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

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Spoofing orders

Most financial markets prohibit unfair trades as they reduce efficiency and diminish the integrity of the market

Spoofing orders

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 as unfair trades

However, how many orders a spoofer needs to place in order to manipulate prices and profit has yet to be clarified

Difficulty of Empirical Study

- ✓ Most financial markets prohibit unfair trades as they reduce efficiency and diminish the integrity of the market
- ✓ Since many factors affect price formation, an empirical study cannot isolate the direct effect of spoofing orders on price formation.

Artificial Market Simulation using Agent-Based Model can do

In this study

I modified a prior market model by Mizuta(2013) 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.

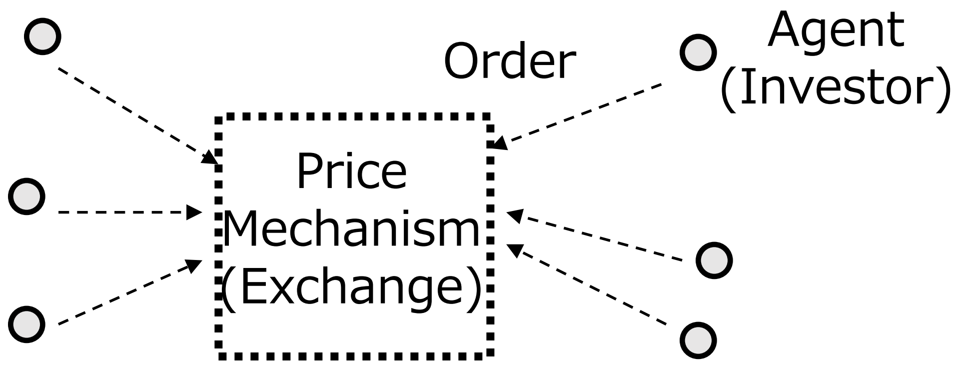
I investigated how many orders the SA needed to place to manipulate market prices and profit illegally.

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 be conducted to isolate the direct effect of Spoofing orders

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Stock Exchange (Price Mechanism)

continuous double auction

Waiting Orders

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

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.

Normal Agents (NAs)

j: agent number (1,000 agents)
ordering in number order
t: tick time

Historical Return + Order Imbalance(Original)

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

Technical

(details are showed later)

Expected Return of each NA

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

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: 0～10

τ_j 0～10000

P_f Fundamental Price
10000 = constant

P^t Market Price at t

ε_j^t
Random of
Normal
Distribution
Average=0
σ=3%

Expected Price of each NA

$$P_{e,j}^{t} = P^{t}\exp(r_{e,j}^{t})$$

Fundamental and Technical Strategies

Fundamental Strategy

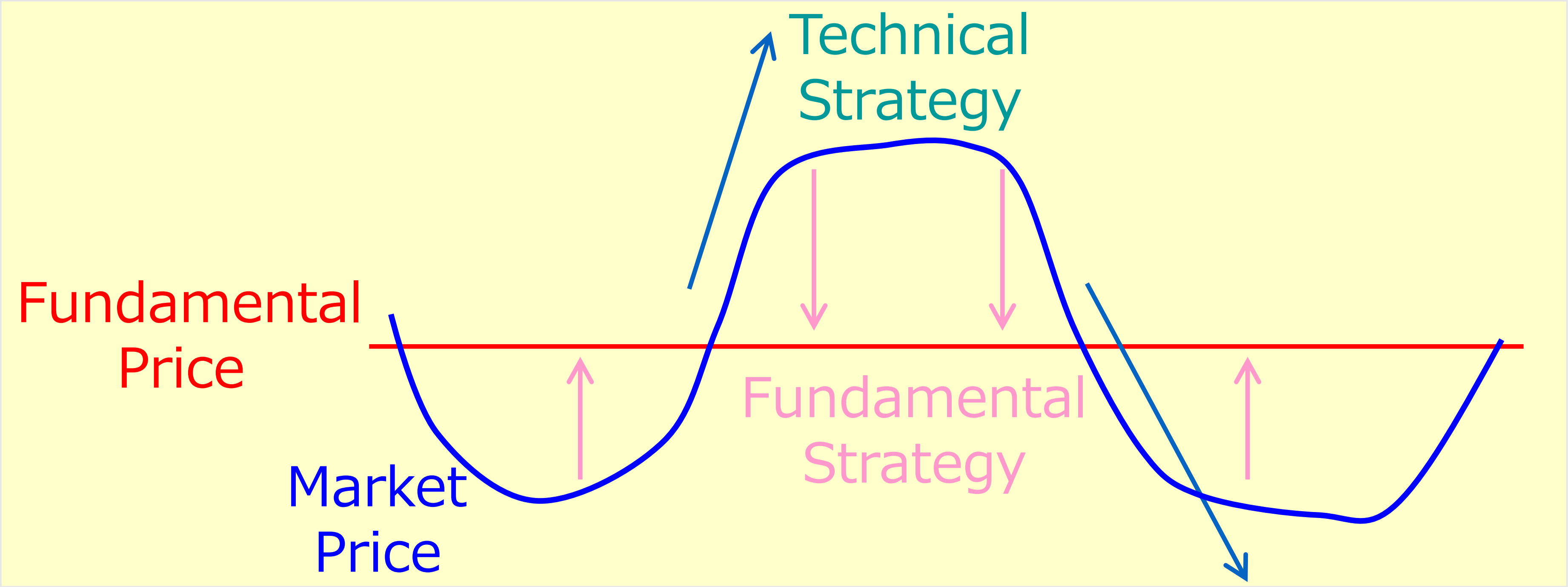
Fundamental Price > Market Price -> Expect + return

Fundamental Price < Market Price -> Expect - return

Technical Strategy (Historical Return)

Historical Return > 0 -> Expect + return

Historical Return < 0 -> Expect - return



Order Imbalance

I modified the model, Mizuta 2013, to show how an imbalance of buy and sell orders affects the expected returns of normal agents (NAs)

Term of Technical Strategy

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

Historical Return   Order Imbalance (original)

$w_{4,j}: 0 \sim 1, \delta d = 0.3\%$

D_b, D_s : the number of buy or sell orders within ±0.3 from the mid-price

expects a positive return, when more waiting buy orders than sell orders
expects a negative return, when more waiting sell orders than buy orders

Many technical traders use the order imbalance as a technical indicator
An empirical study, Chordia 2004, showed that traders will profit when using this indicator https://doi.org/10.1016/S0304-405X(03)00175-2

Spoofer Agent (SA)

Buy one share → Sell one share → Buy one share →

100000 ticks Spoofing buy orders (Dp shares)

100000 ticks Spoofing sell orders

100000 ticks Spoofing buy orders

Dp = No. of Spoofing Orders

1. SA buys one share
2. shows Dp shares of spoofing buy orders
3. sells the share
4. shows Dp shares of spoofing sell orders

within 100000 tick time
to raise market prices

within 100000 tick time
to drive down market prices

repeats these actions in all simulation periods

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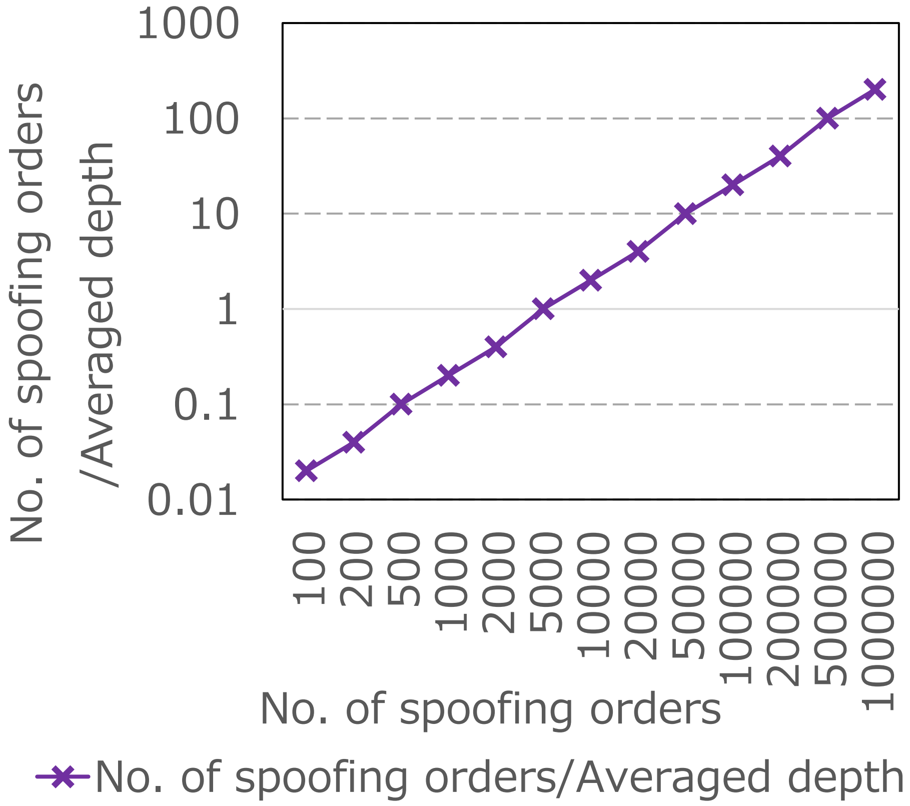
Dp per average depth for various No. of Spoofing orders

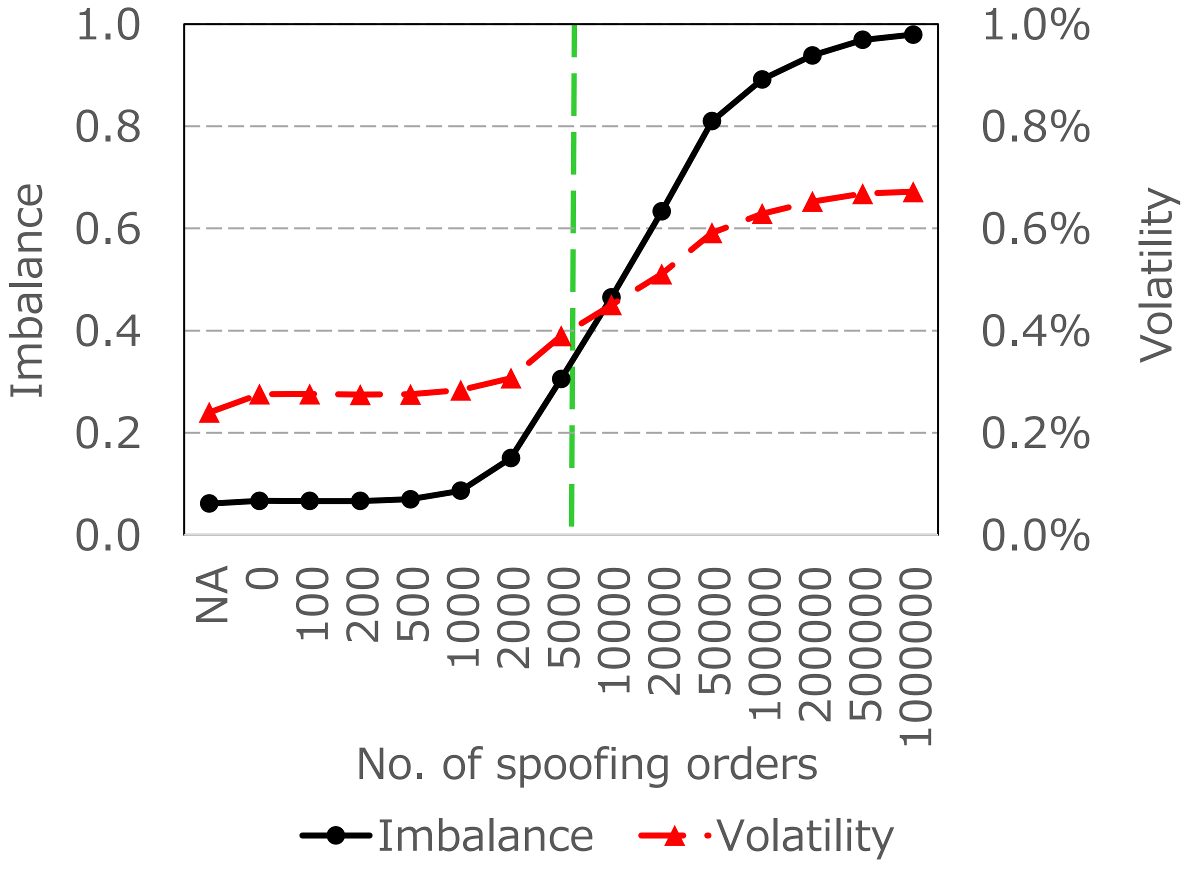


Average depth $= (D_b + D_s)/2$

D_b, D_s : the number of buy or sell waiting orders within ±0.3 from the mid-price

The averaged depths for any No. of Spoofing orders are almost constant, 5000.
The depth is almost the same as No. of Spoofing orders at 5000,
where is an important boundary for changing market price features.

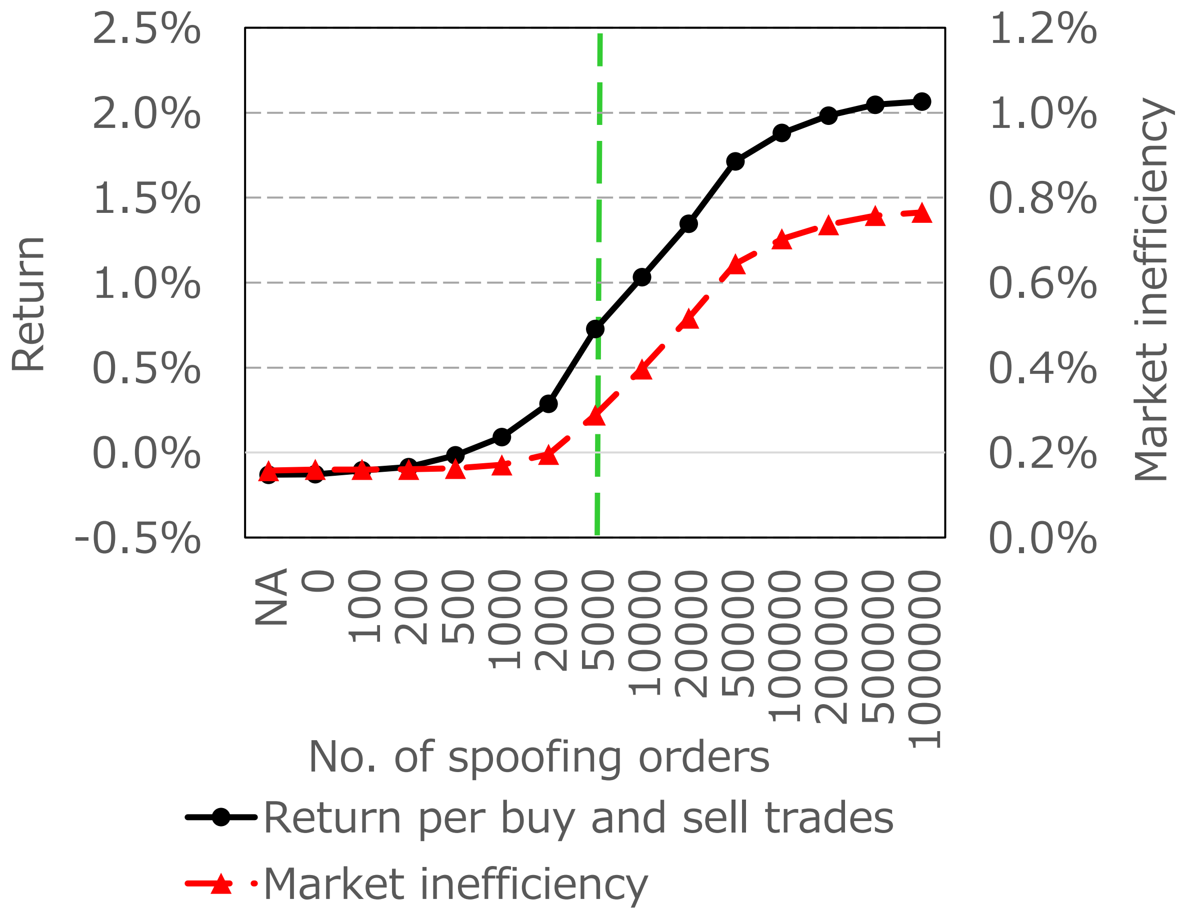
Order Imbalance and Volatility



More Spoofing Orders leads to increased imbalance and volatility
Increasing the spoofing orders amplifies price fluctuation especially in

No. of Spoofing Orders > Average Depth (Waiting orders by NAs)

Returns from the SA’s buy/sell trades and market inefficiency



Higher No. of Spoofing Orders leads to increased return and Mie
especially in No. of Spoofing Orders > Avg. Depth

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

(Illustration)

	Shares Sell	Price	Shares Buy
Waiting Orders by NA	10	103	
	30	102	
spoofing orders by SA	300	101	
	50	100	
Waiting Orders by NA	130	99	
		98	150
		97	
		96	70

Order Imbalance is very negative -> Investors feel bad sentiment -> Sell

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

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Summary

- ✓ In this study I modified a prior market of Mizuta 2013 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.

- ✓ 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 market's efficiency.

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Appendix

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 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
autocorrelation coefficient for square return	lag	
	1	0.225
	2	0.138
	3	0.106
	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.

Normal Agent(NA)

The model of Mizuta (2013) is based on Chiarella (2002).
The model is satisfied with stylized facts (statistical characteristics observed in actual financial markets).

Expected Return of each NA

Technical

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

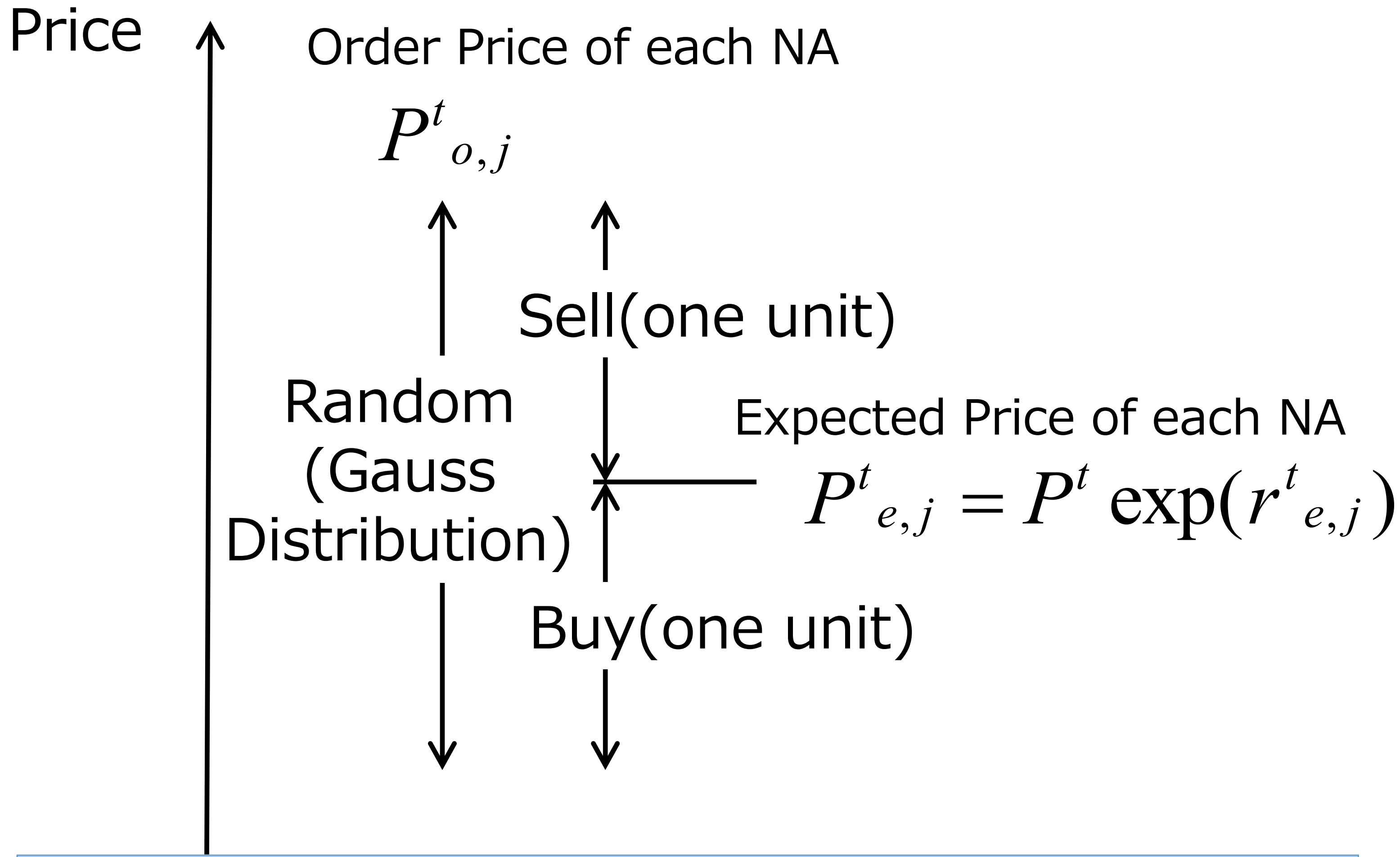
Fundamental

noise

All NAs use this same equation to obtain an expected return, however, because w is different each agents, expected returns are different each agents. This leads heterogeneous (many order prices are diversified) although the model is simple.

The simplicity of the model is very important.
Models include too many related factors prevent understanding and discovery of mechanisms affecting price formation.

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 <u>order price > expected price</u>
NA places one **sell** order when <u>order price < expected price</u>