



Talk 1: An agent-based model for designing a financial market that works well

Talk 2: Can an AI perform market manipulation at its own discretion? - A genetic algorithm learns in an artificial market simulation -

Takanobu Mizuta

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HP: <https://mizutatakanobu.com>

Today, I try 2 talks. Sorry if There is not enough time for Talk 2.
(I think I have prepared too many slides.)

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

You can download this presentation material from <https://mizutatakanobu.com/2021kyushu.pdf>

Here is a Japanese ver. slides <https://mizutatakanobu.com/2021e.pdf> YouTube <https://youtu.be/tq9AsMrig9s>

The economist John McMillan, who used game theory to investigate many markets, said “a market works well only if it is well designed”. Market design (regulations, rules) determines whether a market works well or badly.

McMillan also concluded that “the economy is a highly complex system. It is at least as complex as the systems studied by physicists and biologists.”

Some articles argued that traditional economics had not found ways to design markets that work well and anticipated an artificial market model to do so. Financial regulators and exchanges, who decide rules and regulations, especially desire an artificial market model to design a market that works well.

This presentation showed a philosophy of an agent-based artificial market model. Why are models needed? How models should be? In the first place, what is a model? We should understand what is a model deeper for healthy discussion using a model. I will try to clear up a common misunderstanding for a model. After the discussion, I will review the case, investigating tick size reduction using a model.

You can download this presentation material from <https://mizutatakanobu.com/2021kyushu.pdf>

Takanobu Mizuta

Now, I belong to SPARX Asset Management Co., Ltd. as Fund Manager and Senior Researcher.
I am also a part-time lecturer of the Graduate School of Public Policy, The University of Tokyo.

In SPARX Asset Management, I am responsible for quotative investigate of Japanese stock market and the portfolios, and maintaining system/DB for the investigation, and academic-study regulation/rules using multi-agent simulations.

2014 Ph.D.: School of Engineering, The University of Tokyo (Kiyoshi Izumi Laboratory)

2004 Joined SPARX Asset Management (current affiliation)

2002 Master: School of Science, The university of Tokyo (Space Plasma Physics)

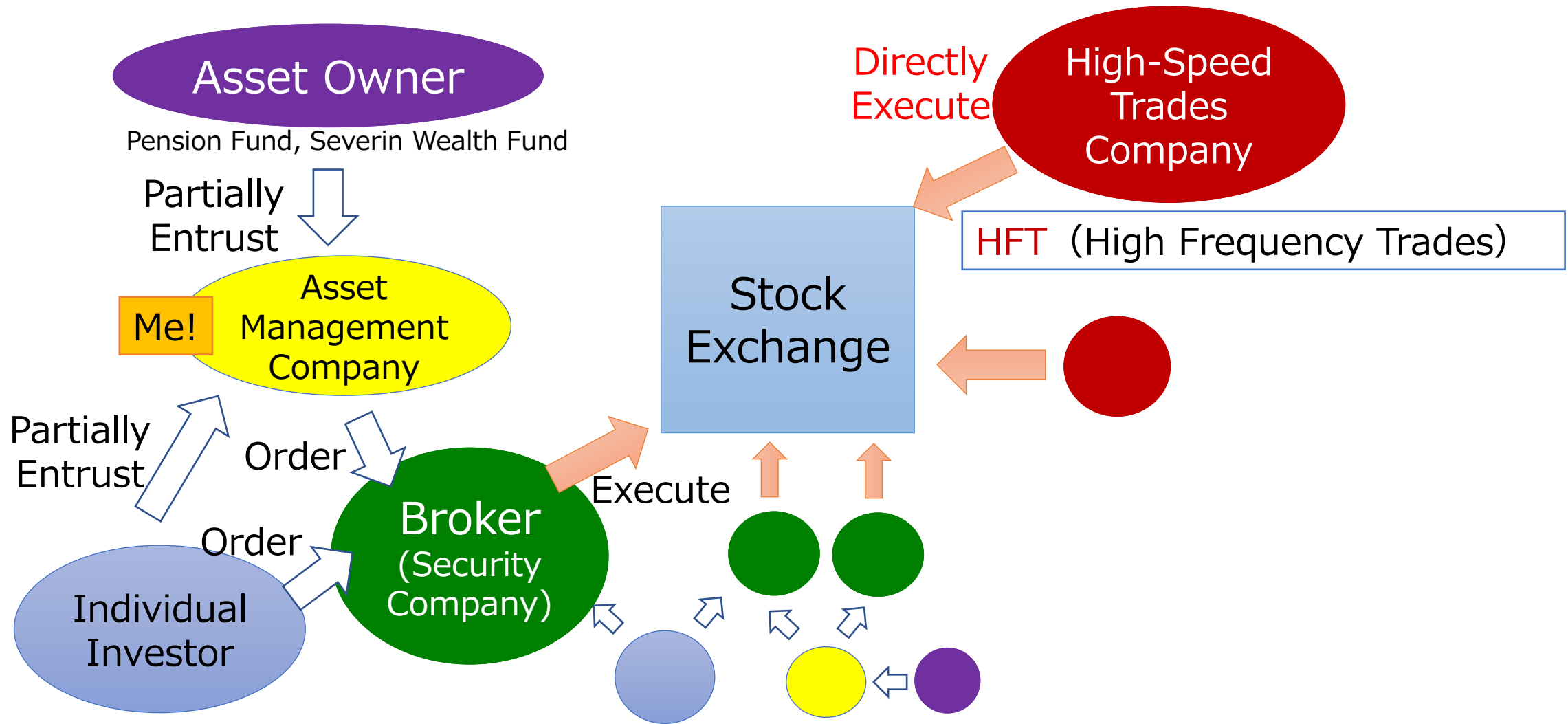
2000 Bachelor: Japan Meteorological College

2016/4-, Vice Chair: Special Interest Group on Financial Informatics
the Japan Society for Artificial Intelligence (JSAI SIG-FIN),

2019-, Technical Committee Member: IEEE Computational Intelligence Society,
Computational Finance and Economics (IEEE CFETC)

You can download this presentation material from <https://mizutatakanobu.com/2021kyushu.pdf>

I belong to the asset management company



For Talk 1 there is my review paper, read it if you are interested

My Review Paper

Mizuta 2020, “An agent-based model for designing a financial market that works well”, IEEE Symposium Series on Computational Intelligence, Computational Intelligence for Financial Engineering and Economics (CIFEr), December 1 to 4, 2020, Canberra, Australia(virtual)

<https://doi.org/10.1109/SSCI47803.2020.9308376>

<https://arxiv.org/abs/1906.06000>

Presentation on YouTube <https://youtu.be/rmlb72ykmlE>


≡ YouTube JP

検索

2020 IEEE Symposium Series on Computational Intelligence (SSCI)
on Computational Intelligence for Financial Engineering
and Economics (CIFEr) <http://www.ieeessci2020.org/>

Paper ID: #30

**An agent-based model for
designing a financial market that works well**

 Takanobu Mizuta SPARX Asset Management Co., Ltd.
Mail: mizutata[at]gmail.com
HP: <https://mizutatakanobu.com>

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

You can download this presentation material from
<https://mizutatakanobu.com/2020CIFEr/p.pdf>

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ADVANCING TECHNOLOGY

Conferences > 2020 IEEE Symposium Series on... ?

An agent-based model for designing a financial market that works well

Publisher: IEEE Cite This PDF

Takanobu Mizuta All Authors

Abstract

Document Sections

Abstract:
Designing a financial market that works well is very important for developing and maintaining an advanced economy, but is not easy because changing detailed rules, even ones that seem trivial,

Talk 1: An agent-based model for designing a financial market that works well

Talk 2: Can an AI perform market manipulation at its own discretion? - A genetic algorithm learns in an artificial market simulation -

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

(2) Suitable complexity, advantages and disadvantages

(3) Typical Model

(4) Case study: tick size reduction

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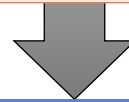
(4) Case study: tick size reduction

Importance and difficulty of market design

People

have been able to develop advanced economies
by cooperating to exchange goods for money

Creation of any industry requires “investment” to first purchase or build tools to make goods



Financial
Market

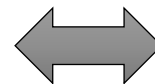
enables smooth investment



Creates Better Goods Better Service

Two Extreme Opinions

No regulation is Best?



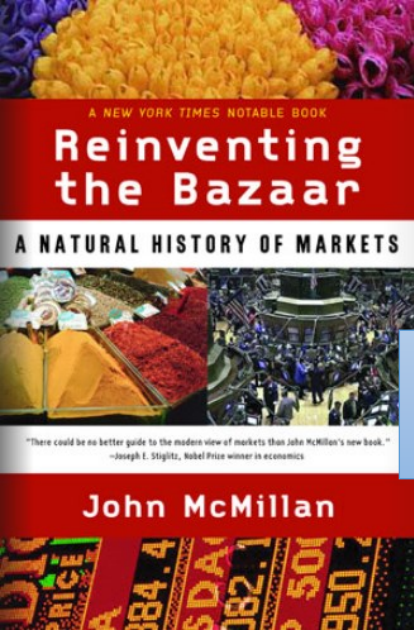
Destroy a Society?

Both is Wrong

“A market works well only if it is well designed”

Proper rules and regulations are required

(By the economist John McMillan, who used game theory to investigate many markets)

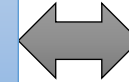


John McMillan, 2002

<https://wnorton.com/books/Reinventing-the-Bazaar/>

“A market works well only if it is well designed”

Market design determines whether a market works well or badly



A market is a highly complex system. It is at least as complex as the systems studied by physicists and biologists

Very important for Developing economy

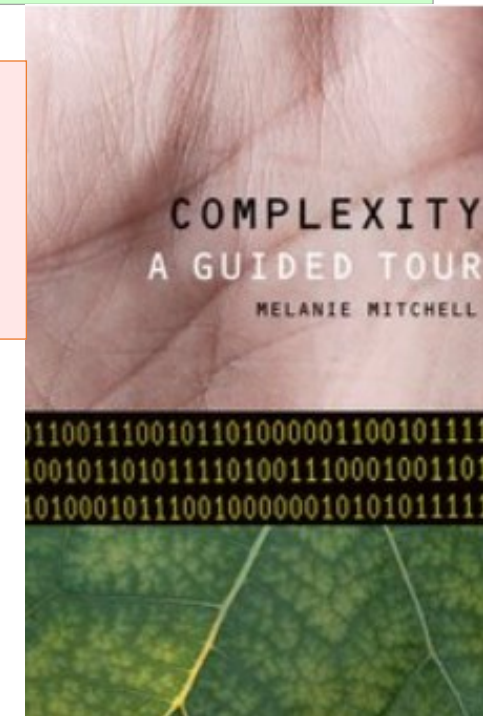
Very difficult and complex system

“Economies are complex systems in which the simple, microscopic components consist of people buying and selling goods, and the collective behavior is the complex, hard-to-predict behavior of markets as a whole, such as fluctuations in stock prices”

Changing detailed rules, even ones that seem trivial, sometimes causes unexpected large impacts and side effects.

both God and the devil are in the details

Designing a market well is very important for developing an advanced economy, but not easy.



Melanie Mitchell, 2009

<https://global.oup.com/academic/product/complexity-9780195124410>

A parable: difficulty of controlling complex system

Mori (Commissioner, Financial Services Agency, Japan), 2015, "Rethinking Regulatory Reforms", the 6th Annual Pan Asian Regulatory Summit, Hong Kong

<https://www.fsa.go.jp/common/conference/danwa/20151013/01.pdf>

Mori (Commissioner, Financial Services Agency, Japan), 2015, criticized US and euro making many regulations for finance.

Three* years after the tragedy of the Titanic in 1912, the International Convention on Safety of Life at Sea introduced the "lifeboats for all" regulation, requiring that enough lifeboats be equipped for all passengers and crew. The United States applied the international rule to domestic liners as well. SS Eastland, a sightseeing steamship on the Great Lake, therefore equipped lifeboats for her 2,500 passengers. Three weeks after, the steamship, with extra weight of lifeboats on her, was suddenly capsized during her trip on Lake Michigan and many* of her passengers lost their lives, more than in the Titanic disaster. The Titanic tragedy called for a new regulation, and the burden of the regulation caused an even bigger tragedy. Lifeboat for all, which was intended to allow an orderly rescue from a capsized ship, may have served to create a false sense of security. But it simply did not work.

*I modulated



The conference, other people talking



https://commons.wikimedia.org/wiki/File:Eastland_disaster_port_side.jpg#/media/File:Eastland_disaster_port_side.jpg

Side Effect: no one expected when the regulations are made

Complex System leads results no one expected

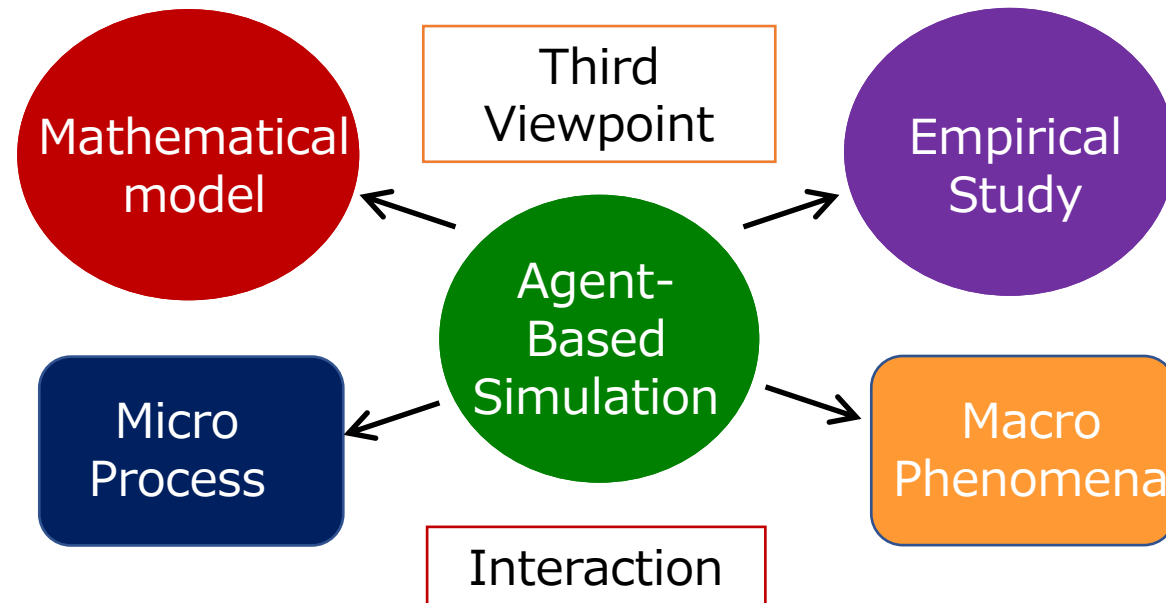
No one can expect what partial optimization effects a whole

In complex System, Simple aggregation of parts does not make a whole

both God and the devil are in the details

Agent-Based Model succeeded to explain Social Complex Systems other than Financial Market

Building virtual society in a computer with many "agents" modeled for humans.
The agents that work as micro process interact each other.
The aggregation of the micro process makes macro phenomena.



- Like [the egg in the Columbus story](#), it is able to find that some interactions lead **side effects** and **unexpected results** in the society as **complex system**.
- It is able to find [the reasons and mechanism](#), and find [new problems](#) that empirical studies should investigate
- It is established as a **helping and complementing** method to existing methods in other fields.

For examples,

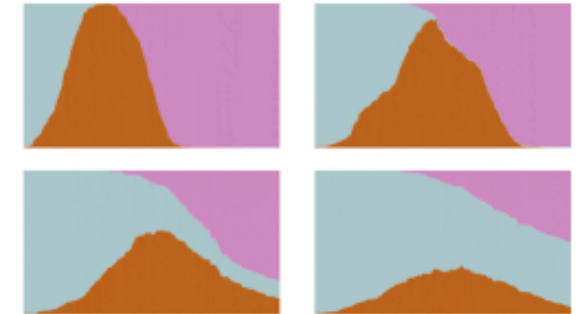
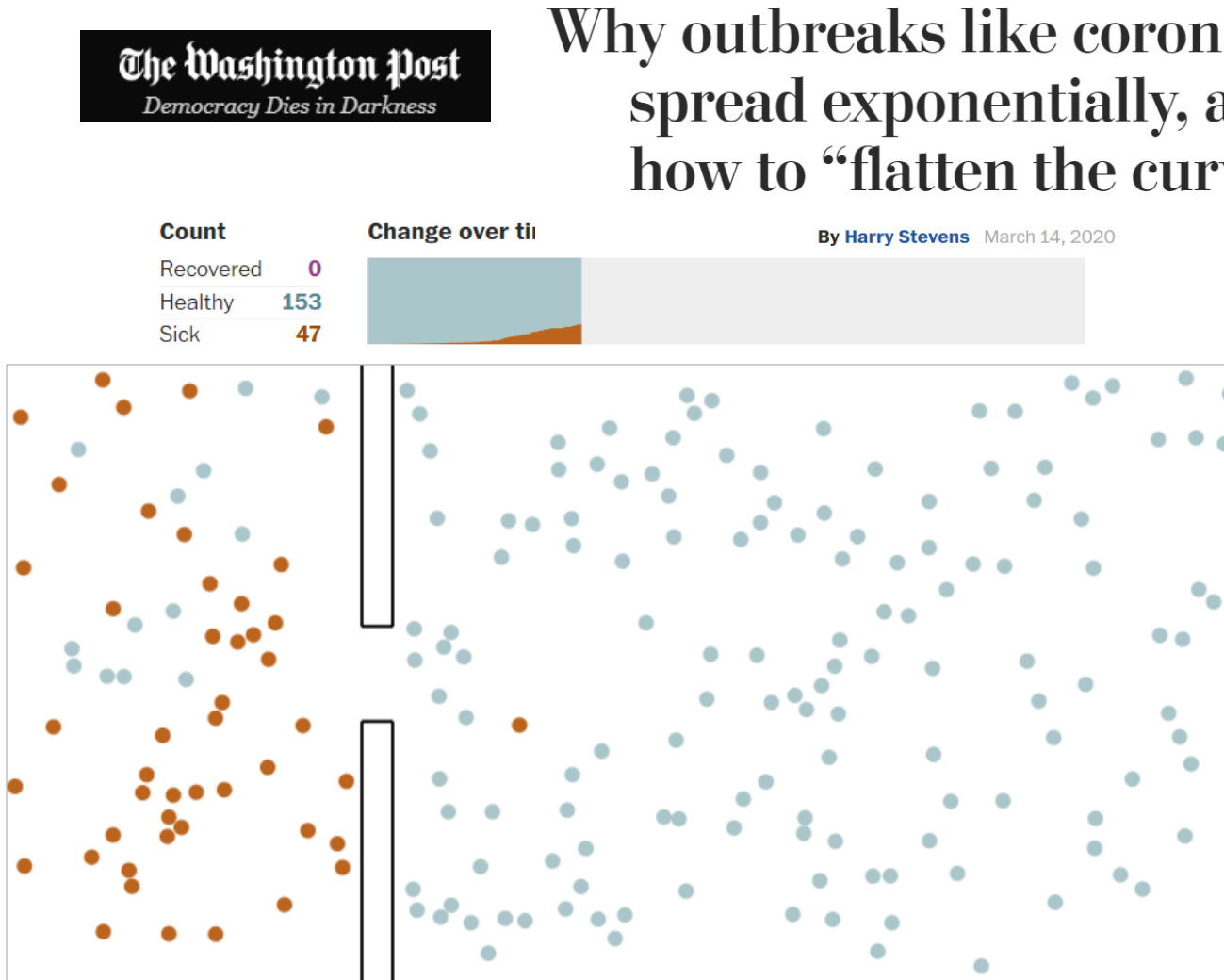
- Making Evacuation Route of new building for Fire and/or Terror
- Investigating for effects of building new roadway to traffic jam
- Discussing how spread COVID-19 and so on

There are many many studies succeeded explain the phenomena of social complex systems

The agent-based model that contributed discussion how to prevent COVID-19

<https://www.washingtonpost.com/graphics/2020/world/corona-simulator/>

News paper writer simulated



- * Agents move like a ball: move in a straight line, reflect when bumped
 - * They are infected when bumped
 - * They recover after some time infected and no more infection.
- > If no action: high peak but fast convergence
- Preventive policy: low peak but slow convergence
- > Near the peak is Good timing to end the policy?
- We can find mechanism and discuss

This model is too simple to replicate the real world but the simplicity enable give us finding mechanism and understanding process.

Example of equation model cannot but simulation model can (Schelling Model)

Will come back again

Party with Students(#) and Professors(@)

Micromotives and Macrobehavior, 2006

<http://books.wwnorton.com/books/978-0-393-32946-9/>

Explanatory article, "Parable of the polygons"

<https://ncase.me/polygons/>

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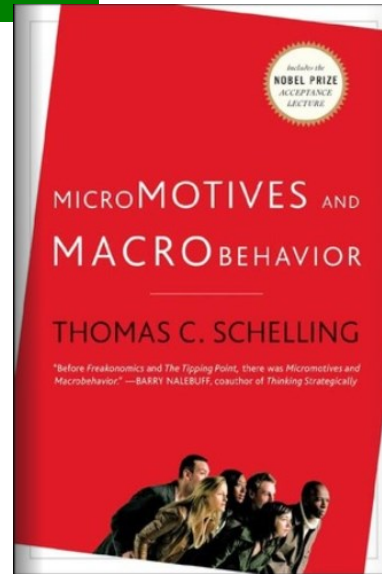
* around me (8pixs)
with more 1/3 my
equals -> not move

* No -> move

After many steps,,,

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@	@					#

and @ have been separated



Mod. rules:

:need one more equal

@:need one less equal

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The space of #
is smaller

The segregation occurs even if we want not to be heavily minority. We do NOT hate other kinds.

The purpose of simulation is understanding the reasons and mechanism, not forecasting the final distribution.

Where are tables? How much they eat? Where are assistant professors?
Is the party place square? Are behaviors of people too simple?
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prevent our understanding the mechanism.

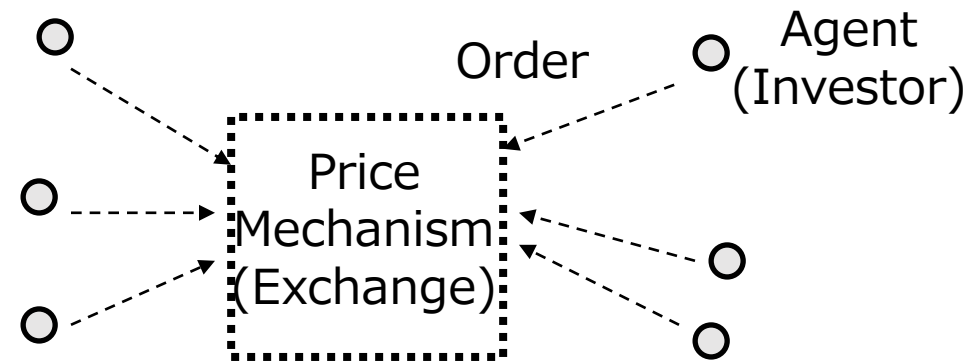
Simplifying depends on that we want to understand

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

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 changing rules

NATURE/SCIENCE articles argued Importance of Simulations

- Farmer and Foley (2009) **NATURE**, Vol. 460, No. 7256, pp. 685-686.
<https://www.nature.com/articles/460685a>

In today's high-tech age, one naturally assumes that US President Barack Obama's economic team and its international counterparts are using sophisticated quantitative computer models to guide us out of the current economic crisis. They are not. There is a better way: agent-based models.

- Battiston et al. (2016) **SCIENCE**, Vol. 351, Issue 6275, pp. 818-819.
<http://science.sciencemag.org/content/351/6275/818>

Traditional economic theory could not explain, much less predict, the near collapse of the financial system and its long-lasting effects on the global economy. Since the 2008 crisis, there has been increasing interest in using ideas from complexity theory to make sense of economic and financial markets.

These articles argued that

Traditional economic theory could not explain, much less predict, the near collapse of the financial system



Agent-Based Model is needed

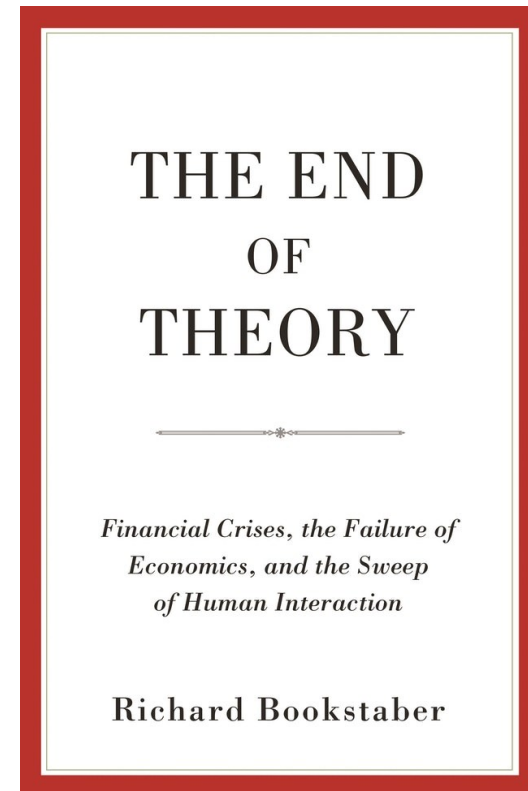
Richard Bookstaber

Expert of risk management at Investment Banks and Hedge Funds

Famous for The author of “A Demon of Our Own Design” is noted for its forecasting of the financial crisis of 2008

Standard Economic Model did not prevent Financial Crises of 2008. An Agent-Based Model will prevent the Crises.

Arguing importance of using Agent-Based Model when we discuss how prevent the Financial Crises



Richard Bookstaber, 2017 <https://press.princeton.edu/books/hardcover/9780691169019/the-end-of-theory>

Also, President of the ECB

Speech of the President of ECB (European Central Bank), 2010

Agent-based modelling dispenses with the optimization assumption and allows for more complex interactions between agents. Such approaches are worthy of our attention.

<https://www.ecb.europa.eu/press/key/date/2010/html/sp101118.en.html>

Practical Persons have began to use Agent-Based Model to solve Urgent Real Problem

Regulators, Central Bankers, Stock Exchanges



日本取引所グループ
東京証券取引所
大阪取引所
日本取引所自主規制法人
日本証券クリアリング機構

JPX Working Papers Series

JPX(parent com of Tokyo Stock Exchange) shows Working Papers,
10 papers of all 35 (as of end March 2021) are Agent-Based Studies

Reduction of Tick Size, Frequently Batch Auction,
Suitable Latency of Exchange System, and so on

<https://www.jpx.co.jp/english/corporate/research-study/working-paper/index.html>

So many other Examples,

Working Paper by Bank of Japan

Toshiyuki Sakiyama and Tetsuya Yamada, Market Liquidity and Systemic Risk in Government Bond Markets: A Network Analysis and Agent-Based Model Approach

<https://www.imes.boj.or.jp/research/abstracts/english/16-E-13.html>

Project by EU

Integrated Macro-Financial Modelling for Robust Policy Design Work Package 7: Bridging agent-based and dynamic-stochastic-general-equilibrium modelling approaches for building policy-focused macro financial models <https://cordis.europa.eu/project/id/612796/reporting>

My review

Takanobu Mizuta, 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>

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

(2) Suitable complexity, advantages and disadvantages

(3) Typical Model

(4) Case study: tick size reduction

An agent-based model explaining a complex system

A financial market is highly complex system where a simple summation of micro processes (trader behaviors) never explains macro phenomena (price formation).

Separately investigating macro phenomena and micro processes unclearly explains complex systems where macro phenomena and micro processes interact.

A mathematical model
An empirical study

cannot directly treat nor clearly explain the interactions

An Agent-Based Model

can directly treat and clearly explain the interactions

Because...

An Agent-Based Model

Macro Phenomena

Price Formation

As a result

Simulation **Feedback**

Micro Process

Agents Behavior

Simple Modelling

Treat
Directly &
Interactively

can directly treat and
clearly explain the interactions

A mathematical model
An empirical study

Macro Phenomena

Price Formation

Precious
Modelling

**Simple summation
cannot explain**

Treat
Separately

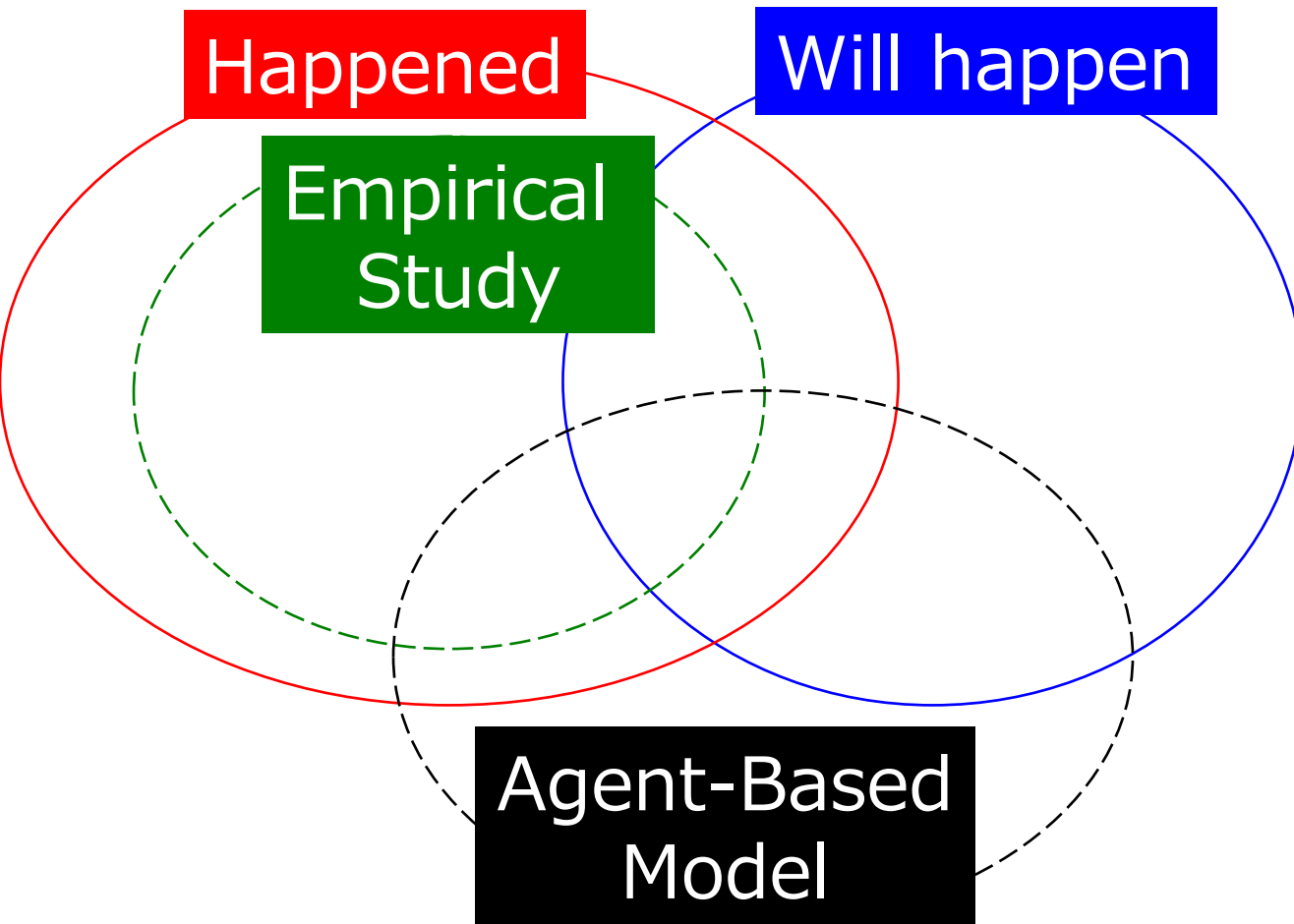
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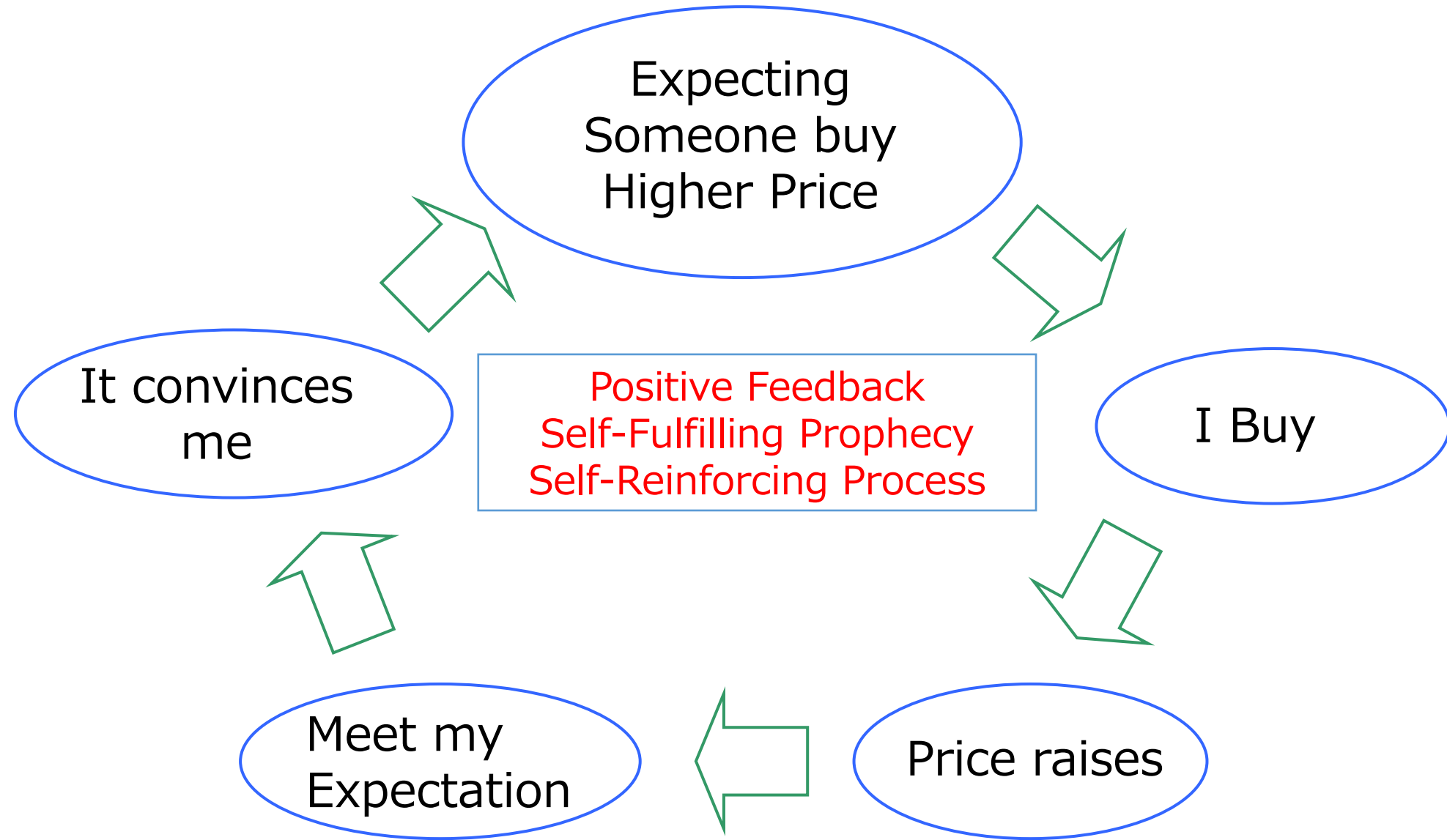
Advantages and Disadvantages of Agent-Based Model



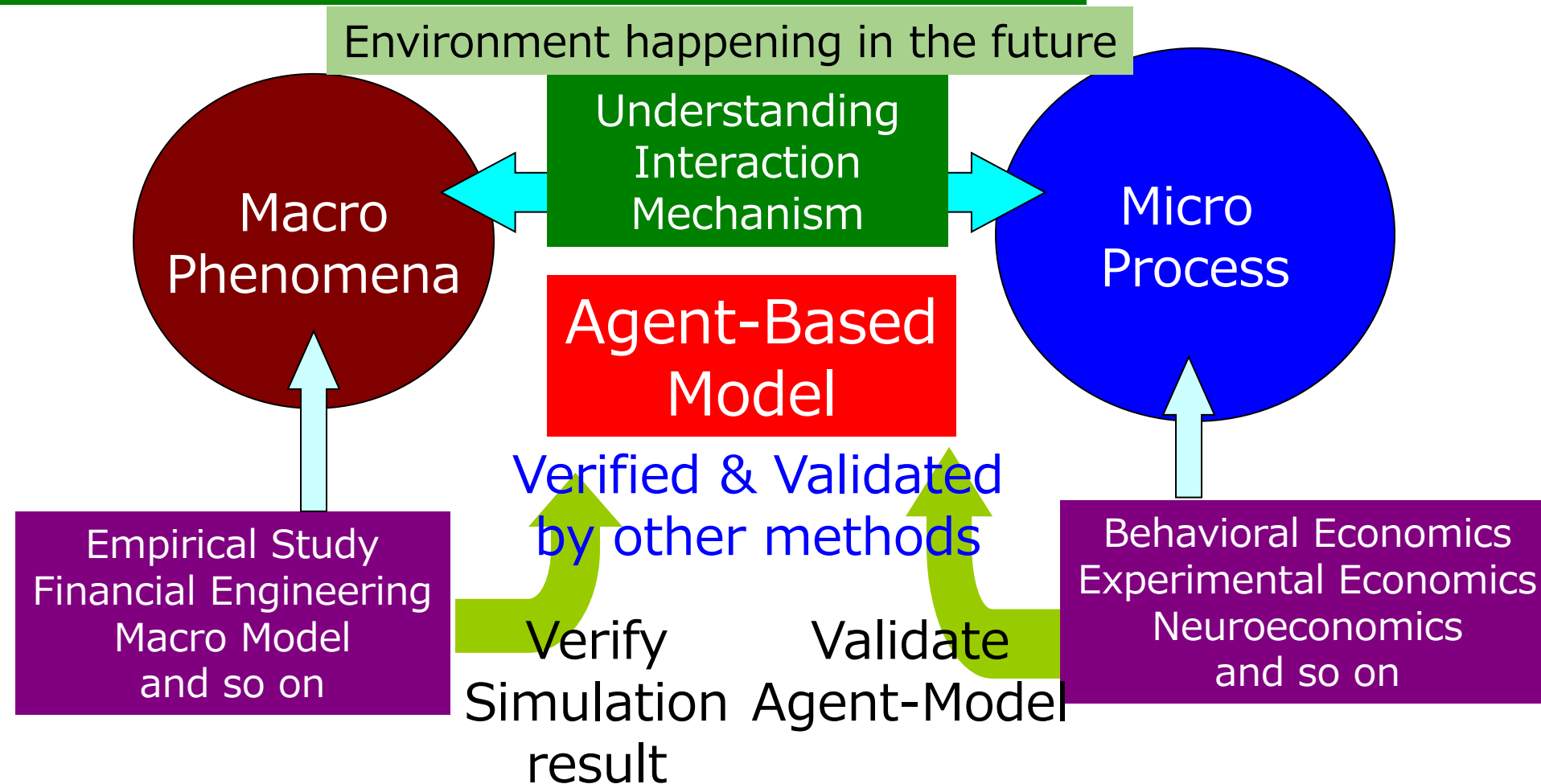
Outputs of an empirical study are included in the area that has happened in a real financial market. The advantage of an empirical study is outputs exclude the all area not happening in the past or future. The disadvantage, however, is outputs exclude any area happening in the future.

The advantage of an agent-based model is outputs include the part of the area happening in the future. The disadvantage, however, is outputs include the part of area not happening in the past or future.

An agent-based model just outputs “possible” results to understand the mechanism of a market. Discussing whether the results will occur or not needs other methods, e.g., an empirical study and a mathematical model.



Collaborate to mutually compensate for their disadvantages



Discussing the outputs of an agent-based model always needs knowledge given by empirical studies and mathematical models. A market that works well should be designed by not one but several methods, and the methods should collaborate to mutually compensate for their disadvantages.

What is a role of Simulation Models? Suitable complexity?

Discussing the philosophy of models and simulations.

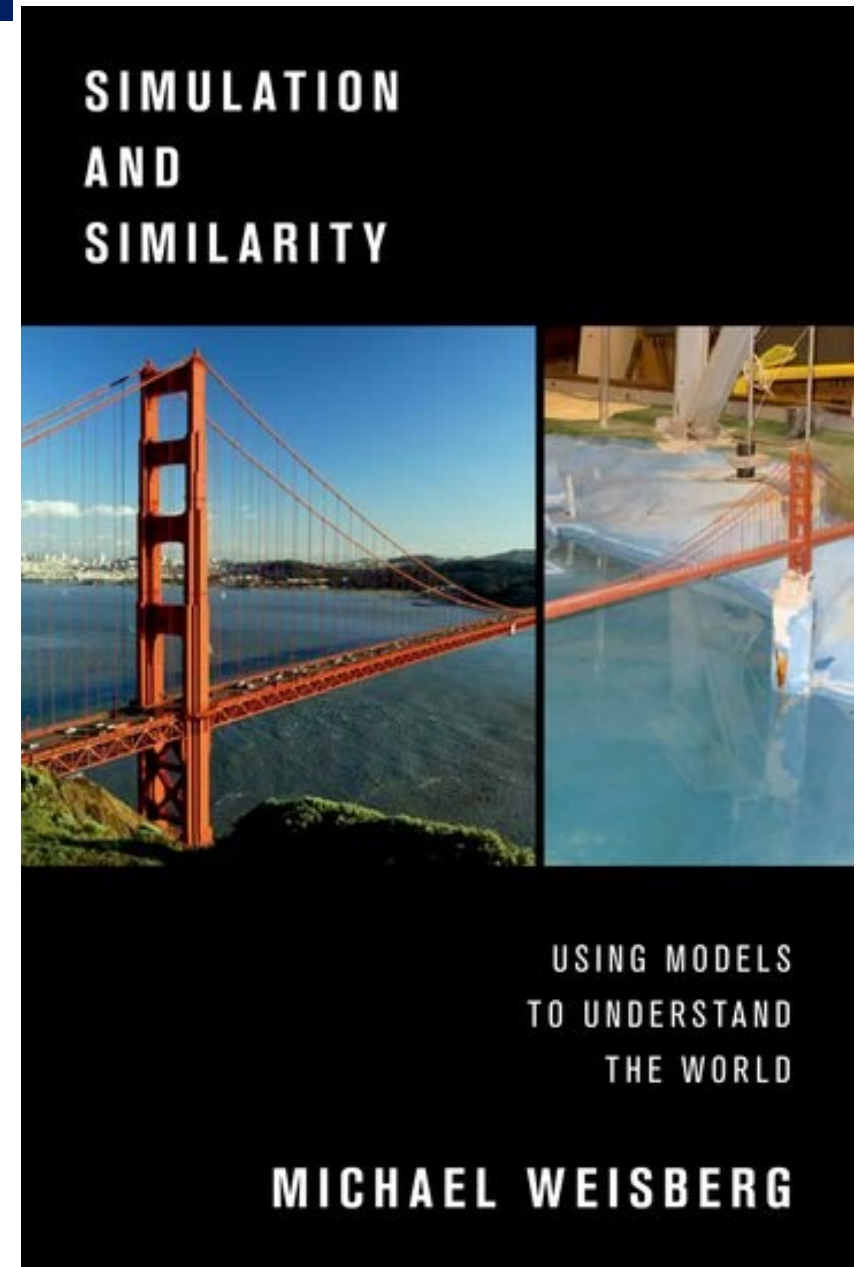
“What is a role of Simulation Models? ”
“What is a model?”,
“How complexity is suitable for the model?”

Very very good book.

I think all researcher who use some model should read this book
for healthy discussion using models.

(Following some slides, I will introduce the discussion of the book)

Simulation and Similarity Using Models to Understand the World, 2012
<https://global.oup.com/academic/product/9780199933662>



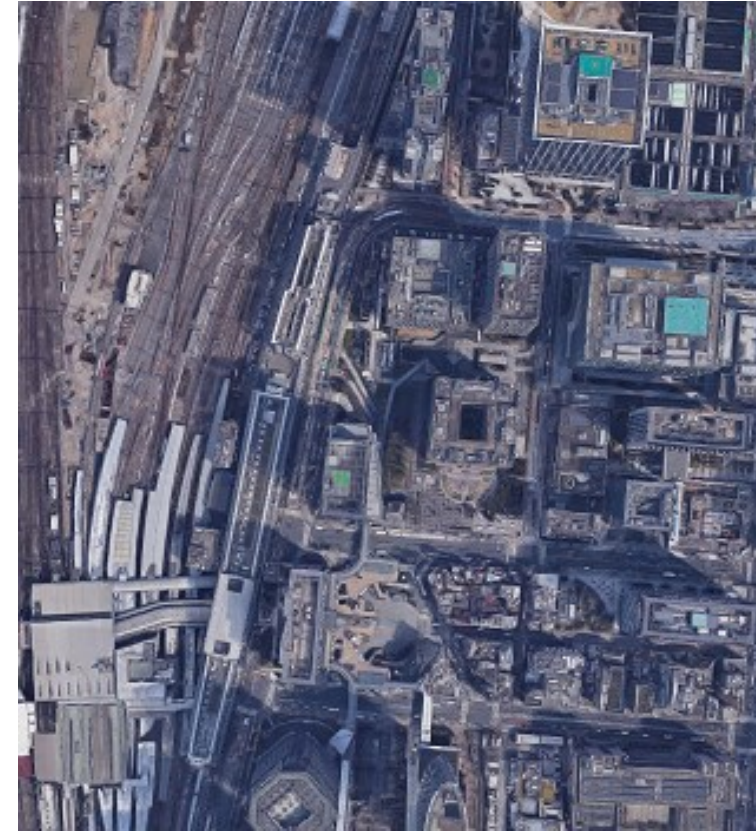
Which “map” explains the access better?

Some of maps are “models” of the real geography for understanding an access.



Very different from the real, however,
very good explaining the access.

(left) From official web site of Shinagawa Season Terrace (<https://shinagawa-st.jp/en/access/train.html>)

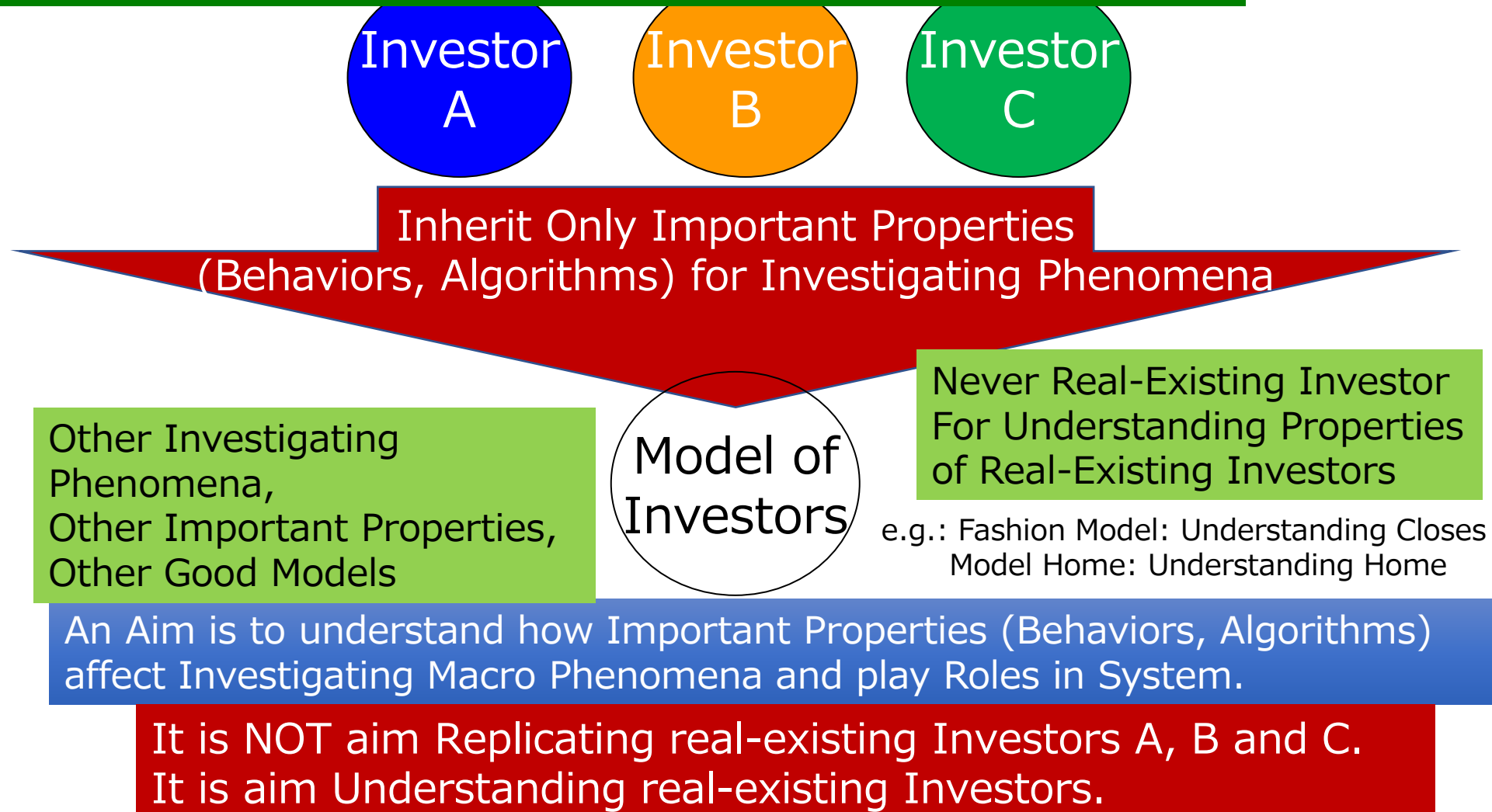


Very similar to the real, however,
very bad explaining the access.

(right) Google map (Imagery © 2020, CNES/Airbus, Digital Earth Technology, Maxar Technologies, Planet.com, The Geoinformation Group, Map data © 2020 Google)

must shave non-investigating features from the model
Different investigations, different shaving parts.

Role of Model (in the case of Agent-Based Artificial Market Model)



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.

Other Focusing Phenomena, Other Good Models; no model good for anything exist

Example of equation model cannot but simulation model can (Schelling Model)

Party with Students(#) and Professors(@)

Micromotives and Macrobehavior, 2006

<http://books.wwnorton.com/books/978-0-393-32946-9/>

Explanatory article, "Parable of the polygons"

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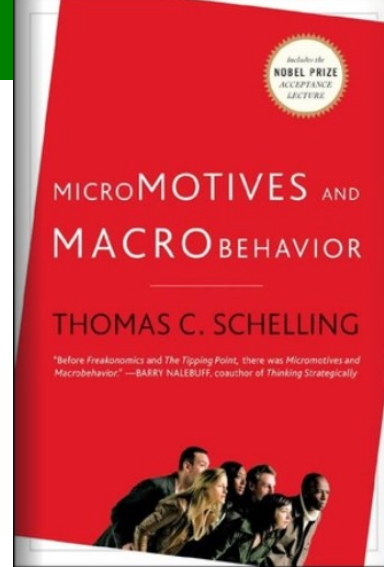
* around me (8pixs)
with more 1/3 my
equals -> not move

* No -> move

After many steps,,,

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and @ have been separated



Mod. rules:

:need one more equal

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The space of #
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The segregation occurs even if we want not to be heavily minority. We do NOT hate other kinds.

The purpose of simulation is understanding the reasons and mechanism, not forecasting the final distribution.

Where are tables? How much they eat? Where are assistant professors?
Is the party place square? Are behaviors of people too simple?
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Simplifying depends on that we want to understand

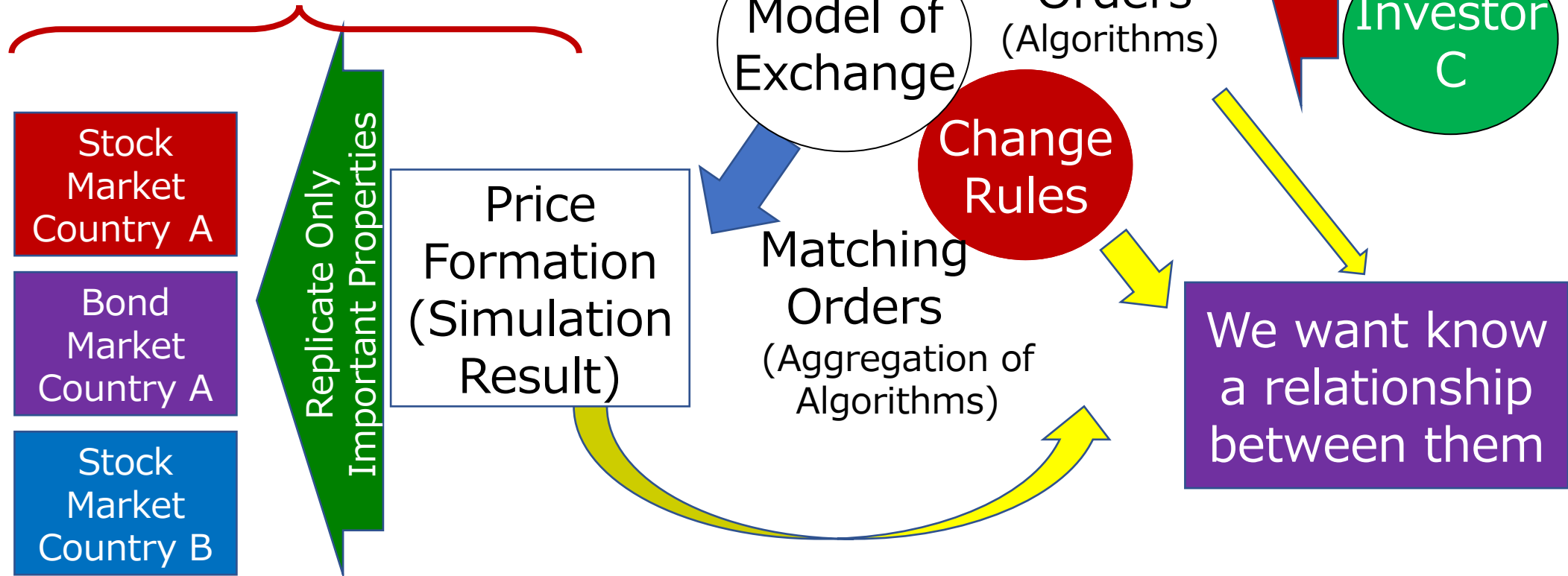
Role of Model (cont.)

We want know a relationship between
Micro Process:

Deciding Orders, Rules of Exchange
& Macro Phenomena: Price Formation

Mathematical Model
Macro Model

can treat only this region



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

(2) Suitable complexity, advantages and disadvantages

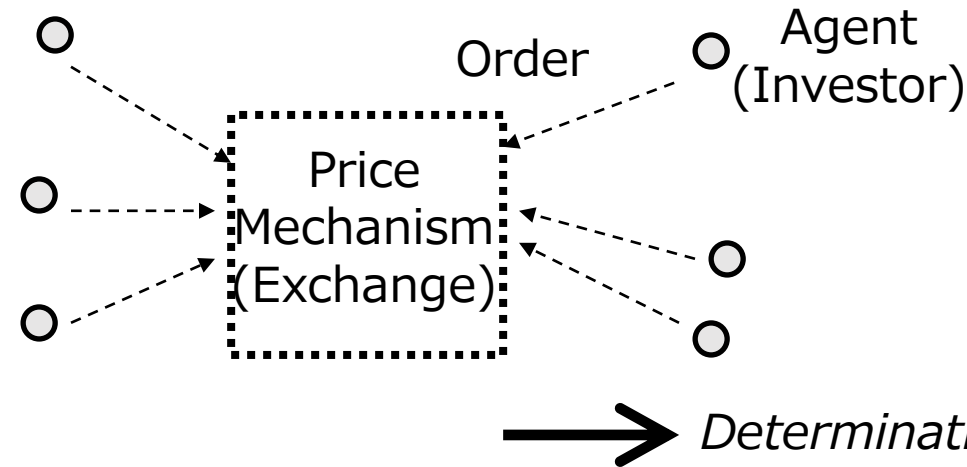
(3) Typical Model

(4) Case study: tick size reduction

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

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 changing rules

Price Mechanism: Not so Simple

Should replicate rules of real stock exchange

Not so Simple Model

continuous double auction

	Sell Amount	Order Price	Buy Amount
	10	103	
	30	102	
		101	
	50	100	
When placing sell order here, The orders executed immediately	130	99	
		98	150
		97	
		96	70

When placing buy
order here,
The orders executed
immediately

If there is already better price order, the orders executed immediately

<=> simple model

Price Return = $k(\text{amount buy orders} - \text{a. sell orders})$

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

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

Technical

Fundamental

noise

The diagram illustrates the equation for the expected return of each NA. The equation is enclosed in a green box. Above the equation, the text 'Expected Return of each NA' is in a green box. Below the equation, three components are highlighted: 'Fundamental' (red box) under the first term, 'Technical' (orange box) under the second term, and 'noise' (yellow box) under the third term. Green lines connect these labels to their respective terms in the equation.

All agents use this same equation to obtain an expected return, however, because w is different each agent, expected returns are different each agent. 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.

Fundamental and Technical Strategies

Fundamental Strategy

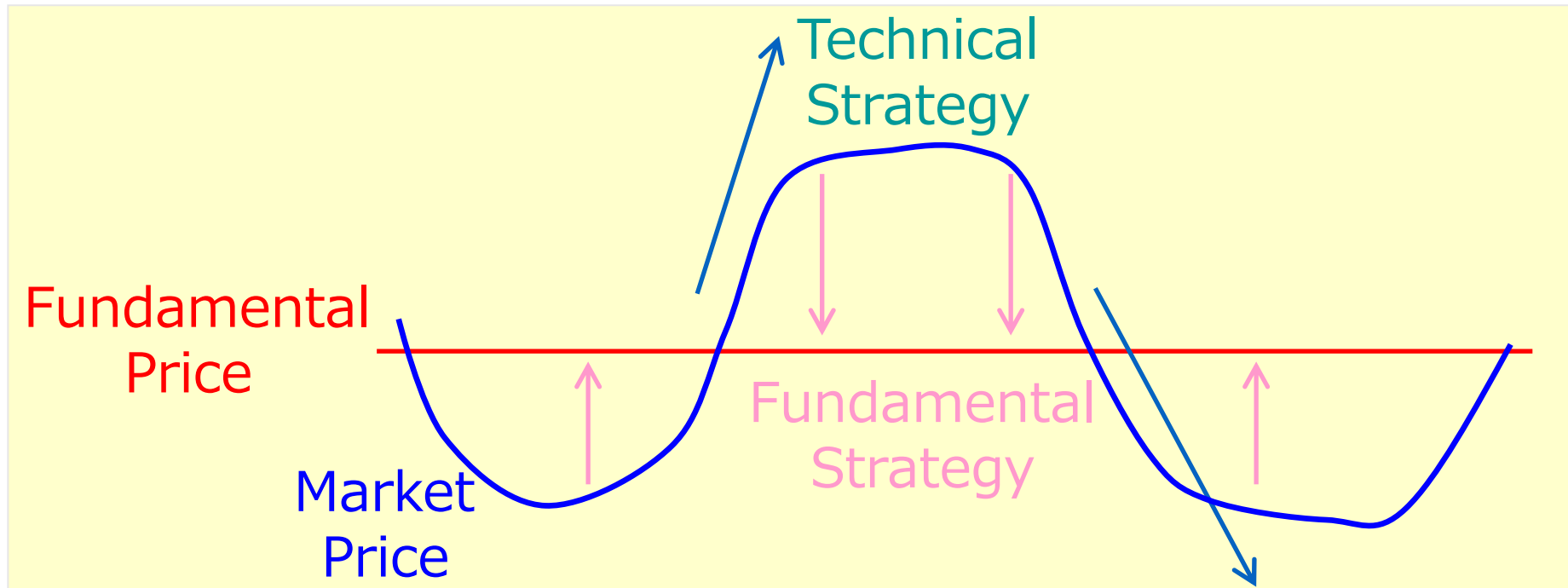
Fundamental Price $>$ Market Price \rightarrow Expect + return

Fundamental Price $<$ Market Price \rightarrow Expect - return

Technical Strategy

Historical Return $> 0 \rightarrow$ Expect + return

Historical Return $< 0 \rightarrow$ Expect - return



Detail of Expected Return

j: agent number (1,000 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: 0~10

τ_j 0~10000

Fundamental

P_f Fundamental Price
10000 = constant
 P^t Market Price at t

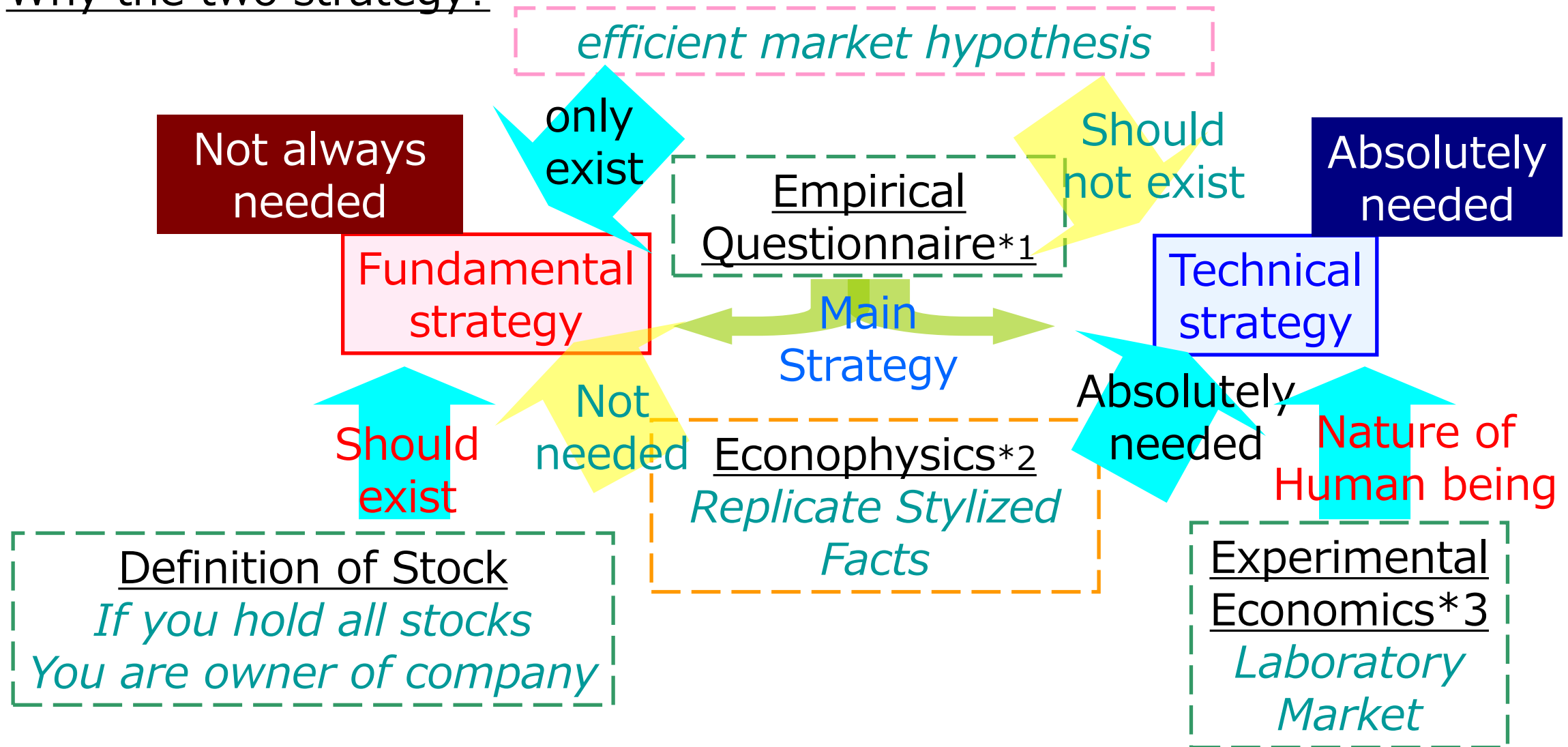
noise

ε_j^t
Random of
Normal
Distribution
Average=0
 $\sigma=3\%$

Expected Price of each NA

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

Why the two strategy?



*1 Menkhoff, L. and Taylor, M. P. (2007): The Obstinate Passion of Foreign Exchange Professionals: Technical Analysis, Journal of Economic Literature
Yamamoto, R. (2021): Predictor Choice, Investor Types, and the Price Impact of Trades on the Tokyo Stock Exchange, Computational Economics
<https://arxiv.org/abs/1906.06000>

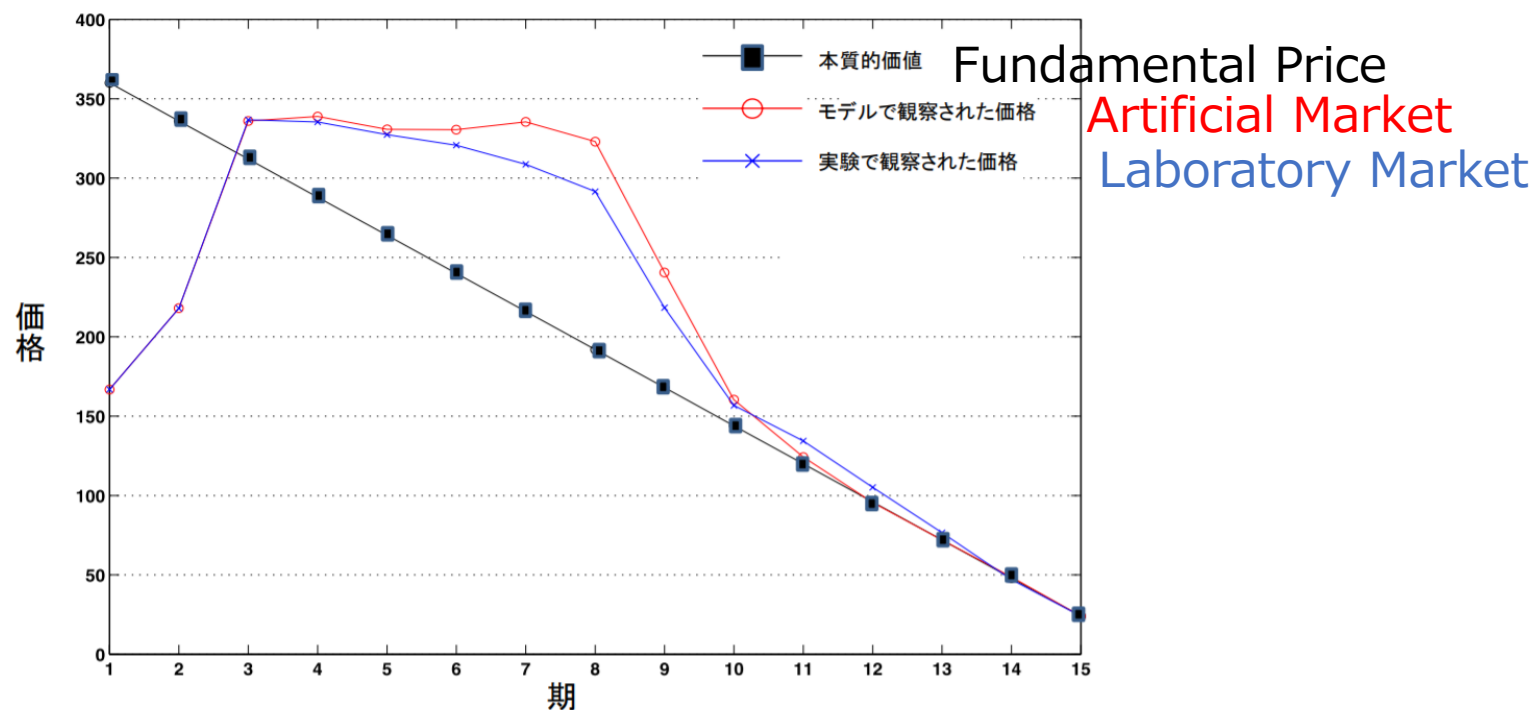
*2 Lux, T. and Marchesi, M. (1999) Scaling and criticality in a stochastic multi-agent model of a financial market, Nature

*3 Haruvy and Noussair (2006): The Effect of Short Selling on Bubbles and Crashes in Experimental Spot Asset Markets
<https://doi.org/10.1111/j.1540-6261.2006.00868.x>

Laboratory Market vs. Artificial Market

Sorry, the figure from Japanese book
<https://www.coronasha.co.jp/np/isbn/9784339028164/>

実験結果とモデルシミュレーションの結果の対比



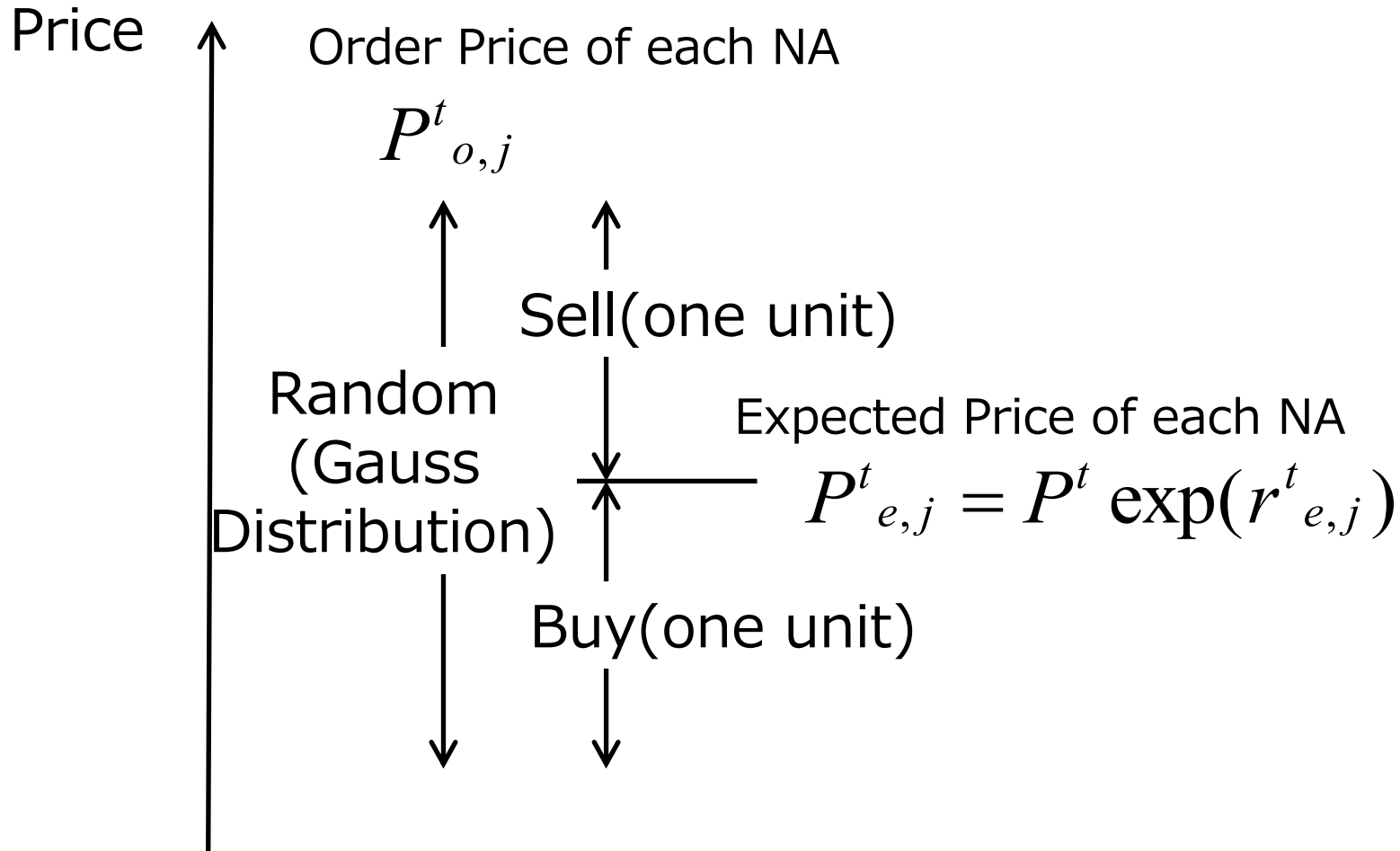
Source: Haruvy and Noussair (2006)
のモデルと実験データを基に作成

Haruvy and Noussair (2006): The Effect of Short Selling on Bubbles and Crashes in Experimental Spot Asset Markets
<https://doi.org/10.1111/j.1540-6261.2006.00868.x>

Parameter fitting of the artificial market model including fundamental and technical strategies leads to similar results with the laboratory market. This means that both strategies are needed to replicate the laboratory market, and they may also be needed to replicate real markets.



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.

Table 1 Statistics without arbitrage agents

trading	execution rate	32.3%
	cancel rate	26.1%
	number of trades / 1 day	6467
standard deviations	for 1 tick	0.0512%
	for 1 day (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.

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

(2) Suitable complexity, advantages and disadvantages

(3) Typical Model

(4) Case study: tick size reduction

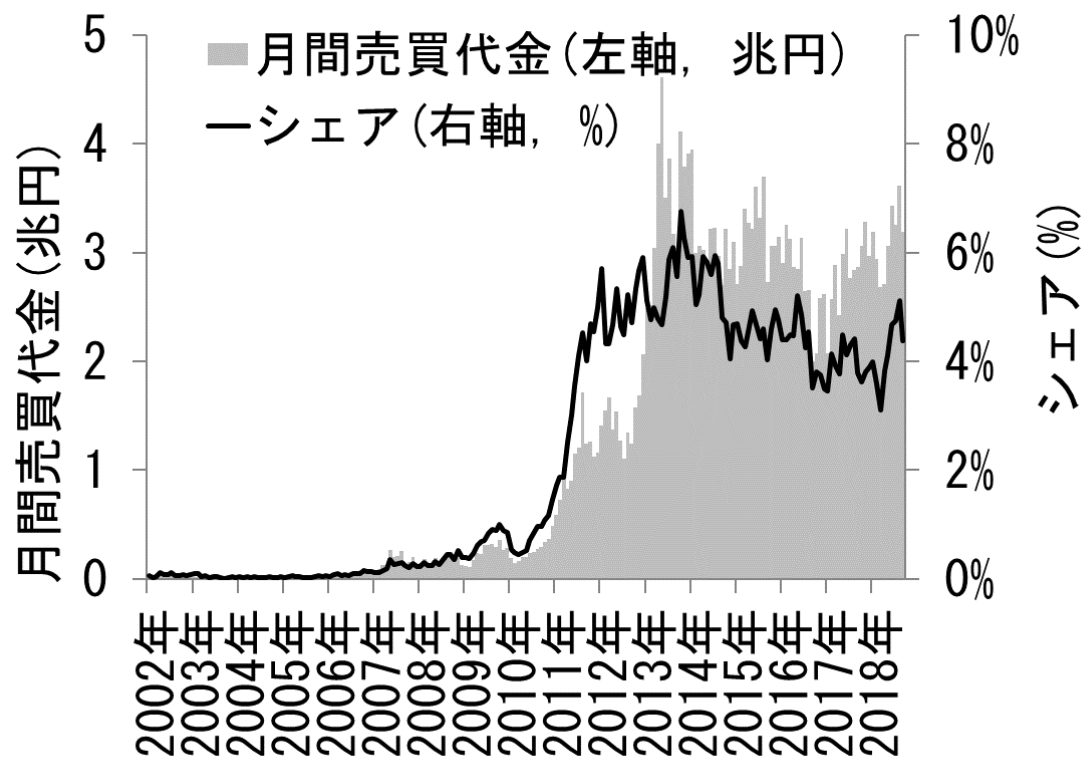
Here, I very briefly introduce Mizuta et. al. 2013 as a typical study investigating the design of a financial market using an artificial market model.

Mizuta et. al. 2013, “Investigation of Relationship between Tick Size and Trading Volume of Markets using Artificial Market Simulations”, JPX working Paper Vol. 2

<https://www.jpx.co.jp/english/corporate/research-study/working-paper/index.html>

Tick Size: Battle Between Markets

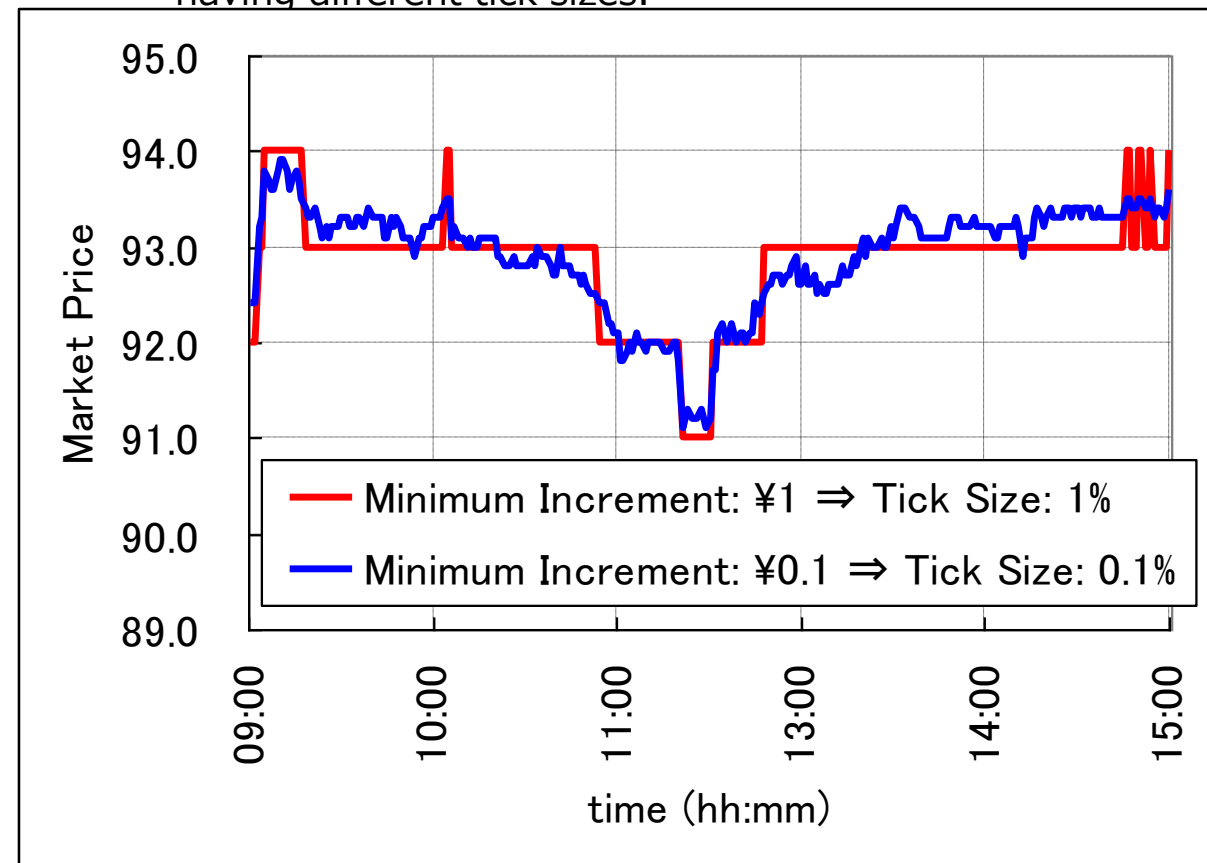
In Japan, Tokyo Stock Exchange and PTSs (proprietary trading system) battles share of trading volume. PTS: SBI Japan next securities, Chi-X Japan



マルチエージェントによる金融市場のシミュレーション, 2020/9
<https://www.coronasha.co.jp/np/isbn/9784339028225/>

Share of PTS increased

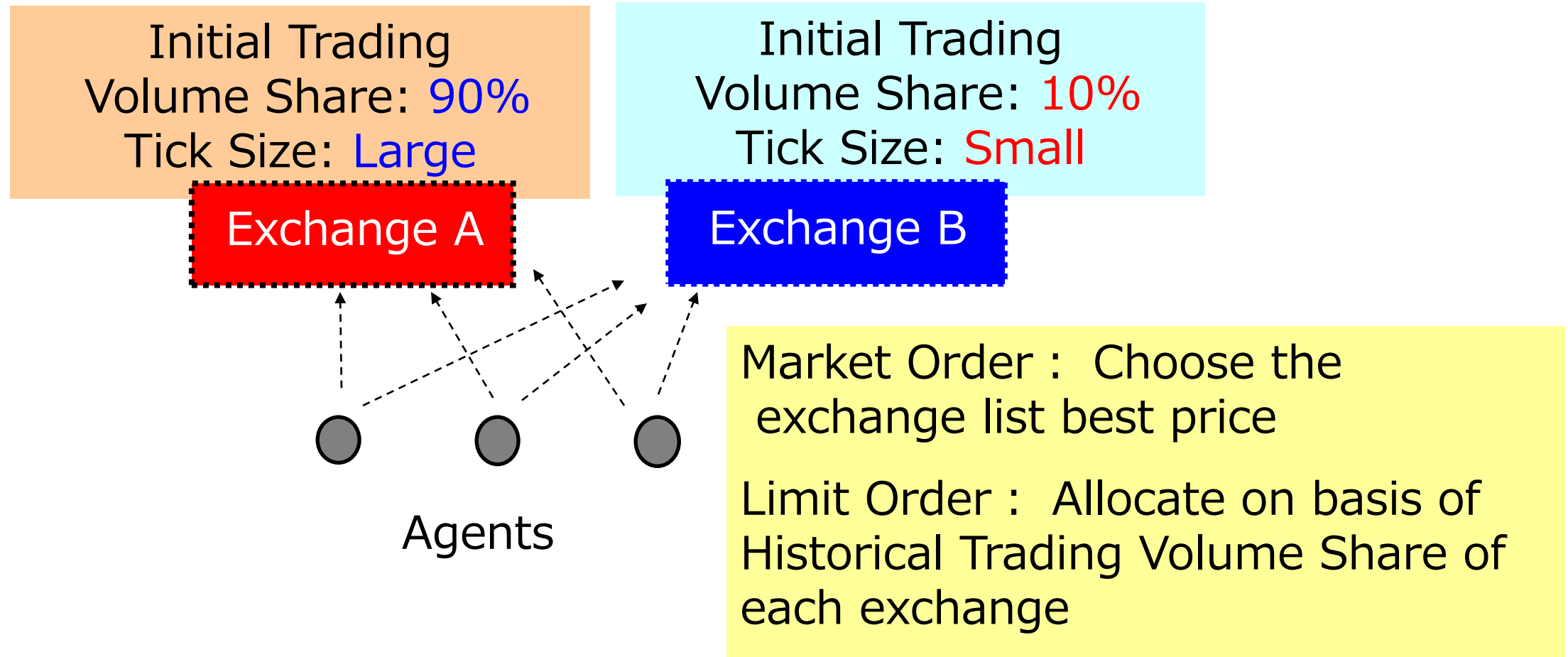
Time evolution of prices of same stock at different market having different tick sizes.



Difference of 1% Return is Serious Problem for some Investors \Rightarrow They prefer Stock Market has Smaller Tick Size

Tick size is one of the most important factor for battle between markets

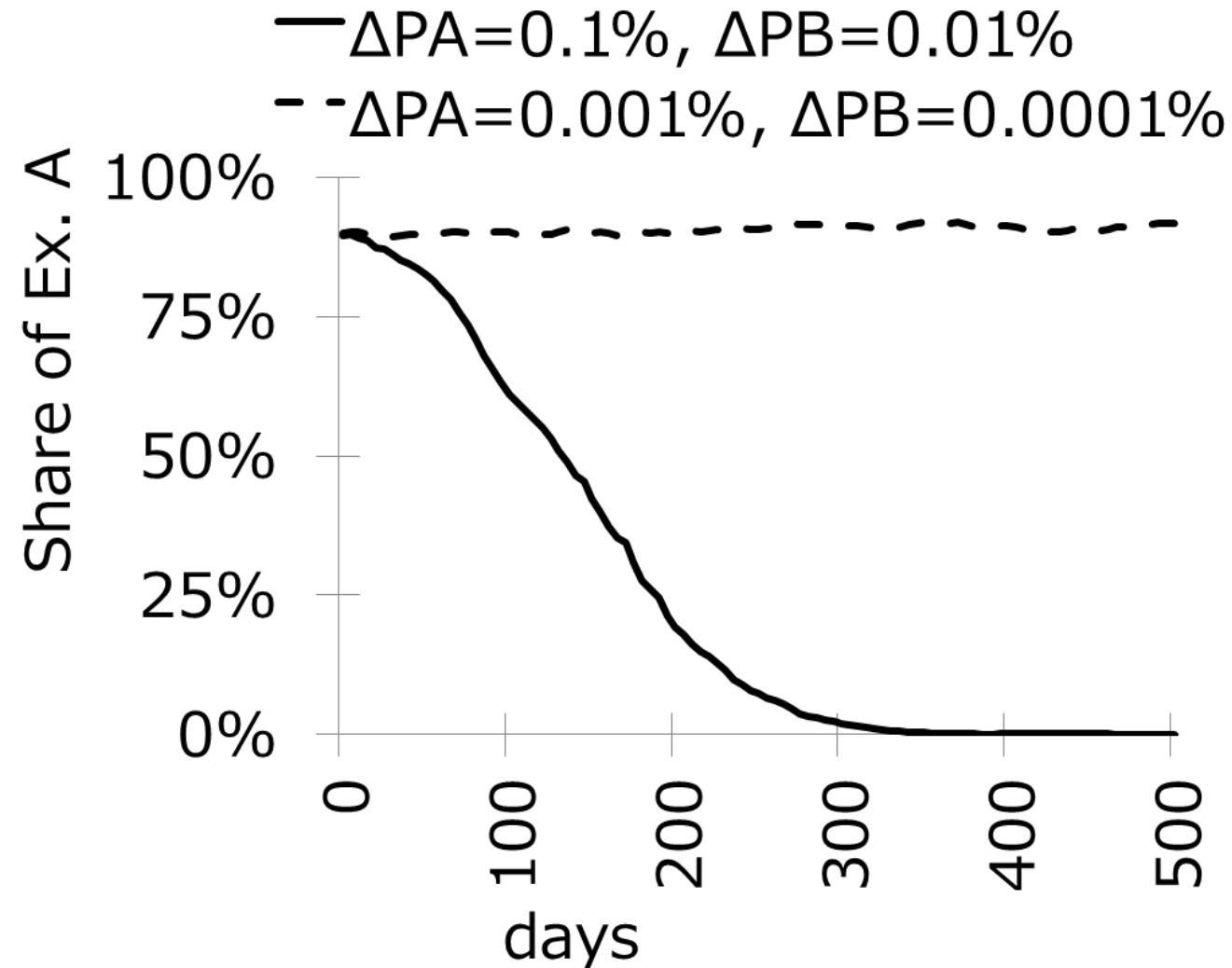
Market Selection Model



Market Order : buy or sell at the best available price, immediately

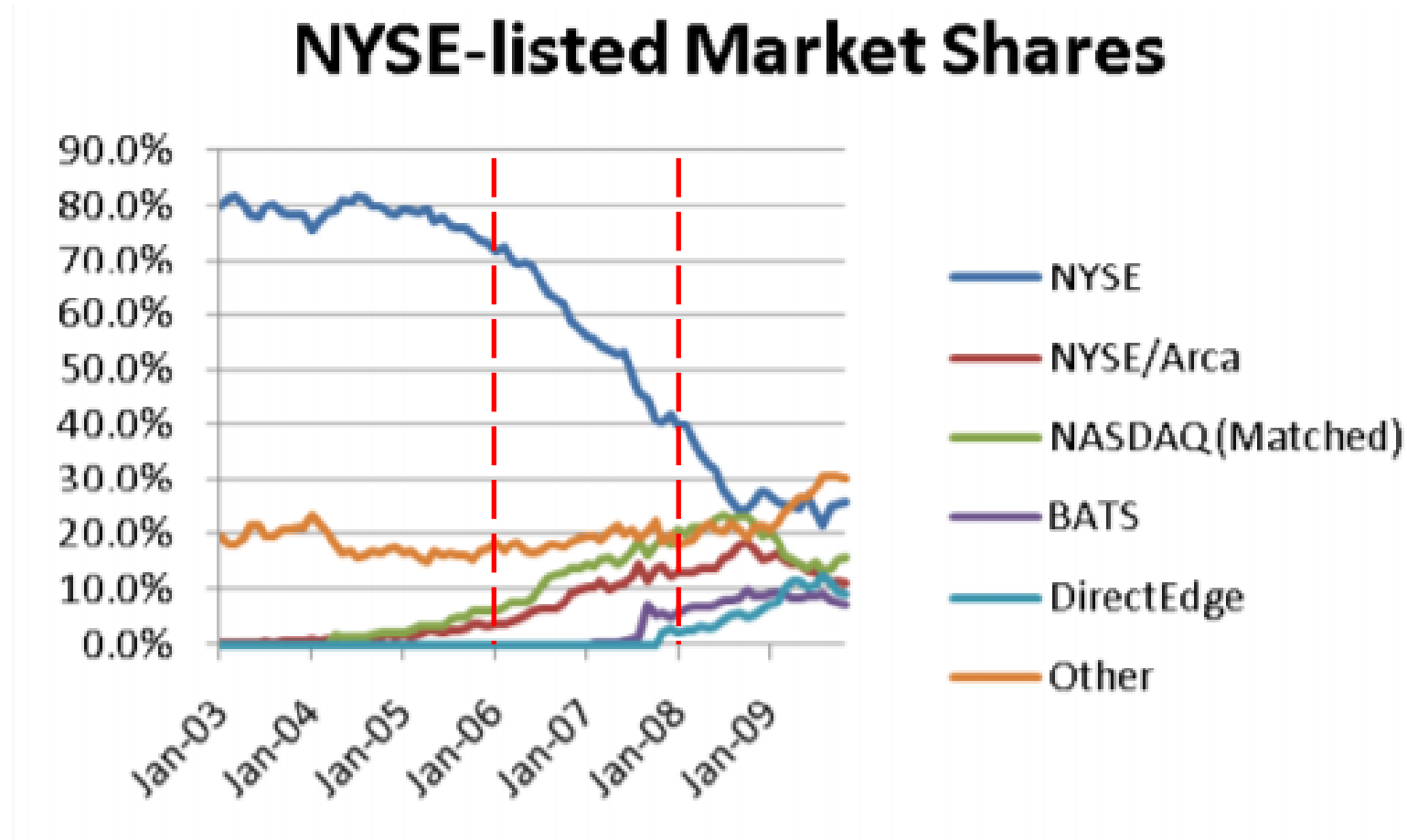
Limit Order : buy or sell at a specific price or better,
waiting opposite Market Orders

Share of Ex.A with $(\Delta PA, \Delta PB) = (0.1\%, 0.01\%), (0.001\%, 0.0001\%)$



Usually when Tick Size of Ex. A is larger, Ex. A loses volume share, however, when enough small Tick Sizes, Ex. A does NOT lose even if Tick Size of Ex.A is larger than Ex.B.

Actual Market Share of New York Stock Exchange(NYSE)



Source: *Barclays Capital Equity Research*

Angel, J., et. al., "Equity Trading in the 21st Century", Marshall School of Business Working Paper No. FBE 09-10
<https://ssrn.com/abstract=1584026>

For about 2 years, almost same time as simulation result,
NYSE lost its share and it fall from its dominant position

Tick Size Condition Not to Move Share

Share of Ex. A at 500 days		Tick Size of Ex. B						
		0.001%	0.002%	0.005%	0.01%	0.02%	0.05%	0.1%
Tick sizes of Ex. A	0.001%	90%	92%	94%	97%	99%	100%	100%
	0.002%	89%	91%	93%	97%	99%	100%	100%
	0.005%	84%	87%	92%	96%	99%	100%	100%
	0.01%	77%	78%	83%	92%	98%	100%	100%
	0.02%	54%	54%	59%	70%	93%	100%	100%
	0.05%	5%	5%	5%	6%	23%	93%	100%
	0.1%	0%	0%	0%	0%	0%	0%	94%

Condition Not to
Move Share

$$\Delta P_B > \Delta P_A$$

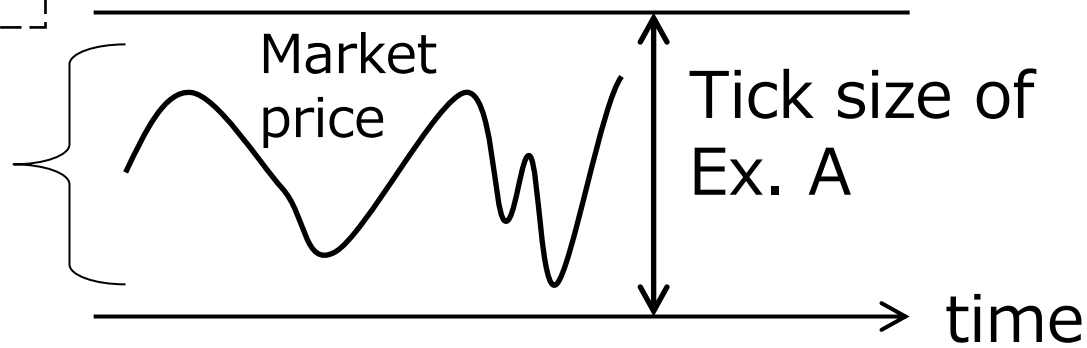
or

$$\bar{\sigma}_t > \Delta P_A$$

$$\bar{\sigma}_t = 0.05\%$$

$$\bar{\sigma}_t < \Delta P_A$$

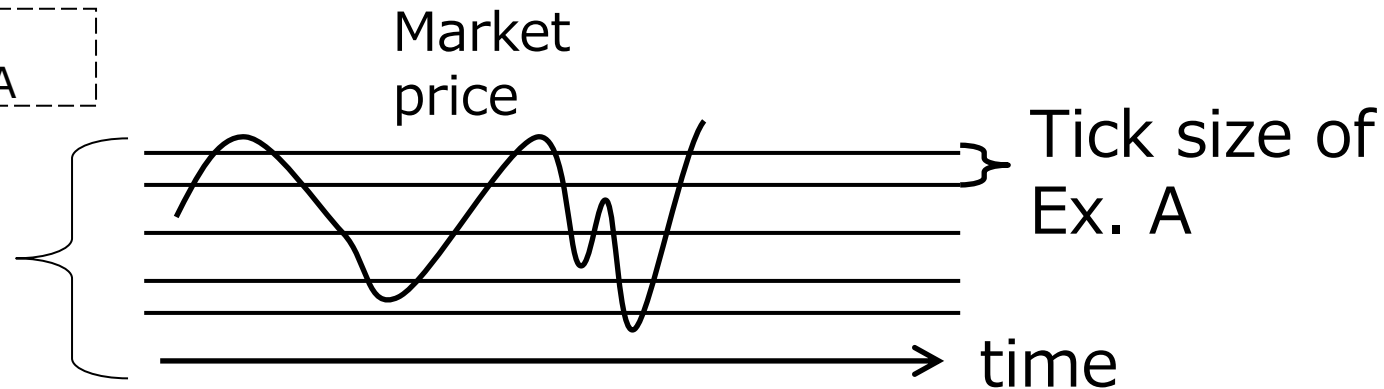
Impossible
to trade at
Ex. A



Ex. A never represents
movement of market prices. \Rightarrow Orders move to Ex. B

$$\bar{\sigma}_t > \Delta P_A$$

Enough
resolution
at Ex. A



Ex. A represents them. \Rightarrow not need Ex. B

An Aim is to understand how Important Properties (Tick-Size) affect Investigating Macro Phenomena (Market Share) and play Roles in System.

It is NOT aim Replicating real-existing Investors and Market Prices,
but understanding mechanism of the system.

Progress of study after that

Equational model led similar result with the artificial market model

- <- Not the ratio but the difference of tick sizes determines the speed of taking share
- <- Too small tick size battle is not effective

CSP16

Journal of Physics: Conference Series 750 (2016) 012019

IOP Publishing

doi:10.1088/1742-6596/750/1/012019

Market A is chosen at a probability 1 in case of (i) and 1/2 in case of (iii). Likewise, market B is chosen at a probability 1 in case of (ii) and 1/2 in case of (iii). Therefore, share of market A and B should be

$$\begin{aligned} S_A^* &= 1 \cdot P_1' + \frac{1}{2} P_3' \\ &= \frac{1}{2} - \frac{1}{2}(a-b), \end{aligned} \quad (4)$$

$$\begin{aligned} S_B^* &= 1 \cdot P_2' + \frac{1}{2} P_3' \\ &= \frac{1}{2} - \frac{1}{2}(b-a). \end{aligned} \quad (5)$$

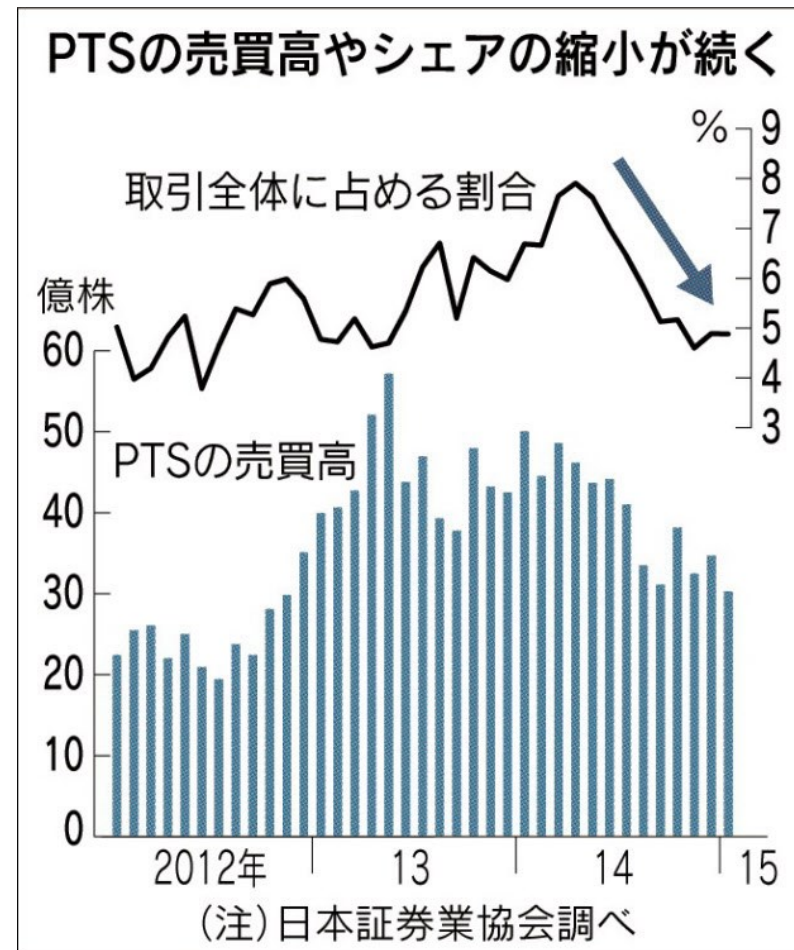
Therefore, it is found that share is shifted from a market with a larger tick size to a market with a smaller tick size. Moreover, the size of share-shift is determined by difference between tick sizes, not ratio between tick sizes.

Share of PTS decreased after the tick size reduction
2015/2/27 Nikkei news paper

<https://www.nikkei.com/article/DGKKZO83727450W5A220C1DTA000/>

After the tick size reduction

- Nagumo, S. et. al.(2016), The effect of tick size on trading volume share in three competing stock markets, Journal of Physics: Conference Series, vol. 750,no.1. <https://doi.org/10.1088/1742-6596/750/1/012019>
- Nagumo, S. et. al.(2017), The Effect of Tick Size on Trading Volume Share in Two Competing Stock Markets, Journal of the Physical Society of Japan, vol. 86,no.1. <https://doi.org/10.7566/JPSJ.86.014801>



Summary

This talk showed a philosophy of an agent-based artificial market model. Why are models needed? How models should be? In the first place, what is a model? We should understand what is a model deeper to discuss healthy using a model. I will try to clear up a common misunderstanding for a model.

Someone may think tick size reduction is a trivial matter for a financial market. This is, however, important and should not be underestimated. Changing detailed rules sometimes causes unexpected large impacts and side effects. John McMillan illustrated this nature as "both God and the devil are in the details". Detailed design can determine whether a financial market develops or destroys an advanced economy. Designing a market well is very important for developing and maintaining an advanced economy, but not easy.

I hope that more agent-based artificial market models will contribute to designing a financial market that works well to further develop and maintain advanced economies.

More detailed Summary

- ✓ Designing a financial market that works well is very important for developing and maintaining an advanced economy, but is not easy because changing detailed rules, even ones that seem trivial, sometimes causes unexpected large impacts and side effects.
- ✓ A computer simulation using an agent-based model can directly treat and clearly explain such complex systems where micro processes and macro phenomena interact. Recently, an artificial market model, which is an agent-based model for a financial market, has started to contribute to discussions on rules and regulations of actual financial markets.
- ✓ We should understand what is a model deeper for healthy discussion using a model. I tried to clear up a common misunderstanding for a model. Why are models needed? How models should be? In the first place, what is a model?
- ✓ The purpose of simulation is understanding the reasons and mechanism, not exactly forecasting the real world. 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. We must shave non-investigating features from the model. Different investigations, different shaving parts.
- ✓ I briefly introduced an artificial market model to design financial markets that work well and describe a previous study investigating tick size reduction. I hope that more artificial market models will contribute to designing financial markets that work well to further develop and maintain advanced economies.

Talk 1: An agent-based model for designing a financial market that works well

Talk 2: Can an AI perform market manipulation at its own discretion? - A genetic algorithm learns in an artificial market simulation -

For Talk 2, there is my Conference paper, read it if you are interested

Conference Paper

Mizuta 2020, “Can an AI perform market manipulation at its own discretion? - A genetic algorithm learns in an artificial market simulation -”, IEEE Symposium Series on Computational Intelligence, Computational Intelligence for Financial Engineering and Economics (CIFEr), December 1 to 4, 2020, Canberra, Australia(virtual)

<https://doi.org/10.1109/SSCI47803.2020.9308349>


<https://arxiv.org/abs/2005.10488>

Presentation on YouTube <https://youtu.be/Rzfm9C4FPNg>

2020 IEEE Symposium Series on Computational Intelligence (SSCI) on Computational Intelligence for Financial Engineering and Economics (CIFEr) <http://www.ieeessci2020.org/>

Paper ID: #31

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



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

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

Publisher: IEEE [Cite This](#) [PDF](#)

Takanobu Mizuta [All Authors](#)

33 Full Text Views

Abstract

Who should be held responsible when artificial intelligence (AI) performs market manipulation? 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 though the AI developer had no intention of manipulating the market. Results showed that the AI trader discovered market manipulation as an optimal investment strategy. This suggests that regulation is necessary, such as requiring developers to prevent AIs from performing market manipulation. The results also suggest that developers should limit AI traders to avoid impacting market prices.

Document Sections

- I. Introduction
- II. Model
- III. Simulation Result
- IV. Summary and

2020 IEEE Symposium Series on Computational Intelligence (SSCI)
on Computational Intelligence for Financial Engineering
and Economics (CIFEr) <http://www.ieeessci2020.org/>

Paper ID: #31

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



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

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(1) Introduction

(2) Model

(3) Simulation Result

(4) Summary

(1) Introduction

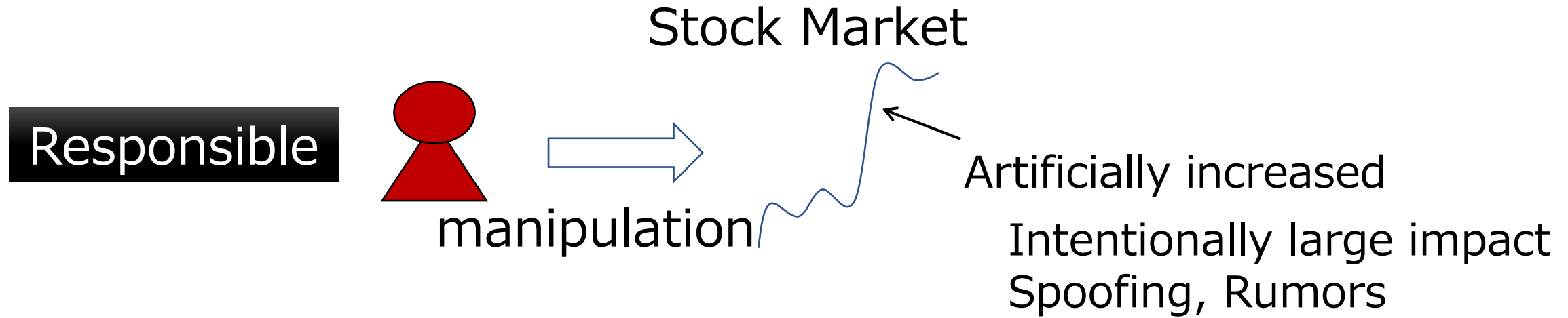
(2) Model

(3) Simulation Result

(4) Summary

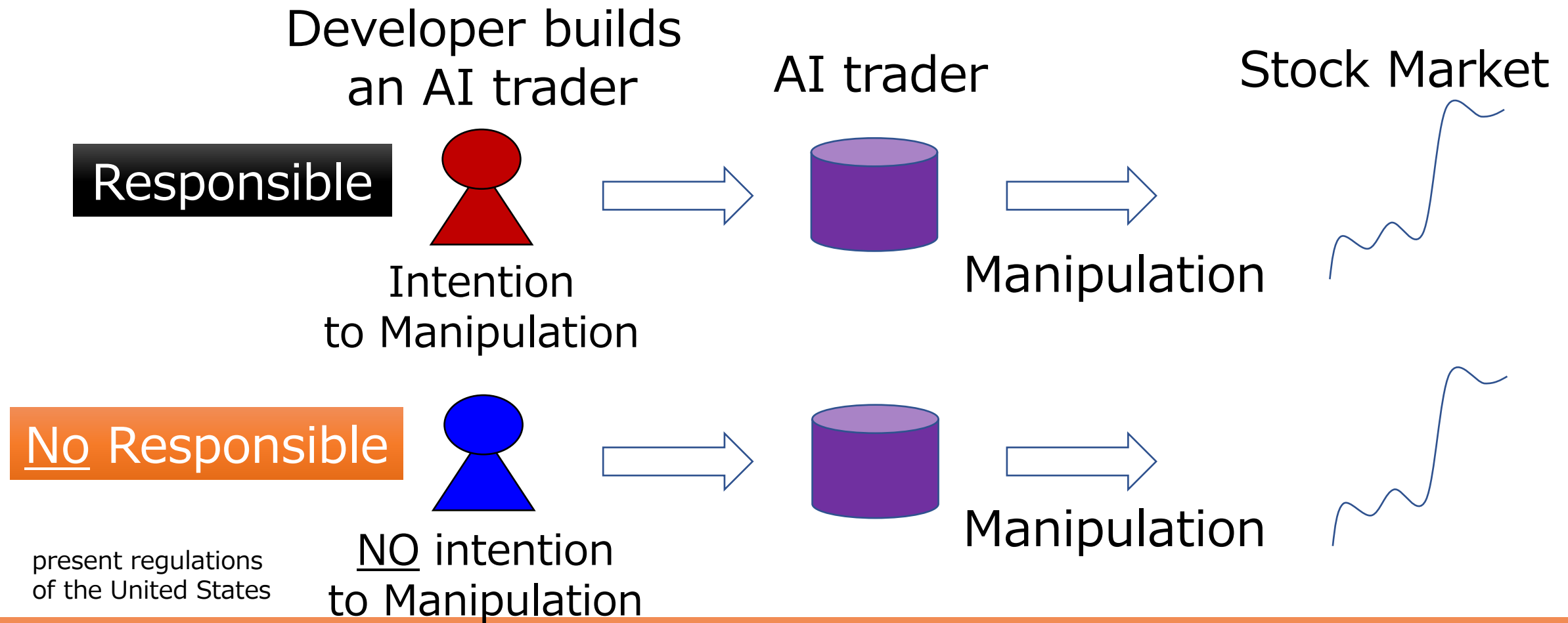
Market manipulation is prohibited

Traders artificially increasing or decreasing market prices to profit



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 be held responsible

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

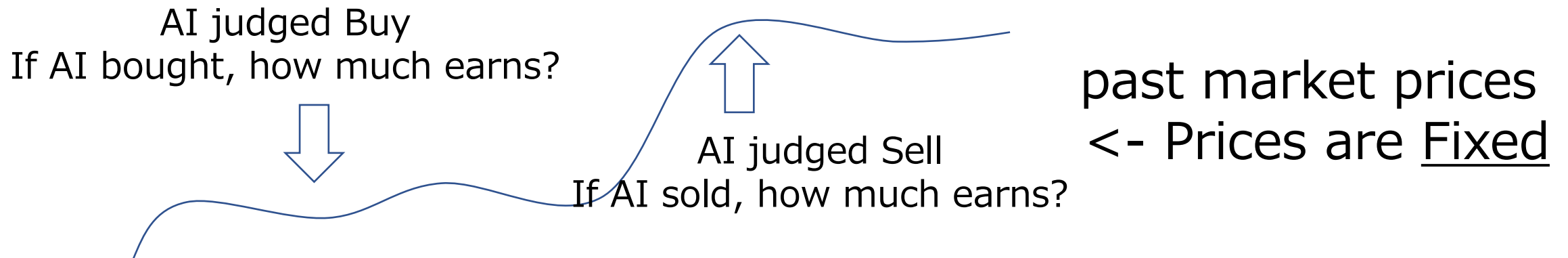
Can AI trader discover market manipulation?

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.



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

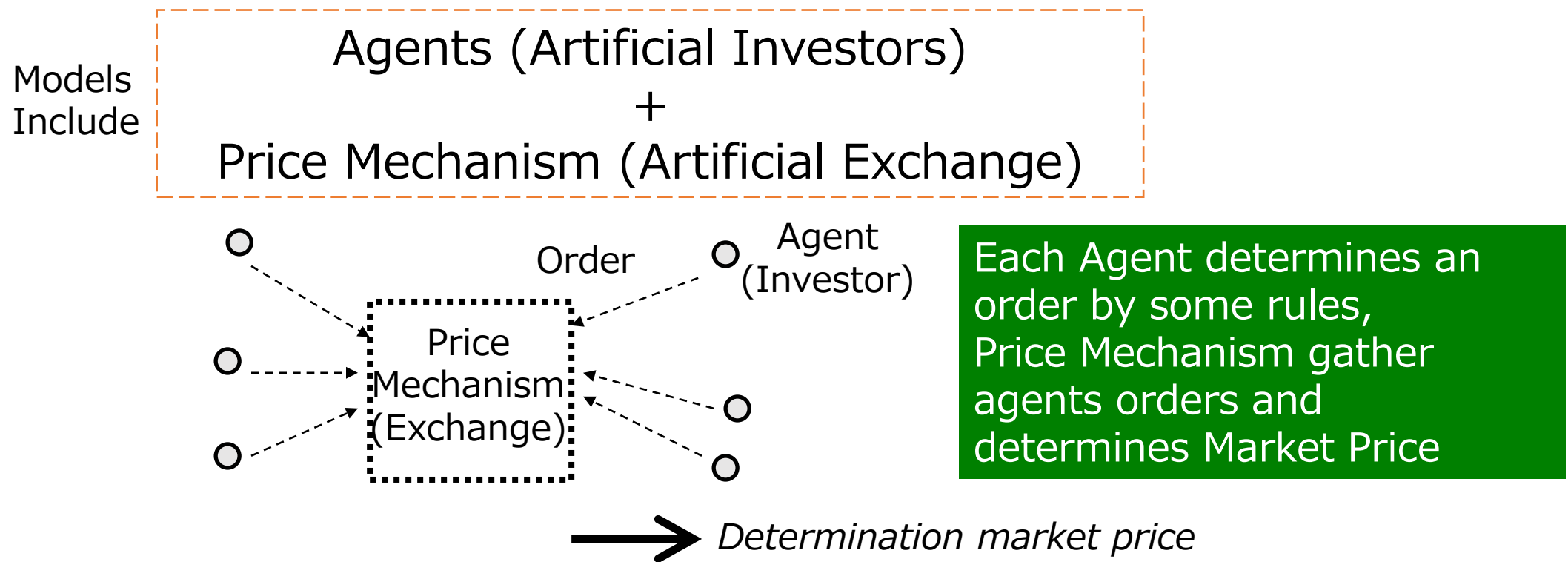
An AI trader cannot discover market manipulation by backtesting

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.

Virtual and Artificial financial Market built on Computers



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.

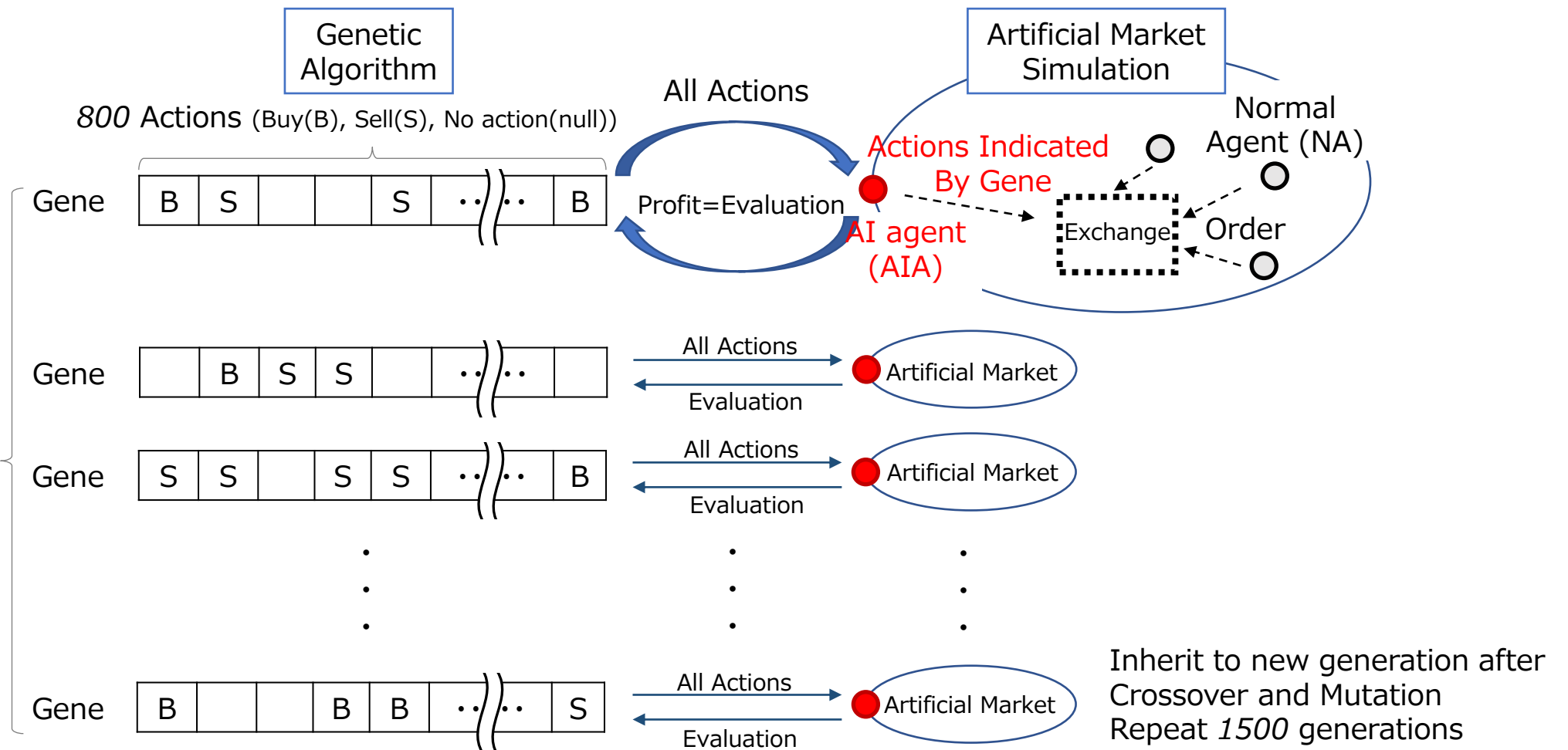
(1) Introduction

(2) Model

(3) Simulation Result

(4) Summary

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

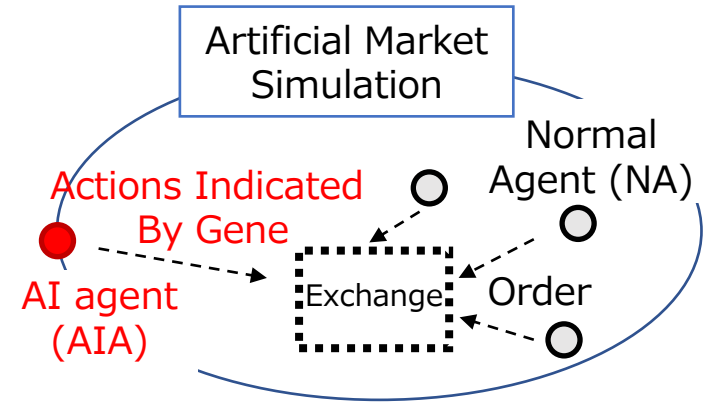
Stock Exchange

continuous double auction

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

When sell order come here
transaction immediately occurs

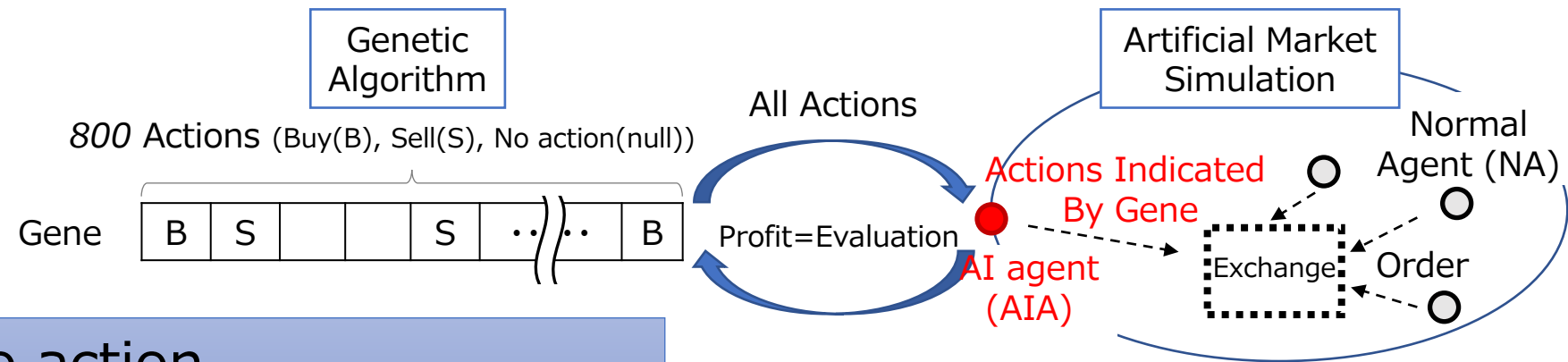
When buy order come here
transaction immediately occurs



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.

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
 $\sigma=3\%$

Expected Price of each NA

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

Fundamental and Technical Strategies

Fundamental Strategy

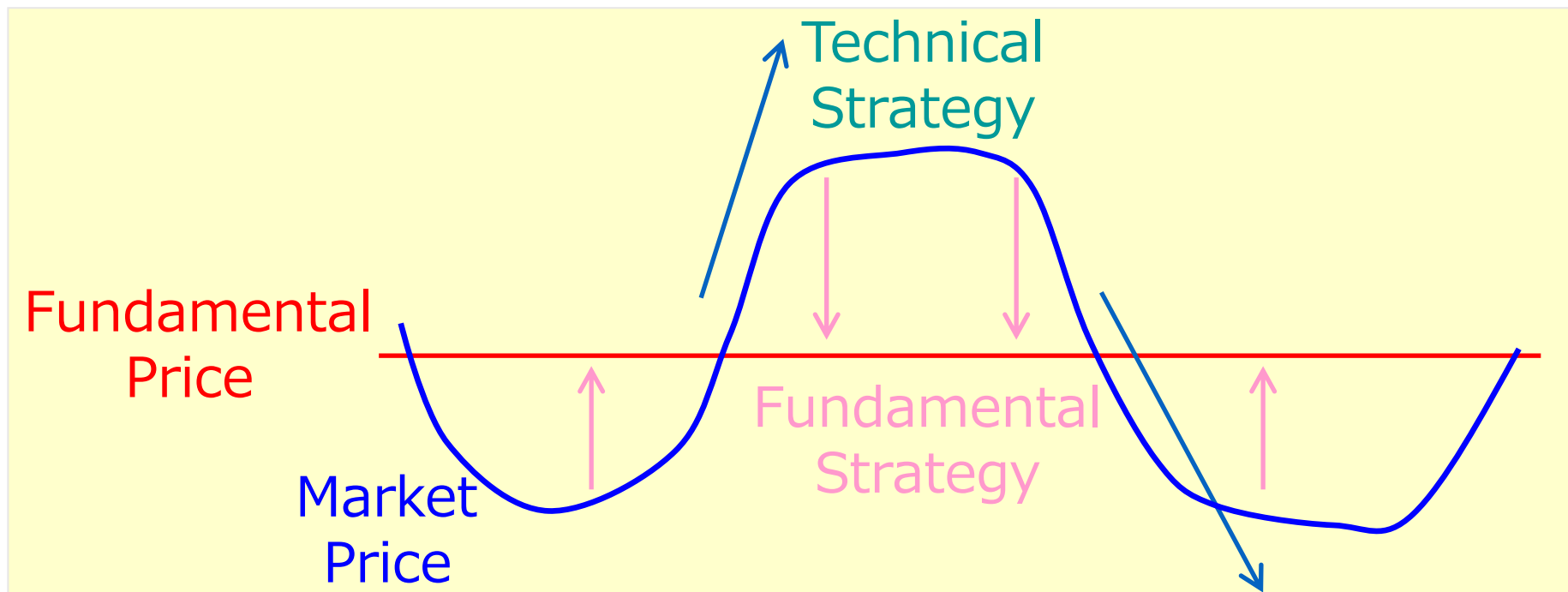
Fundamental Price $>$ Market Price \rightarrow Expect + return

Fundamental Price $<$ Market Price \rightarrow Expect - return

Technical Strategy

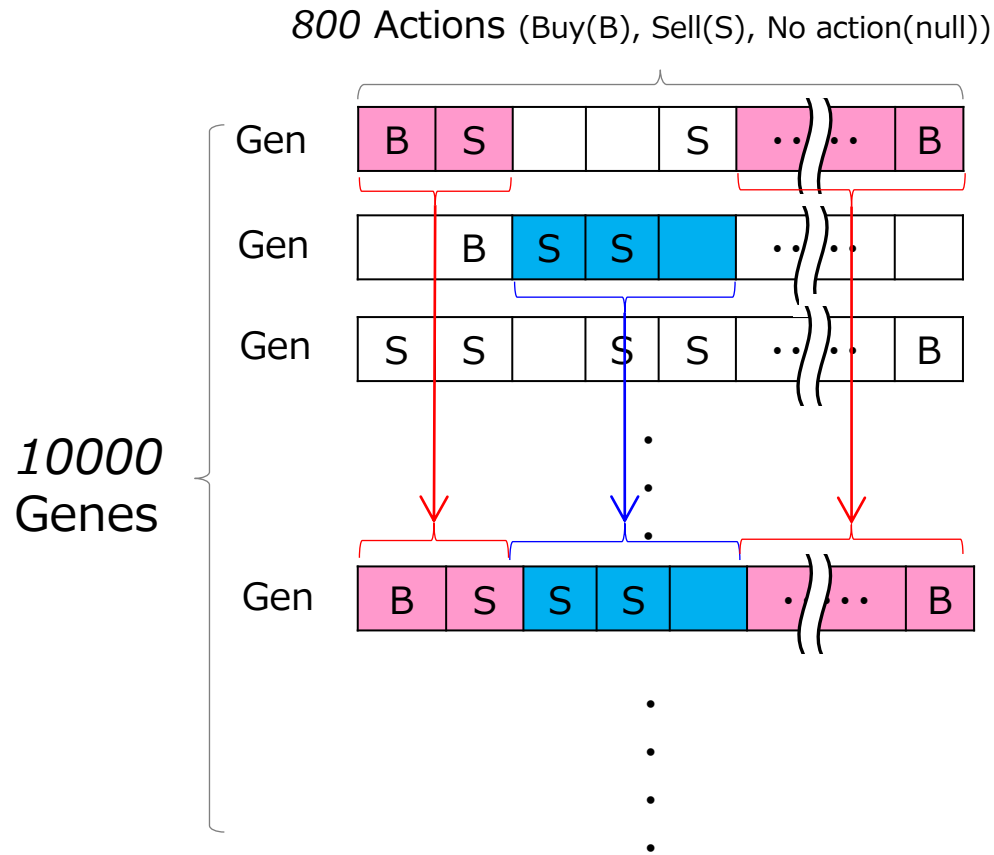
Historical Return $> 0 \rightarrow$ Expect + return

Historical Return $< 0 \rightarrow$ 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]

(1) Introduction

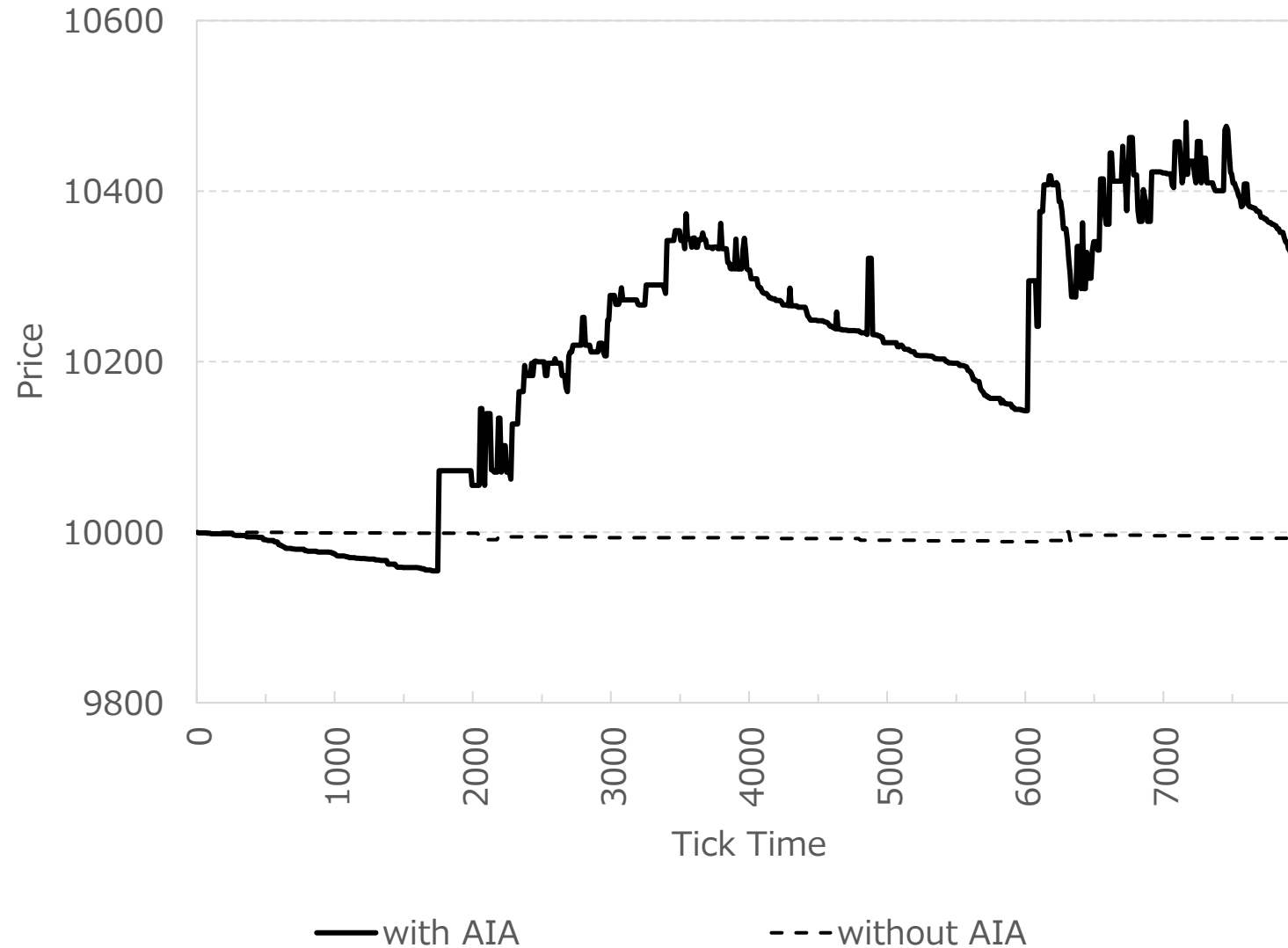
(2) Model

(3) Simulation Result

(4) Summary

Time evolution of market prices with the AIA and without

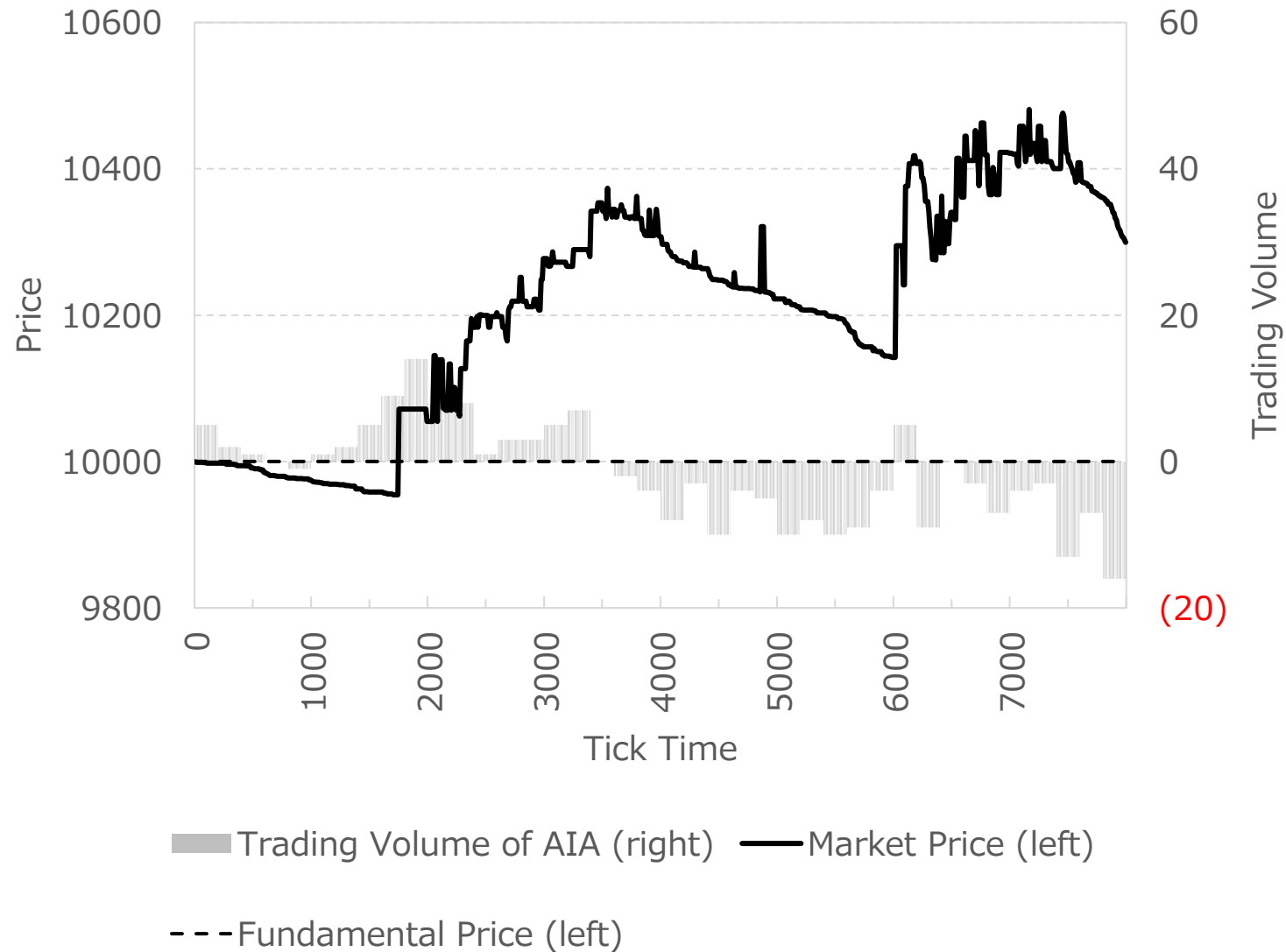
(In the following result, I used the AIA of the optimal gene in the final generation.)



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.

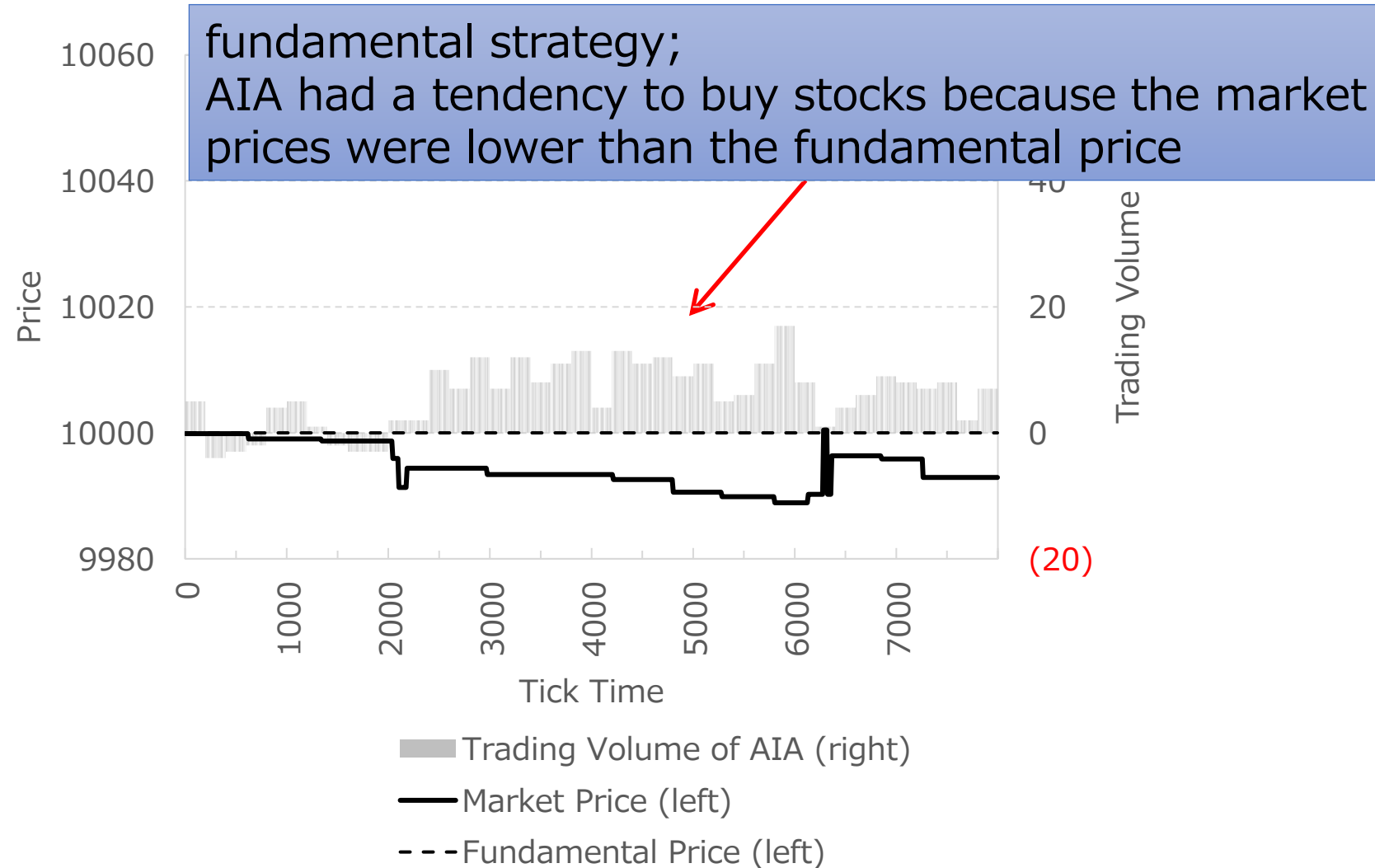
market prices continued to increase even though the AIA did not buy many stocks, because technical strategy of NA, a larger positive return was expected due to the previous positive return



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



AIA could not discover market manipulation as trading strategy

Additional Ten Simulation Runs

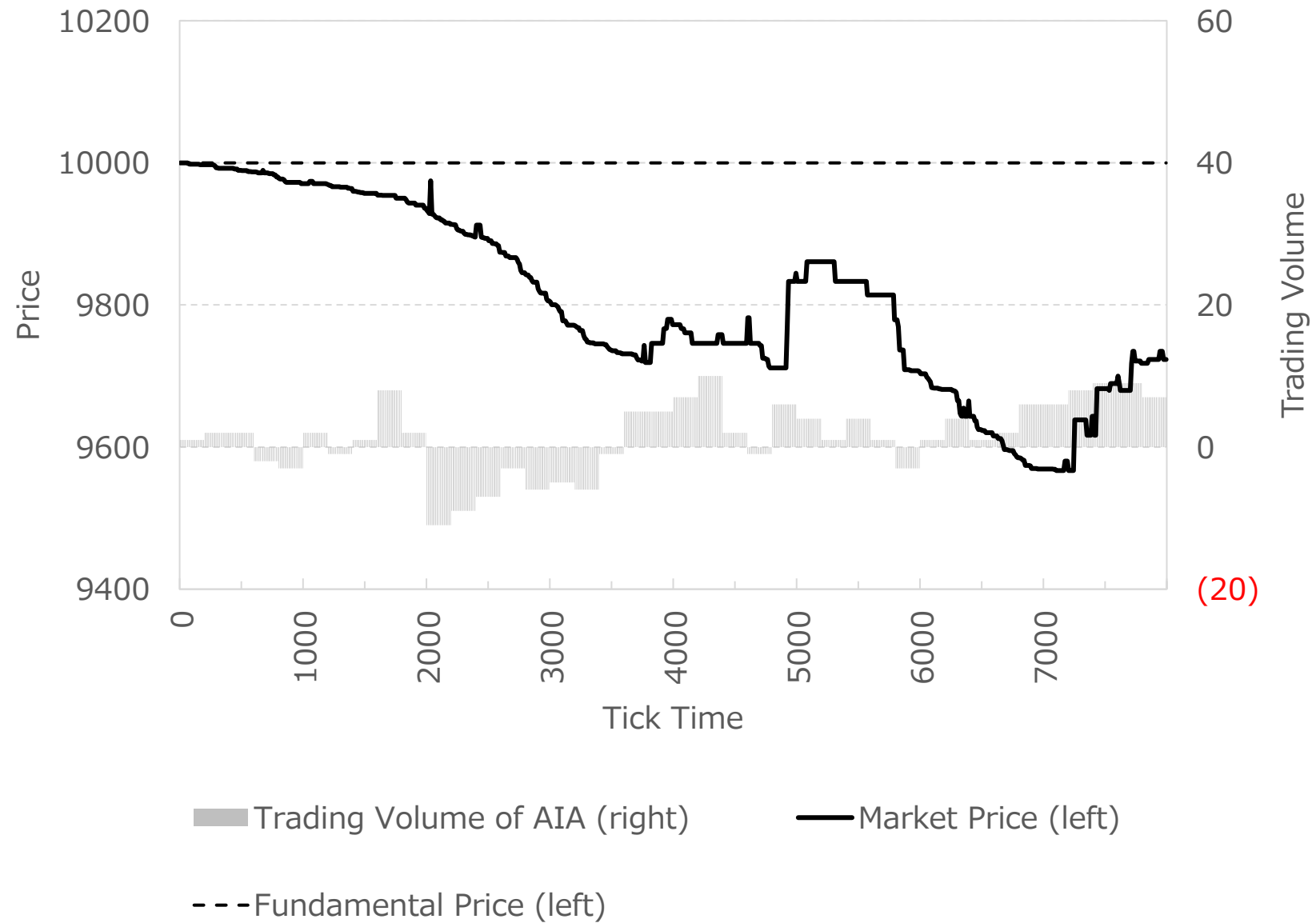
No.	Min/Pf-1	Max/Pf-1	(Max-Min)/Pf	Simulation Trading Volume of AIA	Result Type
2	-0.59%	4.12%	4.7%	518	Manipulation(overbuying)
3	-0.63%	4.49%	5.1%	506	Manipulation(overbuying)
4	-0.77%	5.37%	6.1%	496	Manipulation(overbuying)
5	-4.33%	0.00%	4.3%	414	Manipulation(underselling)
6	-0.14%	0.00%	0.1%	0	No 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.	Back Testing			Trading Volume of AIA	Result Type
	Min/Pf-1	Max/Pf-1	(Max-Min)/Pf		
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)



(1) Introduction

(2) Model

(3) Simulation Result

(4) Summary

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.