the limit order is set to be 1 unit.

We focus on the frequent call auction mechanism, thus the limit order will not be executed as soon as it arrives, even if it crosses the limit order book. In frequent call auctions, there is a clearing interval with length l, and all orders collected during the clearing interval will be aggregated and executed in a batch at the end of the clearing interval.

As for the asset, we assume there exists a fundamental value dynamics, modeled by the following mean-reverting stochastic process:

$$f_t = r\bar{f} + (1-r)f_{t-1} + s_t \qquad f_0 = \bar{f} \qquad s_t \sim N(0, \sigma_s^2)$$

where f_t is the fundamental value at time t and $r \in (0, 1)$ is the reversion rate. Observe that the values of r and σ_s determine the range of the average shift of fundamental value.

3.2 Valuation Model

At each time t, the fundamental value alters, and then all agents will generate their own valuations loosely following the setup in [2, 23]. Specifically, each agent's valuation at time t is the sum of two components, common and private.

The common component is the individual estimation of the fundamental value with a *valuation bias* which is independently generated from a normal distribution $N(0, \sigma_{\text{bias}}^2)$. We use $b_{i,t}$ to denote the valuation bias of agent i at time t.

The private component is a measurement of the personal valuation of different positions. We express this through a vector Θ_i that we call the private value vector of agent i. Assume agents can long or short the asset and the maximum size allowed to long or short is Q, then the collection of allowed positions is $\{-Q, -Q+1, \ldots, Q-1, Q\}$. The element of the private value vector is the marginal surplus of obtaining one more unit of the asset when the agent is in a certain position, thus the length of each Θ_i is $2Q$ and the specific form of Θ_i is $(\theta_{i,-Q}, \theta_{i,-(Q-1)}, \ldots, \theta_{i,0}, \ldots, \theta_{i,Q-1})$, where the element $\theta_{i,q}$ is the marginal surplus of obtaining one more unit of the asset when agent i is in position q. We generate the private value vectors in the following way: we first have $2Q$ independent samples from a normal distribution $N(0, \sigma_{pv}^2)$, then we sort these $2Q$ values in descending order and fill the vector Θ. The private value vector for each agent is fixed throughout the full horizon T. The valuation is the sum of common and private components and we can define the valuation of agent i at time t in position q as

$$v_{i,t,q} = \begin{cases} b_{i,t} + f_t + \theta_{i,q}, & \text{if buying} \\ b_{i,t} + f_t - \theta_{i,q-1}, & \text{if selling} \end{cases}.$$

3.3 Trading Strategies

We consider three types of agents in our experiments. The first group place orders only based on their valuations; we call this the background trading strategy. The second group consider the market information; we call theirs the *heuristic belief learning* (HBL) strategy. Finally, the last group play the spoofing strategy.

3.3.1 Background Trading Strategy. If an agent places a limit order with its real valuation, we call it the truth-telling bidding strategy. However, telling the truth might not be the dominant strategy, thus we follow the strategy space design of Brinkman et al. [2] and consider the situation where agents require extra bonus from a transaction. We set up a required surplus range $[\alpha_{\min}, \alpha_{\max}]$, where $\alpha_{\min}$ represents the minimum acceptable surplus and $\alpha_{\max}$ denotes the maximum expected surplus from trading. If an agent enters the market, its surplus demand is uniformly drawn from the surplus range and the limit order price is exactly the sum of its valuation and the surplus demand. Specifically, the background trading strategy can be described as

$$p_{i,t,q} \sim \begin{cases} U[v_{i,t,q} - \alpha_{\max}, v_{i,t,q} - \alpha_{\min}], & \text{if buying} \\ U[v_{i,t,q} + \alpha_{\min}, v_{i,t,q} + \alpha_{\max}], & \text{if selling} \end{cases}.$$

To decrease the computational cost, we choose a limited strategy space denoted by B1 to B5 as shown in Table 1. Obviously, strategy B1 is exactly the truth-telling strategy and the latter strategies are more greedy than the former ones. We note that related work on EGTA discussed above uses a slightly larger strategy space, excluding B1 and including greedier strategies. However, these greedy strategies account for very small probabilities at equilibrium while the truth-telling strategy is an important component of the equilibrium according to further analyses, thus we believe our limited strategy space is more solid.

Table 1: Background Trading Strategy Space

Strategy	B1	B2	B3	B4	B5
$\alpha_{\min}$	0	0	0	20	50
$\alpha_{\max}$	0	50	100	100	100

3.3.2 HBL Trading Startegy. An agent following the HBL strategy (simply referred to as HBL agent below) observes the current level 1 market data, i.e., the best bid/ask price and the execution price, and stores the observation in its memory. When HBL agents enter the market, their strategy is generated from their belief function defined as following: suppose L is the memory length of HBL agents, i.e., when they enter the market at time t, they can only take the market data between $t - L$ and t into consideration. The design of the HBL strategy follows the research on spoofing in CDA markets [29]. Some required variables are explained in Table 2. Only the market data within the memory length will be used to define these variables.

Table 2: Parameters of HBL Strategy

Variable	Explanation
EB(p)	Volume of executed bid orders with price $\leq p$
SA(p)	Volume of ask orders with price $\leq p$
NB(p)	Volume of non-executed bid orders with price $\geq p$
EA(p)	Volume of executed ask orders with price $\geq p$
GB(p)	Volume of bid orders with price $\geq p$
NA(p)	Volume of non-executed ask with price $\leq p$

The belief function is defined by:

$$g_t(p) = \begin{cases} \frac{\text{EB}_t(p)+\text{SA}_t(p)}{\text{EB}_t(p)+\text{SA}_t(p)+\text{NB}_t(p)}, & \text{if buying} \\ \\ \frac{\text{EA}_t(p)+\text{GB}_t(p)}{\text{EA}_t(p)+\text{GB}_t(p)+\text{NA}_t(p)}, & \text{if selling} \end{cases}. \quad (1)$$

The belief function is an estimation of probability that orders with different price levels will be matched and executed in the market. An HBL agent will choose the price which maximizes the expected surplus from the trade based on her valuation and belief function. Specifically, the strategy, i.e., selected price of agent i with position q at time t is:

$$P^*_{i,t,q} = \begin{cases} \arg\max_p (v_{i,t,q} - p) g_t(p) & \text{if buying} \\ \arg\max_p (p - v_{i,t,q}) g_t(p) & \text{if selling} \end{cases}. \quad (2)$$

We consider two HBL strategies, denoted by HBL1 and HBL2, with memory lengths of 10 and 50, respectively.

3.3.3 Spoofing Strategy. We consider a spoofing agent aiming to sell assets at the end of the horizon, thus it will spoof bid orders. Her spoofing strategy is to place a large amount V of limit bid orders with price just 1 tick smaller than the best bid price. If the spoofing agent observes any updates of the best bid price, she will cancel previous spoof orders and place new spoof bid orders. This strategy expects that the feigned interest to buy will mislead the market belief of HBL agents and the spoofer could benefit from the manipulation.

3.4 Metrics

We consider metrics for both agents and the market. The surplus is the main metric to measure the agent's performance and is defined as the sum of wealth at the end of the trading horizon and the net cash flows in each trading. The key feature of the market we are concerned with is market efficiency. It is measured by the ratio between the realized and the potential total surplus. We also look at the difference between mid price time series and fundamental value time series to reveal the price discovery. To study this difference, we will consider the root-mean-squared deviation (RMSD) of the difference between the two time series. Therefore, lower RMSD indicates better price discovery.

3.5 Environment Parameters

In our comparative analysis, the markets and agents being compared share the same parameters except the market mechanism and the strategies they employ. Some common parameters including $\bar{f}, \sigma_s^2, \sigma_{\text{bias}}^2, \lambda_i, \sigma_{\text{pv}}^2$ are fixed through all the experiments. The asset price is a discrete integer ranging from 1 to 1000 in all experiments. We consider the thickness of the market, assigning 100 agents to a thin market and 200 agents to a thick market. The length of the simulation horizon T is 2000 and the length l of the clearing interval for FCMs is 10. We also consider the stability of the fundamental value which is controlled by the reversion rate r. A higher reversion rate makes a more stable fundamental dynamics. In our experiments, the reversion value r has two options: 0.8 and 0.2. We run 100 simulations for each game and take the average value as an approximation. Suppose there are m different strategies, so we need to simulate C_{N+m-1}^{m} cases to cover all possible profiles for each market setup when applying EGTA. The values of most common parameters are listed in Table 3.

Table 3: Environment Parameters

N	$\bar{f}$	r	σ_s^2	σ_{bias}^2	σ_{pv}^2	λ	V
100,200	500	0.8,0.2	100	50	25	0.01	200

We also list all non-spoofing trading strategies in Table 4.

Table 4: Non-spoofing Trading Strategy Space

	B1	B2	B3	B4	B5	HBL1	HBL2
$\alpha_{\min}$	0	0	0	20	50	-	-
$\alpha_{\max}$	0	50	100	100	100	-	-
Memory length	-	-	-	-	-	10	50

4 EXPERIMENTS AND ANALYSIS

Our analysis contains several steps. We first verify that HBL strategies are profitable in the frequent call market without spoofing. Then we introduce the spoofing agent to examine whether spoofing does harm to the market and the other agents. In the next step, we compare the harm caused by spoofing in the frequent call market and the traditional continuous double auction market, leaving all the other parameters unchanged. Finally, we investigate additional features which help curbing spoofing. In what follows, we refer to the average market efficiency, average total surplus and average trading volume simply as *Efficiency, Surplus* and *Volume*.

4.1 HBL Strategy Profitability

Our investigation starts with the verification of the profitability of HBL strategies in the frequent call market. We divide the agents into two equal groups, Group 1 play background trading strategies shown in Table 1, while Group 2 play HBL strategies. After solving the equilibrium for Group 1, the average surplus for each group in different market setups are listed in Figure 1 (in cases with multiple equilibria, we choose the equilibrium with the smallest regret value).

We can conclude that HBL strategies are profitable compared with background strategies, especially in less stable markets and thick markets. The parameter *memory length* in HBL strategies has little impact on the metrics at equilibrium.

4.2 Introducing Spoofing

In the following experiments, we let one agent play the spoofing strategy and the rest of the agents select their strategy from the extended non-spoofing strategy space listed in Table 4. To do the comparison between the markets with and without spoofing, we also run controlling experiments where all agents select their strategy from Table 4 using the same market setups.

4.2.1 Metrics for Agents. We focus on the changes in agents' surplus after introducing spoofing. The results in FCMs are listed in Table 5 while the results in CDAs are listed in Table 6.

Table 5: Agent Surplus Comparison, FCMs

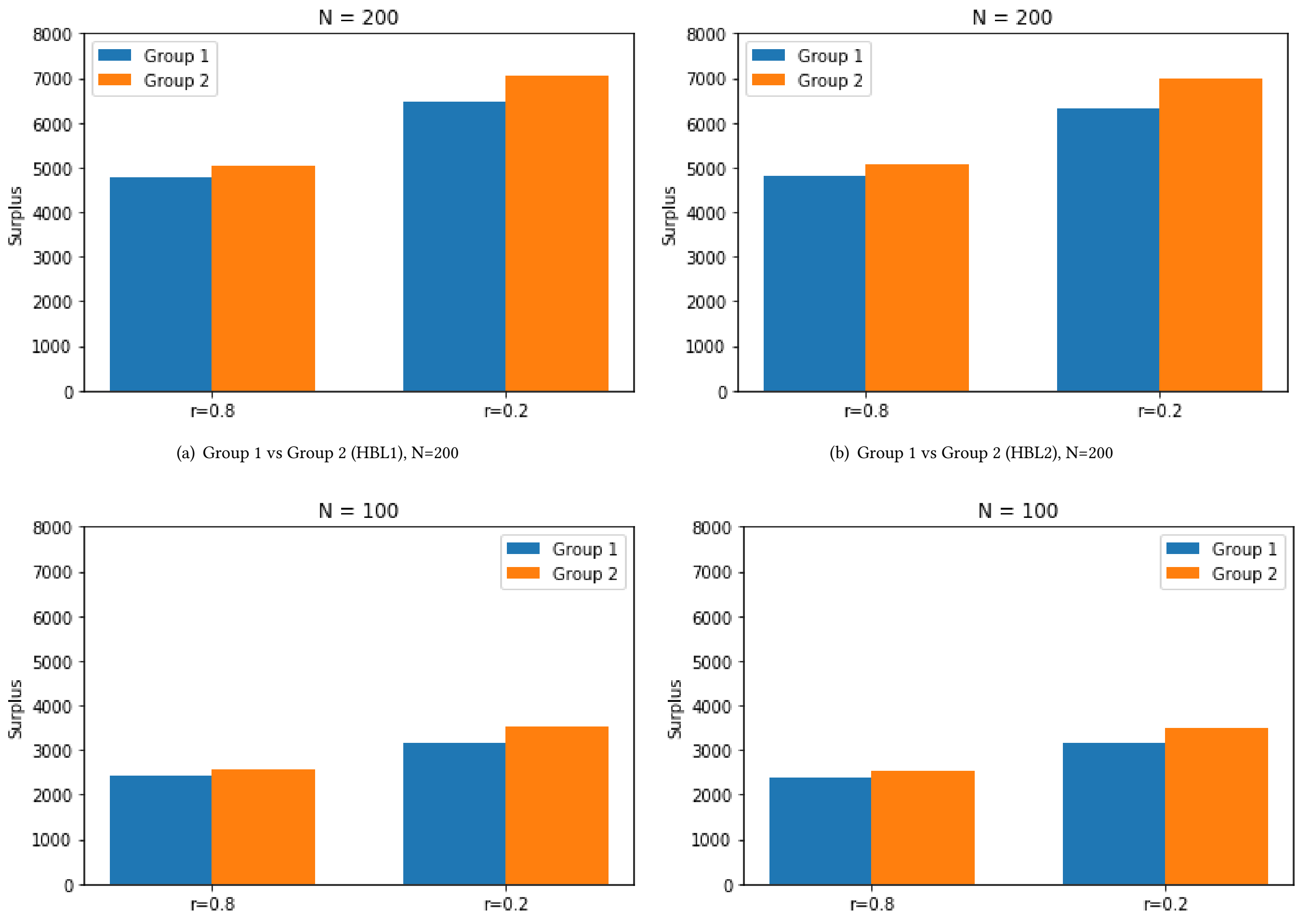
Agents	r	No Spoofing	Spoofing	
			normal agents	spoofer
200	0.2	6417	6739	-20796
200	0.8	5345	5517	-23405
100	0.2	3146	3337	-5135
100	0.8	2509	2621	-3518

Table 6: Agent Surplus Comparison, CDAs

Agents	r	No Spoofing	Spoofing	
			normal agents	spoofer
200	0.2	6420	6049	6664
200	0.8	4948	4709	4749
100	0.2	3211	2929	3391
100	0.8	2438	2326	2357

We find that in CDA markets, the introduction of the spoofing strategy does harm the non-spoofing agents, who suffer a sharp decrease in their surplus. On the other hand, the agent playing spoofing strategy has more surplus at the end of trading horizon than the others. Our experiments support the profitability of spoofing in CDA markets. However, when we introduce the spoofing strategy to frequent call markets, non-spoofing agents all have additional benefits while the agent playing the spoofing strategy bears a huge loss.

Finally, we adjust the strategy space to contain background trading strategy, HBL strategy and spoofing strategy and calculate the equilibria in all market setups. The equilibrium profiles are listed in Table 7, where these numbers are probabilities of playing the corresponding strategies in the equilibrium. We see that agents will not select spoofing strategy in equilibrium in FCMs, which reveals that the frequent call mechanism is better at curbing spoofing than traditional CDA markets.



(a) Group 1 vs Group 2 (HBL1), N=200

(b) Group 1 vs Group 2 (HBL2), N=200

(c) Group 1 vs Group 2 (HBL1), N=100

(d) Group 1 vs Group 2 (HBL2), N=100

Figure 1: Agent Surplus: Background vs HBL

Table 7: Equilibrium Profiles

Market, N, r	Background	HBL	Spoofing
CDA, 200, 0.2	0.21	0.50	0.29
CDA, 200, 0.8	0.30	0.52	0.18
FCM, 200, 0.2	0.56	0.44	0.00
FCM, 200, 0.8	0.64	0.36	0.00

4.2.2 Metrics for Markets. We next look at the market performance. The market efficiency is summarized in Table 8. The results reveal that spoofing has negative effects on the market efficiency. We also compare the trading volume of markets with and without spoofing in Figure 2, which shows that spoofing decreases the trading volume of the market, showing that it might decrease market liquidity.

Finally, we look at the price discovery with and without spoofing in different markets. The RMSDs of the difference between mid price time series and fundamental value time series are listed in Table 9.

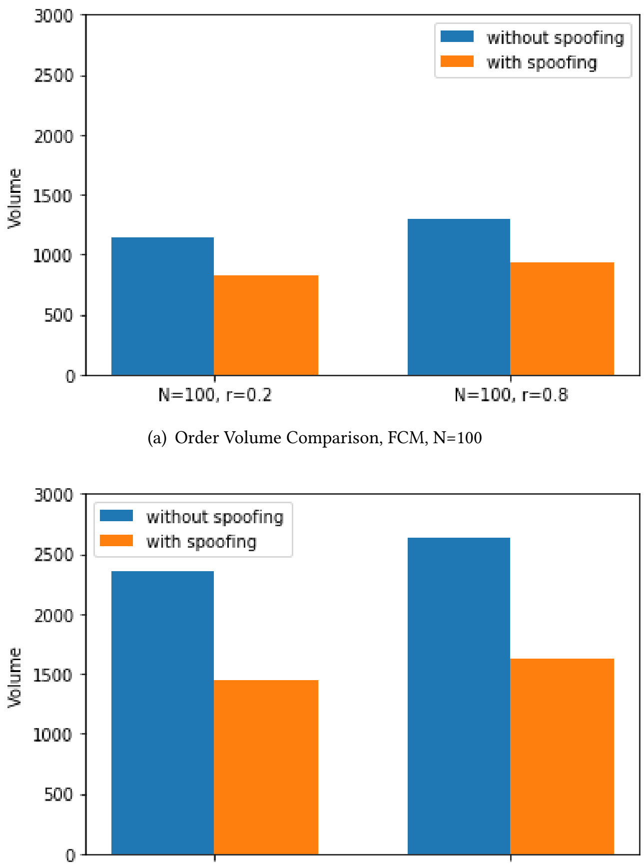
Table 8: Market efficiency, with & without spoofing

Market Type	Agents	r	No Spoofing	Spoofing
CDA	200	0.2	0.68	0.50
CDA	200	0.8	0.62	0.52
CDA	100	0.2	0.64	0.55
CDA	100	0.8	0.67	0.51
FCM	200	0.2	0.77	0.60
FCM	200	0.8	0.75	0.62
FCM	100	0.2	0.80	0.63
FCM	100	0.8	0.75	0.63

We can conclude that the introduction of spoofing has negative effects on price discovery. However, the frequent call markets have better price discovery than CDA markets, with or without spoofing.

Table 9: Price Discovery, with & without spoofing

Market Type	Agents	r	No Spoofing	Spoofing
FCM	100	0.2	120.49	125.56
CDA	100	0.2	136.45	140.89
FCM	200	0.2	120.33	134.37
CDA	200	0.2	143.78	140.49
FCM	100	0.8	162.23	162.11
CDA	100	0.8	177.51	179.13
FCM	200	0.8	170.30	179.18
CDA	200	0.8	179.35	179.28



(a) Order Volume Comparison, FCM, N=100

(b) Order Volume Comparison, FCM, N=200

Figure 2: Volume of Traded Orders

4.3 Slow Spoofer

We investigate the underlying reason why spoofing causes losses in FCMs. We notice that a large amount of feigning orders will be placed in spoofing. If the spoofer fails to update its feigning orders, they could become stale and the source of huge loss if they are traded. We count the volume of traded feigning orders in previous experiments and list the figures in Table 10. It is clear that many more spoofing orders are traded during the trading horizon in FCMs. We believe that in CDA markets, the update of the best bid price is a clear signal for the spoofer to update its feigning orders. However, the FCMs will not update during the clearing interval and the spoofer has no up-to-date information to make any decision except leaving its orders to become stale, which might explain why the spoofer will fail in FCMs.

Table 10: Volume of Traded Feigning Orders

Market Type	Agents	r	Volume of Traded Feigning Orders
CDA	200	0.2	3.2
CDA	200	0.8	3.0
CDA	100	0.2	1.5
CDA	100	0.8	1.8
FCM	200	0.2	1457.3
FCM	200	0.8	1605.4
FCM	100	0.2	485.0
FCM	100	0.8	570.7

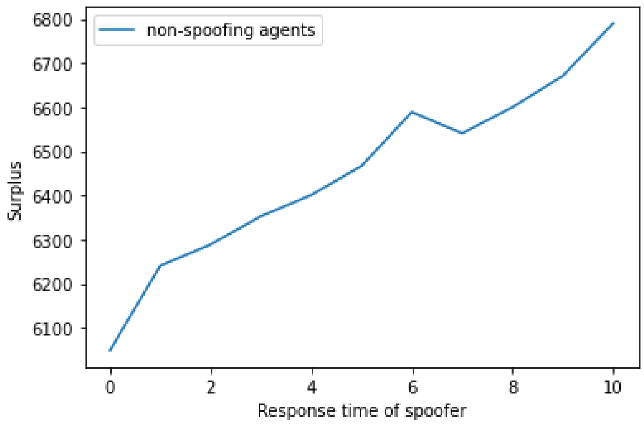
To verify our argument, we test several CDA markets sharing the same environment parameters but different spoofers. The only difference in spoofers is their response time to stale orders. We plot the surplus trends for both non-spoofing agents and the spoofer in Figure 3. The left end of each plot is the surplus in the market with fast spoofer while the right end shows the surplus in the market with slow spoofer. The results show that the response time is the key to taking the advantage of the other non-spoofing agents. Slow spoofers could suffer from huge loss because of failure in cancelling stale orders.

4.4 Random Clearing Interval Length

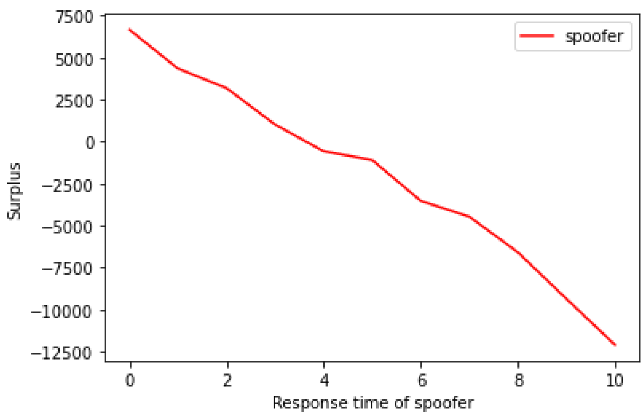
In continuous double auction markets, it is difficult to regulate the response time of agents. However, in frequent call markets, adopting random clearing interval length could lead to further curb spoofing. The underlying principle could be explained as follows: it is risky to leave feigning orders in the limit order book while the random completion of the auction gives no clear signals for agents to update their stale orders. In other words, when an agent plays the spoofing strategy and places a large amount of feigning orders, there exists a great probability that she cannot update her orders in time, and failure to do so will cause losses, finally decreasing the incentive to play the spoofing strategy.

In the previous experiments, the length of clearing interval is set to be 10. After adopting a random ending rule for the auction, the average clearing interval is also 10, but the length of each clearing interval is generated from a uniform distribution $U[0, 20]$. We compare the impact caused by spoofing on FCMs with fixed ending with the impact on random ending, denoted RFCM. The experiment results are summarized in Table 11 and Table 12, showing the metrics for agents and markets, respectively.

We can conclude that a random ending of the auction has enhanced effects on curbing spoofing compared with FCMs with fixed clearing interval, with no sacrifice in terms of market efficiency or the level of price discovery.



(a) Surplus Trend of Non-spoofing Agents



(b) Surplus Trend of Spoofing Agents

Figure 3: Surplus Trends, CDA, N=200, $r = 0.2$

Table 11: Metrics for Agents: FCM vs RFCM

Market, N, r	Normal Agents	Spoofer	Feigning Orders
FCM,200,0.2	6739	-20796	1457.3
RFCM,200,0.2	6874	-22267	1667.2
FCM,200,0.8	5517	-23405	1605.4
RFCM,200,0.8	5643	-24508	1789.1

Table 12: Metrics for Markets: FCM vs RFCM

Market, N, r	Efficiency	Price Discovery
FCM,200,0.2	0.60	134.37
RFCM,200,0.2	0.63	133.56
FCM,200,0.8	0.62	179.18
RFCM,200,0.8	0.62	180.89

5 CONCLUSION

This paper explores the effects on traders' surplus and market performance of introducing a spoofing strategy to frequent call markets using agent-based modeling and the EGTA method.

We conclude from our experimental results that spoofing will decrease market efficiency and order volume of the market, having further negative effects on market liquidity. An interesting finding is that spoofing is not as profitable in the frequent call markets as in traditional continuous double auction markets. We compare the agent surplus between CDA markets and FCMs sharing the same parameters and conclude that spoofing is profitable in CDAs whereas it will benefit others and cause huge loss to the spoofer in FCMs.

Investigating the reasons underpinning this differences, we find that the effect of spoofing is related to the volume of traded feigning orders, which is also equivalent to the speed of accessing updated level 1 market data. If the spoofing agent is able to update its feigning orders immediately after the best bids and asks alter, it can avoid loss from unexpected trades. However, the call auction mechanism delays its access to latest market data and increases the risk of executing spoofing orders. A mechanism that forces the agents to have a longer response to latest market information should then give less incentive to spoof. Following this idea, we test a so-called slow spoofer in CDA markets and the results support our argument.

Finally, we follow this design idea in the frequent call market and set up a random auction ending. This trading mechanism increases the risk for spoofing agents of staying in the market because their stale spoofing orders could be traded at any time before they make the decision from the observation of the market. Our experimental results reveal that this design is beneficial in that it curbs spoofing.

REFERENCES

[1] W Brian Arthur, John H Holland, Blake LeBaron, Richard Palmer, and Paul Tayler. 1996. Asset pricing under endogenous expectations in an artificial stock market. *The economy as an evolving complex system II* 27 (1996).
[2] Erik Brinkman and Michael P Wellman. 2017. Empirical mechanism design for optimizing clearing interval in frequent call markets. In *Proceedings of the 2017 ACM Conference on Economics and Computation*. 205–221.
[3] Eric Budish, Peter Cramton, and John Shim. 2015. The high-frequency trading arms race: Frequent batch auctions as a market design response. *The Quarterly Journal of Economics* 130, 4 (2015), 1547–1621.
[4] Álvaro Cartea, Sebastian Jaimungal, and Yixuan Wang. 2020. Spoofing and Price Manipulation in Order-Driven Markets. *Applied Mathematical Finance* 27, 1-2 (2020), 67–98.
[5] Dave Cliff and Janet Bruten. 1998. Zero is Not Enough: On The Lower Limit of Agent Intelligence For Continuous Double Auction Markets. (1998).
[6] Carole Comerton-Forde and Tālis J Putniņš. 2014. Stock price manipulation: Prevalence and determinants. *Review of Finance* 18, 1 (2014), 23–66.
[7] Douglas Cumming, Shan Ji, Rejo Peter, and Monika Tarsalewska. 2020. Market manipulation and innovation. *Journal of Banking & Finance* 120 (2020), 105957.
[8] Norman Ehrentreich. 2003. A corrected version of the santa fe institute artificial stock market model. *Complexity* (2003), 23.
[9] Dhananjay K Gode and Shyam Sunder. 1993. Allocative efficiency of markets with zero-intelligence traders: Market as a partial substitute for individual rationality. *Journal of political economy* 101, 1 (1993), 119–137.
[10] Blake LeBaron. 2002. Building the Santa Fe artificial stock market. *Physica A* (2002), 1–20.
[11] Eun Jung Lee, Kyong Shik Eom, and Kyung Suh Park. 2013. Microstructure-based manipulation: Strategic behavior and performance of spoofing traders. *Journal of Financial Markets* 16, 2 (2013), 227–252.
[12] Martin Lettau. 1997. Explaining the facts with adaptive agents: The case of mutual fund flows. *Journal of Economic Dynamics and Control* 21, 7 (1997), 1117–1147.
[13] Yiping Lin, David Michayluk, and Mi Zou. 2019. Can Random Auction Ending Curb Market Manipulation? *Available at SSRN 3404507* (2019).

[14] Buhong Liu, Maria Polukarov, Carmine Ventre, Lingbo Li, and Leslie Kanthan. 2021. Agent-based Markets: Equilibrium Strategies and Robustness. In *Proceedings of the 2nd ACM International Conference on AI in Finance*.

[15] Buhong Liu, Maria Polukarov, Carmine Ventre, Lingbo Li, and Leslie Kanthan. 2021. Call Markets with Adaptive Clearing Intervals. In *Proceedings of the 20th International Conference on Autonomous Agents and Multi-Agent Systems*. 1587–1589.

[16] Enrique Martínez-Miranda, Peter McBurney, and Matthew JW Howard. 2016. Learning unfair trading: A market manipulation analysis from the reinforcement learning perspective. In *2016 IEEE Conference on Evolving and Adaptive Intelligent Systems (EAIS)*. IEEE, 103–109.

[17] Luisa Mendonça and Alan De Genaro. 2020. Detection and analysis of occurrences of spoofing in the Brazilian capital market. *Journal of Financial Regulation and Compliance* (2020).

[18] Richard G Palmer, W Brian Arthur, John H Holland, Blake LeBaron, and Paul Tayler. 1994. Artificial economic life: a simple model of a stockmarket. *Physica D: Nonlinear Phenomena* 75, 1-3 (1994), 264–274.

[19] Stephen Craig Pirrong. 1995. The self-regulation of commodity exchanges: the case of market manipulation. *The Journal of Law and Economics* 38, 1 (1995), 141–206.

[20] L Julian Schvartzman and Michael P Wellman. 2009. Stronger CDA strategies through empirical game-theoretic analysis and reinforcement learning. In *Proceedings of The 8th International Conference on Autonomous Agents and Multiagent Systems-Volume 1*. 249–256.

[21] Chris Sparrow. 2012. The failure of continuous markets. *The Journal of Trading* 7, 2 (2012), 44–47.

[22] Xuan Tao, Andrew Day, Lan Ling, and Samuel Drapeau. 2020. On Detecting Spoofing Strategies in High Frequency Trading. *Available at SSRN 3746263* (2020).

[23] Elaine Wah, Dylan Hurd, and Michael Wellman. 2016. Strategic market choice: Frequent call markets vs. continuous double auctions for fast and slow traders. *EAI Endorsed Transactions on Serious Games* 3, 10 (2016).

[24] Elaine Wah, Sébastien Lahaie, and David M Pennock. 2016. An Empirical Game-Theoretic Analysis of Price Discovery in Prediction Markets.. In *IJCAI*. 510–516.

[25] Elaine Wah and Michael P Wellman. 2013. Latency arbitrage, market fragmentation, and efficiency: a two-market model. In *Proceedings of the fourteenth ACM conference on Electronic commerce*. 855–872.

[26] Elaine Wah, Mason Wright, and Michael P Wellman. 2017. Welfare effects of market making in continuous double auctions. *Journal of Artificial Intelligence Research* 59 (2017), 613–650.

[27] Xintong Wang, Chris Hoang, and Michael P Wellman. 2019. Learning-based trading strategies in the face of market manipulation. In *ICML-19 Workshop on AI in Finance*.

[28] Xintong Wang, Yevgeniy Vorobeychik, and Michael P Wellman. 2018. A cloaking mechanism to mitigate market manipulation. In *Twenty-Seventh International Joint Conference on Artificial Intelligence*.

[29] Xintong Wang and Michael Paul Wellman. 2017. Spoofing the limit order book: An agent-based model. In *Workshops at the Thirty-First AAAI Conference on Artificial Intelligence*.

[30] Xintong Wang and Michael P Wellman. 2020. Market Manipulation: An Adversarial Learning Framework for Detection and Evasion.. In *IJCAI*. 4626–4632.

[31] Michael P Wellman. 2006. Methods for empirical game-theoretic analysis. In *AAAI*. 1552–1556.

[32] Basil Williams and Andrzej Skrzypacz. 2020. Spoofing in Equilibrium. *Available at SSRN* (2020).