How Many Orders does a Spoofer Need? — Investigation by Agent-Based Model —

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***Abstract*—Most financial markets prohibit unfair trades as they reduce efficiency and diminish the integrity of the market . Spoofers place orders they have no intention of trading in order to manipulate market prices and profit illegally. Most financial markets prohibit such spoofing orders; however, further clarification is still needed regarding how many orders a spoofer needs to place in order to manipulate market prices and profit. In this study I built an artificial market model (an agent-based model for financial markets) to show how unbalanced buy and sell orders affect the expected returns, and I implemented the spoofer agent in the model. I then investigated how many orders the spoofer needs to place in order to manipulate market prices and profit illegally. The results indicate that showing more spoofing orders than waiting orders in the order book enables the spoofer to earn illegally, amplifies price fluctuation, and reduces the efficiency of the market.**

***Index Terms*—Agent-Based Model, Artificial Stock Market Model, Spoofing, Unfair Trades, Illegal Trades**

I. Introduction

Most financial markets prohibit unfair trades as they reduce efficiency and diminish the integrity of the market [1]. Spoofers place orders they do not intend to trade in order to manipulate market prices and profit illegally. Most financial markets prohibit such spoofing orders; however, how many orders a spoofer needs to place in order to manipulate prices and profit has yet to be clarified.

Empirical studies cannot be conducted to investigate situations that have never occurred in actual financial markets. Since many factors affect price formation, an empirical study cannot isolate the direct effect of spoofing orders on price formation. In contrast, artificial market simulation [2], [3]. using a kind of agent-based model can isolate the contributions of changes to liquidity and simulate changes that have never been observed.

Many previous studies on artificial markets investigated the nature of financial market phenomena such as bubbles and crashes. Recent studies have also contributed to discussions on appropriate financial regulations and rules [2], [3]. The JPX Working Paper series includes various studies contributing to such discussions.[1].

Wang and Wellman investigated the effect of spoofing orders on market prices [4]; however, no study has used an artificial market model investigated how many orders a spoofer needs to place in order manipulate market prices and profit illegally.

In this study I modified a prior market model [5] to show how an imbalance of buy and sell orders affects the expected returns of normal agents (NAs) . I implemented a spoofer agent (SA) in the model and then investigated how many orders the SA needed to place to manipulate market prices and profit illegally.

Note that the opinions contained herein are solely those of the authors and do not necessarily reflect those of SPARX Asset Management Co., Ltd.

[1]https://www.jpx.co.jp/english/corporate/research-study/working-paper/index.html

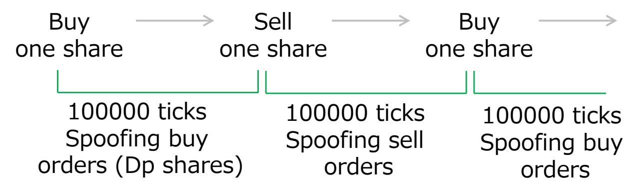

Fig. 1. Behavior of spoofer agent.

II. Artificial Market Model

The model developed by Chiarella and Iori [6], while simple, replicates long-term statistical characteristics observed in actual financial markets, fat tails and volatility clustering. In contrast, Mizuta et. al.’s model [5] replicates high-frequency micro structures, such as execution rates, cancel rates, and one-tick volatility, that cannot be replicated with the model of Chiarella and Iori’s model.

In this study I modified Mizuta et. al.’s model to show how an imbalance of buy and sell orders affects the expected returns of normal agents (NAs), and I implemented the spoofer agent (SA) in the model. I then investigated how many orders the SA needs to place to manipulate market prices and profit illegally. The simplicity of the model is crucial for this study because unnecessary replication of macro phenomena leads to models that are overfitted and too complex. Such models prevent understanding and discovery of mechanisms that affect price formation because of the increase in related factors. I explain the basic concept for constructing our artificial market model in the review article [3].

In the model here, there is one risk asset. The exchange market for each of the three risk assets implements a continuous double auction to determine the market price. In this auction mechanism, multiple buyers and sellers compete to buy and sell financial assets in the market, and transactions can occur at any time whenever an offer to buy and an offer to sell match [7]. The minimum unit of price change is δP. The buy-order price is rounded off to the nearest fraction, and the sell-order price is rounded up to the nearest fraction.

The model includes n normal agents (NAs) and one spoofer agent (SA). An agent's holding positions are not limited, so the agents can take an infinite number of shares for long and short positions.

A. Normal Agent (NA)

To replicate the nature of price formation in actual financial markets, I introduced the NA to model a general investor. The number of NAs is n. Its behavior is as simple as replicating long-term statistical characteristics and very short-term micro -structures in real financial markets. First, at time $t = 1$, NA No. 1 places an order to buy or sell its risk asset; then, at $t = 2, 3, , , n$, NAs No. $2, 3, , , n$ place buy or sell orders. At $t = n + 1$, the model returns to the first NA and repeats this cycle. An NA always places an order for only one share.

An NA determines an order price and buys or sells as follows. It uses a combination of a fundamental value and technical rules to form an expectation of a risk asset's return. The expected return of agent j for each risk asset is

$$r^t_{e,j} = (w_{1,j} \log \frac{P_f}{P^t} + w_{2,j} r^t_{h,j} + w_{3,j}\epsilon^t_j)/\Sigma^3_i w_{i,j} \qquad (1)$$

$$r^t_{h,j} = \log \frac{P^t}{P^{t-\tau_j}} + \log (1 + w_{4,j}\delta d \frac{D_b - D_s}{D_b + D_s}) \qquad (2)$$

where $w_{i,j}$ is the weight of term i for agent j and is independently determined by random variables uniformly distributed on the interval $(0, w_{i,max})$ at the start of the simulation for each agent. P_f is a fundamental value and is a constant[2]. P^t is the market price of the risk asset, and ϵ^t_j is determined by random variables from a normal distribution with average 0 and variance σ_ϵ. Finally, τ_j is independently determined by random variables uniformly distributed on the interval $(1, \tau_{max})$ at the start of the simulation for each agent[3]. δd is a constant. $D_b(D_s)$ is the number of buy or sell orders within $\pm\delta d \times P_f$ from the mid -price (the average of the highest buy order price and the lowest sell order price).

The first term of Eq. (1) represents a fundamental strategy: the agent expects a positive return when the market price is lower than the fundamental value, and vice versa. The second term of Eq. (1) represents a technical strategy using a historical return and imbalance of buy and sell orders. The first term of Eq. (2) indicates that the agent expects a positive return when the historical market return is positive and a negative return when the historical return is negative. The second term of Eq. (2) indicates that the agent expects a positive return when there are more waiting buy orders than sell orders, and vice versa for a negative return. Many technical traders use $(D_b - D_s)/(D_b + D_s)$ as a technical indicator, i.e., imbalance.

[2]This enables the model to focus on phenomena in short time scales, as the fundamental price remains static.

[3]When $t < \tau_j$, however, the second term of Eq. (1) is zero.

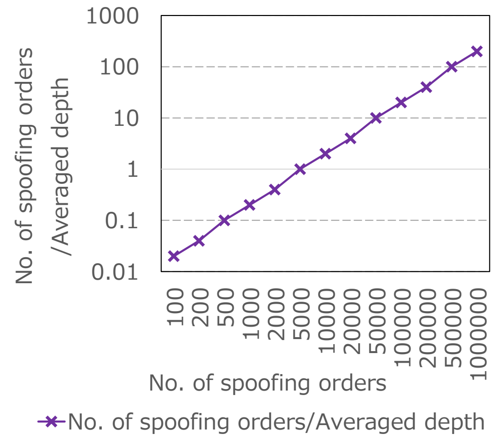

Fig. 2. Number of spoofing orders and average depth.

An empirical study [8] showed that traders will profit when using this indicator. The third term of Eq. (1) represents noise.

After the expected return has been determined, the expected price is

$$P^t_{e,j} = P^t \exp{(r^t_{e,j})}. \qquad (3)$$

An order price $P^t_{o,j}$ is determined by random variables normally distributed with average $P^t_{e,j}$ and standard deviation P_σ, where P_σ is a constant. Whether the agent buys or sells is determined by the magnitude relationship between $P^t_{e,j}$ and $P^t_{o,j}$:

when $P^t_{e,j} > P^t_{o,j}$, the agent places an order to buy one share, and

when $P^t_{e,j} < P^t_{o,j}$, the agent places an order to sell one share[4].

B. Spoofer Agent (SA)

Figure. 1 shows the behavior of the SA. First, the SA buy one share at a sufficiently high price to execute a trade immediately. Then the SA shows Dp shares of spoofing buy orders in the mid-price $+\delta d \times P_f$ within 100000 ticks to raise market prices. After that, the SA sells the share immediately and shows Dp shares of spoofing sell orders in the mid-price $-\delta d \times P_f$ within 100000 ticks to drive down market prices. The SA repeats these actions in all simulation periods.

III. Simulation Results

The parameters in this study were the same as those in [5].[5] Specifically, I set $n = 1000, w_{1,max} = 1, w_{2,max} = 10, w_{3,max} = 1, w_{4,max} = 1, \tau_{max} = 10000, \sigma_\epsilon = 0.06, P_\sigma = 30, t_c = 20000, \delta P = 0.01, k = 0.1$, and $P_f = 10000$. Simulations were run until $t = t_e = 10000000$ for $Dp = 0, 100, 200, 500, 1000, 2000, 5000, 10000, 20000, 50000, 100000, 200000, 500000, 1000000,$ and in one case without

[4]However, to generate enough waiting orders, when $t < t_c$ the agent places an order to buy one share when $P_f > P^t_{o,j}$, or to sell one share when $P_f < P^t_{o,j}$.

[5]I explain how their model was verified in the Appendix "Model Verification."

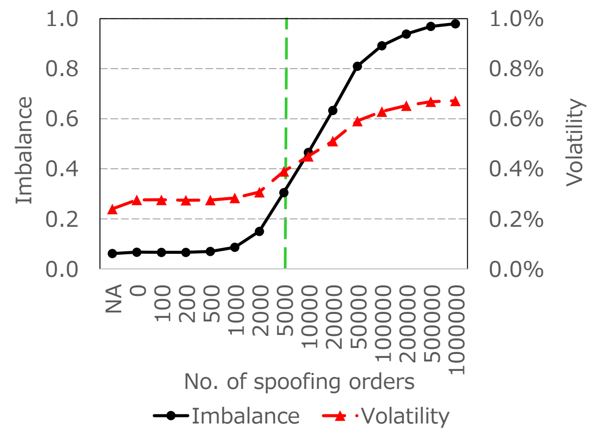

Fig. 3. Imbalance and volatility or returns.

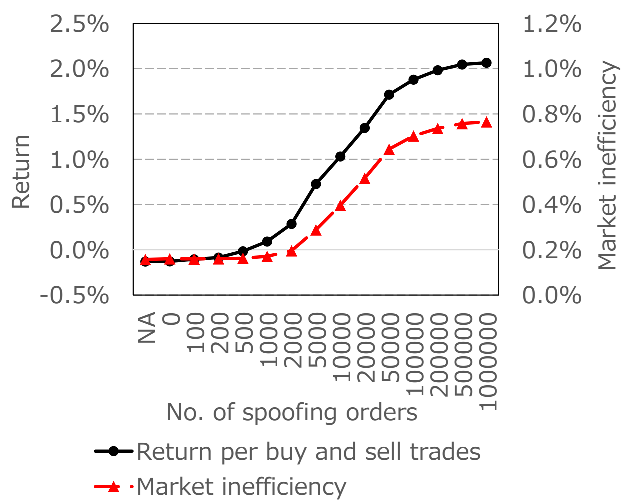

Fig. 4. Return of SA and market inefficiency.

the SA. In all cases, the other parameters were fixed and used the same random number table. I then simulated these runs 100 times, changing the random number table each time, and the results reported here are the averaged statistical values of the 100 runs.

Figure 2 shows the number of spoofing orders Dp per average depth for various Dp. The depth is defined as $(D_b+D_s)/2$. The averaged depths for any Dp are almost constant, 5000. The depth is almost the same as Dp at $Dp = 5000$, which is an important boundary for changing market price features.

Figure 3 shows the imbalance $(D_b - D_s)/(D_b + D_s)$ and volatility (standard deviation of returns within 20000 ticks) for various Dp. "NA" refers to the case without the SA. The green vertical dashed line is the boundary $Dp = 5000$. Higher Dp leads to increased imbalance and volatility. Increasing the spoofing orders amplifies price fluctuation, especially in $Dp \geq 5000$.

Figure 4 shows the returns from the SA's buy/sell trades and market inefficiency M_{ie} for various Dp. To directly measure

TABLE I
STATISTICS WITHOUT THE SPOOFER AGENT

trading	execution rate	32.3%
	cancel rate	26.1%
	number of trades / 20000 ticks	6467
standard deviations	for 1 tick	0.0512%
	for 20000 ticks	0.562%
	kurtosis	1.42
	lag	
autocorrelation coefficient for square return	1	0.225
	2	0.138
	3	0.106
	4	0.087
	5	0.075

market efficiency, M_{ie} is defined as

$$M_{ie} = \frac{1}{t_e} \sum_{t=1}^{t_e} \frac{|P^t - P_f|}{P_f}. \tag{4}$$

Here, M_{ie} is always greater than zero, and $M_{ie} = 0$ means that a market is perfectly efficient[6]. The larger M_{ie} is, the less efficient the market becomes[7].

Higher Dp leads to increased return and M_{ie} especially in $Dp \geq 5000$. These results indicate that showing more spoofing orders than waiting orders in the order book enables the spoofer to profit illegally, amplifies price fluctuation, and reduces the market's efficiency.

IV. SUMMARY

In this study I modified a prior market model [5] to show that the imbalance of buy and sell orders affects the expected returns of normal agents (NAs), and I implemented the spoofer agent (SA) in the model. I then investigated how many orders the SA needs to place to manipulate market prices and profit illegally.

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APPENDIX

A. Model Verification

In many previous studies on artificial markets, the models were verified to determine whether they could explain stylized facts such as a fat tail or volatility clustering [3]. A fat tail means that the kurtosis of price returns is positive. Volatility clustering means that square returns have a positive autocorrelation that slowly decays as its lag becomes longer. Many empirical studies, e.g., Sewell [9], have shown that both stylized facts (fat tail and volatility clustering) exist statistically in almost all financial markets. Conversely, they

[6]Even though I calculated the market inefficiency, I did not intend to discuss the efficient market hypothesis. The market in our model is inefficient because of the technical strategy in Eq. (2)

[7]A feature of M_{ie} is that it is calculated directly using a fundamental price P_f, which is never observed in empirical studies. I can also use M_{ie} in simulation and experimental studies because I can define P_f.

also have shown that only the fat- tail and volatility clustering are stable for any asset and in any period because financial markets are generally unstable.

Indeed, the kurtosis of price returns and the autocorrelation of square returns are stable and significantly positive, but the magnitudes of these values are unstable and vary depending on the asset and/or period. The kurtosis of price returns and the autocorrelation of square returns were observed to have very broad magnitudes of about $1 \sim 100$ and about $0 \sim 0.2$, respectively [9].

For the above reasons, an artificial market model should replicate these values as significantly positive and within a reasonable range. It is not essential for the model to replicate specific values of stylized facts because the values of these facts are unstable in actual financial markets.

Table I lists the statistics, standard deviation of returns, kurtosis of price returns, and autocorrelation coefficient for square returns without the spoofer agent. This shows that the model replicated the statistical characteristics, fat tails, and volatility clustering observed in real financial markets.

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