JAPAN EXCHANGE GROUP

JPX WORKING PAPER

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September 16, 2021

Vol. 37

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Abstract

As there are many stock exchanges in the United States, investors can choose the exchange that suits their purpose and trade shares there. On the other hand, competition among stock exchanges to secure market participants is intensifying. Furthermore, some new exchanges are attempting to open in asset markets where there is already a battle for market share because they think that they have a chance to obtain market share, due to the trading fees that the current stock exchanges charge being relatively high and their structures being complex. One trading fee structure is a maker-taker fee, in which stock exchanges provide makers, which place limit orders, with rebates and demand that takers, which place market orders, pay trading fees. It is said that maker-taker fees contribute to efficient market formation and improve the stock exchanges' market shares; however, this opinion has not been sufficiently investigated. In this study, we built two artificial stock markets, one where the stock exchange employs a maker-taker fee and one where it does not, and observed each market's market share, volatility, and market efficiency. As a result, it was found that the market share of the market where the stock exchange employs a maker-taker fee increases when the stock exchange provides market makers with sufficient rebates. However, when the stock exchange does not provide sufficient rebates, the market share of the market where the stock exchange does not employ a maker-taker fee increases. Also, as the maker's rebate increases, volatility of the market with a maker-taker fee decreases, whereas that of the market without it increases. Finally, the market efficiencies of both the markets increase as the rebate increases.

* Note that the opinions contained herein are solely those of the authors and do not necessarily reflect those of Japan Exchange Group, Inc., its subsidiaries, affiliates, or SPARX Asset Management Co., Ltd. Contact: Isao Yagi (iyagi2005@gmail.com)

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1 Introduction

The presence of many stock exchanges in the United States makes it possible for investors to choose the exchange that suits their purpose and trade shares there. However, competition among stock exchanges to secure market participants is intensifying. Furthermore, some new exchanges are attempting to open in asset markets where there is already a battle for market share because they think that they have a chance to obtain market share, due to the trading fees that the current stock exchanges charge being relatively high and their structures being complex. One trading fee structure employed by markets is a maker-taker fee. Under this structure, stock exchanges provide makers, which place limit orders, with rebates and demand that takers, which place market orders, pay trading fees. Various studies on maker-taker fees have been conducted (Battalio et al. (2016); Brolley and Malinova (2020); Cox et al. (2019); Foucault et al. (2013); Yagi et al. (2020)).

Some previous studies reported the effectiveness of maker-taker fees, whereas others have reported their demerits. One of the merits is that they contribute to improving market efficiency. A market maker places both a buy order and a sell order with a higher price in order to make a profit. However, if stock exchanges provide rebates to market makers, then the market makers can offer orders with narrower price spreads, than is, smaller differences between the buy and sell order prices. As a market maker's order price spread narrows and the market price transition converges between the market maker's buy and sell order prices, the market prices tend to converge to near the fundamental price, and the market becomes more efficient. The other noted merit is that it is expected that the market share of the market with the maker-taker fee will be larger (MacKenzie and Pardo-Guerra (2014)) because more investors may participate in the market with the maker-taker fee as the number of makers that want to receive a rebate increases, thus further increasing market liquidity.

One demerit of maker-taker fees is that transparency of trading cost and price is less. The trading fee rates of the maker-taker fees depend on market participants. Moreover, about eight hundred maker-taker fee structures exist in the United States, so it is considered to be difficult to calculate the total cost of taking orders exactly (CFTC-SEC (2011)). In addition, it is unclear whether the total cost of taking orders increases even if the trading fees that are paid by takers become are raised. This is because the total cost of taking orders includes both the charged fees and the market impact[*1]. If market makers, who provide liquidity in the market, increase due to maker-taker fees, market liquidity increases and market impact decreases. If the decrease in market impact is larger than the increase in the taker's fee, the total cost of the taking orders decreases. However, it is difficult for empirical studies to analyze the market impact because of

[*1] Market impact means the impact of a taker's own trades on the market price. In particular, in an illiquid market, market prices can fluctuate greatly as a result of one's own orders.

the inherent difficulty of measuring market impact from real market data. It is known that the period between placing an order and the order being matched gets longer as both the maker-taker fee and the rebate are decreased (Lin et al. (2016)).

Some studies have confirmed that maker-taker fees can increase market efficiency, stated as the first merit above (Yagi et al. (2020); Hoshino et al. (2021)). However, the effect of maker-taker fees contributing to an improved market share has not been sufficiently investigated. In this study, we built two artificial stock markets, one where the stock exchange employs a maker-taker fee and one where it does not, and observed each market's market share. The reason that we used artificial markets is that it is difficult for empirical studies to distinguish whether a maker-taker fee is the only factor that affects a market.

An artificial market is an agent-based model of a financial market (Chiarella et al. (2009); Chen et al. (2012); Yeh and Yang (2013)). In an artificial market, each agent is given their own trading strategy and allowed to trade a financial asset as an investor, and then the market behavior is observed. An artificial market also allows us to see how agents are affected by the market behavior. Recently, there has been a great deal of research using artificial markets to analyze the intrinsic impact of market regulations and rules on financial markets (Yeh and Yang (2013); Mizuta et al. (2015); Zhou and Li (2017)).

Therefore, in the present study, we built two artificial markets, one with a maker-taker fee and the other without it, and observed how the market shares of the two markets change under variations in the rebate received by the market makers. We also observed market volatility and market efficiency as measures of the impact of agents' market choice strategy in one of the markets.

2 Artificial Market

2.1 Overview

In this study, we built artificial market models on the basis of the artificial market model of Yagi et al. (Yagi et al. (2020)). Whereas the model of Yagi et al. (Yagi et al. (2020)) is a single market, we prepared two markets and observed the market share of each. One is a market where a maker-taker fee is employed (hereinafter referred to as the adopting market) and the other is the market where a maker-taker fee is not employed (hereinafter referred to as the non-adopting market). It is assumed that the same asset is traded in the two markets. There are normal agents, algorithm agents, and a position market maker in our market models (Fig1). The fee structure of the maker-taker fee is described in detail in Section 2.2. We add a market choice strategy to the normal agent in order to measure market share.

The number of normal agents is n and that of algorithm agents is m, where $1 \leq m \leq n$. Each of the normal agents $j = 1, \ldots, n$ places an order in sequence. After the final agent, agent n, has placed an order, the first agent, agent 1, places the next order. Each time $\lfloor n/m \rfloor$ normal agents

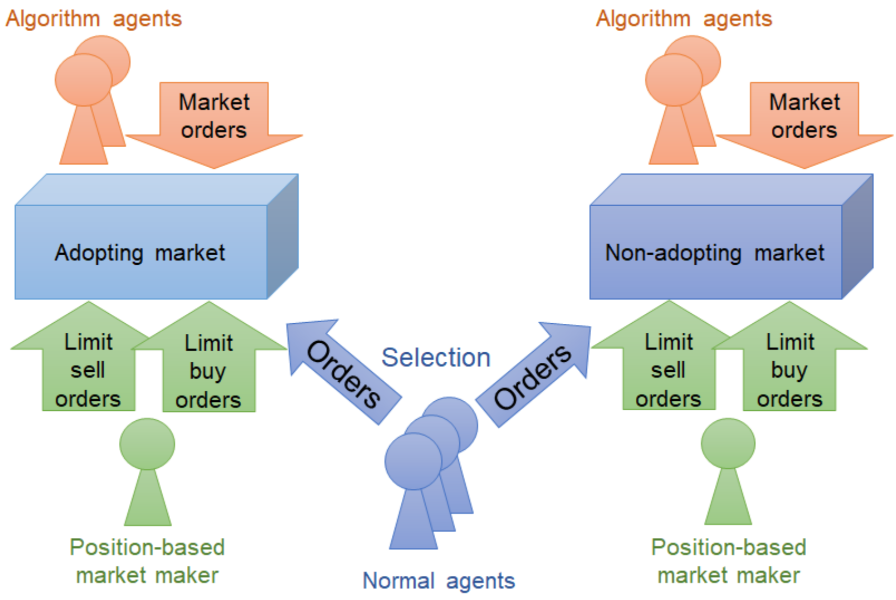

Figure 1 Overview of normal agents' market choice strategy

place orders, one algorithm agent places an order. The algorithm agents $k = 1, \ldots, m$ also place their orders in sequence. Normal agents select the market in which to place their order just before placing it. Algorithm agent k places an order in the adopting market if k is even and in the non-adopting market if k is odd. Each market has one position-based market maker, who places both sell and buy orders before either a normal agent or an algorithm agent places their order.

Time t increases by one each time a normal agent or an algorithm agent place an order. The process moves forward one step even when a trade does not occur. However, the process does not proceed when a market maker places orders. The pricing mechanism is a continuous double auction, which means that if there are sell (buy) order prices in the order book that are lower (higher) than the new buy (sell) order price of the agent, then the agent's order is immediately matched to the lowest sell order (highest buy order) in the order book. We call this new order a market order. When a trade does not occur, the new order remains in the order book. We call this a limit order.

2.2 Maker-taker fee structure

One of the stock exchange's sources of revenue is charging traders for the services that process their trades. Maker-taker fees provide a benefit for stock exchanges in that the exchanges can profit from the difference between the taker fee and the market maker rebate as follows:

$$R_{EX} = C_T - R_M \tag{1}$$

Let R_{EX}, C_T, and R_M be the stock exchange's profit, the taker's fee that the stock exchange has to obtain, and the market maker's rebate which the stock exchange will give to a market maker, respectively. In this study, R_{EX} is set to 0.1% according to Yagi et al. (Yagi et al. (2020)). R_{EX}, R_M, and C_T are expressed as their ratios to the fundamental price described later.

2.3 Normal agent

Normal agents are assumed to be general investors in the real world. Their trading strategies consist of a fundamental strategy component, a technical strategy component, and a noise trading component. The fundamental strategy is a strategy that refers to the fundamental price to make investment decisions. The technical strategy is a strategy that uses market price trends to make investment decisions. The noise trading represents trial-and-error investment decisions. Normal agents switch between the fundamental and technical strategies from time to time, learning as the market environment changes. A normal agent makes a buy or sell decision according to the following procedure. The rate of change in price (i.e., expected return) expected by normal agent j at time t, ${r_e}_j^t$, is given by

$$ {r_e}_j^t = \frac{1}{{w_1}_j^t + {w_2}_j^t + u_j} \left({w_1}_j^t {r_1}_j^t + {w_2}_j^t {r_2}^t + u_j \epsilon_j^t \right), \tag{2} $$

where ${w_i}_j^t$ is the weight of the i-th ($i = 1, 2$) term for agent j at time t and is set according to the uniform distribution between 0 and $w_{i,max}$ at the start of the simulation and then varied using the learning process described later herein. The first term in the right-hand side of Eq. (2), ${w_1}_j^t$, is the weight of the fundamental strategy component. The second term, ${w_2}_j^t$, is the weight of the technical strategy component. Further, u_j is the weight of the noise trading component and is set according to the uniform distribution between 0 and u_{max} at the start of the simulation and is kept constant thereafter. Note that all weights vary independently of each other and the effects of the three types are normalized by the denominator term in the right-hand side of Eq. (2).

${r_i}_j^t$ is the expected return of the i-th term for agent j at time t. The first term, ${r_1}_j^t$, is the expected return of the fundamental strategy component, $\ln\left(P_f/P^{t-1}\right)$ (ln denotes the natural logarithm). This expected return, ${r_1}_j^t$, compares the fundamental price with the market price one period ago and assumes a positive (negative) expected return if the market price is lower (higher) than the fundamental price. P_f is the fundamental price, which does not change with time. P^t is the market price at time t. If a trade does not occur, it is set to the most recently traded price. P^t is set to P_F when $t = 0$. The second term, ${r_2}_j^t$, is the expected return of the technical strategy component, $\ln\left(P^{t-1}/P^{t-1-\tau_j}\right)$. This formulation gives a positive (negative) expected return if the historical return is positive (negative). τ_j is set according to the uniform distribution between 1 and τ_{max} for agent j. ϵ_j^t is the noise trading component of agent j at time t and takes a normally distributed random value with mean zero and standard deviation σ_ϵ.

Based on the expected return obtained from Eq. (2), the expected price ${P_e}_j^t$ is determined as follows[*2]:

$$P_{e}{}_{j}^{t} = P^{t-1} exp\left(r_{e}{}_{j}^{t}\right). \tag{3}$$

The order price $P_{o}{}_{j}^{t}$ is normally distributed with mean $P_{e}{}_{j}^{t}$ and standard deviation $P_{\sigma}{}_{j}^{t}$, where $P_{\sigma}{}_{j}^{t} = P_{e}{}_{j}^{t} \cdot est (0 < est \leq 1)$. Normal agents place a buy (sell) order for one share if $P_{o}{}_{j}^{t}$ is less (greater) than $P_{e}{}_{j}^{t}$. Learning is performed by each agent immediately before the agent places an order. That is, when $r_{i}{}_{j}^{t}$ and $r_{l}{}^{t} = \log(P^{t}/P^{t-t_l})$ are of the same sign, $w_{i}{}_{j}^{t}$ is updated as follows:

$$w_{i}{}_{j}^{t} \leftarrow w_{i}{}_{j}^{t} + k_l |r_l{}^{t}| q_{j}^{t} (w_{i,max} - w_{i}{}_{j}^{t}), \tag{4}$$

where k_l is a constant, and q_{j}^{t} is set according to the uniform distribution between 0 and 1 for agent j. When $r_{i}{}_{j}^{t}$ and $r_l{}^{t}$ have opposite signs, $w_{i}{}_{j}^{t}$ is updated as follows:

$$w_{i}{}_{j}^{t} \leftarrow w_{i}{}_{j}^{t} - k_l |r_l{}^{t}| q_{j}^{t} w_{i}{}_{j}^{t}. \tag{5}$$

Separately from the process for learning based on past performance, $w_{i}{}_{j}^{t}$ is reset with a small probability δ_l, according to the uniform distribution between 0 and w_{imax}. This means that learning is random, and this, in combination with learning based on performance, allows objective modeling of the situation in which agents find the weights of strategies by trial and error.

The normal agents select the market where they place orders after determining their own order prices and type of order (buy or sell). Figure 2 illustrates normal agents' market selection process. To select the market where to place an order, a normal agent performs the following steps. First, the normal agent checks the prices of the lowest sell order and the highest buy order in the order book. If the normal agent's order matches an order in either the adopting market or the non-adopting market but not both, then the normal agent immediately places their order in the market with the matching order. If the normal agent's order does not match any order in the adopting market or the non-adopting market, then the agent places their order with a market at the ratio $Adoptingmarket : Non - adoptingmarket = 50 : 50$. On the other hand, in the case where the order can match an order in either market, the agent places a buy (sell) order in the market that can be traded in at a lower (higher) price, taking into account the trading fees.

2.4 Algorithm agent

Algorithm agents are assumed to be institutional investors who use an algorithmic trading strategy, which is a process in which a big order is divided into small orders and automatically executed little by little. In our model, algorithm agents always place a buy market order for one share. When ordering, the algorithm agent checks whether there is a best-ask order that

[*2] In our research, we use logarithmic returns for the expected return. Therefore, the expected return is the difference between the logarithm of the current market price and that of the expected price; $r_{e}{}_{j}^{t} = \ln P_{e}{}_{j}^{t} - \ln P^{t} = \ln P_{e}{}_{j}^{t}/P^{t}$, which allows us to derive Eq. (3).

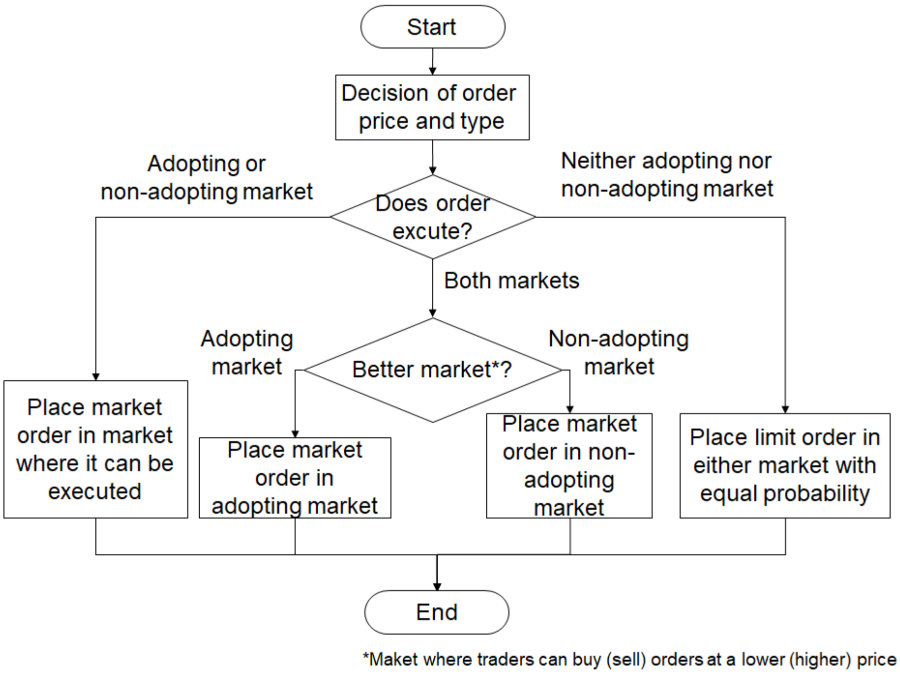

Figure 2　Normal agents' market selection process

immediately matches their buy order. If such the best-ask order exists, then the algorithm agent places a buy order at the price obtained by adding the tick size ΔP to the price of the order and executes it immediately. If no best-ask order exists, then the order is not executed.

2.5 Position-based market maker

A position-based market maker is assumed to be an institutional investor who takes a market maker strategy, which means a strategy of placing both a buy order and a sell order with a higher price, to make a profit. Hereinafter, a position-based market maker is simply called a market maker.

If the previous sell, buy, or both orders of the market maker remain in the order book, the market maker cancels them and places new buy and sell limit orders. Generally, a market maker decides their own order price based on the best-bid, the best-ask, and the spread, which is equal to the amount of their own expected return per transaction. However, the order price of the market maker also depends on their position, i.e., the amount of the asset that they held, as they act to keep their position neutral (Nakajima and Shiozawa (2004); Kusada et al. (2014); Yagi et al. (2020)). Thus, when the market maker has a long position, meaning the agent has bought and holds some amount of an asset, their buy and sell order prices are set lower so that their sell order matches an order from normal agents and algorithm agents easier than their buy order. On the other hand, when the market maker has a short position, meaning the agent is short-selling the asset, their buy and sell order prices are set higher so that their buy order matches an order from normal agents easier than their sell order.

Let the base spread of the market maker and the coefficient of their position (initially set based on Kusaka et al. Kusada et al. (2014) as 5.0×10^{-8}) be θ_{pm} and w_{pm}, respectively. Let the best-bid, the best-ask, the basic order price, the buy order price, and the sell order price at time t, and the position between time t and $t+1$ of the market maker be $P^{t,buy}$, $P^{t,sell}$, $P^t_{fv,pm}$, $P^{t,buy}_{o,pm}$, $P^{t,sell}_{o,pm}$, and s^t_{pm}, respectively. Then, $P^t_{fv,pm}$, $P^{t,buy}_{o,pm}$, and $P^{t,sell}_{o,pm}$ are as follows:

$$P^t_{fv,pm} = \frac{P^{t,buy} + P^{t,sell}}{2}\left(1 - w_{pm}\left(s^t_{pm}\right)^3\right), \tag{6}$$

$$P^{t,buy}_{o,pm} = P^t_{fv,pm} - \frac{1}{2}P_f\theta_{pm}, \tag{7}$$

$$P^{t,sell}_{o,pm} = P^t_{fv,pm} + \frac{1}{2}P_f\theta_{pm}. \tag{8}$$

When the sell (buy) order price of the market maker is lower (higher) than the best-bid (best-ask), the market maker's order is a market order. Therefore, if the following conditions are satisfied, the buy and sell order prices of the market maker are changed Kusada et al. (2014).

If $P^{t,buy}_{o,pm} \geq P^{t,sell}$, then

$$\begin{aligned} P^{t,buy}_{o,pm} &= P^{t,sell} - \Delta P, \\ P^{t,sell}_{o,pm} &= (P^{t,sell} - \Delta P) + P_f \cdot \theta_{pm}. \end{aligned} \tag{9}$$

If $P^{t,sell}_{o,pm} \leq P^{t,buy}$, then

$$\begin{aligned} P^{t,buy}_{o,pm} &= (P^{t,buy} + \Delta P) - P_f \cdot \theta_{pm}, \\ P^{t,sell}_{o,pm} &= P^{t,buy} + \Delta P. \end{aligned} \tag{10}$$

For both conditions, θ_{pm} is set in consideration of the market maker rebate as follows:

$$\theta_{pm} = Re_M - 2R_M, \tag{11}$$

where Re_M is the expected return of the market maker per transaction. Note that Re_M is expressed as a ratio to the fundamental price P_f and is set to 0.300% according to Yagi et al. (Yagi et al. (2020)). The reason why R_M appears in the equation with a coefficient of 2 is that the market maker may receive the rebate both when their buy limit order is executed and when their sell limit order is executed.

Table 1 shows the relationship between θ_M and C_T by listing their values for various market maker rebates R_M under the above conditions. Note that C_T is 0.050% when R_M is -0.050%. This means both makers and takers pay 0.050% as trading fees to the stock exchange. Thus, the adopting market can also be regarded as a non-adopting market when R_M =-0.050%, as the investment behavior of agents participating in the former market will be virtually identical to that in the latter market.

Table 1 Relationship between base spread θ_M and taker fee C_T with respect to market maker rebate R_M when Re_M = 0.300% and R_{EX} = 0.100%

R_M	θ_{pm}	C_T
-0.050%	0.400%	0.050%
-0.025%	0.350%	0.075%
0.000%	0.300%	0.100%
0.025%	0.250%	0.125%
0.050%	0.200%	0.150%
0.075%	0.150%	0.175%
0.100%	0.100%	0.200%
0.125%	0.050%	0.225%
0.140%	0.020%	0.240%
0.145%	0.010%	0.245%

3 Simulation and results

Here, we build the adopting artificial market and the non-adopting artificial market and observe each market's market share. In addition, we investigate the effect of normal agents' market selections on volatility and market efficiency of each market. The rebate for the adopting market R_M is varied from -0.050% to 0.125% in 0.025% increments and also set to the values 0.140% and 0.145%, as shown in Table 1. The rebate for the non-adopting market is kept constant, i.e., R_M=-0.050% as described in Section 2.5. The model parameters are set as shown in Table 2. t_e is the end time of simulations. A total of 50 simulation trials are run for each rebate value and the results are analyzed.

3.1 Market share

As the measure of market share, we use the market volume (the number of times a transaction is executed). Specifically, the volume of each market at the end of the simulation is measured and the ratio of the volume to the combined end volume is calculated as the market share. Thus, market share S_A of the adopting market and market share S_B of the non-adoption market are defined as follows:

$$S_A = \frac{V_A}{V_A + V_B}, \tag{12}$$

$$S_B = \frac{V_B}{V_A + V_B}, \tag{13}$$

where V_A and V_B are the end volumes of the adopting and non-adopting markets, respectively.

Table 2 Model parameters

Parameter	Value
n	980
m	20
w_{1max}	1
w_{2max}	10
u_{max}	1
τ_{max}	10,000
σ_ϵ	0.06
est	0.003
t_c	20,000
ΔP	1.0
P_f	10,000
t_e	1,000,000
δ_l	0.01
k_l	4.0
t_l	10,000
w_{pm}	0.00000005

3.2 Market impact

Market impact is a measure of how much one's own orders have affected the market price. In this study, the market impact MI is defined as the relative amount that the algorithm agents paid above the fundamental price P_f of the asset:

$$MI = \frac{1}{n_{buy}} \sum_{l=1}^{n_{buy}} \frac{p_{buy}^l - P_f}{P_f}, \tag{14}$$

where n_{buy} denotes the total amount of assets which algorithm agents buy during the simulation and p_{buy}^l is the price of at the time of the lth purchase of the asset. When there are no algorithm agents in the market, the average of the market prices is almost equal to the fundamental price (Mizuta et al. (2014)). Thus, we can say that the greater the market impact is, the more the trading of the algorithm agents affects the market. If $MI = 0$, then that of the algorithm agents has no effect. Note that the market impact is expressed as the average deviation of the buy price from the fundamental price. In this study, as algorithm agents always place buy market orders, the total cost of taking orders can be measured as the sum of market impact MI and trading fee C_T.

3.3 Market inefficiency

We define the market inefficiency M_{ie} as follows (Mizuta et al. (2016)):

$$M_{ie} = \frac{1}{t_e} \sum_{t=0}^{t_e} \frac{\left|P_i^t - P_f\right|}{P_f}, \tag{15}$$

where P_i^t is the price in market i at time t. If a trade does not occur, P_i^t is set to the most recently traded price. For $t = 0$, P_i^t is set to P_F. The market inefficiency is defined as the actual difference between the market and fundamental prices. Generally, M_{ie} is non-negative. If M_{ie} is 0, the market is perfectly efficiency. However, the larger M_{ie} is, the less efficient the market is.

3.4 Validation of artificial market model

As many empirical studies have noted Cont (2001); Sewell (2011), a fat tail and volatility clustering appear in actual markets, which are two stylized facts of financial markets. A fat tail is the condition in which the frequency distribution (histogram) created from data on the rate of change of prices has large kurtosis and the bottom of the distribution is thick relative to a normal distribution. Thus, a positive kurtosis means the distribution has a fat tail. Volatility clustering is determined by looking at the autocorrelation of squared returns. Volatility clustering has occurred if this autocorrelation is positive even if there is a large lag.

We set the artificial market parameters so as to replicate these features according to Yagi et al. (Yagi et al. (2020)). As an example, Table 3 shows the stylized facts of the non-adopting market, that is, for R_M=-0.050%. As shown, both the kurtosis and the autocorrelation of the squared returns are positive. Therefore, our artificial market model is valid.

Table 3 Stylized facts (R_M=-0.050%)

Kurtosis		34.644
	lag1	0.0216
Autocorrelation	lag2	0.0205
coefficients	lag3	0.0196
for squared returns	lag4	0.0202
	lag5	0.0205

3.5 Results and discussion

Comparing market shares between the adopting market and the non-adopting market, we find that the market share of the non-adopting market was larger than the market share of the adopting market when the market maker's rebate was low. However, the market share of the adopting market was larger once the rebate in the adopting market rose above a certain threshold. Volatility in the adopting market decreased gradually and volatility in the non-adopting market increased gradually as the rebate increased. Market inefficiency decreased in both the adopting and non-adopting markets as the rebate increased, with little difference between the two markets in this respect.

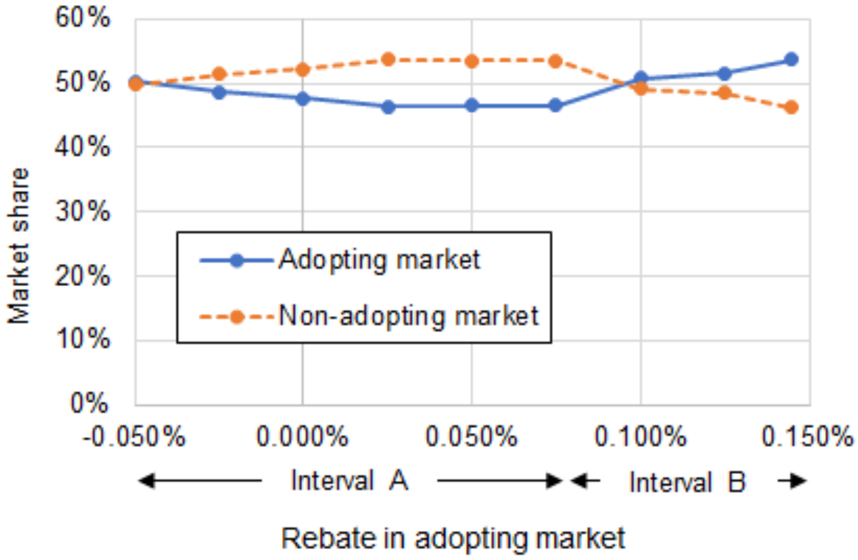

Figure 3 Market share of each market

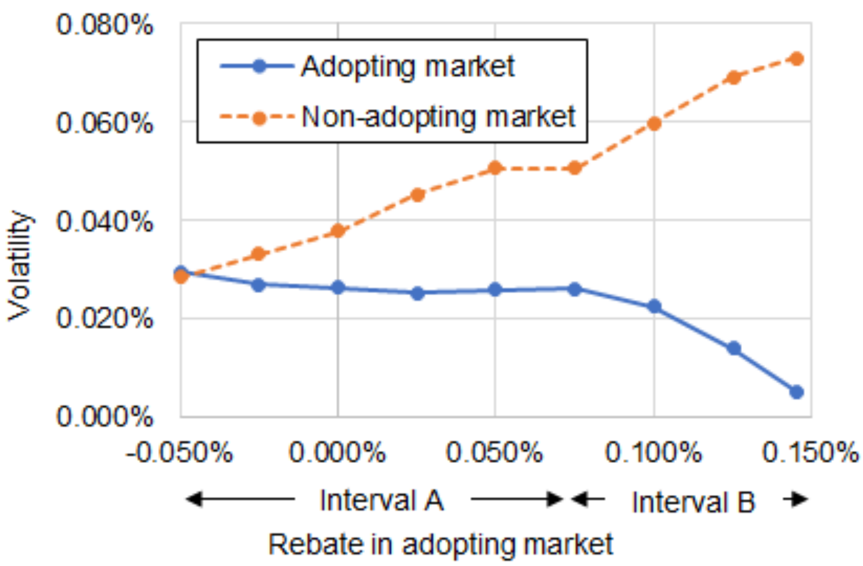

Figure 4 Volatility in each market

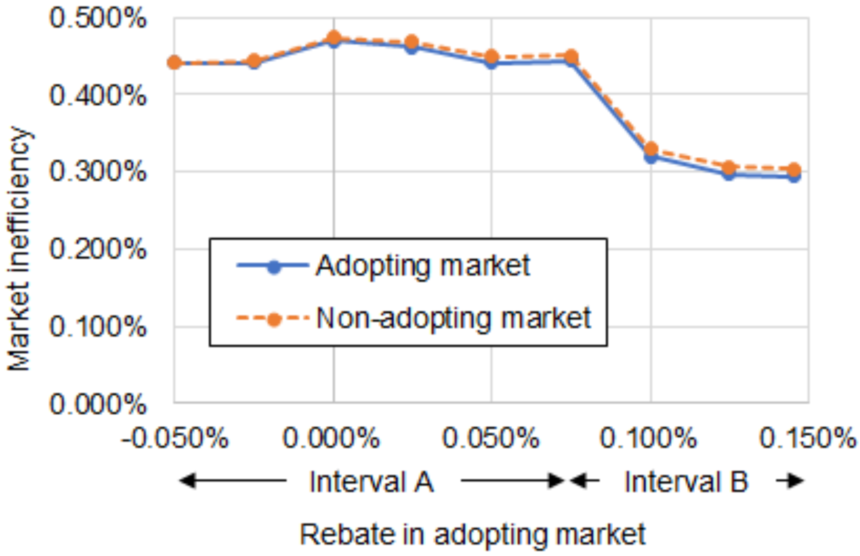

Figure 5 Market inefficiency of each market

3.6 Market share

Figure 3 shows the market shares of the adopting market and the non-adopting market. For the market maker's rebate between −0.050% and 0.075% (hereinafter, this interval is called interval A, and the interval between 0.075% and 0.150% is called interval B) the market share of the non-adopting market was larger than that of the adopting market. The reason for this is as follows. Yagi et al. (Yagi et al. (2020)) indicated that the larger the rebate the maker receives, the smaller the total cost of taking orders is[*3]. When the total cost of taking orders decreases, takers are able to buy or sell orders in the adopting market at a lower price or at a higher price than those in the non-adopting market. Thus, the market share of the adopting market is larger than that of the non-adopting market.

Next, we discuss why the market share of the adopting market gradually decreases, and thus that of the non-adopting market gradually increases, in interval A. In interval A, because market maker's orders do not impact the bid-ask spread in either market, the market impact does not decrease and the total cost of taking orders increases. Therefore, normal agents tend to increasingly place orders in the non-adopting market.

As a result, if the market maker receives enough of a rebate to allow the spread between the market maker's buy and sell order prices to be less than the bid-ask spread, it is possible for the

[*3] This is because, as the rebate increases, the market maker can offer orders with narrower spreads. When the spread between the market maker's orders is less than the market bid-ask spread (which here corresponds to the boundary between intervals A and B), the market maker's orders tend to be best quotes. Therefore, as the market price transition drops and the market impact also decreases, the total cost of taking orders becomes smaller.

adopting market to grab market share from the non-adopting market. However, increasing the rebate does not have an inexhaustible power to increase the market share of the adopting market. This is because the spread between the market maker's buy and sell orders cannot be less than the tick size, so the bid-ask spread of the adopting market will reach a minimum size. Therefore, the market share of the adopting market is expected to reach a ceiling.

3.7 Volatility

Figure 4 shows the volatility of the markets. In this study, the standard deviation of the rate of return was used as the measure of volatility. Volatility of the adopting market does not vary so much in interval A, as the market maker's orders do not affect the bid-ask spread and thus do not affect the market price formation. On the other hand, the volatility of the adopting market decreases in interval B because the market price transition starts to decrease when the spread between the market maker's buy and sell order prices becomes less than the bid-ask spread.

In the non-adopting market, volatility is always increasing as the rebate increases, but note that the mechanism of the change in volatility is slightly different between intervals A and B. In interval A, the market share of the non-adopting market increases as the rebate increases (see Section 3.6). This phenomenon can be attributed to the increase in market orders by normal agents in the non-adopting market. As trading volume increases, the bid-ask spread of the non-adopting market diffuses, the market price moves up or down more, and volatility increases. On the other hand, when the bid-ask spread of the adopting market becomes less than that of the non-adopting market in interval B, normal agents do not place their orders in the non-adopting market. Therefore, the number of normal agents' limit orders decreases, making it difficult for the order book to form, resulting in a thin order book and large price movements accompanying single trades. As a result, volatility continues to increase in interval B.

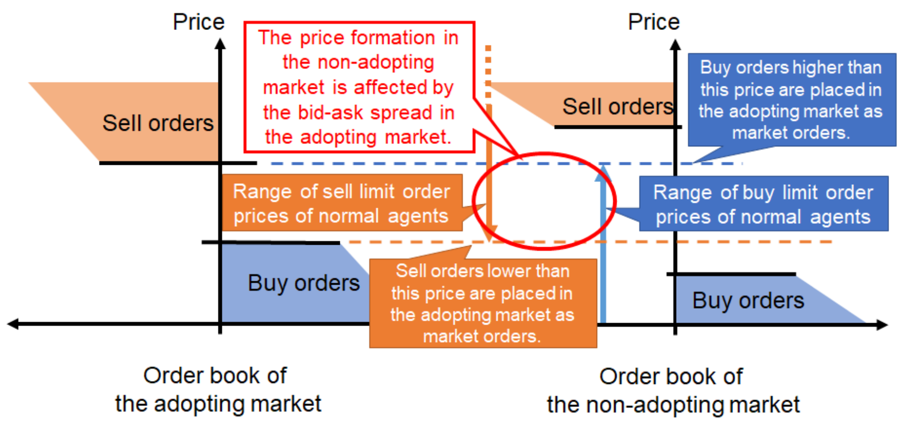

Figure 6 Limit order range for normal agents in non-adopting market

3.8 Market inefficiency

Figure 5 shows the market inefficiency of each market. We can see that in both markets, market inefficiency does not change significantly in interval A; however, it decreases for both in interval B as the maker's rebate increases.

In interval A, the market maker's orders do not affect the bid-ask spread of the markets, so the price transition is similar between the markets. However, in interval B, the market maker narrows the spread between their buy and sell limit order prices around the fundamental price. Then, even if the market price tries to move away from the fundamental price, the orders of normal agents and algorithm agents will be executed around the fundamental price. As a result, market inefficiency is reduced (market efficiency increases).

On the other hand, in the non-adopting market in interval B, market inefficiency decreased like in the adopting market, even though the market maker did not narrow their order spread. The reason for this was that the price movements in the adopting market affected the price movements in the non-adopting market through the market selection of normal agents. This mechanism is illustrated in Figure 6. When the market maker in the adopting market is provided a sufficient rebate, the bid-ask spread in the adopting market is less than that in the non-adopting market. Let us examine how the buy orders of the normal agents are handled. When an order of a normal agent is placed in the non-adopting market, it is a limit buy order at a price lower than the best-ask in the adopting market [*4]. If a sell order which matches the buy order of a normal agent is already on the order book, it could be executed immediately, but in any case, the price would be lower than the best-ask in the adopting market. The same can be said for sell orders, which are limit sell orders at a price higher than the best-bid quote in the non-adopting market. As a result, orders placed in the non-adopting market will be traded between the best-bid and best-ask quotes of the adopting market, forming a price similar to that of the adopting market. Therefore, the market inefficiency of the non-adopting market is reduced by the same extent as that of the adopting market.

4 Conclusion

In this study, we built two artificial markets, one where the stock exchange employs a maker-taker fee (the adopting market) and one where it does not (the non-adopting market), and investigated how the market share of the adopting market changes with the rebate which the market maker receives. We also checked the market volatility and market inefficiency of each market in order to confirm the impact of agents' market selection. As a result, it was confirmed that the

[*4] Because if it is executed in the adopting market, it will be placed in the adopting market as a market order.

market share of the adopting market would increase if the market maker could be provided a sufficient rebate to narrow the bid-ask spread of the market maker's orders. On the other hand, when a sufficient rebate is not provided to the market maker, the non-adopting market loses market share. Volatility was found to decrease in the adopting market and to increase in the non-adopting market, whereas market inefficiency decreased (that is, market efficiency increased) in both markets as the rebate increased, with no significant difference between them.

These results show that when sufficient rebates are provided to market makers, a maker-taker fee can reduce volatility in the market that adopts it, making that market more efficient and possibly making other markets more efficient as well. However, when appropriate rebates are not provided to market makers, the market that adopts the maker-taker fee loses market share to other markets. Furthermore, the results suggest that increasing the rebate does not have an inexhaustible power to increase the market share of the adopting market. Although it is true that as rebates in the stock exchanges increase, the market makers can make the spread between their two-way orders narrower, since the spread cannot be less than the tick size and the bid-ask spread of the adopting market also cannot be less than the tick size. As a result, the market share of the adopting market is expected to reach a ceiling at some point. This means that in markets where the bid-ask spread is too narrow, the effect of the strategy of gaining market share through a maker-taker fee may be limited. Therefore, when a stock exchange adopts a make-taker fee, it should not just offer rebates in the dark, but should carefully examine how much of a rebate the makers want in the market, whether the stock exchange can afford to offer such rebates, and whether the stock exchange can get a commensurate return.

In this study, when orders of normal agents are executed in neither the adopting nor the non-adopting market, the agents place orders as limit orders with equal probability in either market. However, as the rebate becomes larger, it is possible that general investors will also prefer the adopting market. Therefore, as future research, we would like to consider the case in which normal agents place limit orders preferentially in the adopting market as the rebate becomes larger.

Appendix A Total cost of taking orders

Hoshino et al. (Hoshino et al. (2021)) discussed how the total cost of taking orders changed when rebates were increased in the adopting market[*5]. As in our study, the total cost of taking orders was measured based on the transactions of algorithm agents (see Section 3.2). When the rebate is small, the total cost of taking orders tends to increase as the rebate increases, whereas the total cost of taking orders starts to decrease when the spread between limit buy and sell orders offered by the market maker becomes equal to the bid-ask spread of the market (see Figure 7). This can be attributed to the fact that the market impact has started to decrease. Figure 8 shows

[*5] Note that no other markets compete for market share.

total cost of taking orders in the adopting and non-adopting markets in this study. These results are similar to those of Hoshino et al. (Hoshino et al. (2021)). The reason for the lower total cost of taking orders in the non-adopting market is that, in interval A, the taker's fee affects cost more strongly in the adopting market, and in interval B, the market impact of the non-adopting market becomes smaller as the adopting market takes a larger market share (because market orders which are placed in the non-adopting market are reduced). Note that although the decrease in market impact in the adopting market is larger than that in the non-adopting market, the decrease in the adopting market is not large enough to offset the difference in the taker's fee between the adopting market and the non-adopting market, so the total cost of taking orders of the non-adopting market is slightly less.

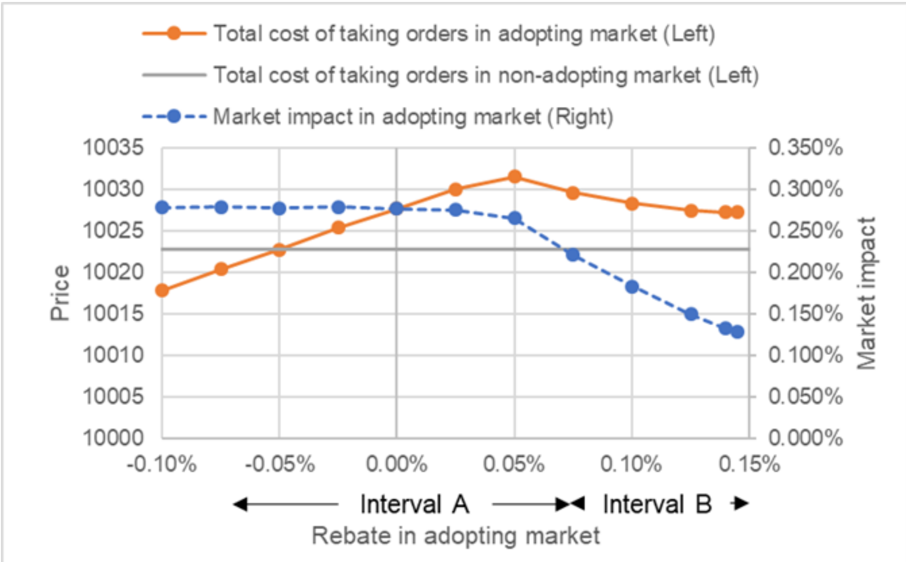

Figure 7 Market impact and total cost of taking orders versus rebate (Hoshino et al. (2021))

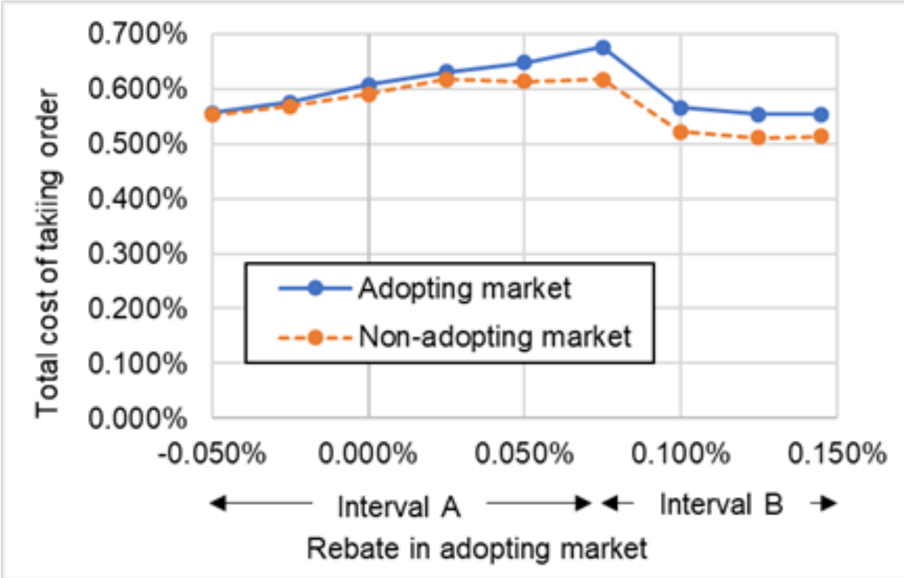

Figure 8 Total cost of taking orders

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