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Frequent Batch Auctions investigated by Agent-Based Model

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(1) Introduction

(2) Our Model

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Increasing Speed of Order Matching Systems on Financial Exchanges is Good or Bad?

Speed up is GOOD

Increasing Speed: causes increasing liquidity by increasing orders of Market Maker Strategies (MM) who earn profits by providing liquidity.

Otsuka(2014)

On FBA, profit risks of MM increase, then the strategies can NOT continue to trade, in the result execution costs increase.

Market Maker Strategies (MM):
earn profits from an order spread by placing both sell and buy waiting orders as long as prices oscillate between the sell and buy orders. MM is the most popular strategy for high-frequency (high-speed) traders.

Conflict

Speed up is BAD

Increasing Speed: causes socially wasteful arms race for speed and these costs are passed to other investors as execution costs.

Budish et al.(2015)

Proposed Frequent Batch Auction (FBA) which reduces the value of speed advantages

Frequent Batch Auction (FBA):
On FBA, buy and sell orders are grouped together and then executed at specific time intervals (e.g., every several minutes) rather than continuously executed one by one, a continuance double auction (CDA).
These intervals lead to a reduction in the value of speed advantages.

An empirical study can not handle changing from CDA to FBA

Empirical studies cannot be conducted to investigate situations that have never occurred in actual financial markets

An “artificial market model”, agent-based models for financial markets, can handle that have never occurred, FBA

And it can isolate the pure contribution of the changes to the price formation

However, no previous study has investigated whether MM can continue to provide liquidity even on FBA using artificial market simulations.

Therefore in this study,

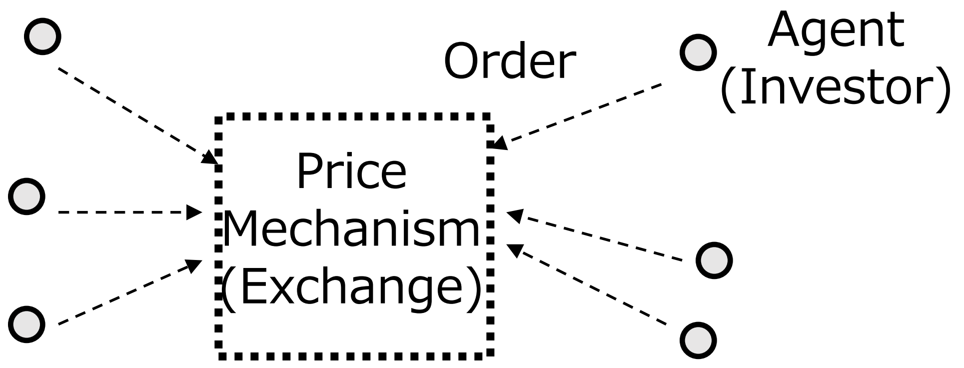
We implemented a price mechanism that is continuously changeable between CDA ($\delta t=1$) and FBA ($\delta t>1$) by introducing a new parameter, a batch auction interval δt, based on the prior model of [Mizuta 2016].
We then analyzed the profits/losses and risks of MM and investigated whether it can continue to provide liquidity even on FBA.

An artificial market model = an agent-based model for a financial market

Virtual and Artificial financial Market built on Computers

Models Include

Agents (Artificial Investors)
+
Price Mechanism (Artificial Exchange)



Each Agent determines an order by some rules, Price Mechanism gather agents orders and determines Market Price

→ *Determination market price*

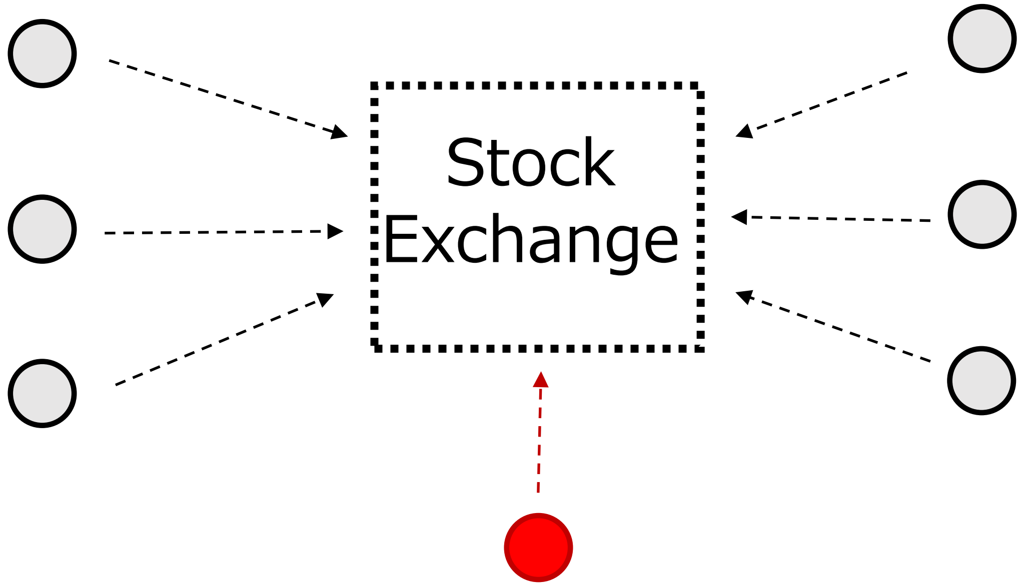
Complete Computer Simulation needing NO Empirical Data

- ✓ can discuss on the mechanism between the micro-macro feedback
- ✓ can be conducted to investigate situations that have never occurred in actual financial markets
- ✓ can effectively handling micro-macro feedback loops

Our Model

Normal Agents (NAs)
exist 1000 agents

To replicate the nature of price formation in actual financial markets, I introduced the NA to model a general investor.



A Market Maker Agent (MM)

We then analyzed the profits/losses and risks of MM and investigated whether it can continue to provide liquidity even on FBA by using an artificial market model.

In this study, the artificial market model was built by adding the Market Maker Agent (MM) to the prior model of [Mizuta 2016]

(The details of both agents will be showed later)

Continuous Double Auction (CDA)

Shares Sell	Price	Shares Buy
10	103	
30	102	
	101	
50	100	
130	99	
	98	150
	97	
	96	70

Waiting Orders

When buy order come here transaction immediately occurs

When sell order come here transaction immediately occurs

Multiple buyers and sellers compete to buy and sell stocks in the market, and transactions can occur at any time whenever an offer to buy and an offer to sell match.

Frequent Batch Auction (FBA)

Introduce: Batch Auction Interval (δt)

To be comparable Continuance Double Auction (CDA,δt=1) with Frequent Batch Auction (FBA,δt>1)

	New Order ->	Sell 99	Buy 100	Buy 101	Sell 98
time	t=0	t=1	t=2	t=3	t=4

CDA δt=1

t=0

Sell	Price	Buy
1	101	
1	100	
	99	1
	98	1

t=1

Sell	Price	Buy
1	101	
1	100	
~~1~~	99	~~1~~
	98	1

Immediately Executed

t=2

Sell	Price	Buy
1	101	
~~1~~	100	~~1~~
	99	
	98	1

Immediately Executed

t=3

Sell	Price	Buy
~~1~~	101	~~1~~
	100	
	99	
	98	1

Immediately Executed

t=4

Sell	Price	Buy
	101	
	100	
	99	
~~1~~	98	~~1~~

Immediately Executed

FBA δt=4

t=0

Sell	Price	Buy
1	101	
1	100	
	99	1
	98	1

t=1

Sell	Price	Buy
1	101	
1	100	
1	99	1
	98	1

Not Executed

t=2

Sell	Price	Buy
1	101	
1	100	1
1	99	1
	98	1

Not Executed

t=3

Sell	Price	Buy
1	101	1
1	100	1
1	99	1
	98	1

Not Executed

t=4

Sell	Price	Buy
1	101	~~1~~
1	100	~~1~~
~~1~~	99	1
~~1~~	98	1

Executed at specific time

Different results: Executed Volume, Remained Orders and Pt

Pt: (Tentative)Market Price: Executed price if orders were executed at the time

Normal Agents (NAs)

1000 agents

j: agent number ordering in number order
t: tick time

This term is needed To replicate stylized facts

Technical

Expected Return of each NA

$$r_{e,j}^{t} = \frac{1}{\sum_i w_{i,j}}\left(w_{1,j}\log\frac{P_f}{P^{t-1}} + w_{2,j}\log\frac{P^{t-1}}{P^{t-\tau_j}} + w_{3,j}\varepsilon_j^t\right)$$

Fundamental

noise

Parameters for agents

$w_{i,j}$ and τ_j

Random of Uniform Distribution

$w_{i,j}$	i=1,3: 0～1 i=2: 0～100
τ_j	0～10000

P_f Fundamental Price
10000 = constant

P^t Market Price at t

This term is needed to prevent the prices go out far away

ε_j^t

Random of Normal Distribution
Average=0
σ=3%

To keep agents varied
To keep simulation runs stably

Expected Price of each NA

$$P^{t}{}_{e,j} = P^t \exp(r^{t}{}_{e,j})$$

Fundamental Strategy

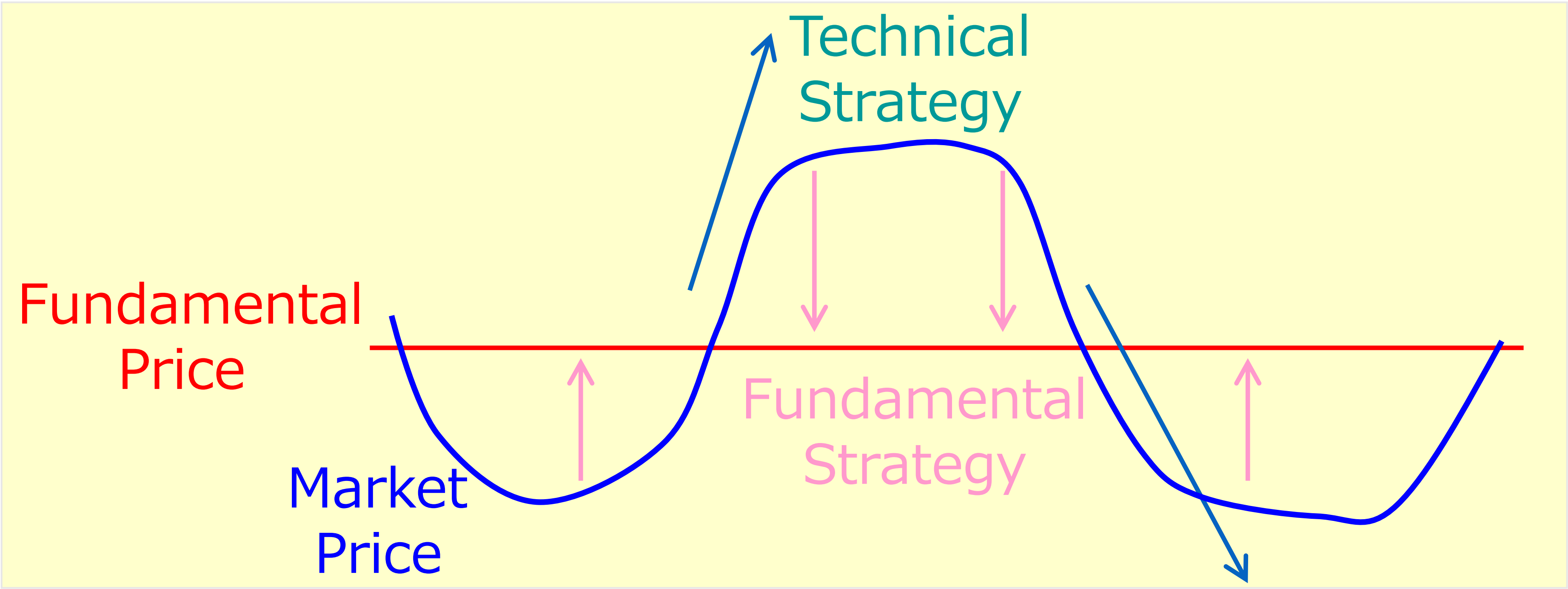
Fundamental Price ＞ Market Price -> Expect + return

Fundamental Price < Market Price -> Expect - return

Technical Strategy (Historical Return)

Historical Return ＞ 0 -> Expect + return

Historical Return < 0 -> Expect - return



Market Maker Agent (MM)

Order both Sell and Buy at once

Sell order

$P_{fair} + P_{spread}$

Sell	Price	Buy
	10011	
1	10010	
	10009	
	10008	
	10007	
	10006	
	10005	
	10004	
	10003	
	10002	1
	10001	
	10000	

P_{fair}

Fair value

$P_{fair} - P_{spread}$

Buy order

Order every time within a batch auction

$P_{fair} + P_{spread}$

Sell	Price	Buy
1	10011	
1	10010	
	10009	
	10008	
	10007	
	10006	
	10005	
	10004	
	10003	1
	10002	1
	10001	
	10000	

P_{fair}

$P_{fair} - P_{spread}$

- ✓ Order both Sell and Buy at once
  Buy: $P_{fair} - P_{spread}$
  Sell: $P_{fair} + P_{spread}$
- ✓ Order every time on both FBA and CDA
  → Cancel all its orders immediately after a batch auction
  On CDA, every time cancel after NA places an order

P_{fair} Fair value: calculation ways are different from MM types (details are showed later)

P_{spread} Spread: Constant

A whole number of orders Do not depend on δt
-> <u>Amount of liquidity supply is constant</u>

Four kinds of MM

- ✓ Simple MM

  $P_{fair} = P^t$

  Holding position risk is very high: impracticable

- ✓ Position MM

  $P_{fair} = (1 - kS^3)P^t$ S: Holding Position of MM, k: constant

  Control order prices not to make position too much

  Holding position risk is reduced in intra-day, but remain over night risk: impracticable

- ✓ Position MM3, Position MM4 [Our Original]

  It trade making position Zero Within Last 2,000 time steps in One day(20,000 time steps)

  To eliminate over night risk, inventory risk:

  -> when MM has over night position it's very risky if there is a big news within over night

<u>Position MM3</u>

<u>Do not order increasing position</u>

To make position Zero to avoid over night risk

In the case of negative position, within last 2,000 time steps

Do not order↑

Sell	Price	Buy
~~1~~	10011	
	10010	
	10009	← Pfair
	10008	
	10007	1

<u>Position MM4</u>

<u>Change order price that of opposite side (buy/sell)</u>

More aggressively make position Zero to avoid over night risk

In the case of negative position, within last 2,000 time steps

Sell	Price	Buy
	10011	1 ←change order price here
	10010	
	10009	← Pfair
	10008	
	10007	

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Holding Position of several kinds of MM

Pspread/Pf = 0.03%

Average of ‖S‖		Simple MM		Position MM		Position MM3		Position MM4	
		Whole Period	End Period on a day	Whole Period	End Period on a day	Whole Period	End Period on a day	Whole Period	End Period on a day
δt	1(CDA)	12,357	12,371	3.18	3.08	2.90	0.00	2.89	0.00
	2	17,422	17,441	3.10	3.25	2.79	0.00	2.79	0.00
	5	4,409	4,414	3.87	3.95	3.48	0.00	3.48	0.00
	10	1,744	1,744	4.44	4.34	4.01	0.02	3.96	0.00
	20	548	548	4.84	4.71	4.52	0.78	4.35	0.00
	50	384	385	5.27	5.14	5.02	2.63	4.63	0.00
	100	369	370	5.57	5.51	5.56	4.26	4.80	0.00
	200	174	174	5.91	6.11	5.92	5.69	4.38	0.00
	500	72	71	5.75	6.06	5.70	5.81	2.32	0.03
	1000	290	290	5.94	6.11	5.61	5.80	1.76	0.06

δt is Larger (FBA), only Position MM4 can make its position Zero
So, only MM4 is reality

Execution Rate of MM for Order Spread (Pspread) and δt

In the case of Position MM4

Execution Rate of MM		Pspread/Pf 0.03%	0.10%	0.30%	1.00%
δt	1(CDA)	8.06%	1.53%	0.00%	0.00%
	2	6.30%	0.88%	0.00%	0.00%
	5	3.93%	0.37%	0.00%	0.00%
	10	2.47%	0.14%	0.00%	0.00%
	20	1.49%	0.02%	0.00%	0.00%
	50	0.77%	0.00%	0.00%	0.00%
	100	0.48%	0.00%	0.00%	0.00%
	200	0.32%	0.00%	0.00%	0.00%
	500	0.21%	0.00%	0.00%	0.00%
	1000	0.22%	0.00%	0.00%	0.00%

δt is Larger (FBA), Execution Rate of MM is Smaller

Decrease Liquidity Supply

Final Profit

In the case of Position MM4, Pspread/Pf = 0.03%

		Final Profit of MM /Pf	Average of ‖S‖ Whole Period	Average of ‖S‖ End Period on a day	Execution Rate of MM	Execution Rate of NA
δt	1(CDA)	51.98	2.89	0.00	8.1%	39.1%
	2	-29.42	2.79	0.00	6.3%	39.1%
	5	-14.90	3.48	0.00	3.9%	37.6%
	10	-4.08	3.96	0.00	2.5%	36.3%
	20	1.51	4.35	0.00	1.5%	34.9%
	50	3.68	4.63	0.00	0.8%	33.4%
	100	2.53	4.80	0.00	0.5%	32.5%
	200	0.93	4.38	0.00	0.3%	31.8%
	500	-0.06	2.32	0.03	0.2%	31.0%
	1000	-0.10	1.76	0.06	0.2%	30.5%

δt is Larger (FBA), MM take few profits or lose money

Market Maker Strategies can NOT continue to trade

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Conclusion

We implemented a price mechanism that is changeable between a comparable continuance double auction (CDA, $\delta t=1$) and a frequent batch auction (FBA, $\delta t>1$) by continuously introducing a new parameter, a batch auction interval δt, based on a prior model of [Mizuta 2016].

Our simulation results showed that when δt is larger, the execution rates of MM are smaller, and this causes the liquidity supplied by MM to be reduced. Further, when δt is larger (FBA), MM cannot avoid both an overnight risk and a price variation risk intraday. We also found that when $\delta t >1$(FBA), it is very difficult for MM to be rewarded for risks and to continue providing liquidity. MM is rewarded for risks and continues to provide liquidity only in the case of $\delta t =1$ (CDA).

These findings imply that while MM provides liquidity on CDA, it cannot continue to provide liquidity on FBA, which leads to many MMs being retired and ultimately to liquidity being reduced. This implication is consistent with the findings of prior research [Otsuka 2014].

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Reference

[Mizuta 2016] Mizuta, T., Kosugi, S., Kusumoto, T., Matsumoto, W., Izumi, K., Yagi, I., and Yoshimura, S., “Effects of Price Regulations and Dark Pools on Financial Market Stability: An Investigation by Multiagent Simulations”, Intelligent Systems in Accounting, Finance and Management, Vol. 23, No. 1-2, pp. 97-120, 2016, https://doi.org/10.1002/isaf.1374

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[Budish 2015] Budish E., et al., “The high-frequency trading arms race: Frequent batch auctions as a market design response,” The Quarterly Journal of Economics, vol. 130, no. 4, pp. 1547–1621, 2015. https://doi.org/10.1093/qje/qjv027

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Reference (Reviews of agent-based models for a financial market)

Review of an agent-based model for designing a financial market

Mizuta (2020) An agent-based model for designing a financial market that works well, CIFEr 2020
arXiv https://arxiv.org/abs/1906.06000
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YouTube: https://youtu.be/rmlb72ykmlE

Mizuta (2022) Artificial Intelligence (AI) for Financial Markets: A Good AI for Designing Better Financial Markets and a Bad AI for Manipulating Markets https://doi.org/10.1007/978-981-19-0937-5_13

Citing many previous studies

Mizuta (2016) A Brief Review of Recent Artificial Market Simulation Studies for Financial Market Regulations And/Or Rules, SSRN Working Paper Series
https://ssrn.com/abstract=2710495

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Appendix

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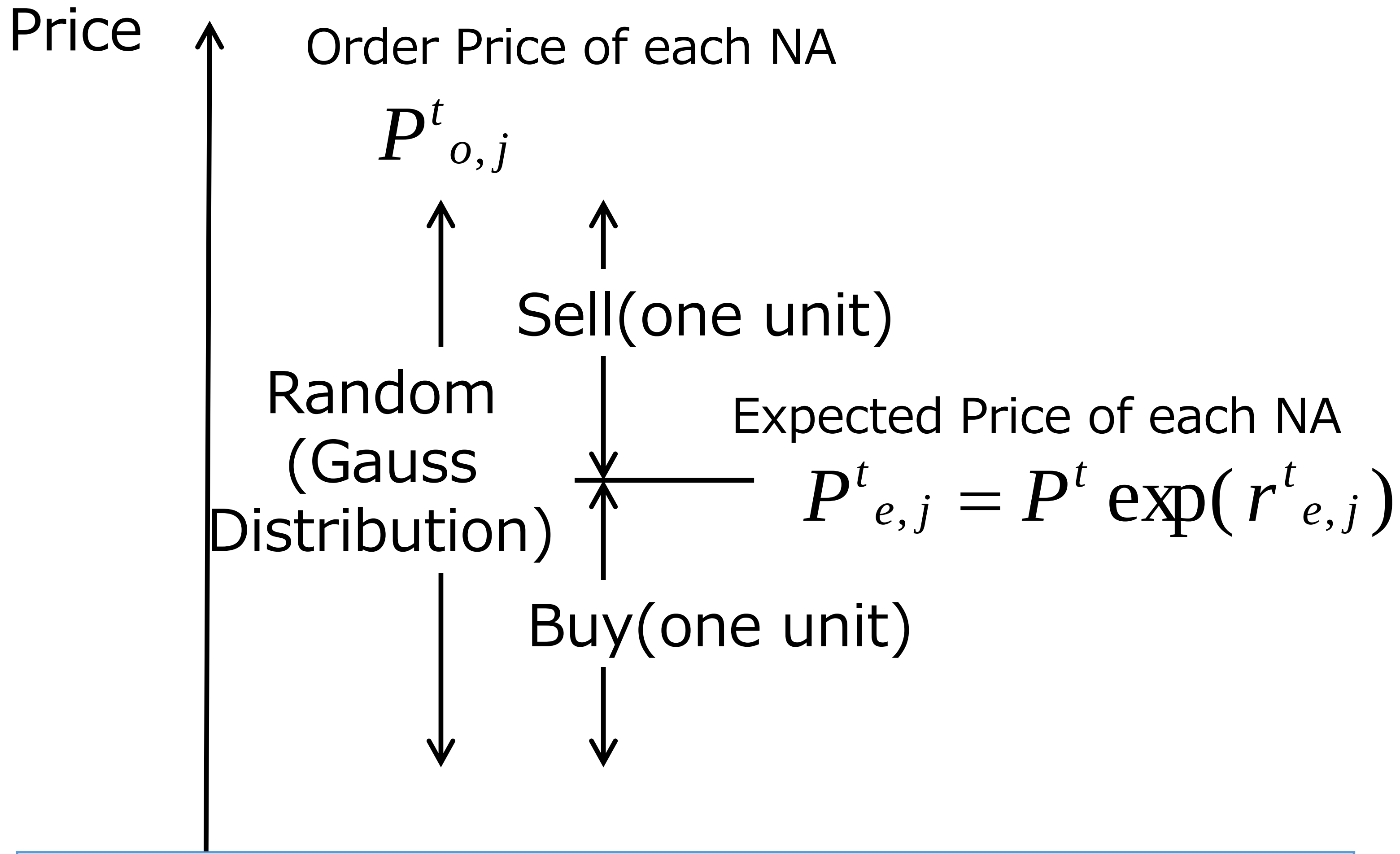
Order Price and Buy or Sell



To replicate many waiting limit orders,
order price is scattered around expected price

NA places one **buy** order when order price > expected price
NA places one **sell** order when order price < expected price

Verification: Stylized Facts

The purpose of simulation is understanding the reasons and mechanism, not replicating ALL Stylized Facts

The simplicity of the model is very important because unnecessary replication of macro phenomena leads to models that are overfitted and too complex. Such models prevent understanding and discovery of mechanisms affecting price formation because of the increase in related factors.

Many empirical studies, e.g., Sewell 2006 have shown that both stylized facts (fat-tail and volatility-clustering) exist statistically in almost all financial markets.
Conversely, they 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.

Fat-tail 1 to 100

kurtosis of price returns is positive

Volatility-clustering 0 to 0.2

square returns have a positive auto-correlation

The magnitudes of these values are unstable and vary greatly depending on the asset and/or period.

For the above reasons, an artificial market model should replicate these values as significantly positive and within a reasonable range as I mentioned. 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.

Stylized Facts

Table 1 Statistics without arbitrage agents

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

The model of Chiarella (2002) is very simple but replicates long-term statistical characteristics observed in actual financial markets: a fat tail and volatility clustering.

In contrast, Mizuta (2013) replicates high-frequency micro structures, such as execution rates, cancel rates, and one-tick volatility, that cannot be replicated with the model of Chiarella (2002).

The simplicity of the model is very important 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 affecting price formation because of the increase in related factors.