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Agent-Based Model of Liquidity and Arbitrage Cost Between ETF and Stocks

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(1) Introduction

(2) Artificial Market Model

(3) Simulation Result

(4) Summary

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ETF and Liquidity

Exchange-Traded Fund (ETF)

- ✓ a mutual fund that invests in a diversified portfolio of many stocks or bonds
- ✓ listed and traded at a stock exchange

ETFs have been widely spread to individual investors as an easy way to diversify their investments.

On the other hand,

Some ETFs have not been traded with enough volume (low liquidity) to discover an adequate price, making them difficult for individual investors to trade.

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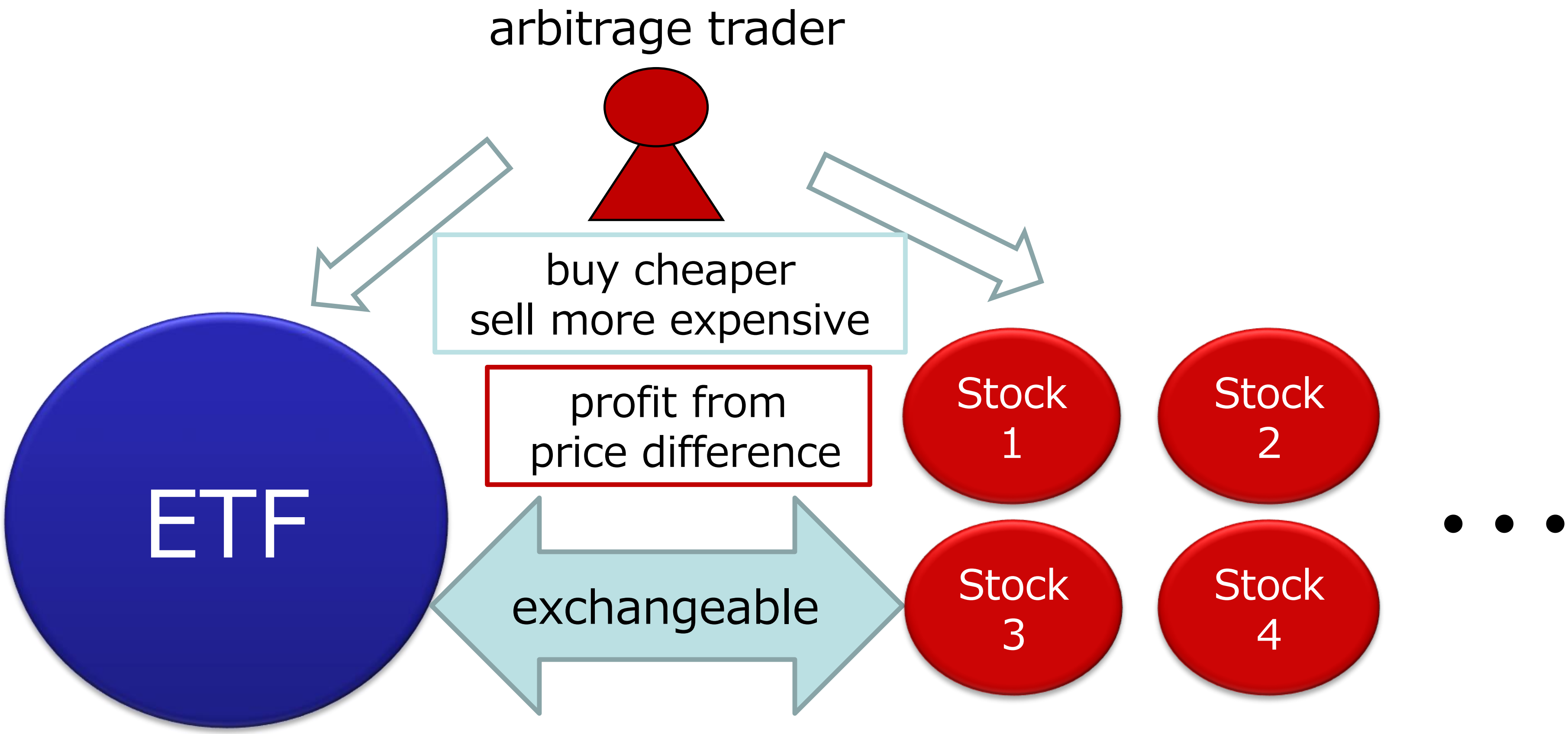
Exchangeable, Arbitrage Trades

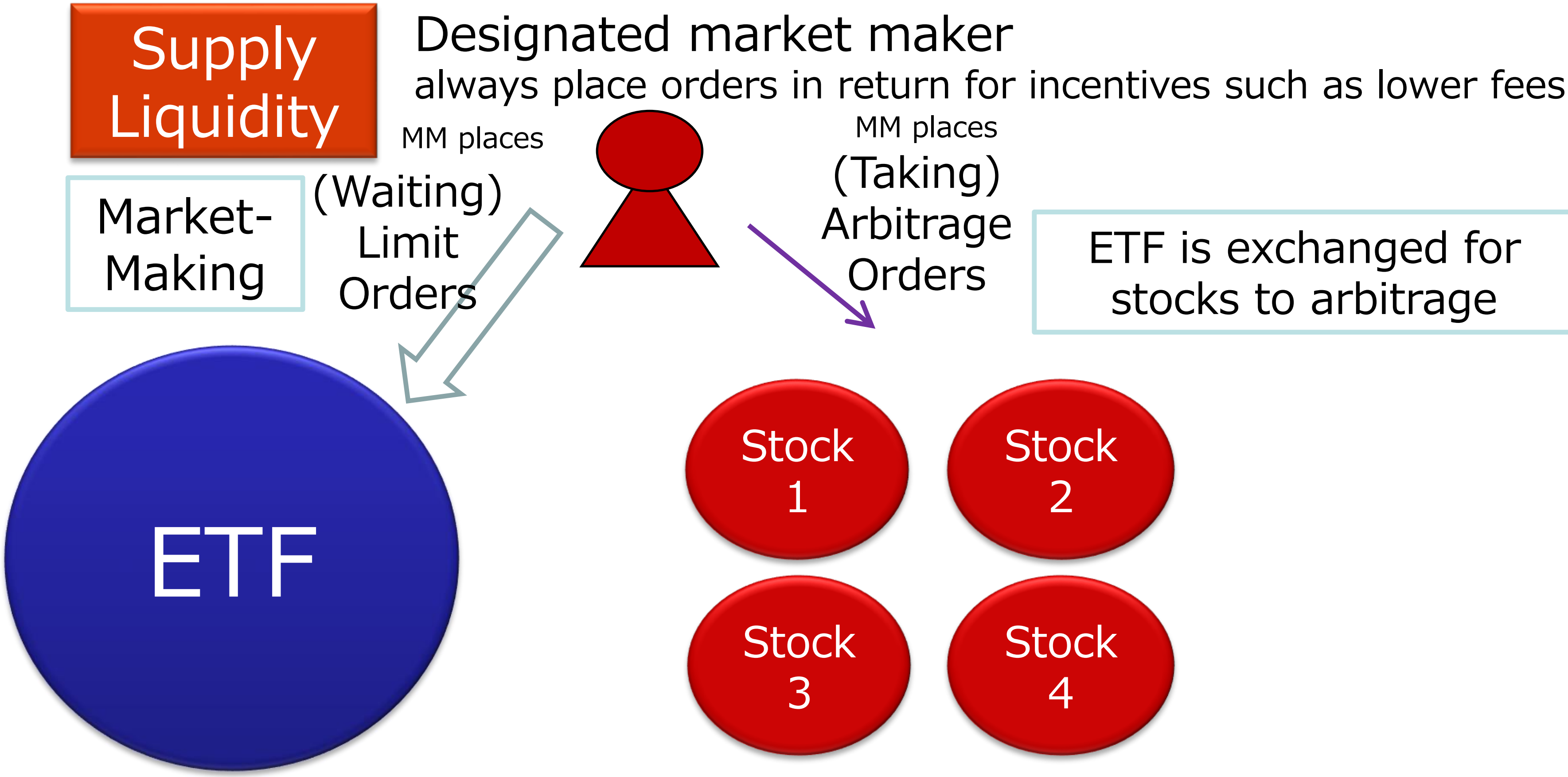


An ETF is exchangeable with all stocks held by the ETF.

When the price of the ETF and the total value of the stocks held by the ETF differ, a trader can buy the cheaper asset, exchange, sell the more expensive asset, and thus earn a profit from the price difference.

Increasing arbitrage traders is increasing liquidity

Market-making incentive Scheme



To increase the liquidity of low-liquidity ETFs, in 2018 the Tokyo Stock Exchange introduced a market-making incentive scheme, in which designated market makers always place orders in return for incentives such as lower fees [JPX 17].

The questions, however, of how liquidity changes depending on arbitrage trading costs and of what the mechanism is remain to be answered.

Difficulty of Empirical Study

Empirical Studies

- ✓ cannot be conducted to investigate situations that have never occurred in actual financial markets
- ✓ cannot be conducted to isolate the direct effect on liquidity because so many factors affect price formation and liquidity in actual markets

Therefore, in this study,

I expanded the artificial market model of [Mizuta 13] to include three risk assets, two stocks and an ETF. I also added an arbitrage agent to perform arbitrage trading among these risk assets.

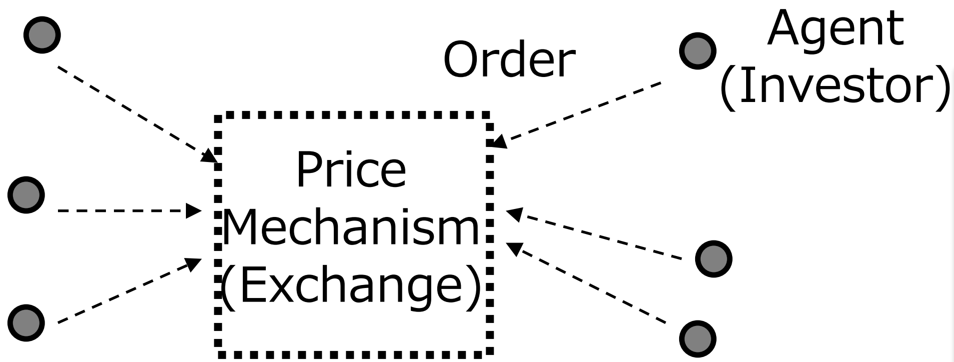
I then investigated the relationship between the liquidity of an ETF and the trading costs.

Artificial Market Simulation (Agent-Based Model)

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 changing the cost of arbitrage trades

Previous Contributions of Artificial Market Simulations

Many studies have investigated the effects of several changing financial regulations and rules by using artificial market,

Reduction of Tick Size, Up-Tick Rule,
Price Variation Limit, Dark Pool, Frequently Batch Auction,
Contribution of HFTs for share competition among Exchanges,
Suitable Latency of Exchange System, VaR Shock,
Chain Bankruptcy of Banks,
Regulations and Rules to prevent Financial Crush

- Mizuta (2019) An agent-based model for designing a financial market that works well, arXive, https://arxiv.org/abs/1906.06000
- Mizuta (2016) A Brief Review of Recent Artificial Market Simulation Studies for Financial Market Regulations And/Or Rules, SSRN Working Paper Series http://ssrn.com/abstract=2710495

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

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

Regulators, Central Bankers, Stock Exchanges

JPX
JAPAN EXCHANGE GROUP
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,
9 papers of all 31 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 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
http://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 http://www.macfinrobods.eu/research/workpackages/WP7/wp7.html

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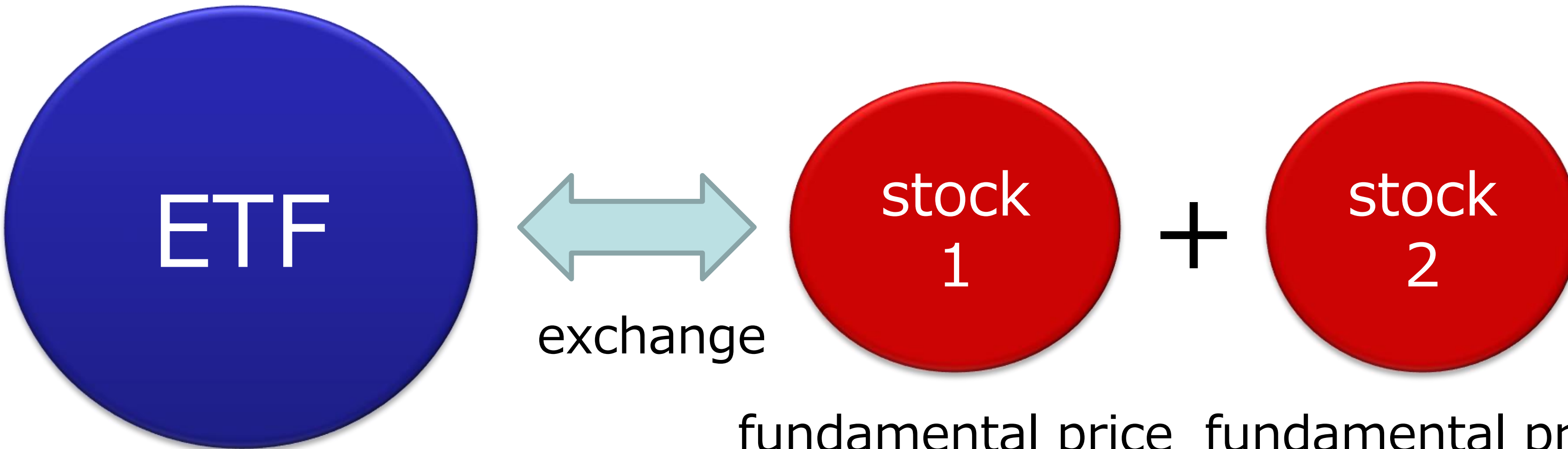
exchangeable like as

ETF(one share) = Stock 1(one share) + Stock 2(one share)

There are 3 assets,

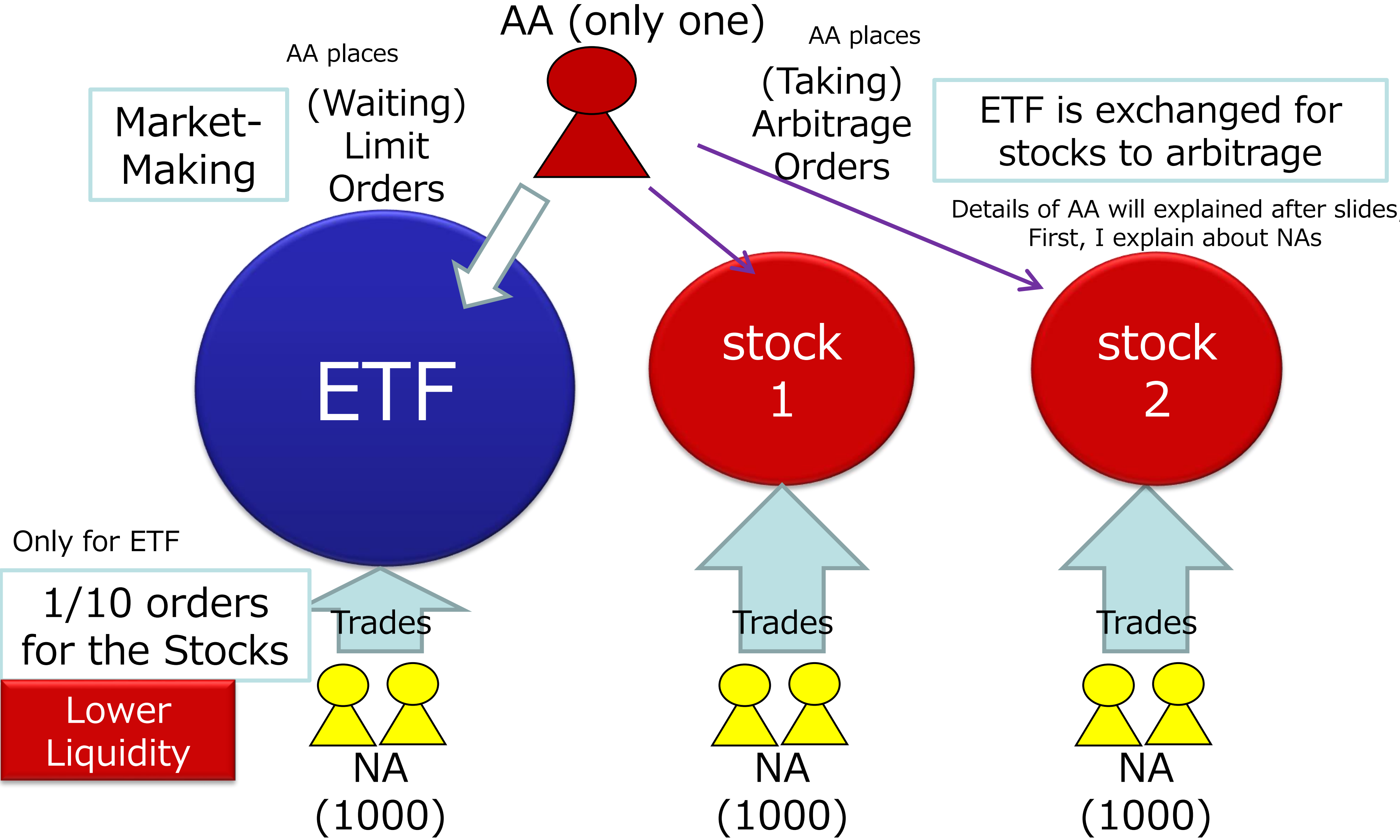


fundamental price 20000

fundamental price 10000

fundamental price 10000

Normal Agent(NA) & Arbitrage Agent(AA)



NAs place orders with 10% probability to investigate for low liquidity

For each risk asset, the model includes 1000 normal agents (NAs) that trade only that risk asset, giving a total of 3000 NAs.

Normal Agent(NA)

I used the model of Mizuta (2013), which 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.

Fundamental and Technical Strategies

Fundamental Strategy

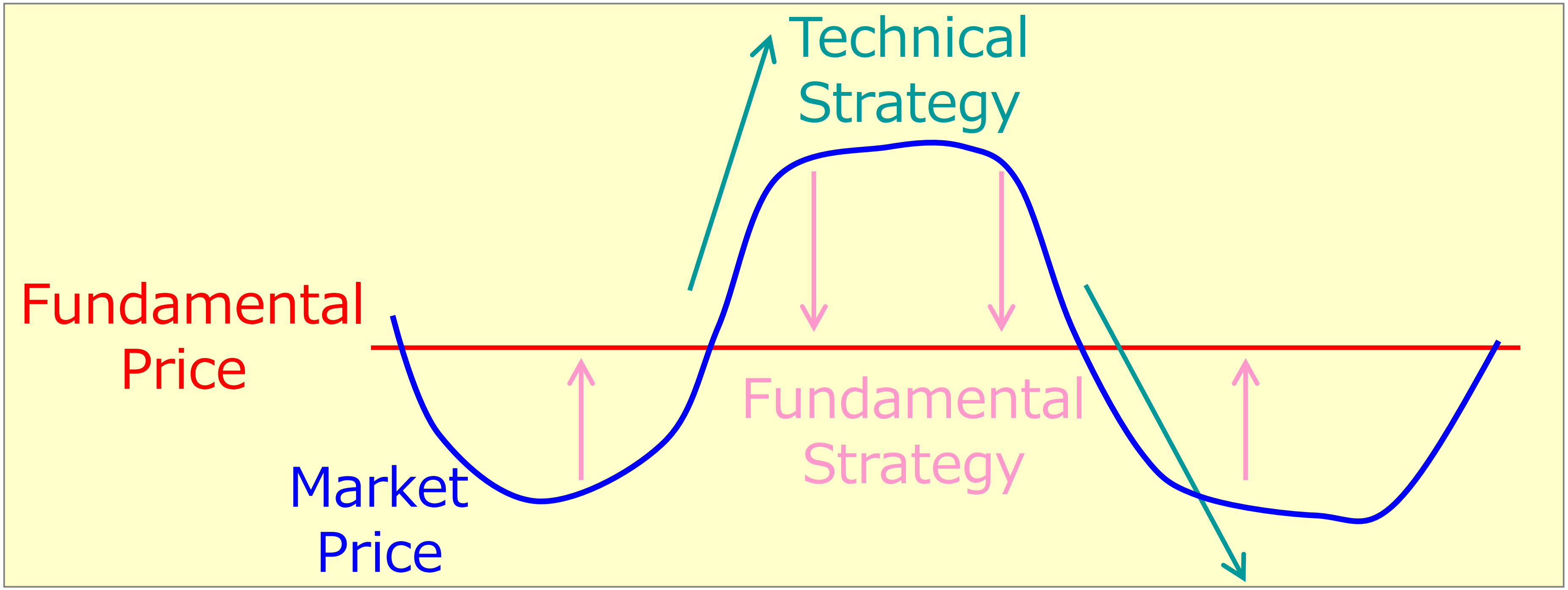
Fundamental Price > Market Price -> Expect + return

Fundamental Price < Market Price -> Expect - return

Technical Strategy

Historical Return > 0 -> Expect + return

Historical Return < 0 -> 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

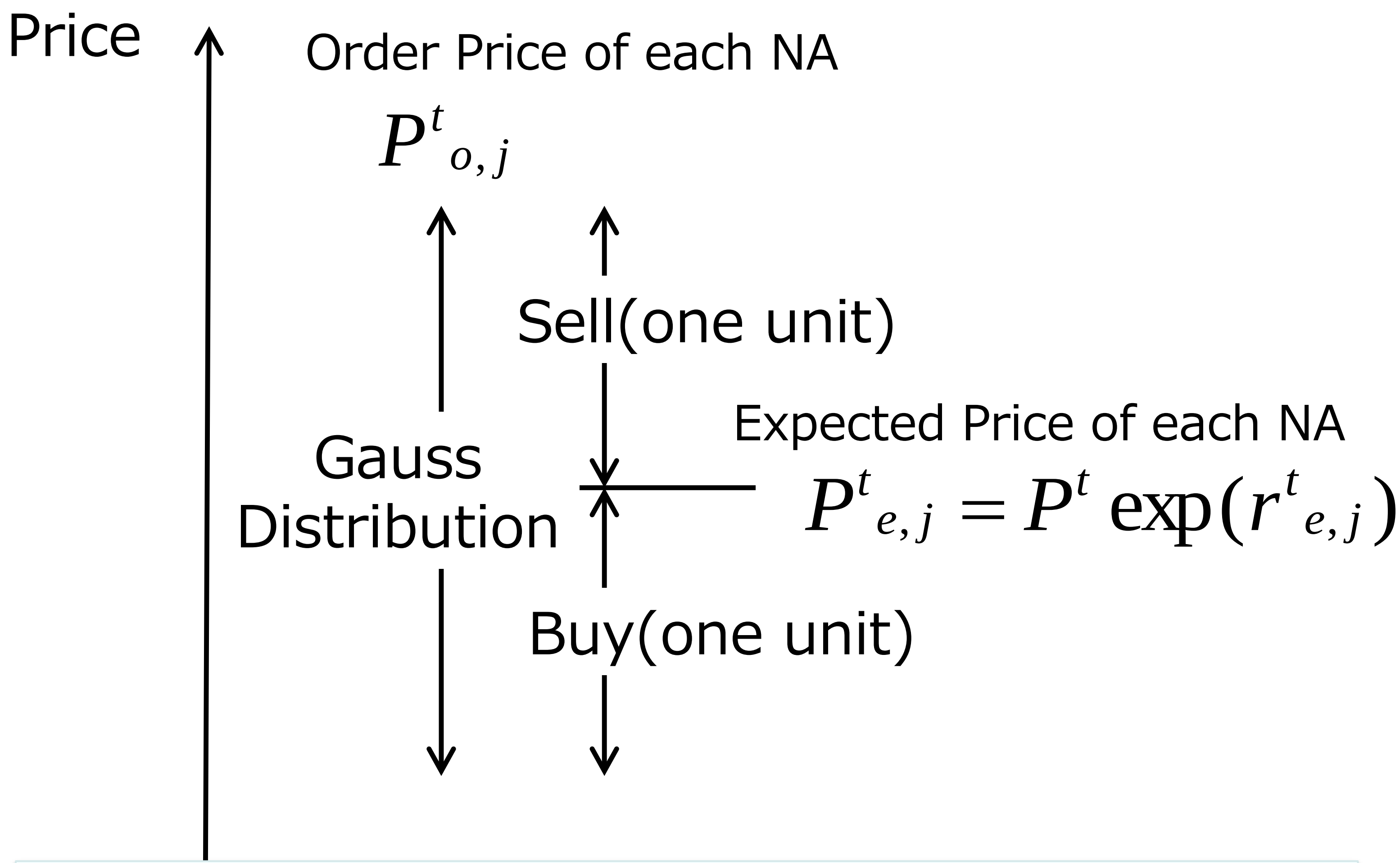
noise

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

Expected Price of each NA

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

Order Price and Buy or Sell

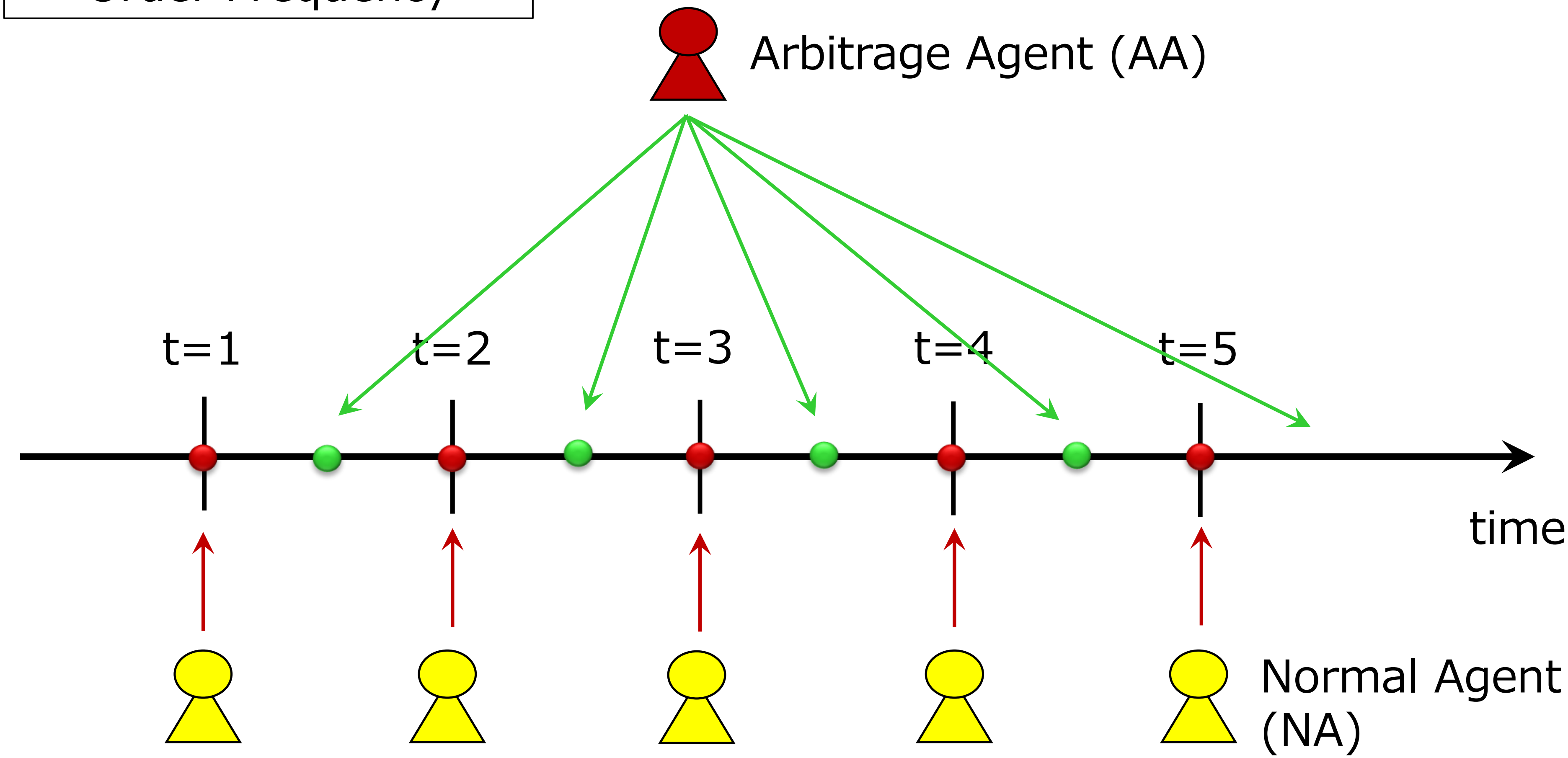


To replicate many waiting limit orders,
order price is scattered around expected price

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

Arbitrage Agent (AA) (1/4)

Order Frequency



The AA can always place orders, change orders, or cancel orders.

Arbitrage Agent (AA) (2/4)

ETF(one share)＝ Stock 1(one share)+ Stock 2(one share)

ETF sell	ETF price	ETF buy	stock 1 sell	stock 1 price	stock 1 buy	stock 2 sell	stock 2 price	stock 2 buy
7	20300		30	10400		50	10400	
10	20200		44	10300		70	10300	
	20100		70	10200		90	10200	
	20000		134	10100		116	10100	
	19900 ←		→	10000	120	→	10000	154
	19800	10		9900	88		9900	60
	19700	6		9800	52		9800	55
	19600	4		9700	25		9700	31

These are for examples of order books.

The sum of the highest buy-order prices for stocks 1 and 2 is 20000 (=10000+100000).
The highest buy-order price for ETF is 19800, and there is no buy order at 19900.
In this case, the AA first places an order to buy one share at 19900 and then waits.

Arbitrage Agent (AA) (3/4)

ETF(one share) = Stock 1(one share) + Stock 2(one share)

	ETF			stock 1			stock 2	
sell	price	buy	sell	price	buy	sell	price	buy
7	20300		30	10400		50	10400	
10	20200		44	10300		70	10300	
	20100		70	10200		90	10200	
	20000		134	10100		116	10100	
→	19900	**1**	→	10000	120	→	10000	154
	19800	10		9900	88		9900	60
	19700	6		9800	52		9800	55
	19600	4		9700	25		9700	31

Once the order is matched and the AA buys ETF,
it exchanges the ETF share for stocks 1 and 2
and then sells them each at 10000.

AA earns a profit of 100 from the price difference,
10000 (Stock 1) + 10000 (Stock 2) – 19900 (ETF) = 100

Of course, the AA can also earn a profit in the opposite case, by first selling borrowed ETF at a higher price, buying the stocks at lower prices, exchanging the stocks for ETF, and returning the ETF, again earning the price difference as a profit.

Arbitrage Agent (AA) (4/4)

ETF(one share)＝ Stock 1(one share)+ Stock 2(one share)

	ETF			stock 1			stock 2	
sell	price	buy	sell	price	buy	sell	price	buy
7	20300		30	10400		50	10400	
10	20200		44	10300		70	10300	
	20100		70	10200		90	10200	
	20000		134	10100		116	10100	
→	19900	**1**	→	10000	120	→	10000	154
	19800	10		9900	88		9900	60
	19700	6		9800	52		9800	55
	19600	4		9700	25		9700	31

When Highest buy-order prices(HBPs) consist

HBP for ETF + Cost ＜ HBP for stocks 1 + HBP for stocks 2

AA first places an order to buy one share at HBP + one tick and then waits.

Note that

cost

includes the required profit, when the price difference of risk assets is over c, the AA always do an arbitrage trade.

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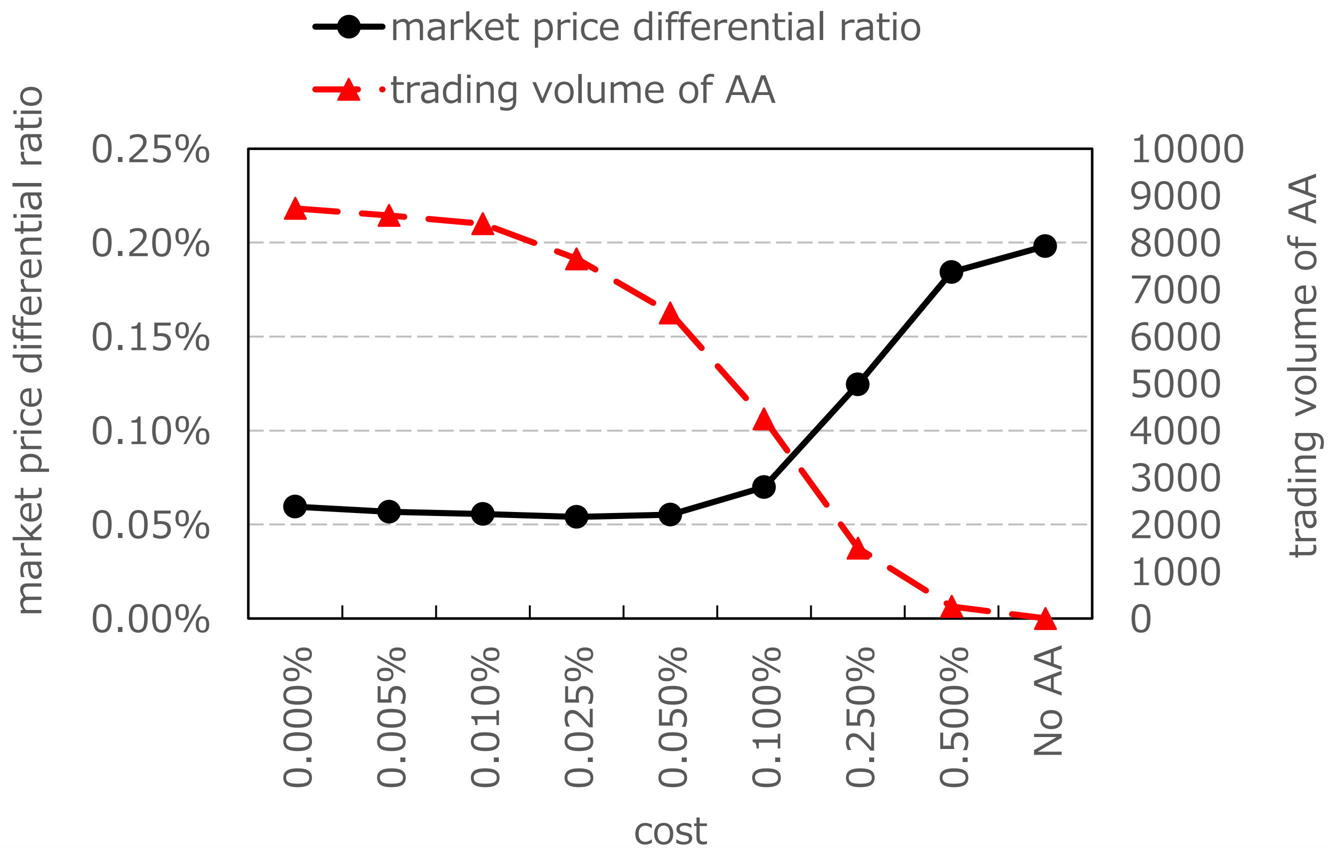
Market Price Differential rate & Trading Volume of AA

Market price differential rate＝Mid price of ETF/Sum of Mid prices of stocks - 1

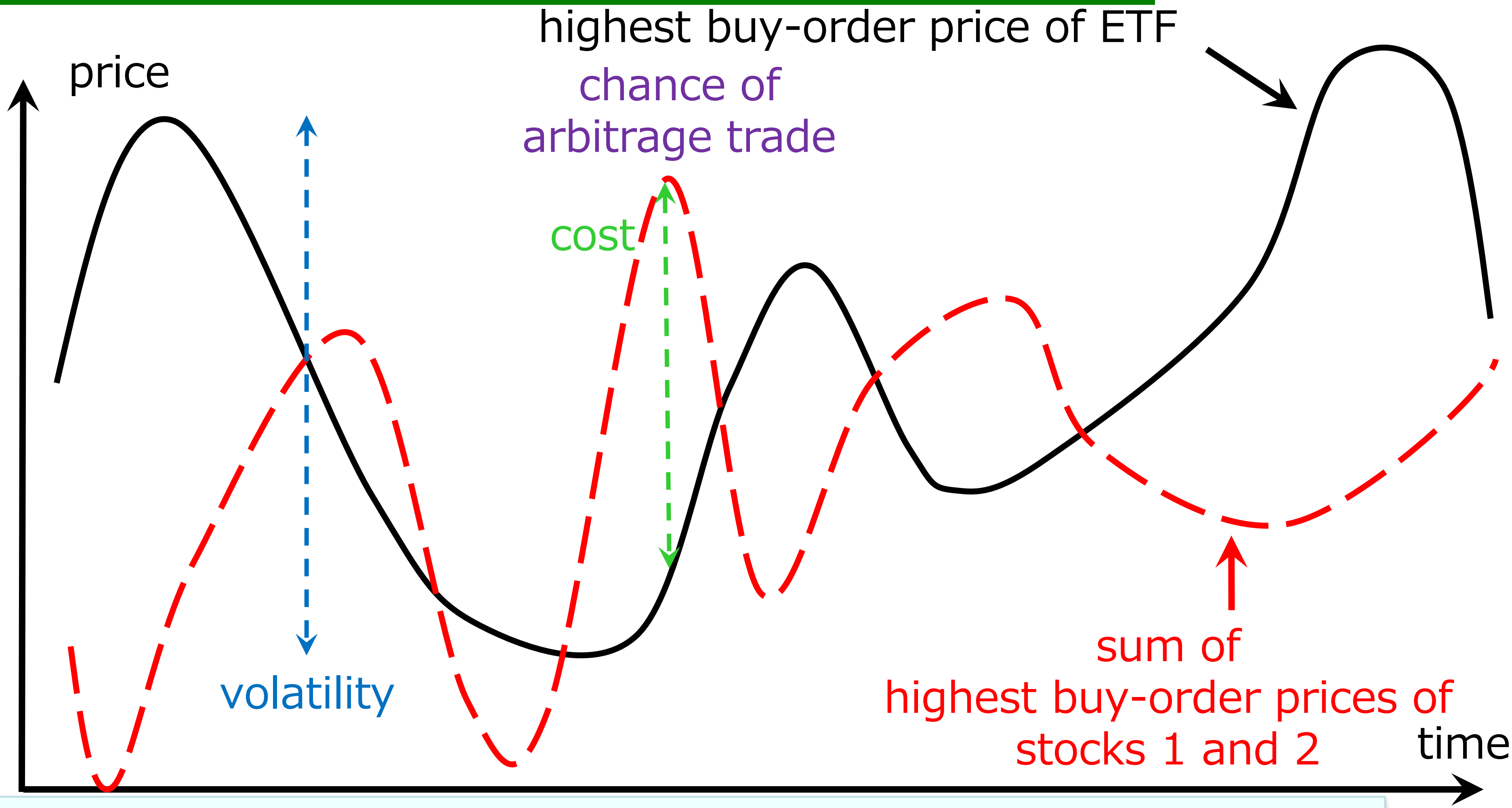


Lower cost leads more trading volume and a lower price differential

The price differential sharply changed when the cost was near 0.1%, similar to the volatility

Whether the cost is higher or lower than the volatility seems to indicate a very important boundary.

Relationship between Cost and Volatility



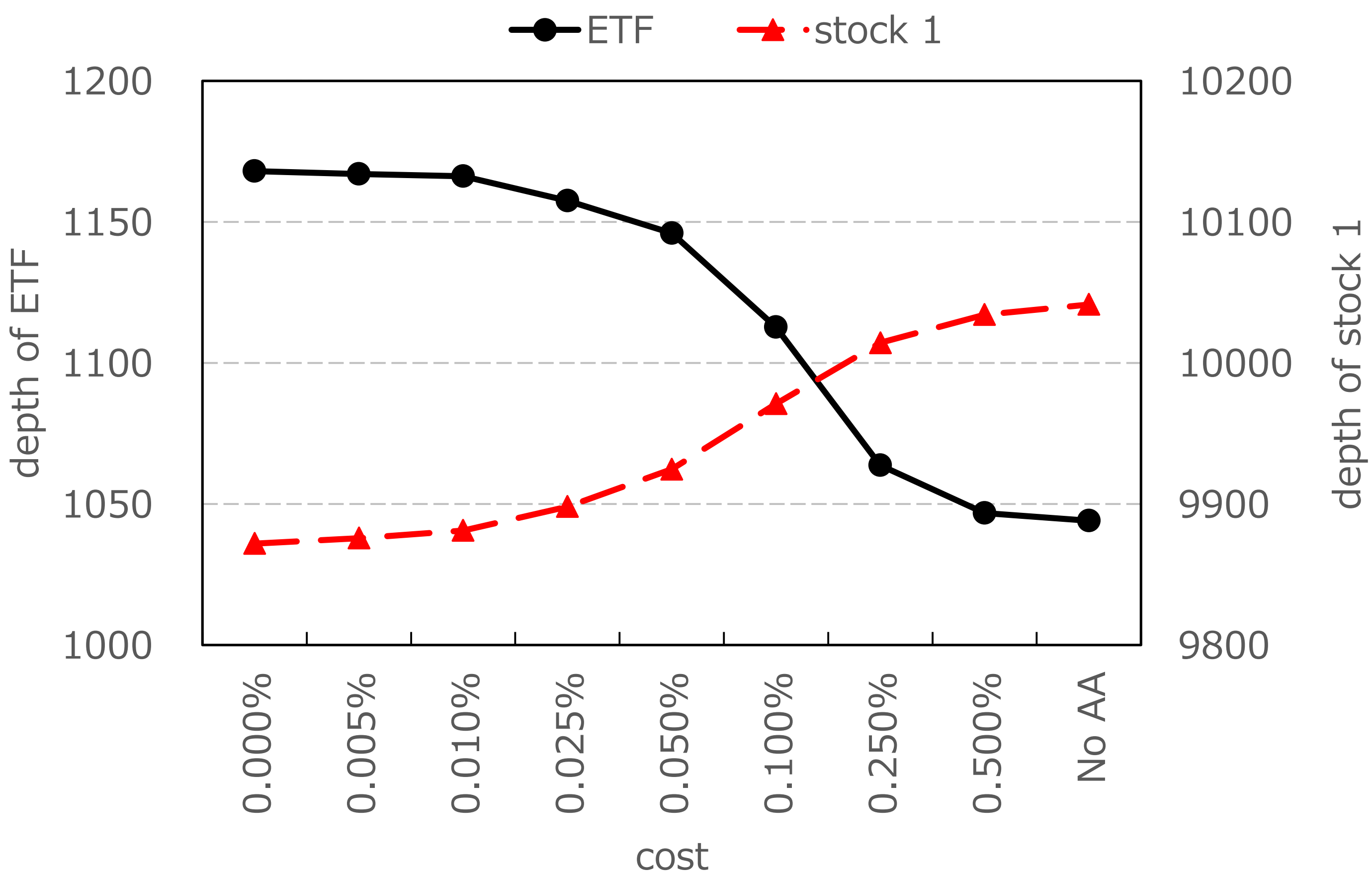
AA can make an arbitrage trade only when the red dashed line is above the black solid line plus the cost.

Prices of each risk asset fluctuate in their volatility

Volatility > Cost → **AA has more chances for arbitrage trades**

Depths of Waiting Orders

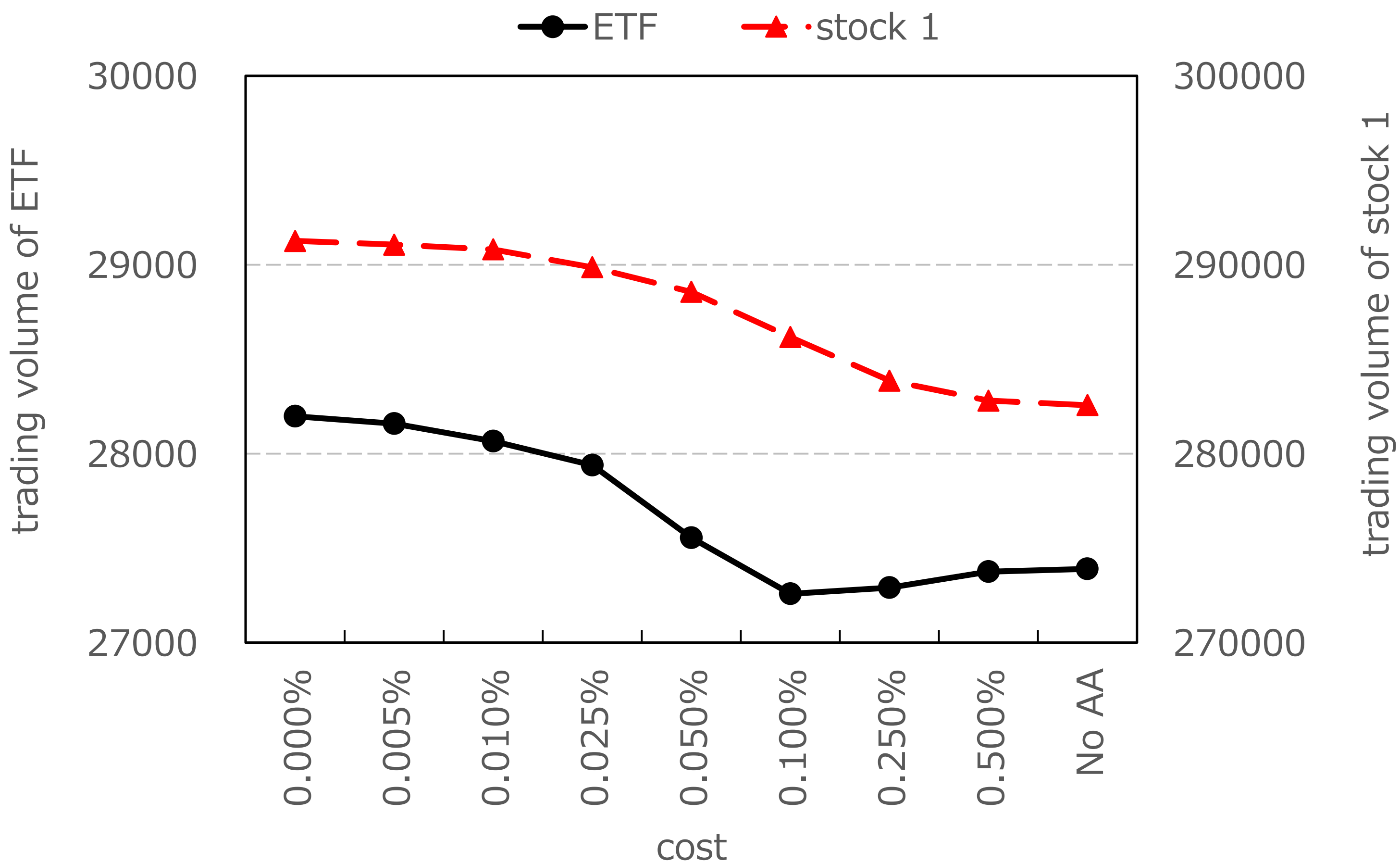
Sum of waiting orders between Mid Price ± 0.1%



Lower cost leads more depth for ETF and sharply changed when the cost was near 0.1%. On the other hand, the depth for stock 1 had the opposite tendency.

AA transfers waiting orders (liquidity) from Stocks to ETF

Trading Volume



Lower cost meant higher trading volume for both

Lower cost makes the depth for stock 1 thinner and the trading volume larger, because orders for arbitrage trades and waiting orders for stock 1 are matched.

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Summary

- ✓ I expanded the artificial market model of [Mizuta 13] to include three risk assets, denoted as stock 1, stock 2, and ETF, along with an arbitrage agent (AA) that could perform arbitrage trades among these risk assets. I then investigated the relationship between the liquidity of ETF and the trading costs.

- ✓ My results showed that, because the prices of each risk asset fluctuate in their volatility, when the volatility is sufficiently greater than the cost, the AA has more chances to make arbitrage trades. As the AA trades more, the market price differential becomes lower.

- ✓ In addition, lower cost means a thicker depth of waiting trades for ETF, whereas the depth tendency of a stock is the opposite. Furthermore, lower cost increases the trading volume of both. Lower cost makes the depth thinner and the trading volume greater for a stock because the orders for arbitrage trades and the waiting orders for the stock are matched.

Future Work

- ✓ Real financial markets, however, include traders who place more orders when the trading volume increases. My model did not implement this behavior. It is possible that lower cost would increase both the depth and the trading volume with such behavior. This remains for a future work.

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That’s ALL, Thanks!!

References

-- market-making incentive scheme --

- [JPX 17] Overview of ETF Market Making Scheme, Japan Exchange Group(JPX), https://www.jpx.co.jp/english/equities/products/etfs/market-making/

-- working paper --

- [Mizuta 19] Mizuta, T. : Liquidity and Arbitrage Cost between ETF and Stocks using Agent-Based Model, JPX Working Paper, No. 27, Japan Exchange Group(JPX), https://www.jpx.co.jp/english/corporate/research-study/working-paper/index.html

-- review paper –

- [Mizuta 19] Mizuta, T.: An agent-based model for designing a financial market that works well, arXive, https://arxiv.org/abs/1906.06000

- [Mizuta 16] Mizuta, T.: A Brief Review of Recent Artificial Market Simulation Studies for Financial Market Regulations And/Or Rules, SSRN Working Paper Series http://ssrn.com/abstract=2710495

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Appendix

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Stylized Facts

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.

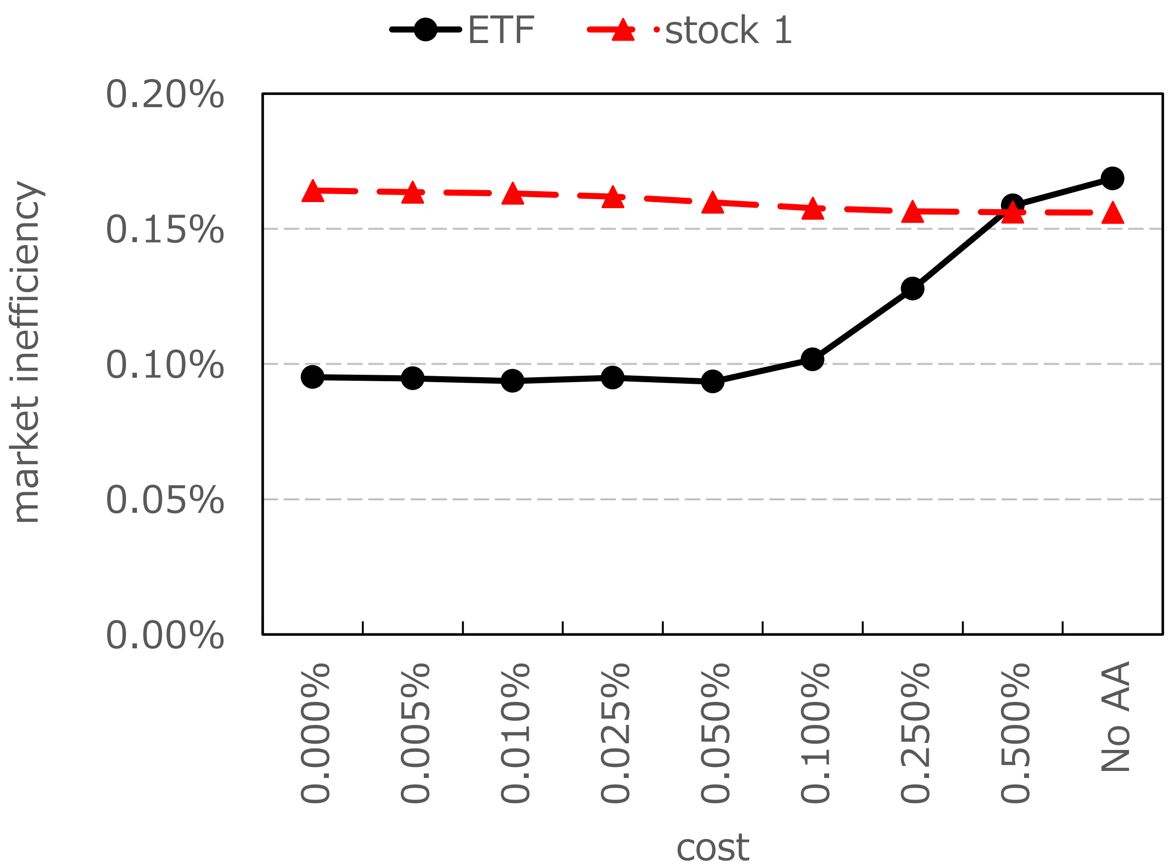
In contrast, Mizuta (2013) replicates high-frequency micro structures, such as execution rates, cancel rates, and one-tick volatility, that cannot be replicated with the model of Chiarella (2002).

In this study, I expanded the artificial market model of Mizuta (2013) to include three risk assets, denoted as stock 1, stock 2, and ETF and I added an arbitrage agent to perform arbitrage trading among these risk assets.

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.

Market Inefficiency

Market Inefficiency = Mid Price/Fundamental Price - 1

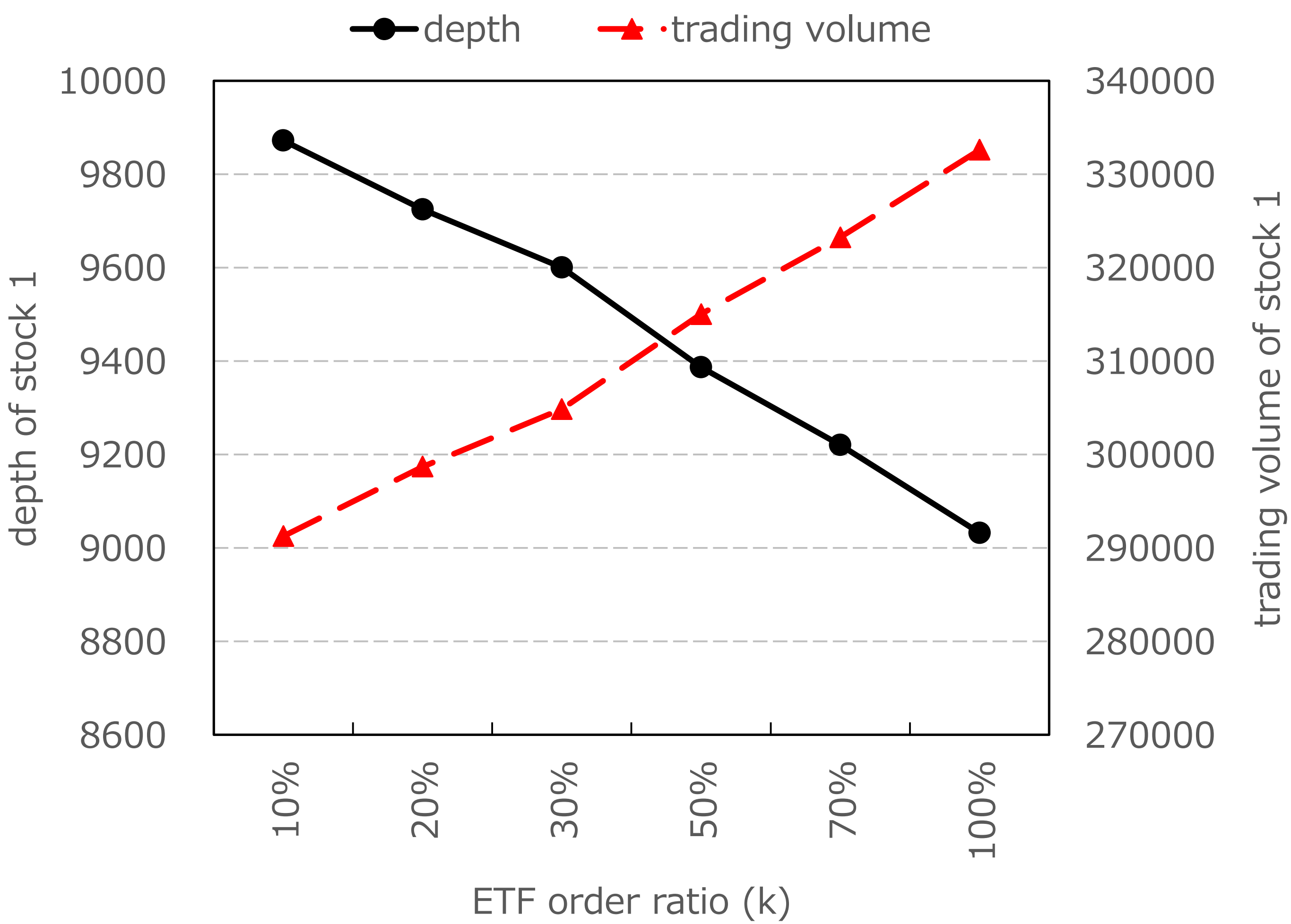


With lower cost, the ETF market became more efficient, but that of stock 1 did not change.

The reason why the ETF market becomes more efficient is NOT because it gains efficiency from the stock 1 market.

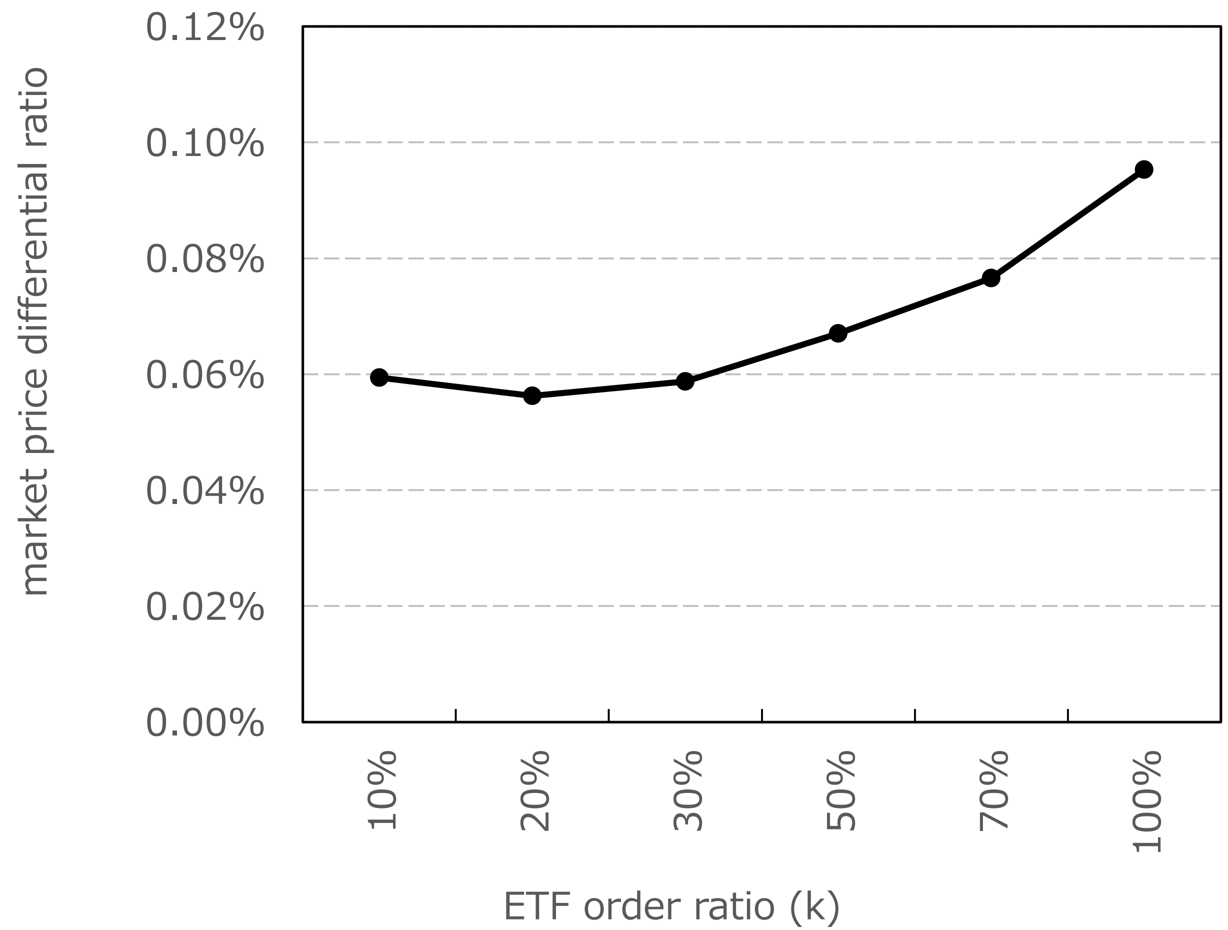
Case with more Liquidity for ETF (Cost=0)

(Actually, I fixed the ETF order ratio to k=0.1)



Larger ETF order ratio meant thinner depth and more trading volume.
More ETF orders caused more matching of arbitrage trade orders and waiting orders for stock 1.

Market Price Differential rate

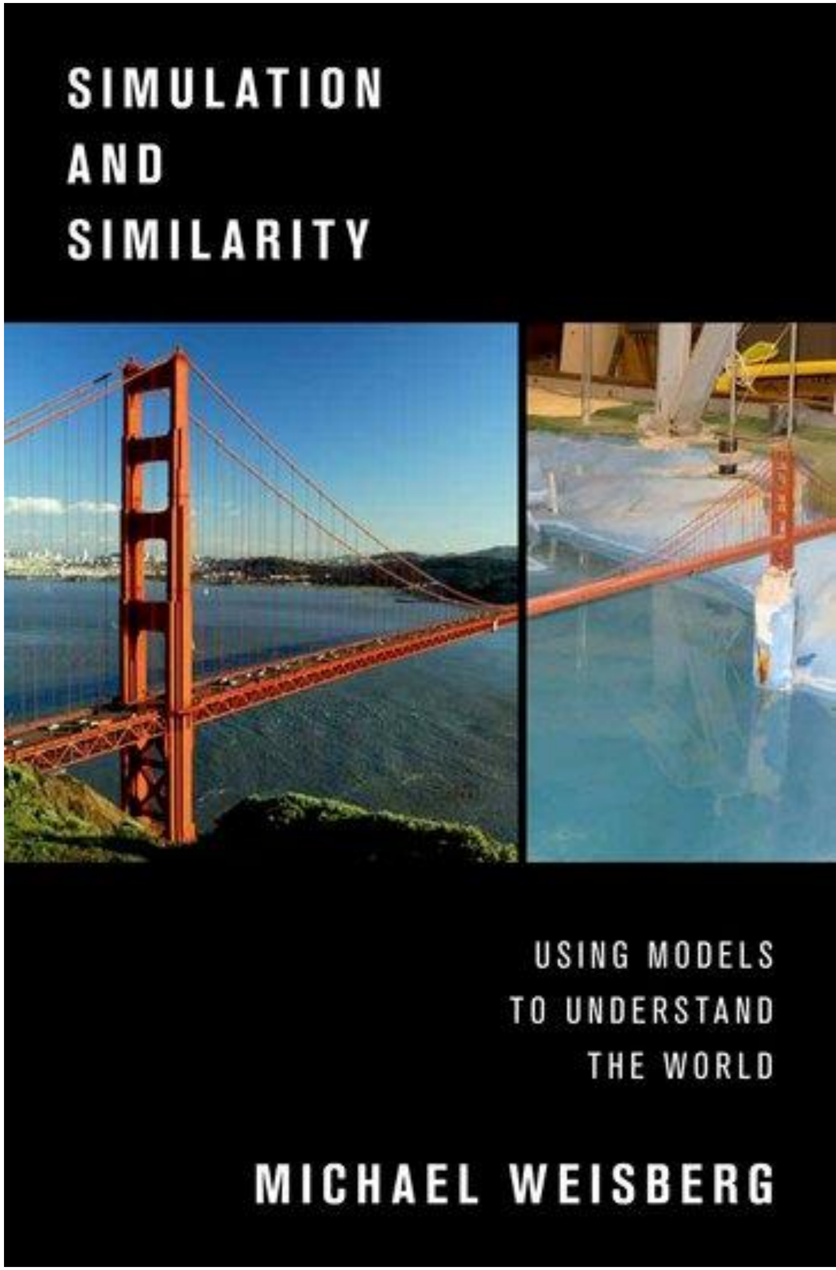


As ETF order ratio increased, market price differential ratio increased.

Even though more arbitrage trades occurred because of the larger ETF order ratio, the market price differential rate did not improve.

What is a role of Simulation Models?

This book answer the question.
And also answer “What is a model?”



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

Aim is not replicating nor forecasting real world

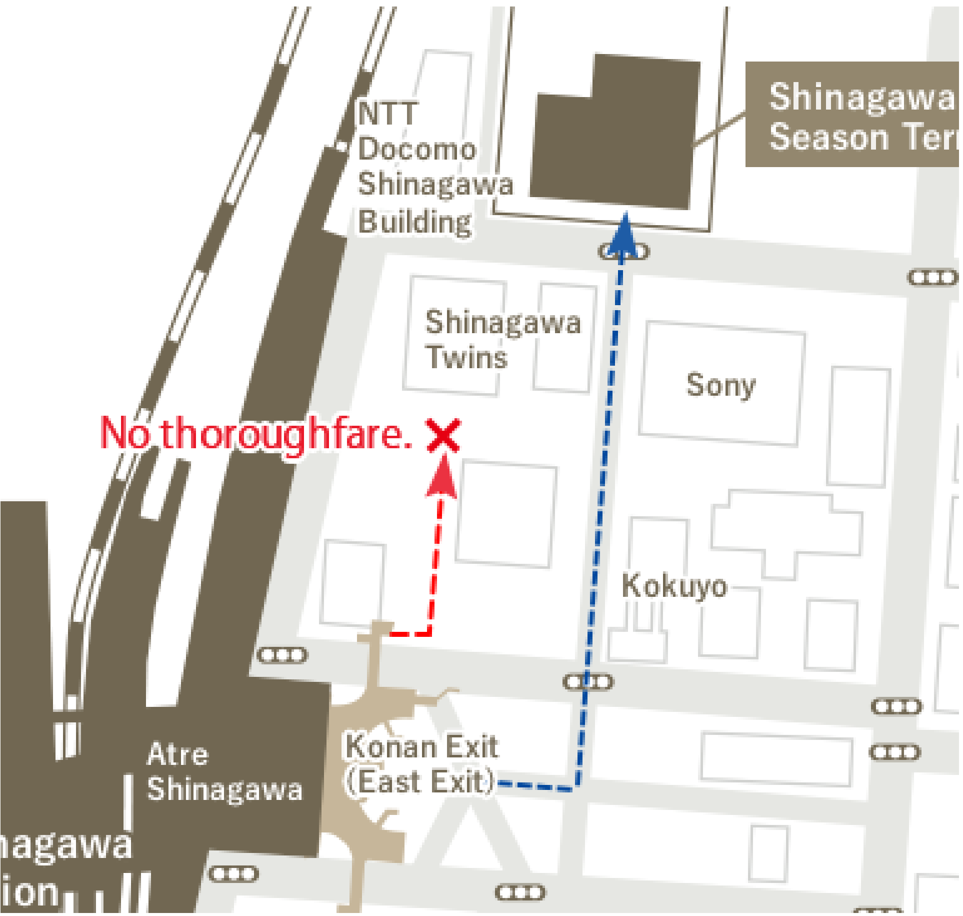
In time, those Unconscionable Maps no longer satisfied, and the Cartographers Guilds struck a Map of the Empire whose size was that of the Empire, and which coincided point for point with it . . . In the Deserts of the West, still today, there are Tattered Ruins of that Map, inhabited by Animals and Beggars;

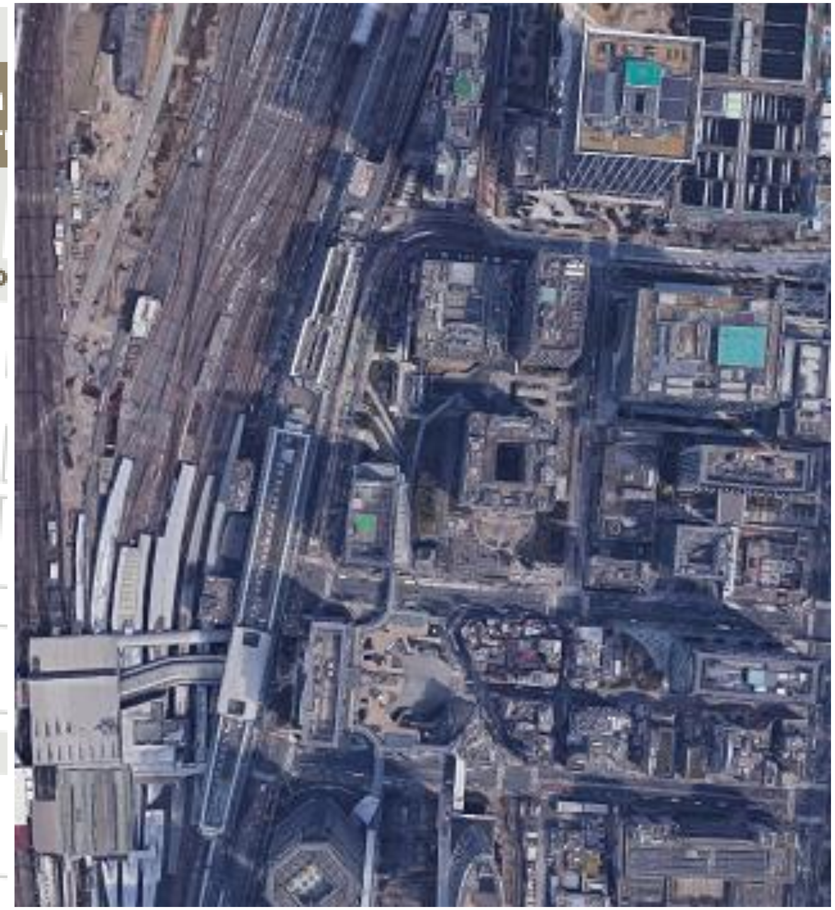
On Exactitude in Science Jorge Luis Borges

* Modeling, (is) the indirect study of real-world systems via the construction and analysis of models.
* Modeling is not always aimed at purely veridical representation. Rather, they worked hard to identify the features of these systems that were most salient to their investigations.
* Textbook model of the cell is both abstract and idealized relative to any real cell. It is abstract because it isn't a model of any particular kind of cell; it is a model of properties shared by all eukaryotic cells. Relatedly, it is idealized because its generality forces some parts of the model to be distorted relative to any real cell. I think these are both interesting properties,

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 a

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

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)

Investor A

Investor B

Investor C

Inherit Only Important Properties (Behaviors, Algorithms) for Investigating Phenomena

Other Investigating Phenomena,
Other Important Properties,
Other Good Models

Model of Investors

Never Real-Existing Investor
For Understanding Properties
of Real-Existing Investors

e.g.: Fashion Model: Understanding Closes
Model Home: Understanding Home

An Aim is to understand how Important Properties (Behaviors, Algorithms) affect Investigating Macro Phenomena and play Roles in System.

It is NOT aim Replicating real-existing Investors A, B and C.
It is aim Understanding real-existing Investors.

Other Focusing Phenomena, Other Good Models

What simulation(computational) model can do and mathematical model can not do

* When one invokes a computational model to explain some phenomenon, one is typically using transition rules or algorithm as the explanans. Schelling explained segregation by pointing out that small decisions reflecting small amounts of bias will aggregate to massively segregated demographics. Neither the time sequence of the model's states nor the final, equilibrium state of the model carries the explanatory force; the algorithm itself is needed.

Algorithms: The As want at least 30% of their neighbors to be As and likewise for the Bs. An agent standing on some grid element e can have anywhere from zero to eight neighbors in the adjoining elements.

Figure 2.2 An example of Schelling's model of segregation on a 51 × 51 grid with 2000 agents. Each agent prefers 30% of its Moore neighbors to be the same shape and color. The initial distribution of agents was random, and the model equilibrated after fourteen time steps.

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/

	#		#	@	#		@
#	#	#	@		@	#	@
	#	@			#	@	#
	@	#	@	#	@	#	@
@	@	@	#	@	@	@	
#		#	#	#			@
	#	@	#	@	#	@	
	@		@			#	

Rules:
* around me (8pixs) with more 1/3 my equals -> not move
* No -> move
After many steps,,,

	#	#		@	#	#	
#	#	#	@	@	@	#	#
#	#	@	@			@	#
#	@		@		@	@	@
@	@	@	#	@	@	@	
	@	#	#	#	@	@	@
		#	#	#	#		
@	@					#	

and @ have been separated

Mod. rules:
#:need one more equal
@:need one less equal

#	#	#	#	@			@
#	#	#	#	@	@		@
#	#	#	#			@	
	@	#	@	@	@		@
@	@	@	#	@	@	@	
			#	#	@		
		@	#	#	#	@	
	@		@	#	#	#	

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?
---- Silly questions for the purpose of simulation. prevent our understanding the mechanism.

Simplifying depends on that we want to understand

Schelling recommended you simulate this manually using coins to understand what is simulation model.

Role of Model (cont.)

We want know a relationship between Micro Process:
Deciding Orders, Rules of Exchange
& Macro Phenomena: Price Formation