[This is] Today’s Talk, [table of contents].

[At first, I will describe] Motivation and our artificial market model (Multi-Agent Simulation)

[In] Experiment 1, [we will investigate about] Characteristics of Erroneous-Order Turbulence [and will show that]
Market prices declined not only during but also for a while after the period of erroneous orders.
[And] The amount of erroneous orders decided ranges of price falls.

[In] Experiment 2, [we will investigate about] Effects of Price Variation Limits to the Turbulence [and will show that]
[The] Condition to Prevent the Large Turbulence [is], the limit time span should be shorter than the time of erroneous orders existing.

[Lastly, I will mention] Summary & Implication to market regulations.

http://www.slideshare.net/mizutata/cifer2014a
First, I will describe Motivation and our artificial market model.

<table>
<thead>
<tr>
<th>Motivation</th>
<th>Our Artificial Market Model (Multi-Agent Simulation)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experiment 1</td>
<td>Characteristics of erroneous-Order Turbulence</td>
</tr>
<tr>
<td></td>
<td>Market prices declined not only during but also for a while after the period of erroneous orders.</td>
</tr>
<tr>
<td></td>
<td>The amount of erroneous orders decided ranges of price falls.</td>
</tr>
<tr>
<td>Experiment 2</td>
<td>Effects of Price Variation Limits to the Turbulence</td>
</tr>
<tr>
<td></td>
<td>Condition to Prevent the Large Turbulence</td>
</tr>
<tr>
<td></td>
<td>$t_p l &lt; t_g$</td>
</tr>
<tr>
<td></td>
<td>$t_p l$: limit time span</td>
</tr>
<tr>
<td></td>
<td>$t_g$: time of erroneous orders existing</td>
</tr>
</tbody>
</table>

Summary & Implication to market regulations

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Motivation.

[In financial markets], large erroneous orders [sometimes] induce large price fluctuations.

[Such] fluctuations [often cause] financial market turmoil.

For example, Flash Crush, in US, 2010.

[Therefore, there is] a big debate over which price regulations prevent [this inducing].

[In] this study, [we build] Artificial Market Model (Multi-Agent Simulation) [to investigate]

[Characteristics of Erroneous-Order Turbulence]

[And, Effects of] Price Regulations

This presentation only shows the case of “Price Variation Limit”

Although the proceeding shows other cases of price regulations.
Empirical Studies are very difficult to discuss such price regulations.

★ So many factors cause price formation in actual markets that an empirical study cannot isolate the pure contribution of these regulations to price formation.

★ It is impossible to conduct experiments for new regulations in real financial markets.

[On the other hand], Artificial Market Model (Multi-Agent Simulation) can do [them].
This study's model is similar to previous my presentation, previous technical session. I think, some people did not attend it. So, I will give similar talk here, again.

We built an artificial market model on basis of Chiarella et. al. 2009.

- Pricing mechanism is Continuous Double Auction. It is not simple, but, we need to implement realistic price variation limit
- Agent Model is Simple. This is to avoid arbitrary result, “Keep it short and simple” principle.

We think Artificial Market Models should explain Stylized Facts as Simply as possible.

There are heterogeneous 1000 agents. All agents calculate Expected Return using this equation.

And, the strategy weights are different for each agent
- First term is a Fundamental Strategy: When the market price is smaller than the fundamental price, an agent expects a positive return, and vice versa.
- Second term is a technical strategy: When historical return is positive, an agent expects a positive return, and vice versa.
- Third term is noise.

Plus, We implemented Learning Process. This is different from Chiarella’s study and previous my presentation.
Even thought without Learning Process
→ the model could replicate **static** characters of price variations.
→ however the model could NOT replicate **Dynamic** characters of price variations, such as large fluctuations.

[About] Learning Process,
Previous Our Study Mizuta et. al., 2013a Last year’s CIFEr (SSCI in Singapore) [showed that]

Even thought without Learning Process
→ the model could replicate static characters of price variations.
→ however the model could NOT replicate Dynamic characters of price variations, such as large fluctuations.

[therefore,] This Study also need Learning Process Because of treating large price fluctuations
Details of Learning Process

**Agents are** comparing Historical Return and each Strategy’s term, Fundamental strategy term, and Technical strategy term.

When the strategy’s expected return and Historical Return are *Same Sign*,

*This means* good performer Strategy.

*The strategy’s* Weight is *Up*.

When the strategy’s expected return and Historical Return are *Opposite Sign*,

*This means* bad performer Strategy.

*The strategy’s* Weight is *Down*.

We also added random learning.

In this way, agents learn better parameters and switch to the investment strategy that estimates correctly.
[Next, I show simulation results of] Experiment 1 [about] Characteristics of Erroneous-Order Turbulence

- Market prices declined not only during but also for a while after the period of erroneous orders.
- The amount of erroneous orders decided ranges of price falls.

<table>
<thead>
<tr>
<th>Condition to Prevent the Large Turbulence</th>
<th>( t_{pl} &lt; t_g )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( t_{pl} ): limit time span</td>
<td></td>
</tr>
<tr>
<td>( t_g ): time of erroneous orders existing</td>
<td></td>
</tr>
</tbody>
</table>

Summary & Implication to market regulations

http://www.slideshare.net/mizutata/cifer2014a
Model of Erroneous Orders

[There are] two parameters for the model: pg, density of erroneous orders, tg, time of erroneous orders existing.

With a probability pg, His order is changed to Market Order Sell.

[Such market sell orders are] immediately done, and induce market price down.

This situation is maintained during tg.
This figure shows a time evolution of market prices with erroneous orders. We shade the time range in which erroneous orders exist. Market prices declined not only during but also for a while after the period of erroneous orders.
During erroneous-Order Existing switching Fundamental strategy to Technical Strategy.
Because of increased technical strategy weight, market prices continued to decline, even after erroneous orders were gone.

This figure shows a time evolutions of strategies weights. During erroneous-Order Existing switching Fundamental strategy to Technical Strategy. Because of increased technical strategy weight, market prices continued to decline, even after the erroneous orders were gone,
Next, we measure maximum Range of Price Declines and Reaching times to the minimum price for various $t_g$, $p_g$ under $s_g = t_g \times p_g = \text{const.}$

Maximum Range of Price Decline [is defined like this, from minimum market price to initial market price].

Reaching times to the minimum price [is defined like this, from starting erroneous orders to reaching time at minimum market price].
[This figure shows] maximum ranges of price declines for various \(tg\), \(pg\) under \(sg = tg \times pg = \text{const.}\)

[Horizontal axe is] times of erroneous orders existing \(tg\).

[The amount of erroneous orders, \(s_g\) on each line is constant.]

Ranges of price declines were almost the same when \(sg\) was constant, and when, \(sg\), was increasing more, the ranges were increasing more.

[Therefore], The amount of erroneous orders, \(Sg\), decided ranges of price falls, [and] \(sg\) is a key parameter.
This figure shows reaching times to the minimum price under $s_g = t_g \times p_g = \text{const.}$

- Reaching times to the minimum price increase sufficiently less than incrementation of $t_g$.
- When $s_g$ was larger, reaching times were longer.

15
Next, I show simulation results of Experiment 2 about Effects of Price Variation Limits to the Turbulence.

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We modeled the price variation limit like this.

There are two constant parameters. Tpl is a limit time span, and \( \Delta P_{pl} \) is limit price range.

We referred market price before \( t_{pl} \). and any agents can not order out side \( Pt - t_{pl} \pm \Delta P_{pl} \)

I mean, any buy order prices above here, they are changed to this price. and any sell order prices under here they are changed to this price.
[This figure shows a time evolution of market prices] with the price variation limit.

[In these parameters], The price variation limit succeeded to prevent the large turbulences.
What is parameters’ Condition to Prevent Large Turbulence?

Large Erroneous Orders [have] 2 parameters: tg, pg
Price Variation Limits [have] 2 parameters: ΔPpl, tpl

We want to know
How should we set ΔPpl, tpl to prevent inducing
Large price fluctuation?

We measured Maximum Range of Price Declines
for various parameters, tg, pg, ΔPpl, tpl
Parameter Searching for 4 parameters is too heavy,

[Therefore, we] Reduce Searching Space Dimension 4 → 2

[As mentioned in] Experiment 1,
Characteristics of large erroneous orders are similar when Amount of erroneous orders (Sg=tg × pg)= constant.
[Therefore, we] fix Sg.

[As mentioned in] Previous Our Study Mizuta et. al., 2013a,b
Price Variation Limits have the same effectiveness when Limit Price Range (∆Ppl) / Limit Time Span (tpl) = constant.
[Therefore, we] ∆Ppl / tpl

Under these conditions,
We measured Maximum Range of Price Declines for various parameters, tg, pg, ∆Ppl, tpl
### Maximum Range of Price Declines for various Parameters

<table>
<thead>
<tr>
<th>Price Variation Limit</th>
<th>2,000</th>
<th>5,000</th>
<th>10,000</th>
<th>20,000</th>
<th>30,000</th>
<th>40,000</th>
<th>50,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>tpl / pg</td>
<td>0.75%</td>
<td>3.0%</td>
<td>15%</td>
<td>7.5%</td>
<td>5.0%</td>
<td>3.75%</td>
<td>3.00%</td>
</tr>
<tr>
<td>1,000</td>
<td>92</td>
<td>158</td>
<td>241</td>
<td>370</td>
<td>497</td>
<td>616</td>
<td>719</td>
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<tr>
<td>2,000</td>
<td>95</td>
<td>175</td>
<td>243</td>
<td>380</td>
<td>513</td>
<td>638</td>
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<td>5,000</td>
<td>147</td>
<td>152</td>
<td>222</td>
<td>368</td>
<td>515</td>
<td>654</td>
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<tr>
<td>10,000</td>
<td>174</td>
<td>175</td>
<td>181</td>
<td>339</td>
<td>502</td>
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<tr>
<td>20,000</td>
<td>317</td>
<td>317</td>
<td>315</td>
<td>321</td>
<td>615</td>
<td>642</td>
<td>788</td>
</tr>
<tr>
<td>30,000</td>
<td>457</td>
<td>468</td>
<td>467</td>
<td>463</td>
<td>470</td>
<td>664</td>
<td>850</td>
</tr>
<tr>
<td>40,000</td>
<td>610</td>
<td>618</td>
<td>614</td>
<td>617</td>
<td>615</td>
<td>619</td>
<td>755</td>
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<tr>
<td>50,000</td>
<td>765</td>
<td>770</td>
<td>760</td>
<td>766</td>
<td>760</td>
<td>765</td>
<td>770</td>
</tr>
<tr>
<td>100,000</td>
<td>1,494</td>
<td>1,454</td>
<td>1,447</td>
<td>1,393</td>
<td>1,375</td>
<td>1,345</td>
<td>1,326</td>
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<tr>
<td>non</td>
<td>1,656</td>
<td>1,594</td>
<td>1,526</td>
<td>1,437</td>
<td>1,398</td>
<td>1,390</td>
<td>1,331</td>
</tr>
</tbody>
</table>

**Green Area:** tpl < tg ⇒ Small Price Decline

**Condition to Prevent the Large Turbulence:** tpl < tg

**Limit Time Span should be Shorter than Time of Erroneous Orders Existing**

[This table lists] maximum ranges of price declines for various parameters. Green Area [satisfy], tpl smaller than tg. [In these regions], Small Price Decline. Condition to Prevent the Large Turbulence [is the] limit time span should be shorter than [the] time of erroneous orders existing.
[Lastly, I will mention] Summary & Implication to market regulations.

http://www.slideshare.net/mizutata/cifer2014a
[We built a simple] artificial market model to investigate effects of price variation limits in large price fluctuation caused by large erroneous orders.

[In] Experiment 1, [we investigated about] Characteristics of Erroneous-Order Turbulence [and showed that]

Market prices declined not only during but also for a while after the period of erroneous orders.

[And], The amount of erroneous orders decided ranges of price falls.

[In] Experiment 2, [we investigated about] Effects of Price Variation Limits to the Turbulence [and showed that]

[The] Condition to Prevent the Large Turbulence is, the limit time span should be shorter than the time of erroneous orders existing.

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**Summary**

A simple Artificial Market Model (Multi-Agent Simulation) to investigate effects of price variation limits in large price fluctuation caused by large erroneous orders.

**Experiment 1**

- Characteristics of Erroneous-Order Turbulence
  - Market prices declined not only during but also for a while after the period of erroneous orders.
  - The amount of erroneous orders decided ranges of price falls.

**Experiment 2**

- Effects of Price Variation Limits to the Turbulence

  Condition to Prevent the Large Turbulence

  \[ t_p < t_g \]

  \( t_p \): limit time span
  \( t_g \): time of erroneous orders existing

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23
Implication to market regulations

In these days HFT (High Frequency Trading) are growing, very short time and very dense amount erroneous-orders may happen.

Price Variation Limit

Condition to Prevent the Large Turbulence

$ t_{pl} < t_{g} $

$t_{pl}$: limit time span
$t_{g}$: time of erroneous orders existing

This result implies that Price Variation Limit having very short $t_{pl}$ is needed.

Tokyo Stock Exchange: two Price Variation Limits

- "special quote": $t_{pl} = 3$ min
- "daily price limits": $t_{pl} = 1$ business day (5 hours)

Too longer than time scale of HFT
Need shorter $t_{pl}$ Price Variation Limit.

[Lastly, I will mention] Implication [of this study result] to market regulations

In these days HFT (High Frequency Trading) are growing, very short time and very dense amount erroneous-orders may happen.

[As I mentioned], price variation limit [should have] smaller limit time span [than] time of erroneous orders existing.

This result implies that Price Variation Limit having very short $t_{pl}$ is needed.

[For Example], Tokyo Stock Exchange: two Price Variation Limits

- "special quote": $t_{pl} = 3$ min
- "daily price limits": $t_{pl} = 1$ business day (5 hours)
That’s all for my presentation.

Thank you very much for your cooperation!

http://www.slideshare.net/mizutata/cifer2014a
References

http://www.slideshare.net/mizutata/cifer2013 (slide)


http://www.slideshare.net/mizutata/cifer2014a
Appendix

http://www.slideshare.net/mizutata/cifer2014a
We built an artificial market model on basis of Chiarella et. al. [2009]. Chiarella’s model did not include Learning Process, however, we built Learning Process of agents. And we are comparing between the case with Learning Process and without it.

Our Agent Model is Simple. This is to avoid arbitrary result, “Keep it short and simple” principle.

We think Artificial Market Models should explain Stylized Facts as Simply as possible,

Our pricing mechanism is Continuous Double Auction

It is not simple, but, we need to implement realistic price variation limit

Learning process

Here, Learning process means agents are switching strategy, fundamental strategy or technical strategy.

We will show that, an Overshoot occurred in the case With the learning process, however, overshoot did not occur in the case Without the process.
Next, I will describe agent model.

All agents calculate Expected Return using this equation.

First term is a Fundamental Strategy:
When the market price is smaller than the fundamental price, an agent expects a positive return, and vice versa.

Second term is a technical strategy:
When historical return is positive, an agent expects a positive return, and vice versa.

Third term is noise.
After the expected return has been determined, an expected price is determined like this.
And, agents order base on this Expected Price.
Next, agents determine order price and, buy or sell.

To Stabilize simulation runs for the continuous double mechanism, Order Prices must be covered widely in Order Book.

We modeled an Order Price, Po, by Random variables of Uniformly distributed in the interval from Expected Price, Pe, minus constant, Pd, to Pe plus Pd.

And then,
When Po larger than Pe, the agent orders to sell one unit.
When Po smaller than Pe, the agent orders to buy one unit.
This Table lists Traditional stylized facts in each case. In all cases, both kurtosis and autocorrelation for square returns for all $i$ are positive. This means that all cases replicate Traditional stylized facts: fat-tail and volatility-clustering.

<table>
<thead>
<tr>
<th></th>
<th>Non Mistaken orders</th>
<th>Mistaken orders</th>
</tr>
</thead>
<tbody>
<tr>
<td>kurtosis</td>
<td>5.39</td>
<td>5.54</td>
</tr>
<tr>
<td>lag</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.13</td>
<td>0.49</td>
</tr>
<tr>
<td>2</td>
<td>0.11</td>
<td>0.42</td>
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<tr>
<td>3</td>
<td>0.09</td>
<td>0.40</td>
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<td>4</td>
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<td>0.38</td>
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<tr>
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<tr>
<td>$q$</td>
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</tr>
<tr>
<td>1</td>
<td>55%</td>
<td>55%</td>
</tr>
<tr>
<td>2</td>
<td>53%</td>
<td>48%</td>
</tr>
<tr>
<td>3</td>
<td>49%</td>
<td>42%</td>
</tr>
<tr>
<td>4</td>
<td>47%</td>
<td>36%</td>
</tr>
<tr>
<td>5</td>
<td>44%</td>
<td>30%</td>
</tr>
<tr>
<td>6</td>
<td>44%</td>
<td>25%</td>
</tr>
</tbody>
</table>

All cases replicated: Fat Tail and Volatility Clustering
Market price with Up–tick Rule
adopted Trigger method without unlock
Market price with Up–tick Rule
adopted Trigger method with time unlock, tut=50,000

(price)

(time (x1000))
We examined two Cases, Case 1, Fundamental Value is constant, Case 2, Fundamental value is rapid incremented like this. This is bubble inducing trigger.

For Each cases, we examined With learning process And Without learning process.

Therefore, we examined four cases in all.
This Figure shows time evolution of market prices in case 1, Fundamental Value is constant.

In both cases, With learning process and without learning process, the results are very similar.

The prices were small fluctuating around Fundamental Value, here, Ten Thousand
This Figure shows time evolution of prices in case 2.
Fundamental value was changed at this time, increased to New Fundamental Value, Fifteen Thousand.
This is the bubble inducing trigger.

Without Learning Process, Black line, Overshooting was not occurred.

On the other hand, with Learning Process, Red line, the price went far beyond the new fundamental value.
Only with learning process, Overshoot occurred.
This Table lists Traditional stylized facts in each case.

In all cases, both kurtosis and autocorrelation for square returns for all $i$ are positive.

This means that all cases replicate Traditional stylized facts: fat-tail and volatility-clustering.

<table>
<thead>
<tr>
<th></th>
<th>case 1</th>
<th></th>
<th>case 2</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>non-learning learning</td>
<td></td>
<td>non-learning learning</td>
<td></td>
</tr>
<tr>
<td>kurtosis</td>
<td>3.018 5.394</td>
<td></td>
<td>2.079 3.180</td>
<td></td>
</tr>
<tr>
<td>lag</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>0.134 0.125</td>
<td>0.219 0.325</td>
<td>0.164 0.293</td>
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<tr>
<td>2</td>
<td>0.101 0.105</td>
<td>0.164 0.293</td>
<td>0.133 0.274</td>
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<tr>
<td>3</td>
<td>0.076 0.087</td>
<td>0.118 0.261</td>
<td>0.108 0.253</td>
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<td>autocorrelation</td>
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<td>0.118 0.261</td>
<td>0.108 0.253</td>
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<tr>
<td>coefficient for</td>
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<td>0.108 0.253</td>
<td>0.100 0.247</td>
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<tr>
<td>square return</td>
<td>0.040 0.054</td>
<td>0.092 0.241</td>
<td>0.087 0.237</td>
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<td>7</td>
<td>0.036 0.048</td>
<td>0.092 0.241</td>
<td>0.087 0.237</td>
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<tr>
<td>8</td>
<td>0.030 0.045</td>
<td>0.082 0.238</td>
<td>0.082 0.238</td>
<td></td>
</tr>
<tr>
<td>9</td>
<td>0.026 0.039</td>
<td>0.082 0.238</td>
<td>0.082 0.238</td>
<td></td>
</tr>
</tbody>
</table>

All cases replicated: Fat Tail and Volatility Clustering
We propose **Hazard Rate** as a new stylized fact to verify model replicating overshoot.

**Hazard Rate** $H(i)$ is the conditional probability that a sequence of positive returns ends at time $i$, given that it lasts until $i$.

For example, if $i = 3$, $H(3)$ means:
- 1st, positive return,
- 2nd, positive,
- 3rd, positive,
- In this condition, $H(3)$ is the probability of the 4th return becoming negative.

**Empirical Studies** showed:
- Any cases: $H(i) < 50\%$,
- Overshoot period: $H(i)$ declines rapidly with $i$.

McQueen and Thorley [1994], Chan et al. [1998],

$\Rightarrow$ Overshoot returns tend to continue to be positive,
this tendency stronger continuing positive returns longer.
This Table lists New Stylized Facts: Hazard Rate in each case.

In case 2 with learning, hazard rate declined rapidly.
This case can replicate a significant Overshoot like actual markets.
On the other hand, the case without learning, hazard rate dose not declined rapidly.
The case can not replicate Overshoot.

Case 1, without learning, Hazard rates are upper 50% for all i.
This is Not consistent with empirical study.
On the other hand, Case 1, with learning, Hazard rates for most of i are smaller than 50%, even when price fluctuations are stable.

This consistent with empirical study.

Therefore, only cases with Learning Process were verified by Hazard Rate, and only Case 2 can replicate overshoot.
Result Summary Experiment 1: Learning and Overshoot

<table>
<thead>
<tr>
<th>Case1</th>
<th>Without Learning Process</th>
<th>With Learning Process</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fundamental Value = constant</td>
<td>Stable</td>
<td>Stable</td>
</tr>
<tr>
<td></td>
<td>Not-Verified by Hazard Rate</td>
<td>Verified by Hazard Rate</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Case2</th>
<th>No-Overshoot</th>
<th>Overshoot (Bubble &amp; Crush)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fundamental Value → rapid increment</td>
<td>Not-Verified by Hazard Rate</td>
<td>Verified by Hazard Rate</td>
</tr>
</tbody>
</table>

Result Summary Experiment 1 relationship between Learning process and replicating Overshoot

The cases With learning process, both case 1 and case 2, were Consistent with Empirical study verified by Hazard Rate.
And case 2 can replicate overshoot, bubble and crush

The cases Without Learning Process were Not consistent with Empirical study Not verified by Hazard Rate.