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Can an AI perform market manipulation at its own discretion?
- A genetic algorithm learns in an artificial market simulation -

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(1) Introduction

(2) Model

(3) Simulation Result

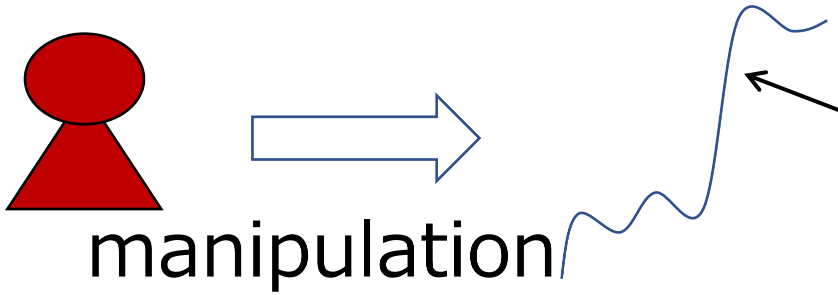
(4) Summary

Market manipulation is prohibited

Traders artificially increasing or decreasing market prices to profit

Stock Market

Responsible



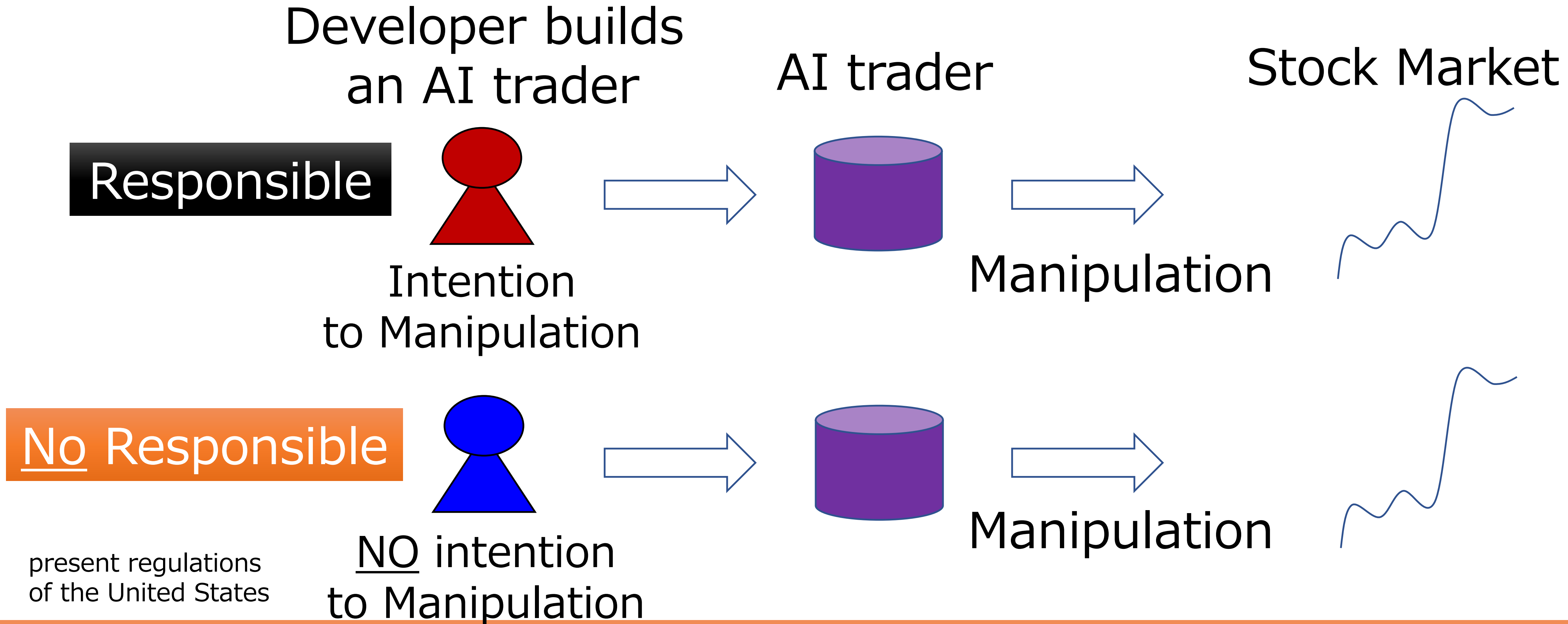
manipulation

Artificially increased

Intentionally large impact
Spoofing, Rumors

Market manipulation is prohibited in many countries as it leads to unfair trades.

Who should be held responsible when AI trader performs market manipulation?



Scopino(2016) indicated that when a developer builds an AI trader with no intention to perform market manipulation and the AI trader actually performs market manipulation at its own discretion, the developer should not held responsible

Even though market prices are manipulated, no one is held responsible, which presents difficulties in maintaining the integrity of the market.

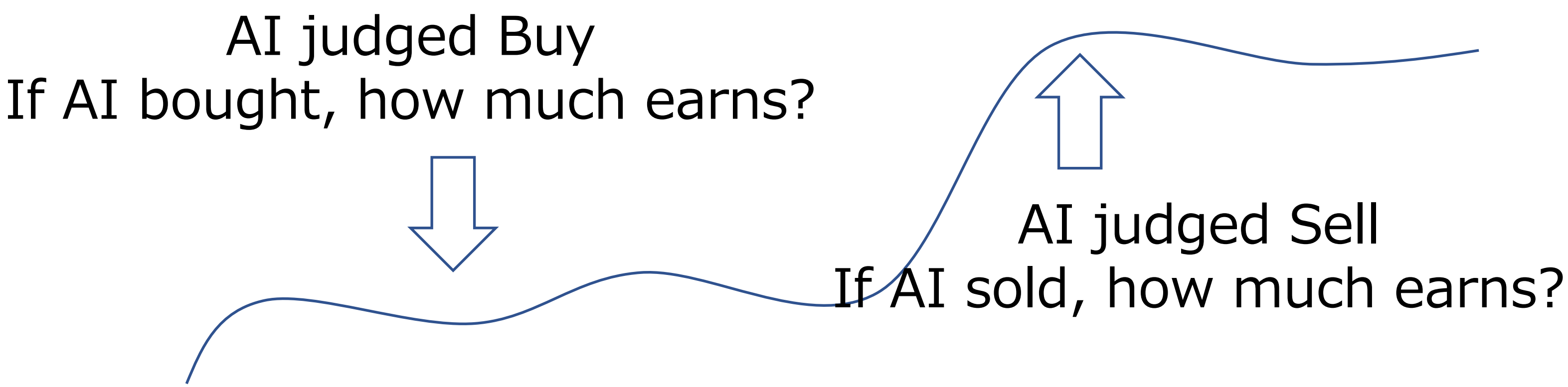
Can AI trader discover market manipulation?

An AI trader must automatically learn the impacts of its trades on market prices in order to discover that market manipulation earns profit.

However, AI traders are usually evaluated by backtesting

Backtesting

The profit is estimated if the AI traders were trading at a certain point in time using historical real data on past market prices.



past market prices
<- Prices are <u>Fixed</u>

An AI trader cannot learn the impacts of its trades to market prices

An AI trader cannot discover market manipulation by backtesting

However, an artificial market simulation enables an AI trader to automatically learn the impacts of its trades on market prices because the trades alter the market prices in the simulation.

In this study,

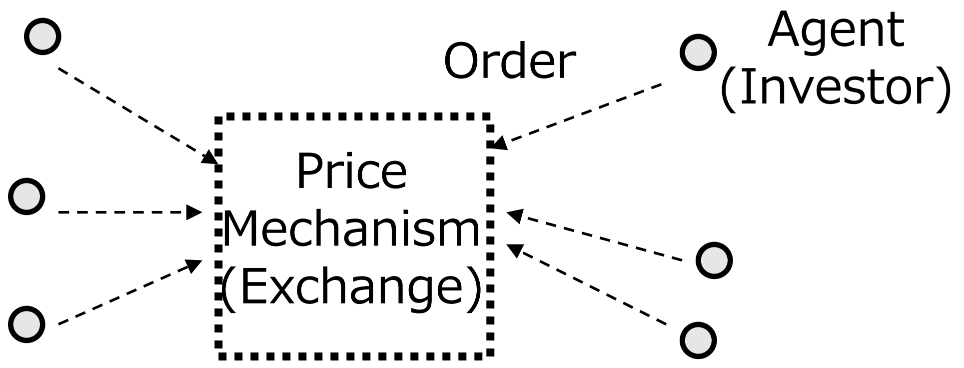
I constructed an AI trader using a genetic algorithm that learns in an artificial market simulation.
I investigated whether the AI trader discovers market manipulation through learning even when the developer of the trader has no intention of market manipulation.

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)



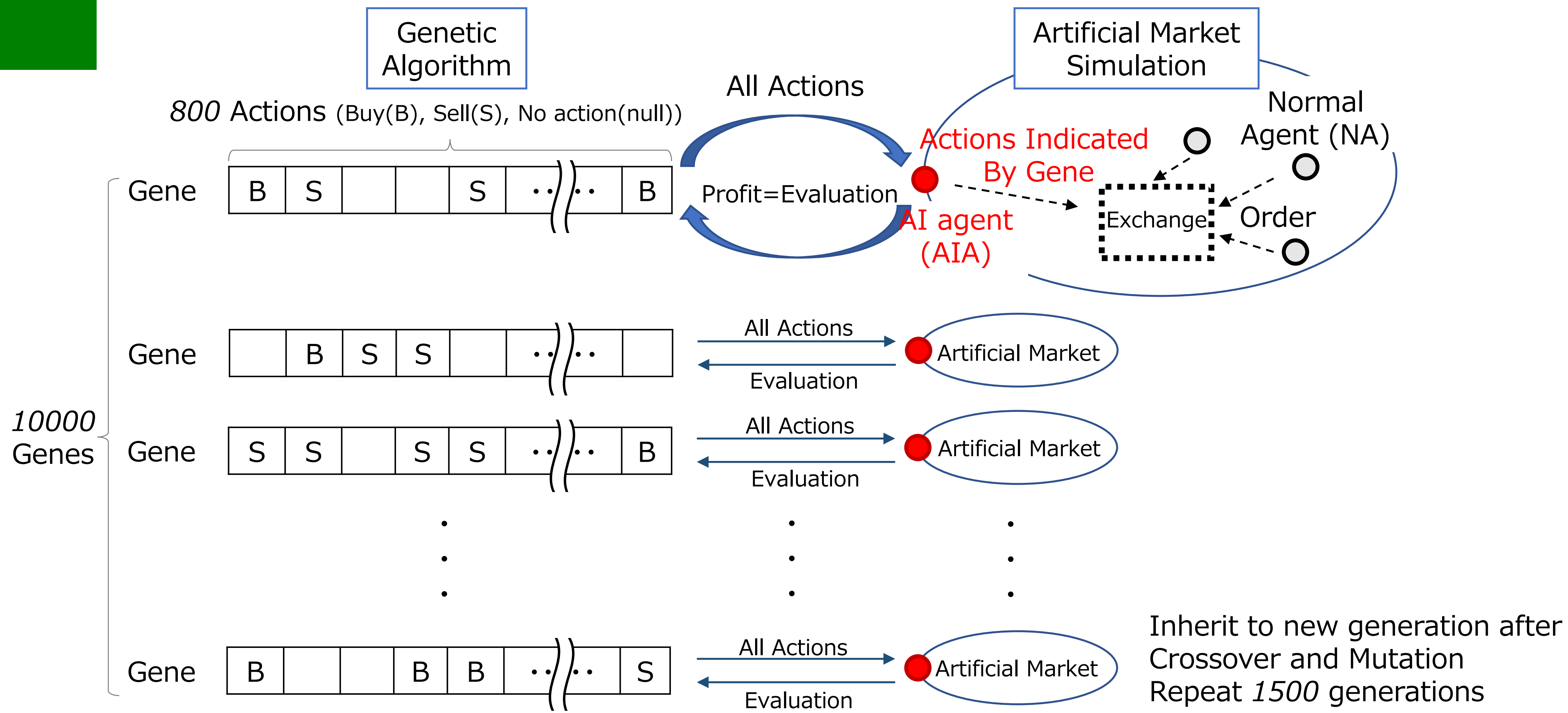
→ *Determination market price*

Each Agent determines an order by some rules, Price Mechanism gather agents orders and determines 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
- ✓ Of course, in the simulation the trades alter the market prices.

Model



One Gene: indicates all 800 trades of AI agent(AIA)

is evaluated by the AIA's profit in an artificial market simulation

One artificial market: includes one gene and 1000 normal agents.

Normal agents: have same parameters for artificial markets.

-> when AIA' trades are same, normal agents' trade are same

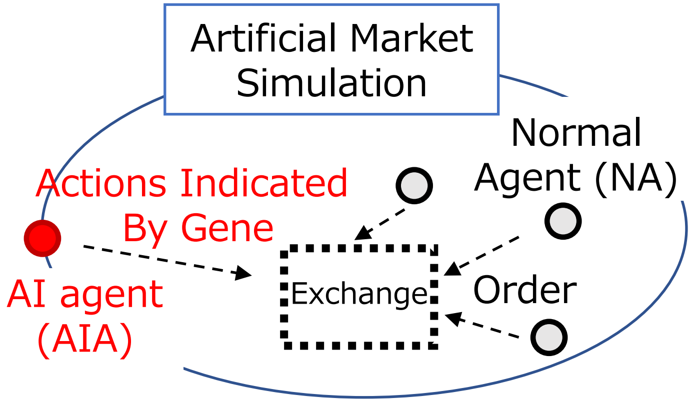
Genetic algorithm: searches for the gene that earns the most profit inheriting 1500 times

includes 10000 genes(10000 artificial markets)

Artificial Market Simulation

Stock Exchange

continuous double auction



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

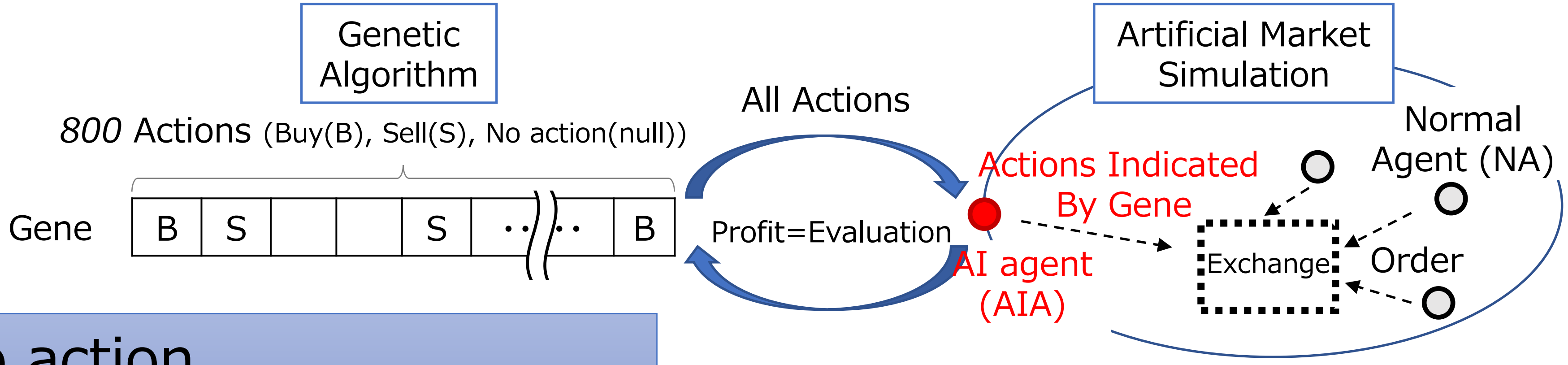
When buy order come here transaction immediately occurs → 99

When sell order come here transaction immediately occurs → 98

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.

AI agent(AIA)

This study focuses on whether an AI trader can discover market manipulation through learning even if the builder has no intention of market manipulation.
Therefore, I do not intentionally model trading strategies, and my model directly searches for all the optimal trades in an artificial market environment.



Buy, Sell or, no action
(every 10 tick time, one share)

The trades of AIA impacts market prices
in artificial market simulation

AIA can automatically learn the impacts of its trades on market prices

Normal Agents

j: agent number (900 agents)
ordering in number order
t: tick time

Historical Return

$$r_{h,j}^{t} = \log(P^{t} / P^{t-\tau_j})$$

Technical

Expected Return of each NA

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

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		0～1000

Fundamental

P_f Fundamental Price
10000 = constant

P^t Market Price at t

noise

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

Expected Price of each NA

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

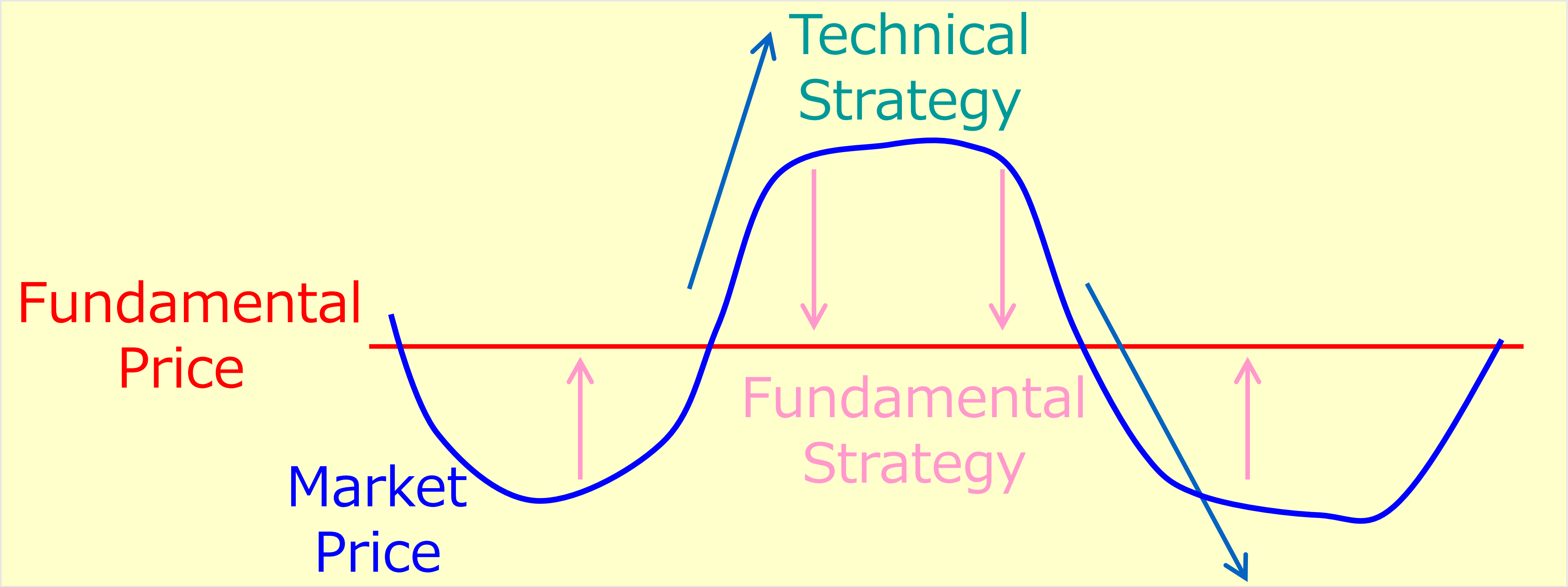
Fundamental and Technical Strategies

<u>Fundamental Strategy</u>

Fundamental Price > Market Price -> Expect + return
Fundamental Price < Market Price -> Expect - return

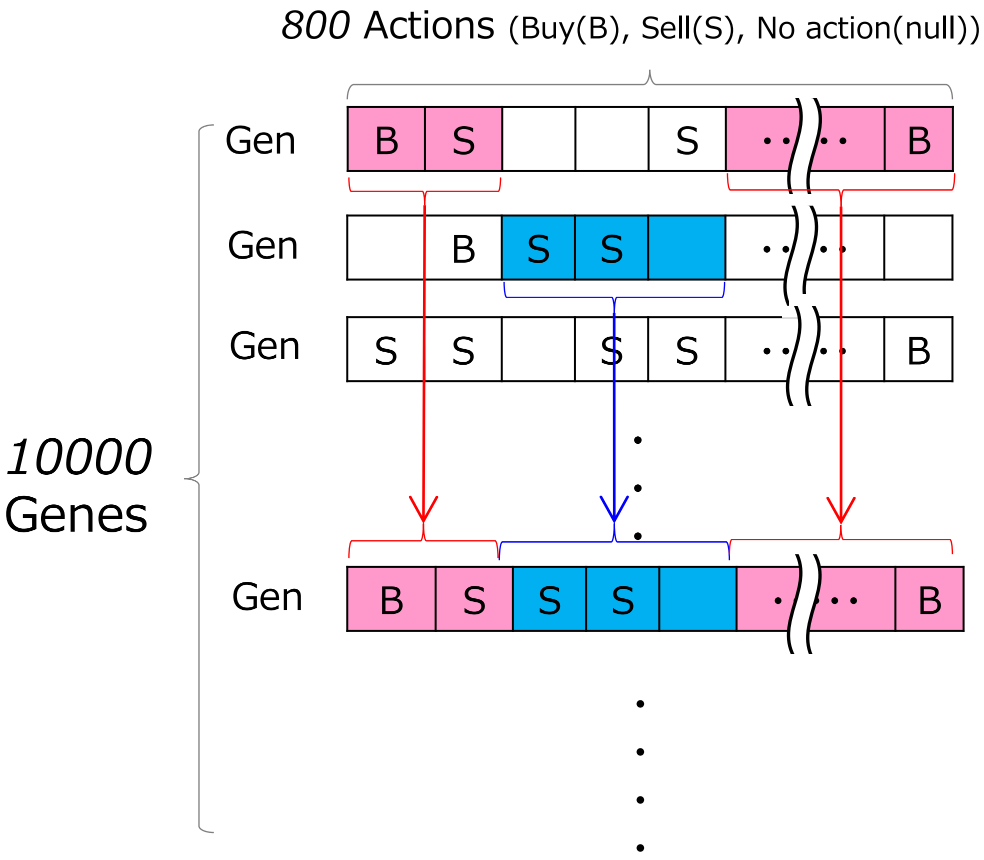
<u>Technical Strategy</u>

Historical Return > 0 -> Expect + return
Historical Return < 0 -> Expect - return



Genetic algorithm

Genes are ordered by profit



The top 400 genes

Not changed

Non-top 400 genes

are replaced with a probability of 65% by a crossover gene containing two genes randomly selected from the top 400 genes.

After crossovers, the actions are mutated with a probability of 20%

Genetic algorithm searches for the gene that earns the most profit inheriting 1500 times includes 10000 genes

Genetic algorithm is very popular way generally used by many many studies [Goldberg 1989]

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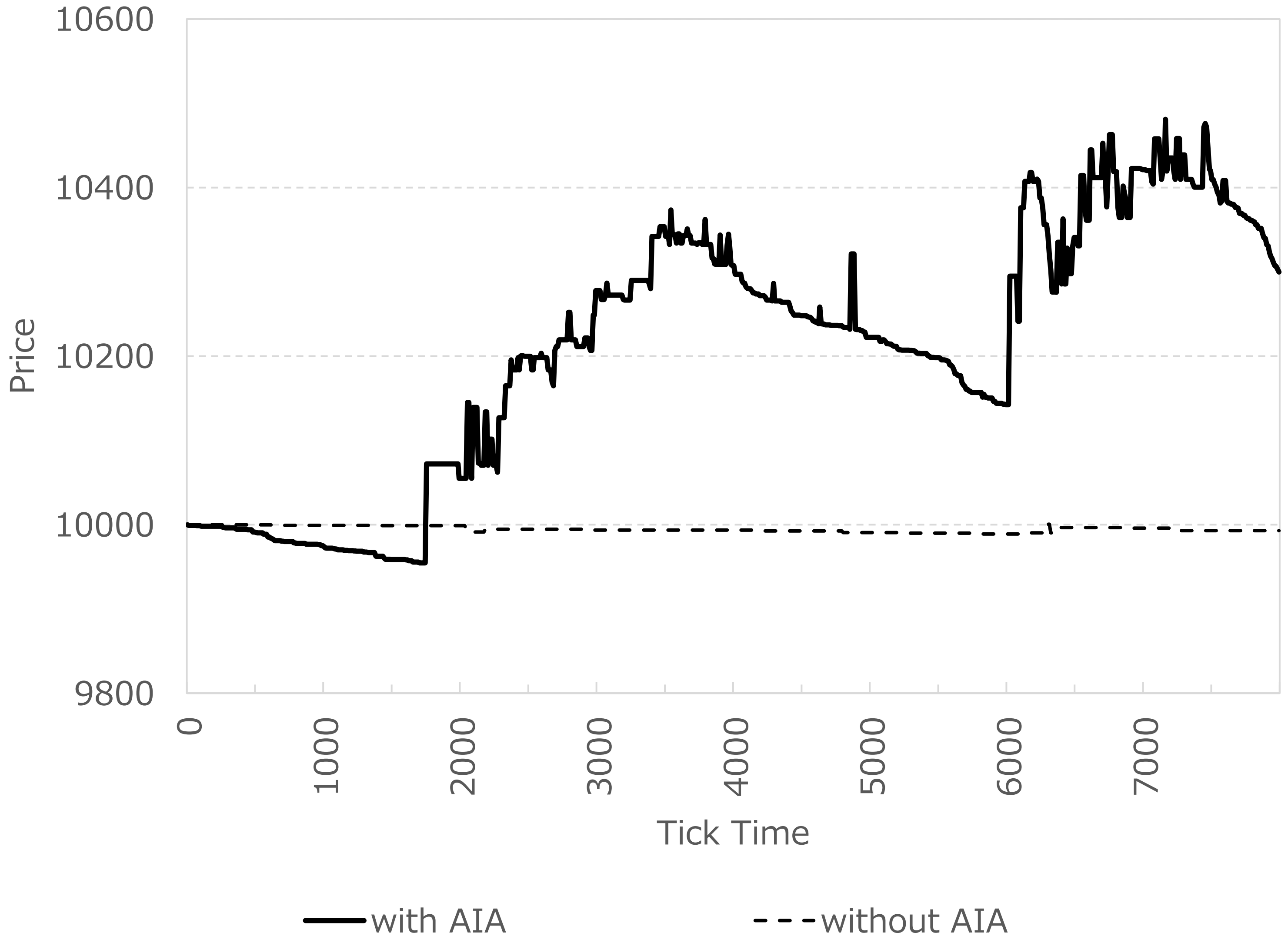
Time evolution of market prices with the AIA and without

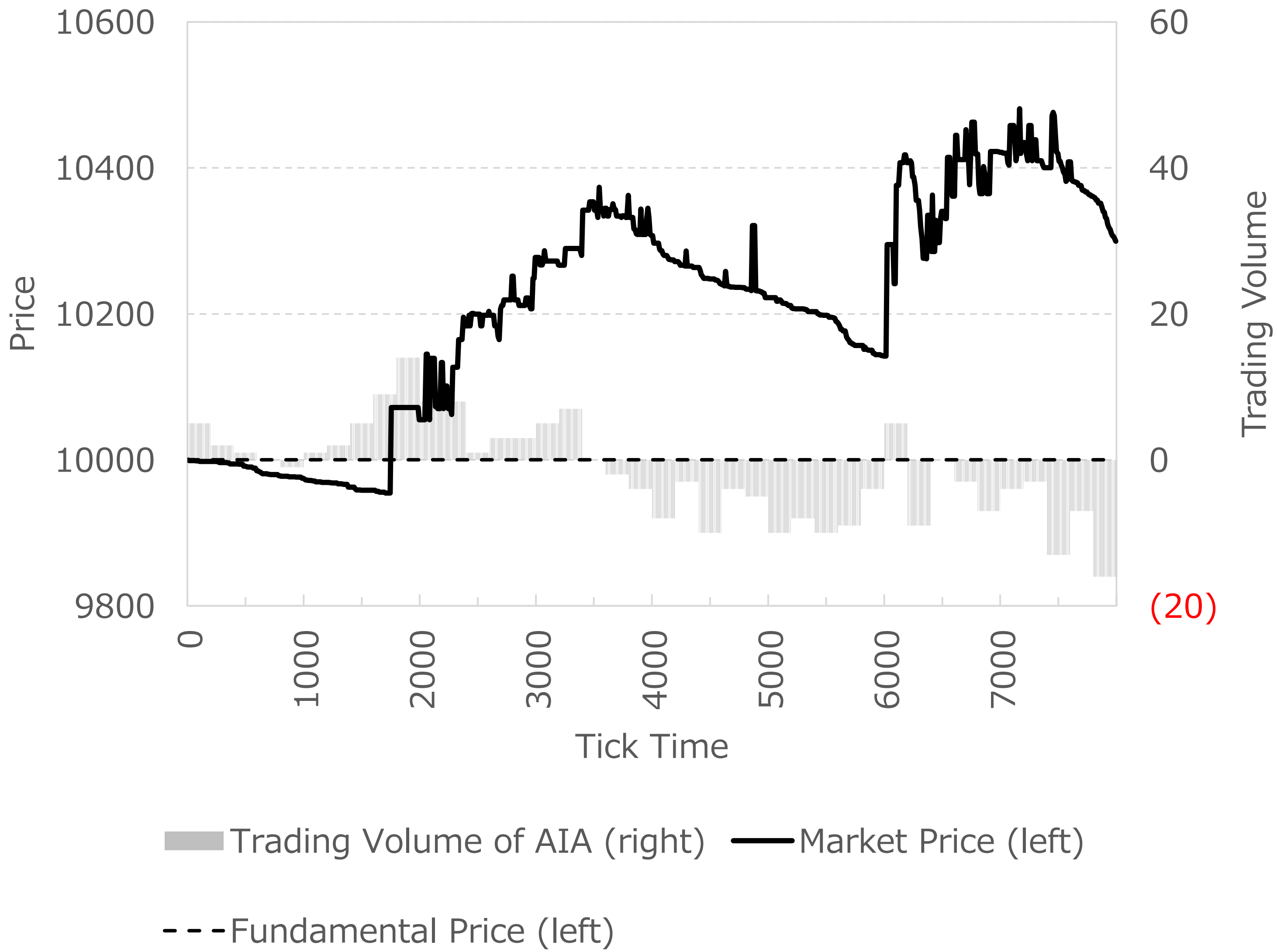
(In the following result, I used the AIA of the optimal gene in the final generation.)



The AIA amplified the variation in the market prices.

Time evolution of market prices with the AIA and trading volume

trading volume (positive and negative numbers indicate buying and selling, respectively)
aggregated within every 200 tick times.)

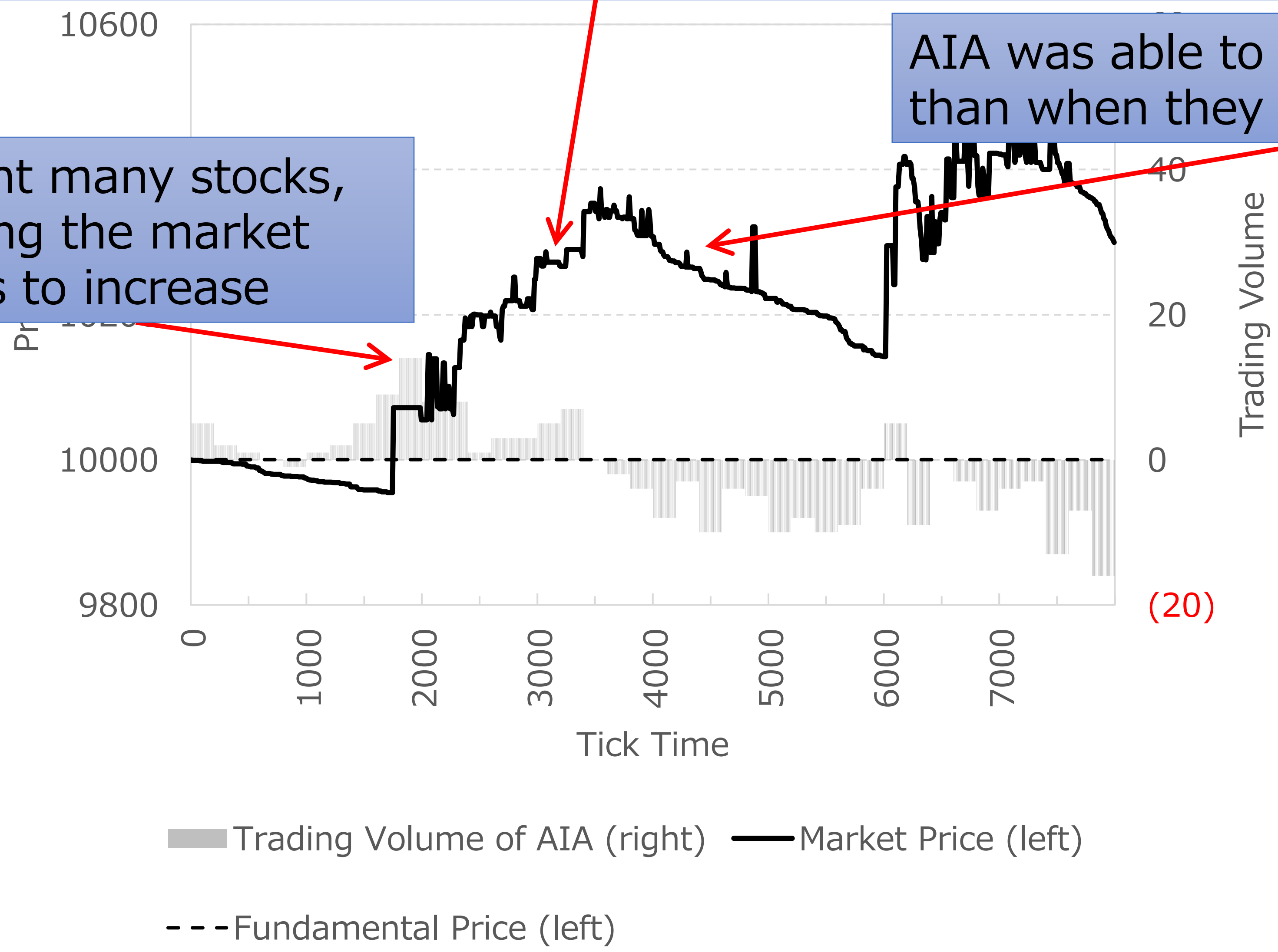


The AIA's trades are evidently market manipulation.

market prices continued to increase even though the AIA did not buy many stocks, because technical strategy of NA, a larger positive return was expected due to the previous positive return

AIA was able to sell at higher prices than when they were bought

bought many stocks, causing the market prices to increase

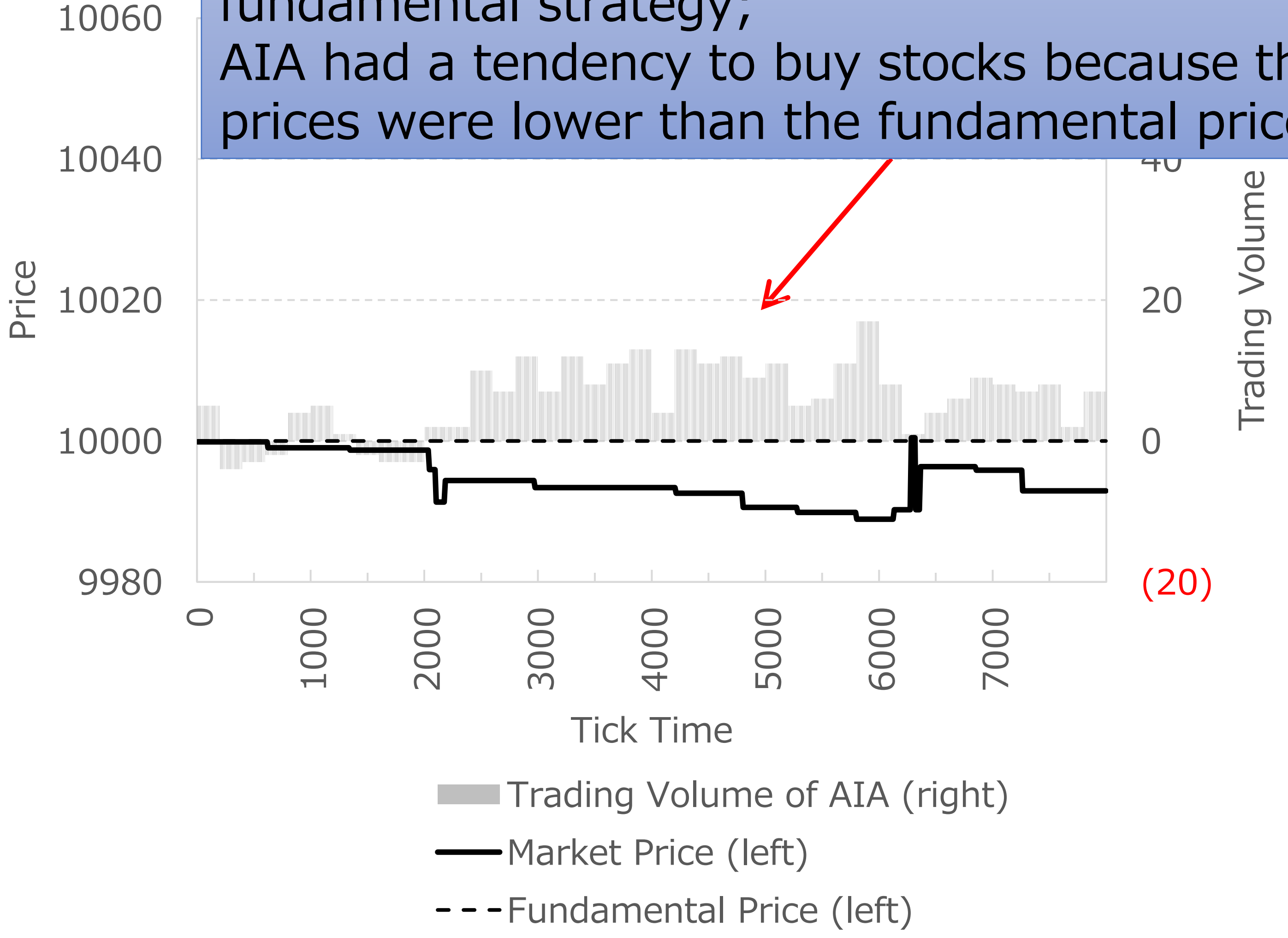


The AIA's trades are evidently market manipulation.

Backtesting (without the impacts on market prices)

time evolution of market prices is the same as that without the AIA because the AIA's trades never impact market prices

fundamental strategy;
AIA had a tendency to buy stocks because the market prices were lower than the fundamental price



AIA could not discover market manipulation as trading strategy

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Suggestion the need for regulation

- ✓ In this study, I constructed an AI trader using a genetic algorithm that learns in an artificial market simulation. Then I investigated whether the AI trader discovers market manipulation through learning even when the person who built the AI trader has no intention of market manipulation.

- ✓ The results showed that the AI trader discovered market manipulation as an optimal investment strategy. This indicates that even though the developer has no intention of market manipulation, the AI trader can discover market manipulation as an optimal investment strategy through learning with an artificial market simulation in which the AI trader automatically learns the impacts of its trades on market prices.

- ✓ This also indicates the possibility that an AI trader cannot discover market manipulation through learning with backtesting in which there are no impacts on market prices.

Suggestion the need for regulation

- ✓ The results suggest the need for regulation, such as obligating AI developers to prevent AIs from performing market manipulation.

- ✓ Another suggestion is that developers should limit trades performed by AI to avoid impacting market prices.

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- ✓ This indicates that even though the developer has no intention of market manipulation, the AI trader can discover market manipulation as an optimal investment strategy through learning with an artificial market simulation in which the AI trader automatically learns the impacts of its trades on market prices.
- ✓ This also indicates the possibility that an AI trader cannot discover market manipulation through learning with backtesting in which there are no impacts on market prices.
- ✓ The results suggest the need for regulation, such as obligating AI developers to prevent AIs from performing market manipulation.
- ✓ Another suggestion is that developers should limit trades performed by AI to avoid impacting market prices.

Appendix

Verification: Stylized Facts

The purpose of simulation is understanding the reasons and mechanism, not repricating 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 II
STATISTICS FOR RETURNS IN THE ARTIFICIAL MARKET

standard deviation of returns		0.0103%
kurtosis of returns		11.54
	lag	
	1	0.081
auto-correlation	2	0.041
coefficient of	3	0.032
square returns	4	0.047
	5	0.018

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).

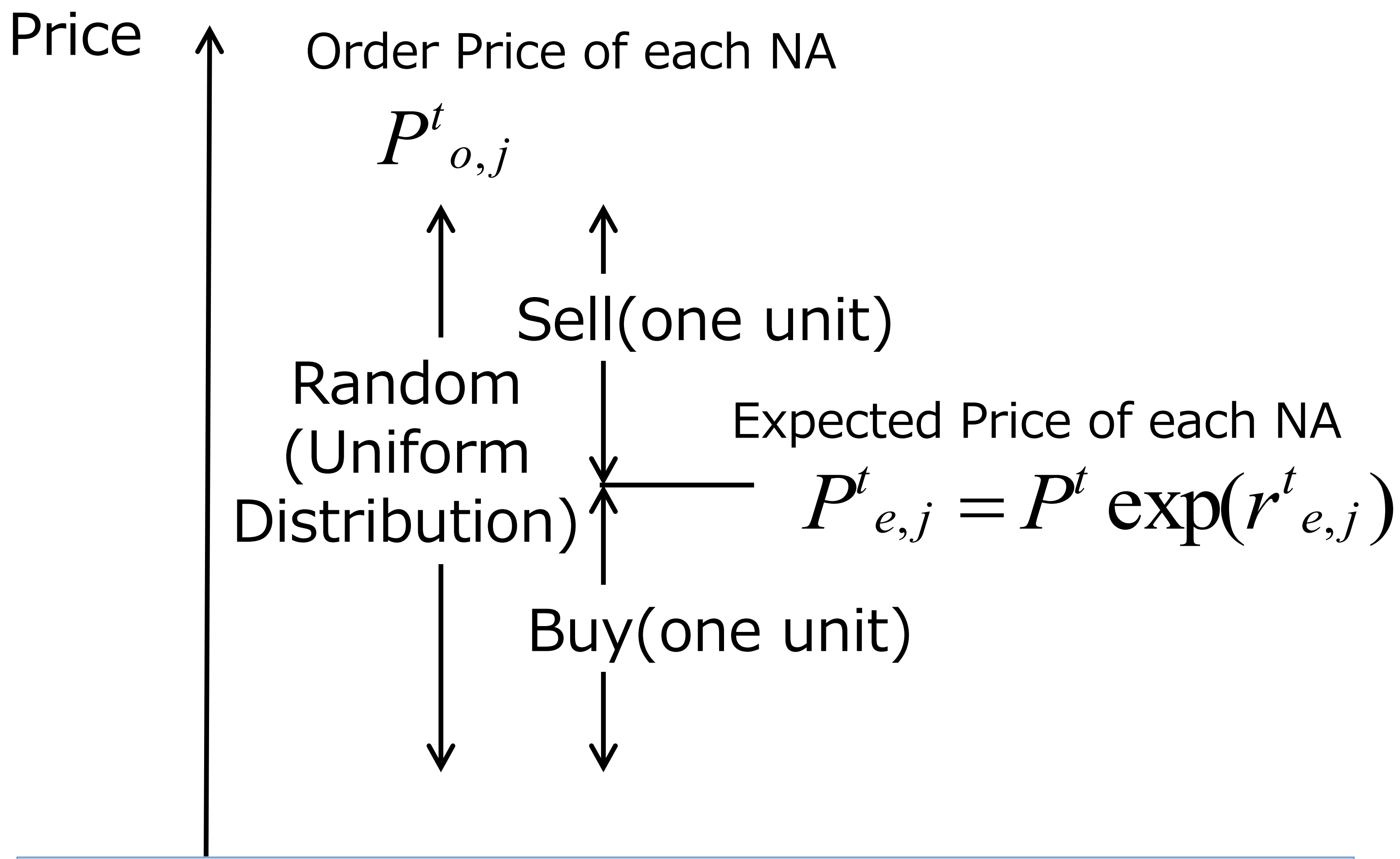
Expected Return of each NA

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

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>

Additional Ten Simulation Runs

No.	Min/Pf-1	Max/Pf-1	(Max-Min)/Pf	Simulation Trading Volume of AIA	Result Type
2	-0.59%	4.12%	4.7%	518	Manipulation(overbuying)
3	-0.63%	4.49%	5.1%	506	Manipulation(overbuying)
4	-0.77%	5.37%	6.1%	496	Manipulation(overbuying)
5	-4.33%	0.00%	4.3%	414	Manipulation(underselling)
6	-0.14%	0.00%	0.1%	0	No Trades
7	-3.67%	0.03%	3.7%	489	Manipulation(underselling)
8	-0.77%	5.02%	5.8%	511	Manipulation(overbuying)
9	-0.61%	4.96%	5.6%	507	Manipulation(overbuying)
10	-3.68%	-0.01%	3.7%	491	Manipulation(underselling)
11	0.00%	0.17%	0.2%	0	No Trades

- ✓ Eight runs resulted in manipulation including two underselling
- ✓ Two were no trades
- ✓ No fundamental strategy

No.	Min/Pf-1	Max/Pf-1	(Max-Min)/Pf	Back Testing Trading Volume of AIA	Result Type
2	-0.04%	0.13%	0.2%	221	Fundamental Strategy
3	-0.08%	0.21%	0.3%	230	Fundamental Strategy
4	-0.10%	-0.03%	0.1%	0	No Trades
5	-0.10%	0.01%	0.1%	0	No Trades
6	-0.14%	0.00%	0.1%	413	Fundamental Strategy
7	-0.05%	-0.01%	0.0%	0	No Trades
8	-0.05%	0.23%	0.3%	482	Fundamental Strategy
9	-0.04%	0.11%	0.2%	529	Fundamental Strategy
10	-0.01%	0.13%	0.1%	567	Fundamental Strategy
11	0.00%	0.17%	0.2%	484	Fundamental Strategy

- ✓ Seven fundamental strategy
- ✓ No manipulation

No. 5; Manipulation(underselling)