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# Effect of Trading Halt System on Market Functioning: Simulation Analysis of Market Behavior with Artificial Shutdown

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Abstract

This paper explores how we determine when an observed plunge in stock prices is 'critical,' and considers what trading halt system design would guarantee more benefits than costs. We use an artificial market model demonstrated in Muranaga and Shimizu [1999a] and analyze the market crash generating mechanism and the effects of the trading halt system on market behavior. We find that a market crash is observed in cases which include feedback mechanism to a trader's expected value. The probability of a crash increases when there is a relatively limited transmission range of exogenous shock or a high ratio of momentum traders, who trade by only considering market price changes. We also find that in order to have a stable market after trading resumes, it is important to resume trading after the declining speed of the market participants' expected values has become small enough.

Key words: Artificial market model, Feedback mechanism, Market crash, Trading halt system

JEL Classification: G18

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# CONTENTS

## 1. Purpose of the Study

The trading halt system, an institutional mechanism, that artificially stops trading in order to prevent further price fall during a market crash, was proposed as one of the four recommendations by the Presidential Task Force on Market Mechanism [1988] following the 1987 market crash, and has actually been introduced in various stock exchanges.[1] Market participants and theorists have presented their evaluations of such a trading halt system, although few analyses have proved the system to be effective, by showing that the system actually prevented or restricted great market movement. The main reason for this is Rule 80B, the trading halt system in the New York Stock Exchange (NYSE), was never actually used until last autumn, while several theoretical problems in its institutional design have been pointed out. Greenwald and Stein [1991] argued that a trading halt increases trade execution risk (uncertainty of trade execution) and thus induces market instability. Brennan [1986] pointed out that a trading halt leads to a decline in price information. In addition, when the circuit breakers were activated during the rapid stock price fall last autumn, market participants felt "the trading halt increased investor anxiety and thus spurred the turmoil."

As Brennan [1986] pointed out, a trading halt system imposes costs on market participants by depriving them of profitable trading opportunities. Therefore, based on the belief that such a system should not be activated unless there are obvious benefits versus the costs, in February 1998, the NYSE decided to reconsider use of its circuit breakers.[2] The new rules set "standard value[3]," and trading is halted according to the

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[1] As circuit breakers, by which imposes limits on trading activity, there are trading halt, price limit, collar, transaction cost, margin requirement, and position limit. This paper focuses on the mechanism in which all trading is halted.

[2] Another trading halt system is activated when important information significantly affecting investor judgement prevails in the market. Since April 1998, the Tokyo Stock Exchange (TSE) shortened the trading halt period from the whole day to 90 minutes after the relevant information has been publicly released.

daily "rate of decline[4]" of the Dow Jones Industrial Average (DJIA) from the standard value. When the DJIA declines 10% and 20% from the standard value, all stock trading is halted for a certain period of time[5], and when the decline reaches 30%, all trading is halted for the day. Given the current level of stock prices, the new rules indicate significant relaxation, and can be regarded as responsive to the claims of market participants who favor minimal activation of such a system. Once trading is resumed, if the DJIA declines by additional 20%, trading will be halted again for two hours if the decline takes place by 1 p.m., for one hour if it takes place by 2 p.m., and for the day if it takes place after 2 p.m.

Review of the NYSE circuit breakers highlighted several important issues inherent in the trading halt system. The first issue relates to the timing of trading halts. Even in the case of a 'stock price plunge,' if such a phenomenon is due to rational behavior of market participants, and represents faster-than-normal trade execution and a continuous decline in prices, there may be no need to artificially halt trading (Greenwald and Stein [1988]). We should examine what kind of market phenomenon deserves an artificial trading halt. The second issue is to consider a system design which guarantees a smooth resumption of trading after the halt without inducing a further crash in the market. We should develop an effective system design which supports the stabilization effects of the trading halt system and improves market conditions.

This paper tries to provide answers to these issues. Specifically, we will focus on the following two questions:

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[3] The standard value is regularly reviewed four times a year.

[4] The current circuit breakers halt trading according to the 'magnitude of decline.' When the Dow Jones Industrial Average declines 350 points from the previous day's close, all stock trading is halted for 30 minutes, and when the decline totals 550 points, all trading is halted for one hour.

[5] In the case of a 10% decline, trading will be halted for one hour if the decline takes place by 2 p.m. Trading will be halted for 30 minutes if the decline takes place by 2:30 p.m. Trading will not be halted if the decline occurs after 2:30 p.m.

1) How do we determine when an observed plunge in stock prices is not a price adjustment phase resulting from rational trading behavior, but is instead, a 'critical' situation which requires trading to be artificially halted?

2) Provided that we can judge whether the market is in a 'critical' situation, what system design would guarantee more benefits than costs for a trading halt? We will examine institutional design, which enables trading to resume smoothly after the halt, without delaying the possibility of a market crash or accumulation of downward pressure in the future.

The composition of this paper is as follows. Section 2 presents the framework of our analysis. We consider the market crash generating mechanism in Section 3. In Section 4 we analyze the effects of the trading halt system on market behavior in the case that market crash would occur. In Section 5 conclusions and future tasks are shown.

## 2. Framework of the Analysis

In order to consider the merits and drawbacks of the trading halt system, we use the Monte Carlo simulation based on an artificial market model. This is an analytical method demonstrated in Muranaga and Shimizu [1999a]. This model is composed of two stages: a micro stage, in which each trader's decision making and ordering are described; and a macro stage, in which trade execution through the trade execution model and subsequent information distribution are described. The underlying flow of simulation and the trader's decision making model are shown in Appendix 1. In the following, we first look at a mechanism which generates a market crash, and execution of the trading halt system.

While traders make trades based on their own expected values and confidence in their forecasts, they seem to, in fact, feed back available market information in their decision making process in various ways. Given the variety and complexity of such mechanisms, this paper focuses on the two simplest mechanisms, as was done in Muranaga and Shimizu [1999a,b]: feedback to trader's expected value, and feedback to confidence in trader's forecast, and analyze the effects of such feedback mechanisms on market behavior. The details of these two feedback mechanisms are shown in Appendix 2.

A market crash is not necessarily triggered by exogenous shocks. However, since we are dealing with post-crash measures, we will give an explicit exogenous shock to our model and analyze issues such as whether a crash will be generated and what role trading halt measures will play during a market crash. We add exogenous shocks to the artificial market model used in Muranaga and Shimizu [1999a], and focus our analysis on the subsequent market behavior. If a shock is added to an efficient market in which all information is perfectly reflected in the prices, such shock will also be instantaneously reflected in the prices, and thus paths of market prices derived from the Monte Carlo simulation are those shown in Figure 1. In the actual market, however, since various market microstructures do affect price formation in the market, price paths can also be those shown as Line A in Figure 2 (the shock is reflected in market prices over time), Line B (market prices continue to fall), or Line C (trade not executed for a while ).

By conducting simulations according to various types of exogenous shock and settings of market condition, we explore the relationship between various settings and likelihood of a market crash. We consider four types of shock impact in our analysis, which reduce value traders'[6] expected values by 2.5%, 5.0%, 7.5%, and 10.0%, respectively. As for the range in which such shocks will be transmitted, we have

[6] We define 'value traders' as traders who place limit orders based on their expected values. See Appendix 1 for detailed information.

considered the portion of traders who directly receive such shock as 20%, 40%, 60%, 80%, and 100% of the whole value traders. By adding these 20 types of shock (Table 1) to the market, we will observe the subsequent market behavior.

Table 1. Types of exogenous shocks

| | | Shock impact* | | | |
|---|---|---|---|---|---|
| | | 2.5 % | 5.0 % | 7.5 % | 10.0 % |
| Transmission Range of shock | 20 % | Case 1 | Case 2 | Case 3 | Case 4 |
| | 40 % | Case 5 | Case 6 | Case 7 | Case 8 |
| | 60 % | Case 9 | Case 10 | Case 11 | Case 12 |
| | 80 % | Case 13 | Case 14 | Case 15 | Case 16 |
| | 100 % | Case 17 | Case 18 | Case 19 | Case 20 |

*Ratios by which traders reduce their own expected values.

## 3. Analysis of market crashes

### 3-1. Market consisting solely of value traders

#### (1) Feedback to expected value

First, we assume the market follows a mechanism which allows traders to modify their expected values in response to large changes in market prices. We assume that the feedback is triggered when changes in market prices exceed 90 percentile of the traders' expected value distribution of the market (that is, trigger level=10%)[7]. All 50 market participants are value traders. 20 types of shock shown in Table 1 are added to this market, and subsequent market behavior will be monitored.

[7] "Trigger level=10%" means that traders will change their expected values if they observe market prices lower/higher than the price at the 90 percentile of their expected value distribution.

Figures 3 and 4 show movements of market prices and traders' expected values of asset. Each black line indicates movements of one trader's expected value. The black bold line indicates movements of mean of all traders' expected values. The gray bold line shows movements of market price. In both figures, exogenous shocks are added to the market at the 26th period. In Figure 3 market price reaches a new equilibrium, while traders modify their expectations one after another, and the market falls into a crash in Figure 4.

Figure 5 shows the resulting market prices (mean of bid and ask prices) of the simulation conducted 20 times using 20 different types of shock impact and transmission range. We can see that a crash is more likely due to a large shock (7.5% or more) compared with the price variance during normal times (about 5%) when it is transmitted to 40-60% of the market participants (Figures 5-7, 5-8, 5-11, 5-12). When a shock is transmitted to relatively few (20%) participants, even a large shock (10%) will be mostly absorbed. In contrast, when a shock has been transmitted quite broadly to the market (80% or more of the participants), the shock will be properly reflected in prices regardless of its impact (Figures 5-13 to 5-20).

Figure 6 depicts the mean of traders' expected values. We can see that, except when a shock has been transmitted to all participants, traders adjust their expected values after the shock by reacting to changes in market price which are generated endogenously.

Figure 7 shows the divergence between the development in market price and that in mean of traders' expected values, that is, an overshoot ratio.[8] The positive spike of the

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[8] We define overshoot ratio ($O_t$) as follows:

$$O_t = \frac{P_t}{\sum_{i=1}^{N} V_{i,t} \Big/ N} - 1$$

where $P_t$ denotes the mean price in term $t$, $V_{i,t}$ denotes the expected value of trader $i$ in term $t$, and $N$ denotes the number of value traders.

overshoot ratio in 26th period represents the situation in which, upon receiving an exogenous shock, traders have reduced their expected values while market prices cannot quite follow such reduction, keeping its level quite higher than those of traders' expected values. When the shock transmission range is between 80-100%, the market price seems to reach a new equilibrium within 10 terms, in which all traders have traded at least once (Figures 7-13 to 7-20). When the transmission range is between 40-60%, there is a price overshoot when a strong shock (7.5% or more) has been added (Figures 7-7, 7-8, 7-11, 7-12).

Figure 8 summarizes the development in limit order book accumulated in the market. What is plotted on the positive side of the vertical axis illustrates buying order volume, while selling order volume is plotted on the negative side. As added shock increases, order imbalance (difference between buying and selling order volume) increases. In addition, when shock impact is 7.5% or more and transmission range is between 40-60%, post-crash supply-demand imbalance and its lasting period increase (Figures 8-7, 8-8, 8-11, 8-12).

(2) Feedback to confidence

Second, we analyze cases where traders modify their confidence in response to large changes in market price. In such cases, traders will not adjust their expected values, but they will modify their confidence in their forecasts and adjust their estimates for risk. When traders' risk amount increases, expected return on risk will decrease more rapidly than the extent of risk aversion, and thus the traders will not place orders. We have shown the developments in market prices, mean of expected values, overshoot ratio, and order imbalance in Figures 9, 10, 11, and 11, respectively. From Figure 9, we can see that crashes are not generated regardless of the size and transmission range of the exogenous shock. In addition, price overshoots rarely occur as shown in Figure 11. We can point out that market liquidity plays a role as a built-in-stabilizer behind the phenomena in which crashes are not generated in the cases of feedback to confidence (Muranaga and Shimizu [1999b]).

## 3-2. Market consisting of value traders and momentum traders

In the previous part, we analyzed a market composed solely of value traders who make arbitrage transactions by comparing market prices to their expected values. Here, we add momentum traders, who are indifferent to the level of market prices and place market orders taking into account only the trends and volatility of market price changes. Momentum traders buy when market prices rise and sell when prices fall, therefore they make market prices more volatile.

### (1) Feedback to expected value

As we have done earlier, we first look at a market where traders modify their expected values in response to large changes in market price. In this setting, when we compare developments in market prices, expected values, overshoot ratio, and order imbalance in the market with 10 additional momentum traders (Figures 13-16) with those of the market without momentum traders (Figures 5-8), we can see the following two features:

a) When shock impact is 7.5% or more and shock transmission range is between 40-60%, market crashes are generated in both cases and probability is larger in the market with momentum traders (Compare Figures 13-7, 13-8, 13-11, 13-12 with Figures 5-7, 5-8, 5-11, 5-12).

b) There are some shock patterns which induce market crashes only markets with momentum traders. Specifically, market crashes are generated under conditions such as: 10% shock impact and 20% transmission range (Figure 13-4), 5.0% shock impact and 60% transmission range (Figure 13-10), and 10.0% shock impact and 80% transmission range (Figure 13-16).

(2) Feedback to confidence

Next, we turn to the market where traders make changes in market prices feedback to their confidence. In this setting, we compare developments in market price, mean of expected values, overshoot ratio, and order imbalance in the market with 10 additional momentum traders with the same categories of the market without momentum traders (Figures 9-12). Price volatility increases with accordance with the number of momentum traders, because variance of traders' expected values increases..

We can summarize our above findings as follows.

a) As for feedback to expected values, a market crash or price overshoot is observed when the exogenous shock is larger than variance of market participants' expected values and the transmission range of the shock is relatively limited. As the share of momentum traders rises, market prices are more likely to overshoot.

b) As for feedback to confidence in expectation, neither market crash nor price overshoot may occur regardless of the number of momentum traders. This result does not necessarily mean that feedback mechanism to confidence is more favorable for price discovery function than feedback to expected value. Feedback to confidence has another problem that market liquidity evaporates and price discovery function halts spontaneously.[9]

## 4. Activation of the trading halt system

As described in Section 1, since the overshooting of market prices only leads to income transfer among market participants, we should note that artificial halting of the price

[9] See Muranaga and Shimizu [1999b].

overshooting may not be a desirable system design. However, we regard such market price overshooting, or a market crash, as a destabilizing factor of the economy. Next, we will examine the effectiveness of trading halt systems as a crash preventing mechanism. Specifically, as an example, we examine the case with feedback to expected value, which are likely to lead to a market crash. We conduct our simulations by changing the price level which triggers the trading halt system and halt period, and analyze the relationship between such setting and the market behavior after resumption of the trade.

First, we conduct our analysis based on the setting used in Figure 13-8, where there were most crashes among the cases which include feedback mechanism to expected values. Specifically, we construct a market composed of 50 value traders, who revise their expected values at the 10% trigger level, and 10 momentum traders. We then add to the market a 10.0% exogenous downward shock with a 40% transmission range. The trigger price levels of the trading halt system are set at -10% level (900 yen) and -20% level (800 yen) of the initial price (1,000 yen), and the trading halt period set at 5, 10, 15, and 20. Figures 17-20 illustrate developments in market price, mean of expected values, price overshoot ratio, and order imbalance.

The simulation results show us that market prices after resumption of trading are relatively stable when the trading halt period exceeds the length of the trader's memory (10 periods). In contrast, when the trading halt period is shorter than the length of the trader's memory (that is, in the cases of 5 and 10 trading halt periods), a crash cannot be avoided. When we examine each a simulation path, we can see how the declining speed of mean of traders' expected values at the point of trading resumption has a substantial effect on subsequent market behavior. Figure 21 shows the relationship between the declining speed of expected values at the point trading resumes and market behavior after resumption of trading. In cases where the market moves towards a crash after resumption of trading, the declining speed of the fundamental values at the point of trading resumption is large. On the other hand, in cases where the market shows stable movement after resumption of trading, the rate of change in expected values approaches zero during the trading halt period. The length of time needed for the declining speed of expected values to reach zero will depend on how much market participants incorporate past market price changes (memory horizon) in adjusting their individual fundamental values. Therefore, the effectiveness of the trading halt system may be improved by setting the trading halt period long enough relative to the length of the memory horizon. In order to apply this finding in the actual market design, we need to observe the declining speed of the market participants' expected values. Such speed cannot be directly observed, although there may be a source which would enable us to determine the optimal timing in which to resume trading in a stable way.[10]

In our simulation, there was a case in which market prices rallied and diffused upward with 15 trading halt periods. Upon examining this case in detail, we found that market price rallied because trading resumed at the point when market participants' expected values also rallied. Although we may not be able to see such a phenomenon in the actual market, this finding may imply that the market can be distorted according to the timing of the resumption of trading.

## 5. Conclusions and future tasks

By using the Monte Carlo simulation based on an artificial market model, an analytical method used in Muranaga and Shimizu [1999a], we have analyzed the market crash generating mechanism and the trading halt system. With respect to the mechanism which allows traders to feedback market information to their trading behavior, this paper focused on the following two: feedback to expected value, and feedback to confidence in forecast. As for the effects of exogenous shocks, we added to our model

[10] We have tried to estimate the optimal timing for resumption of trading by using the development of traders' limit order book as a proxy for change rates of their expected values, but the results were not relevant.

20 types of shocks with different impact and transmission range, and analyzed the subsequent market behavior.

As a result, we found that a market crash (substantial fall in market prices) is observed in cases which include feedback mechanism to expected value. In addition, the probability of a crash increases when there is a limited transmission range of exogenous shock or a high ratio of momentum traders, who trade by only considering market price changes.

We then examined the market behavior when the trading halt system is activated. Specifically, we observed how market behavior differs when the price level which triggers the trading halt system and halt period are changed. The results implied that, in order to have a stable market after resumption of trading, it is important to resume trading after the declining speed of the market participants' expected values has become small enough. Because the declining speed of traders' expected values cannot be directly observed, we need to find a certain proxy based on available market price or order flow information.

The above simulation results are only valid in the simplified hypothetical market model, and this model should be verified through the use of actual market data. However, given the difficulty in collecting data related to market crashes, we believe that our approach to understanding the market mechanism by aggregating micro-level behavioral mechanism through simulation can be deemed reasonable.

In order to explore the mechanisms operating in the actual market, we need to make our model more realistic. For this purpose, the following four points deserve attention.

a) Inclusion of trader's position and its market value

Our model does not consider the trader's position and its market value when he/she trades. In the actual market, however, traders seems to change their trading behaviors based on their position and profit/loss situation (e.g. loss cutting rules).

b) Consideration of traders' memory effects

As stated in Section 1, it has become generally recognized that the role of the circuit breaker system including the trading halt system is to give the human mind the chance to catch up with market developments (Brady [1998]). We have also confirmed in our analysis that, when the market is likely to overshoot because of exogenous shocks, activation of the trading halt system prevents market prices from overshooting. Such phenomenon tells us that market participants' behavior is affected by price changes of the past. We have used traders who trade according to the average and variance of price changes over the past 10 periods. By deepening our understanding of traders' "memory effects," we may be able to obtain insight into market dynamics, particularly the market's recursive process.

c) Activation level of the trading halt system

While we have observed the effects of the length of trading halt period, the effects of the activation price level of trading halt system have not been clearly identified and require future research. As for the effects of the activation level, we can conceive a situation where the existence of the trading halt system induces a market crash where trading is halted prematurely despite a substantial decline in market participants' expected values.

d) Activation of the trading halt system based on price change ratio

Because momentum traders' behavior is literally determined by momentum (historical trend of market price change) in the market where momentum traders are influential, we need to examine other factors such as declining speed of price in addition to price levels as activation standards of the trading halt system.

Figure 1.　Image of developments in market prices: Complete markets

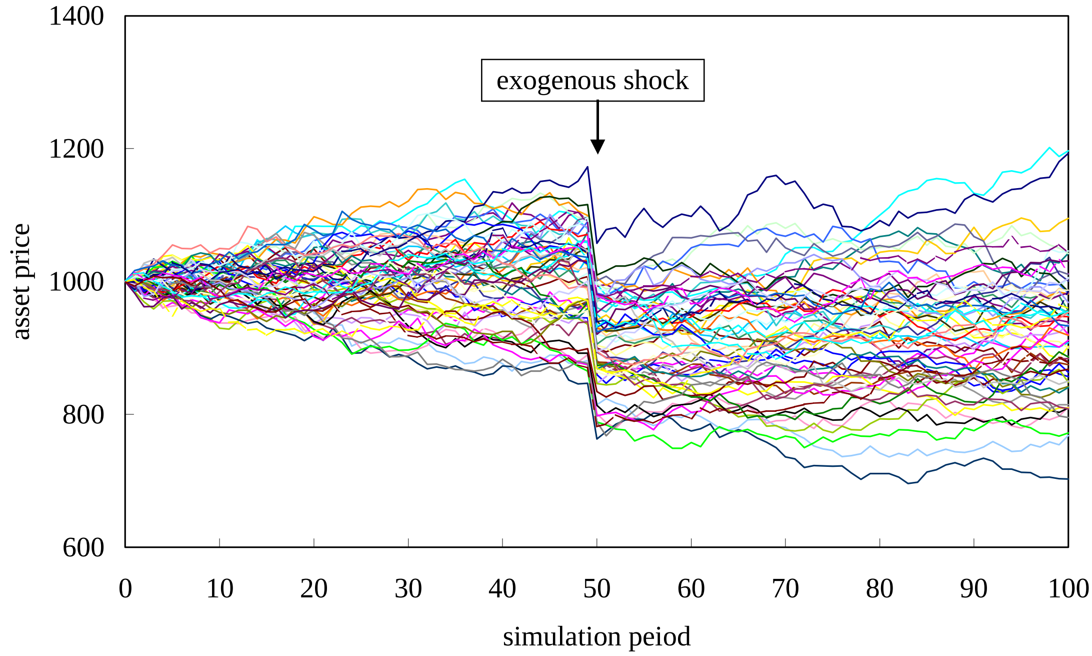



Figure 2.　Image of paths of market prices: Incomplete markets

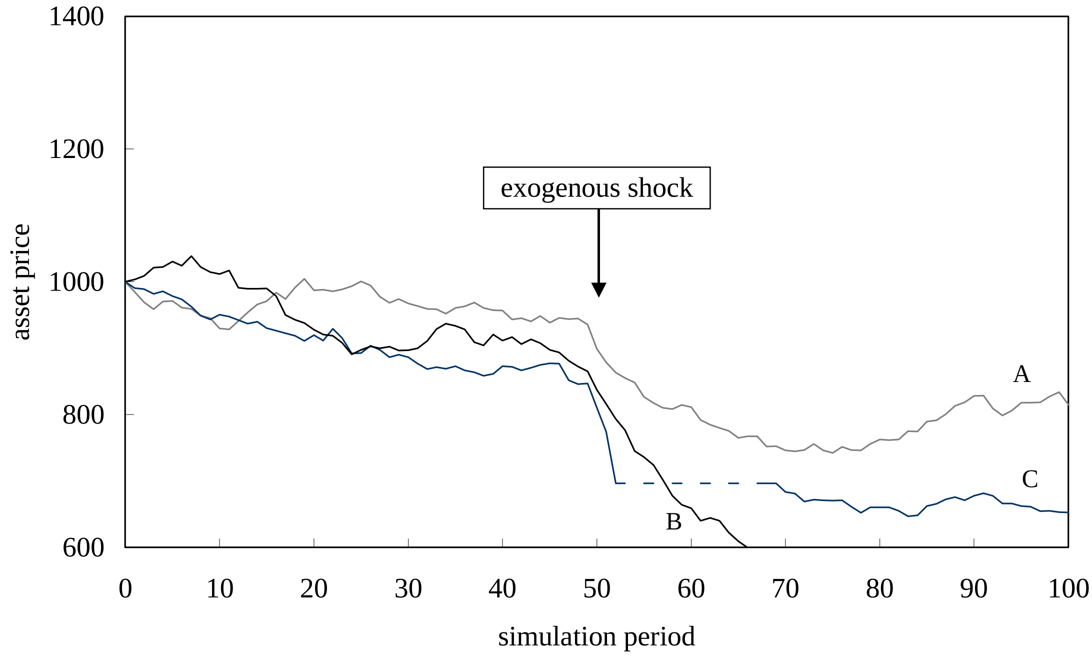


Figure 3.　A sample simulation result: New equilibrium

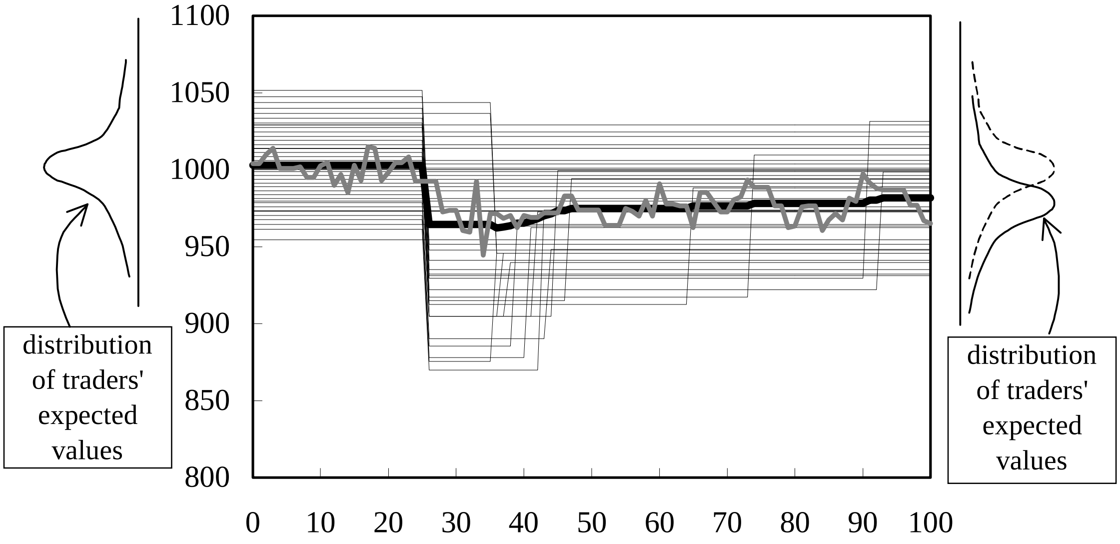



Figure 4.　A sample simulation result: Crash

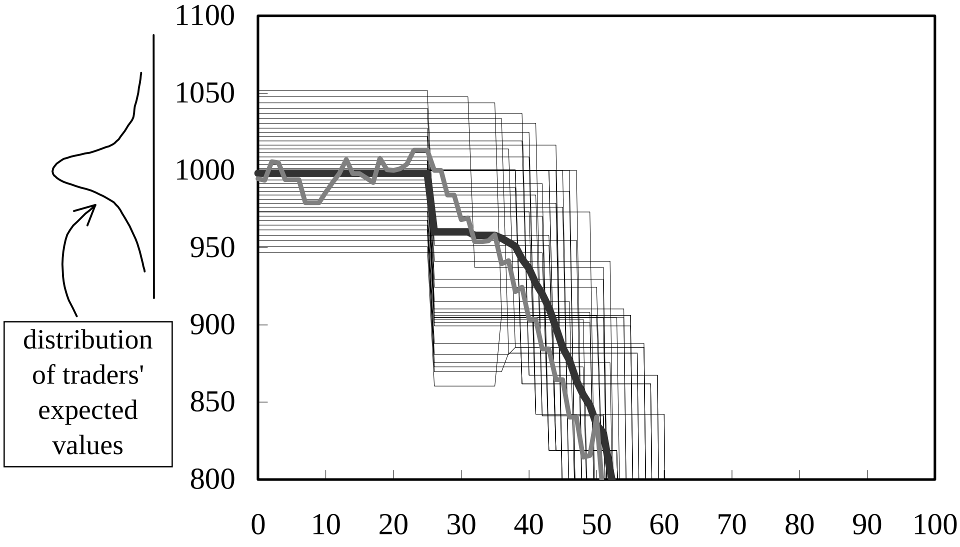


Figure 5.　Developments in market prices (Feedback to expected value)

Figure 5-1 (Impact:-2.5%, Range:20%)

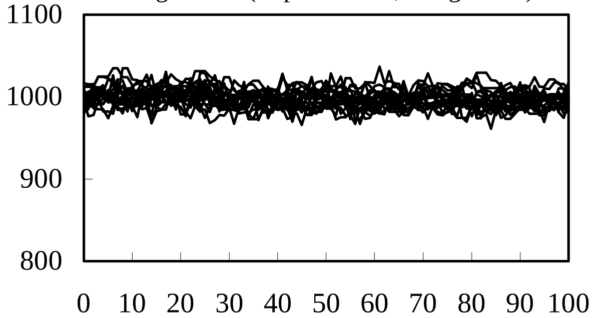



Figure 5-2 (Impact:-5.0%, Range:20%)

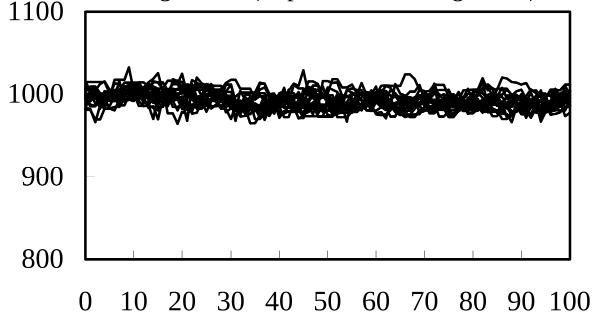



Figure 5-5 (Impact:-2.5%, Range:40%)

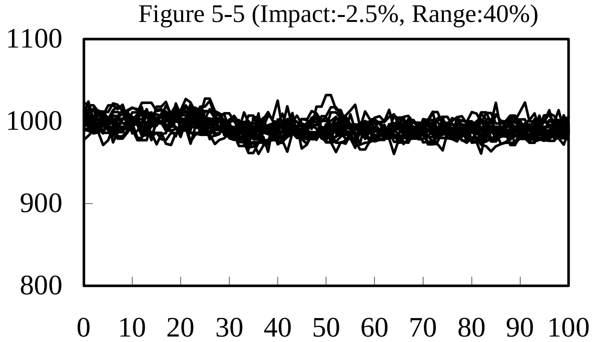
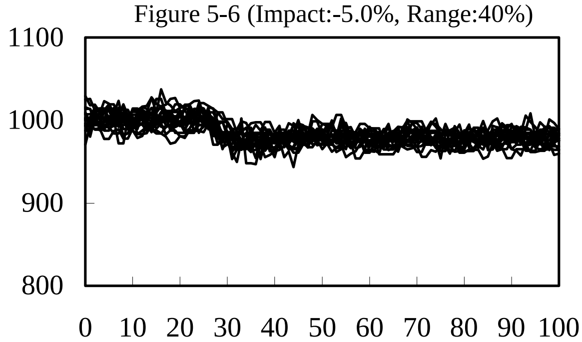



Figure 5-6 (Impact:-5.0%, Range:40%)

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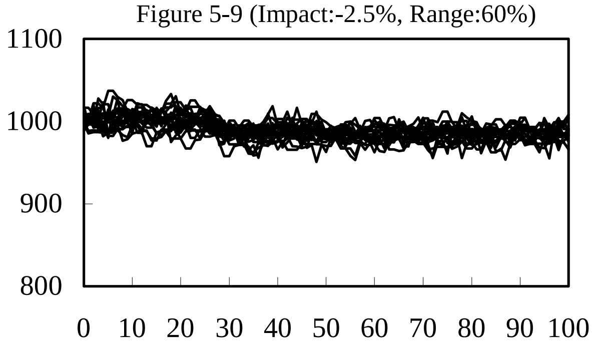
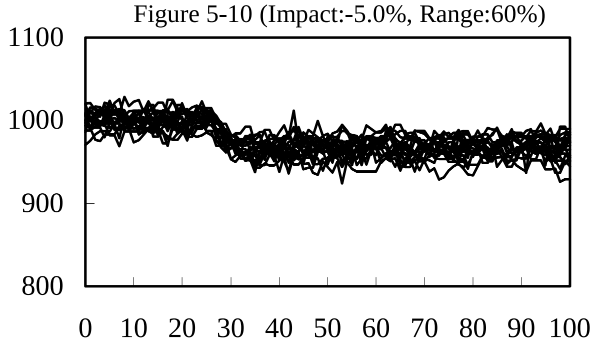



Figure 5-10 (Impact:-5.0%, Range:60%)

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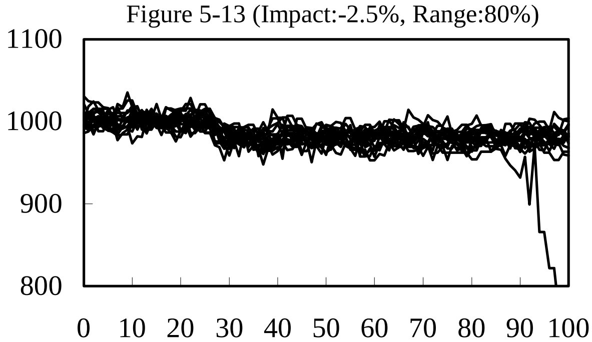
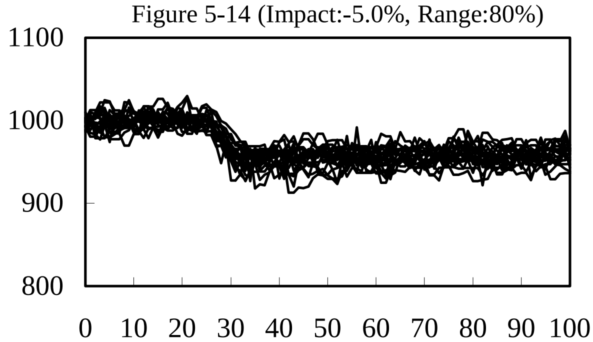



Figure 5-14 (Impact:-5.0%, Range:80%)

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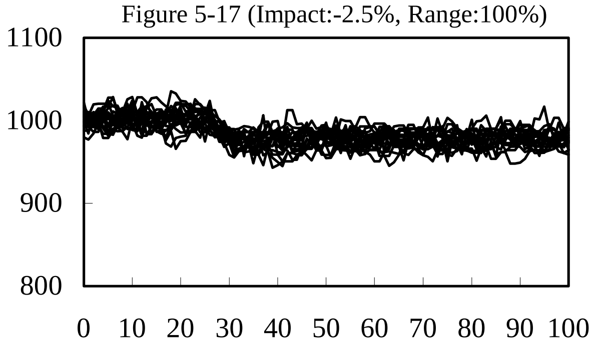



Figure 5-18 (Impact:-5.0%, Range:100%)

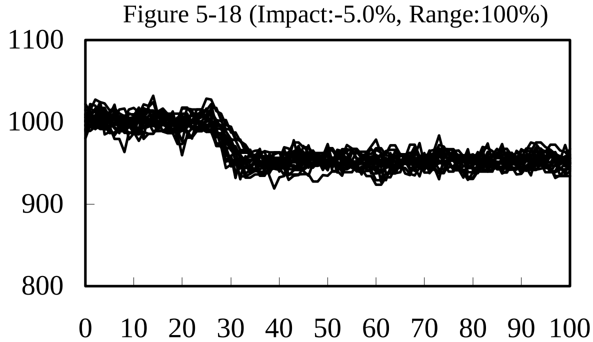
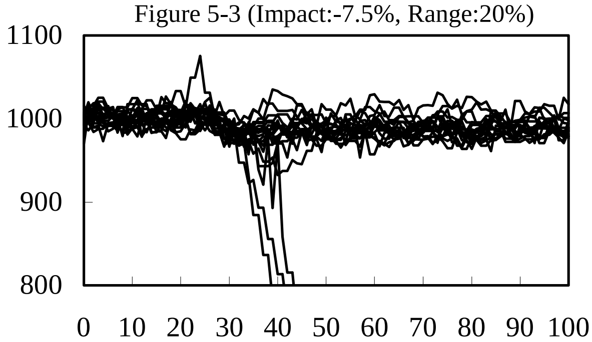


Figure 5. Developments in market prices (Continued)

Figure 5-3 (Impact:-7.5%, Range:20%)

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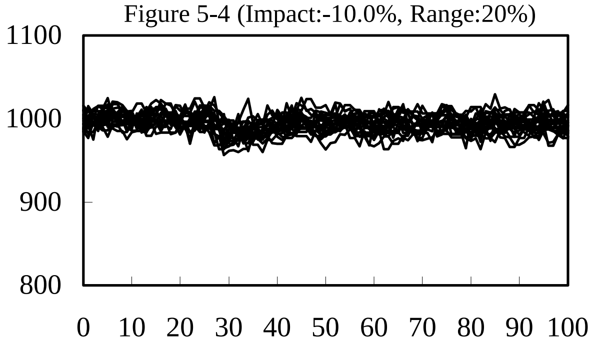


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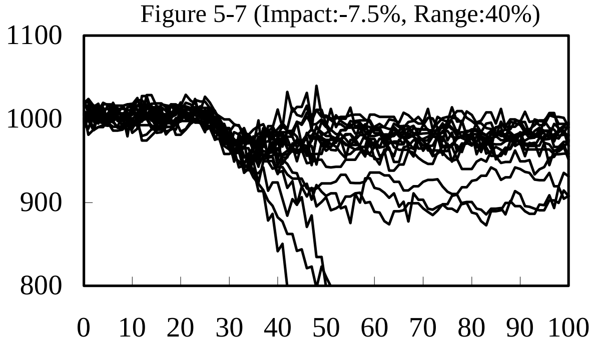



Figure 5-8 (Impact:-10.0%, Range:40%)

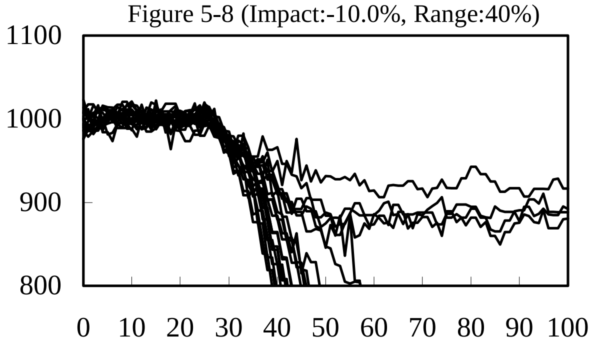



Figure 5-11 (Impact:-7.5%, Range:60%)

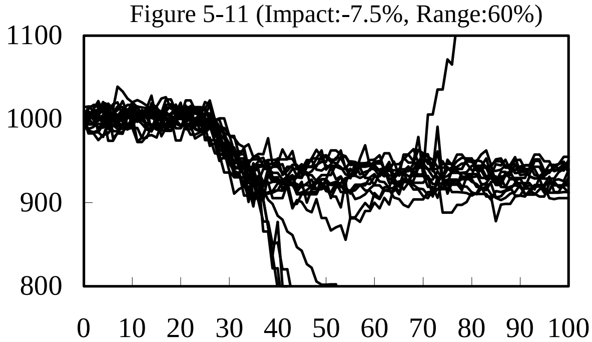



Figure 5-12 (Impact:-10.0%, Range:60%)

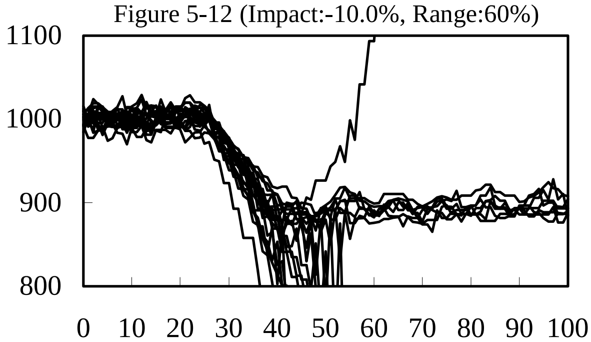



Figure 5-15 (Impact:-7.5%, Range:80%)

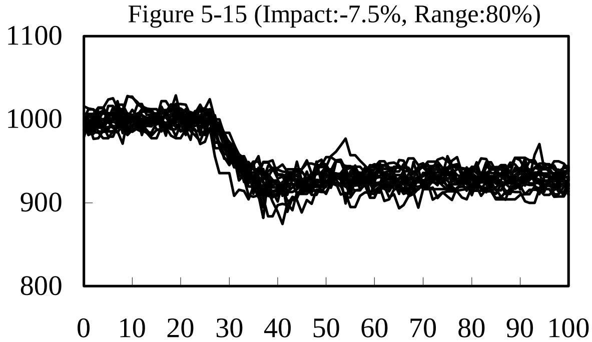



Figure 5-16 (Impact:-10.0%, Range:80%)

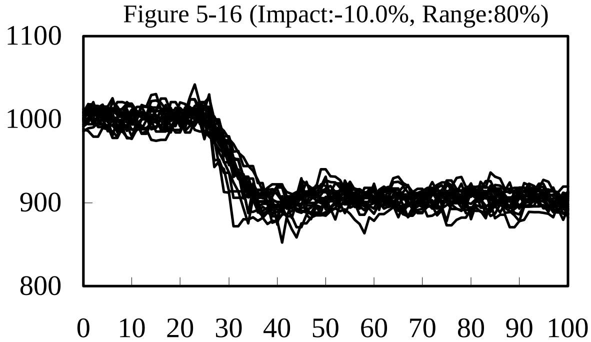



Figure 5-19 (Impact:-7.5%, Range:100%)

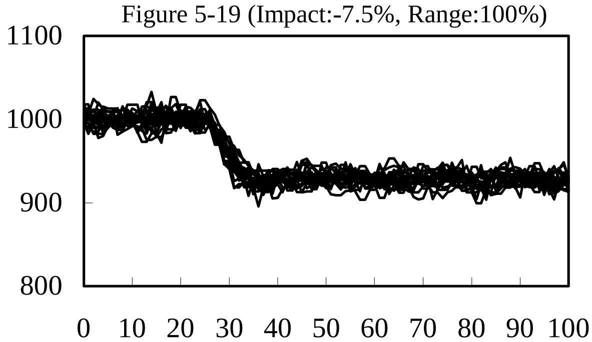



Figure 5-20 (Impact:-10.0%, Range:100%)

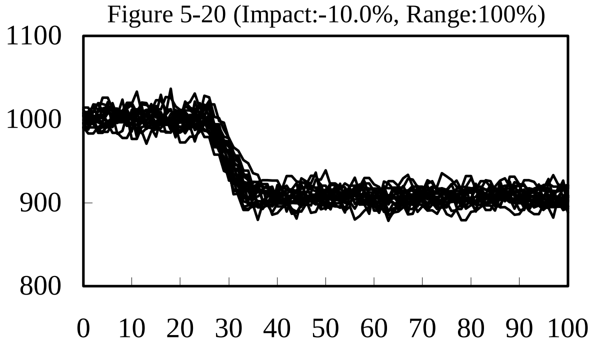


Figure 6. Developments in mean of traders' expected values (Feedback to expected value)

Figure 6-1 (Impact:-2.5%, Range:20%)

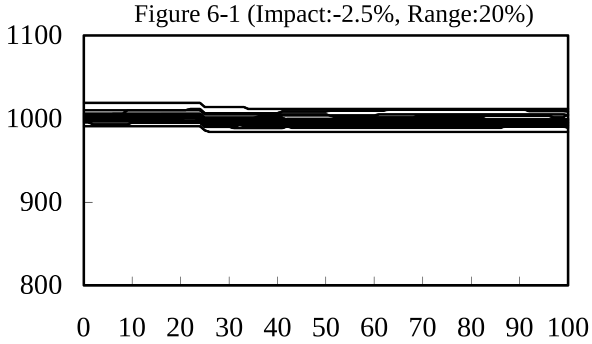



Figure 6-2 (Impact:-5.0%, Range:20%)

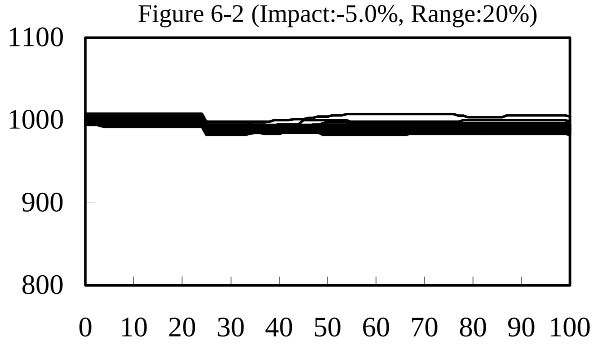



Figure 6-5 (Impact:-2.5%, Range:40%)

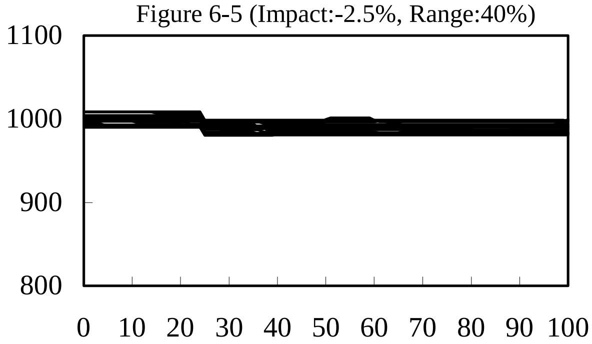



Figure 6-6 (Impact:-5.0%, Range:40%)

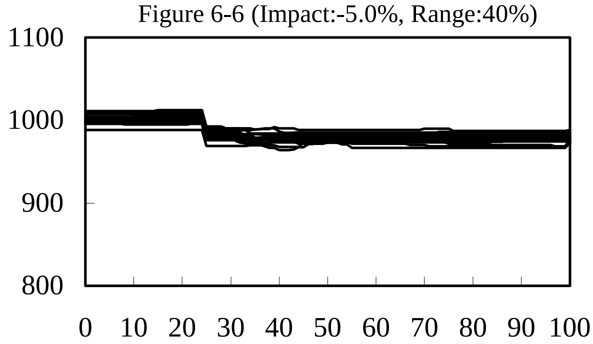



Figure 6-9 (Impact:-2.5%, Range:60%)

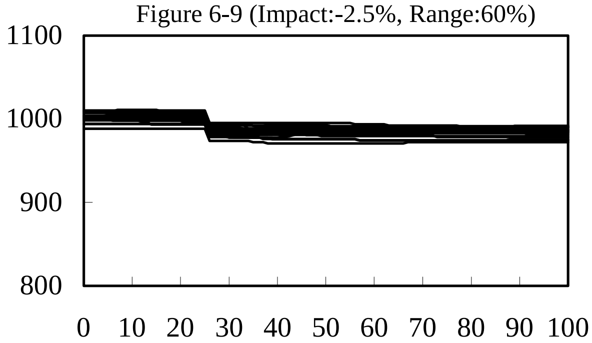



Figure 6-10 (Impact:-5.0%, Range:60%)

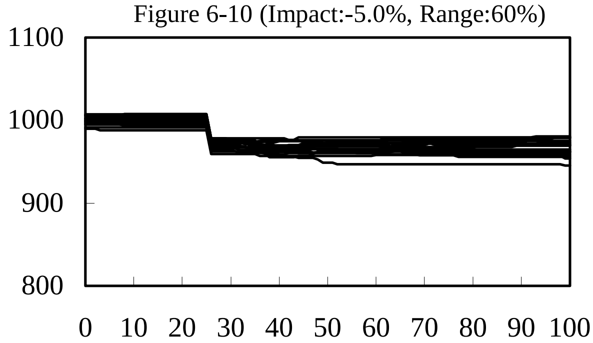



Figure 6-13 (Impact:-2.5%, Range:80%)

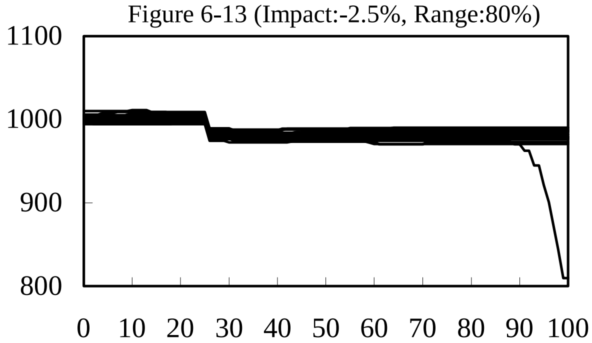



Figure 6-14 (Impact:-5.0%, Range:80%)

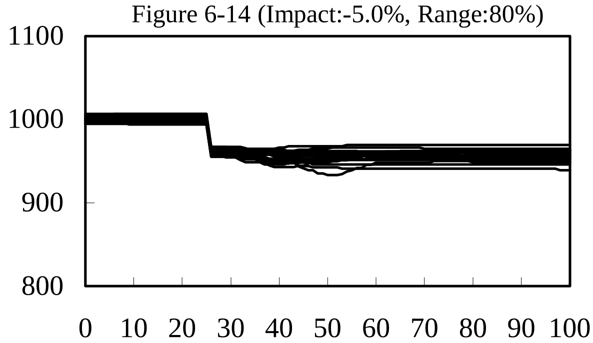



Figure 6-17 (Impact:-2.5%, Range:100%)

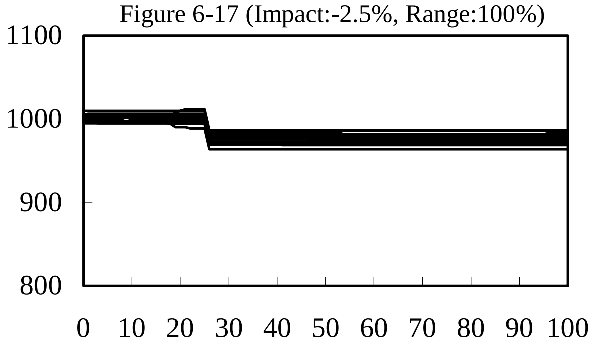



Figure 6-18 (Impact:-5.0%, Range:100%)

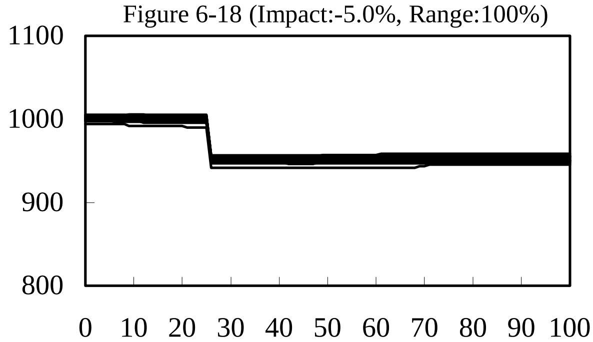


Figure 6. Developments in mean of traders' expected values (Continued)

Figure 6-3 (Impact:-7.5%, Range:20%)

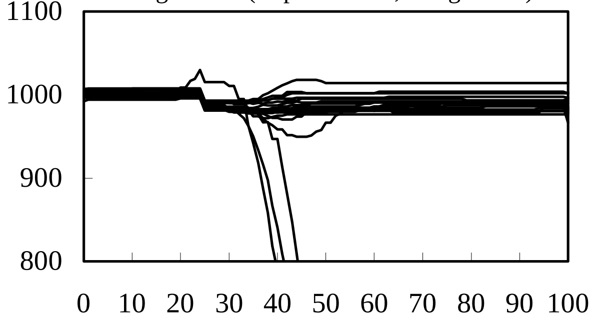



Figure 6-4 (Impact:-10.0%, Range:20%)

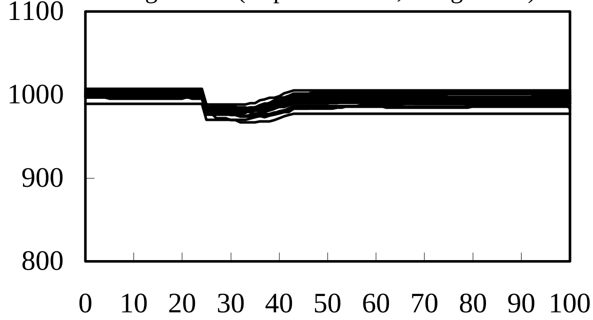



Figure 6-7 (Impact:-7.5%, Range:40%)

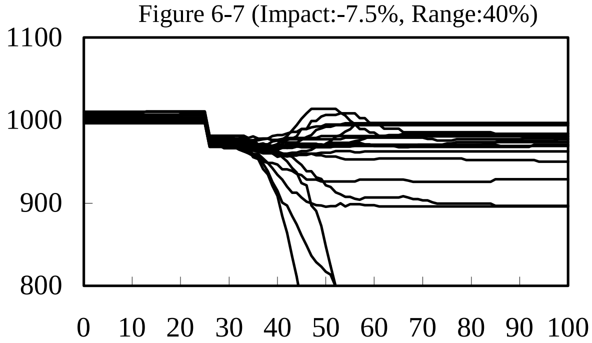



Figure 6-8 (Impact:-10.0%, Range:40%)

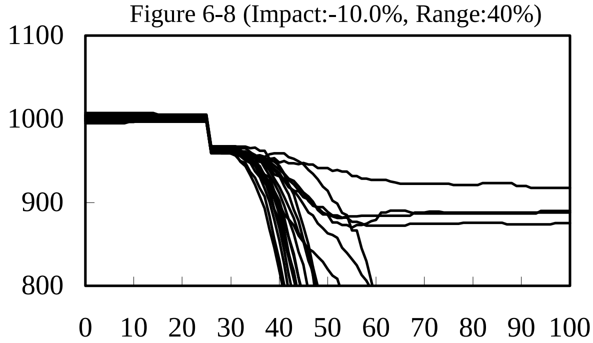



Figure 6-11 (Impact:-7.5%, Range:60%)

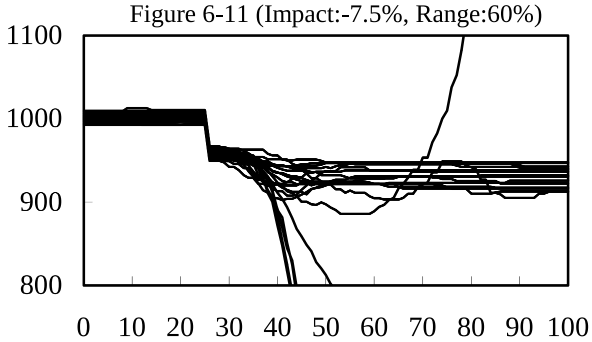



Figure 6-12 (Impact:-10.0%, Range:60%)

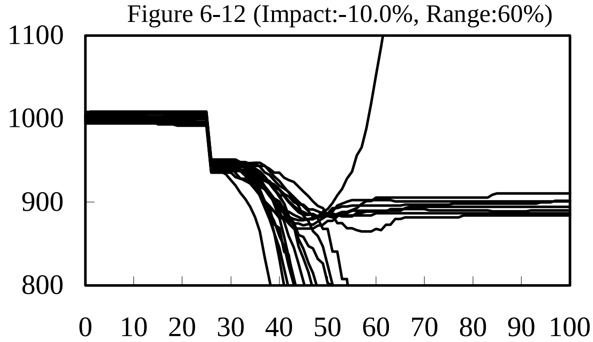



Figure 6-15 (Impact:-7.5%, Range:80%)

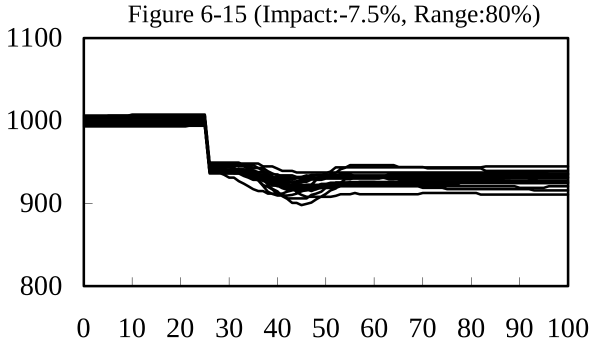



Figure 6-16 (Impact:-10.0%, Range:80%)

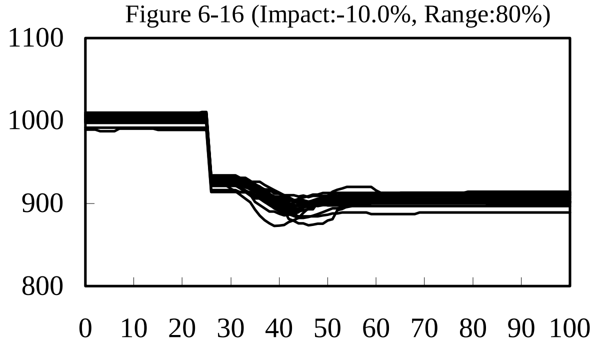



Figure 6-19 (Impact:-7.5%, Range:100%)

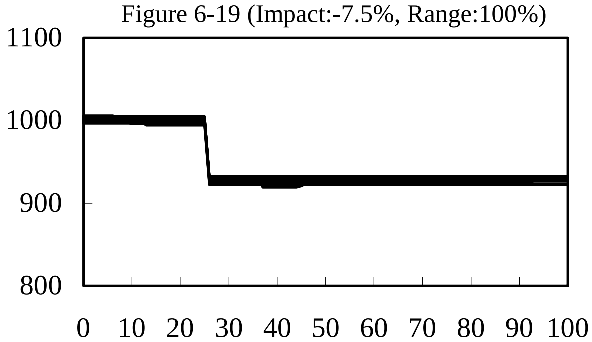



Figure 6-20 (Impact:-10.0%, Range:100%)

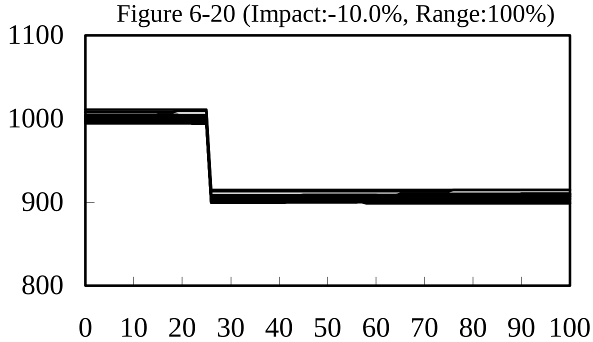


Figure 7. Developments in price overshoot ratio (Feedback to expected value)

Figure 7-1 (Impact:-2.5%, Range:20%)

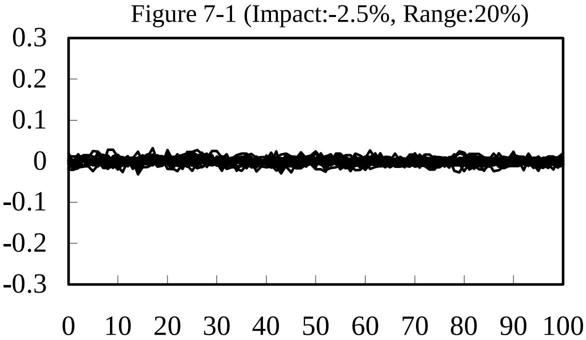



Figure 7-2 (Impact:-5.0%, Range:20%)

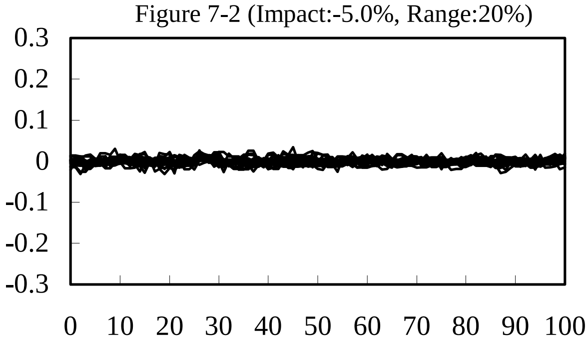



Figure 7-5 (Impact:-2.5%, Range:40%)

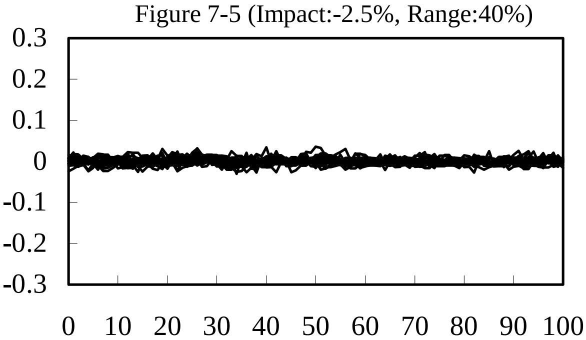



Figure 7-6 (Impact:-5.0%, Range:40%)

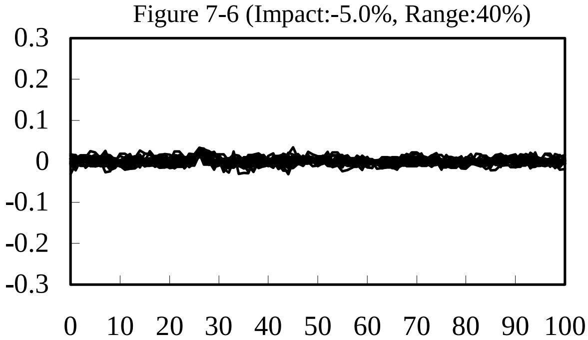



Figure 7-9 (Impact:-2.5%, Range:60%)

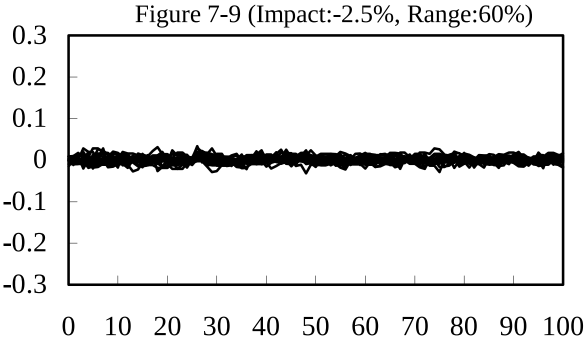



Figure 7-10 (Impact:-5.0%, Range:60%)

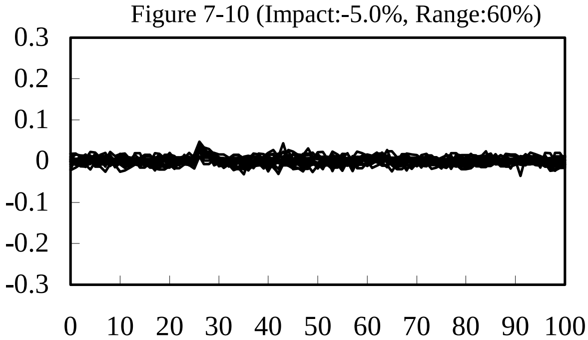



Figure 7-13 (Impact:-2.5%, Range:80%)

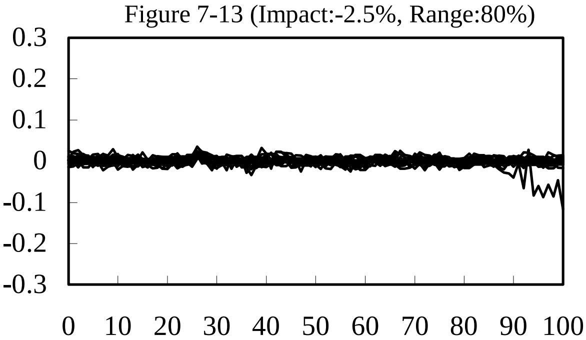



Figure 7-14 (Impact:-5.0%, Range:80%)

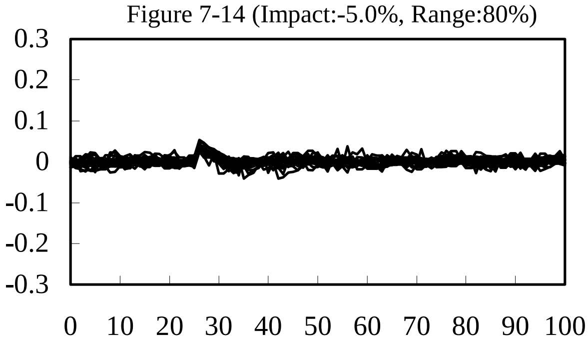



Figure 7-17 (Impact:-2.5%, Range:100%)

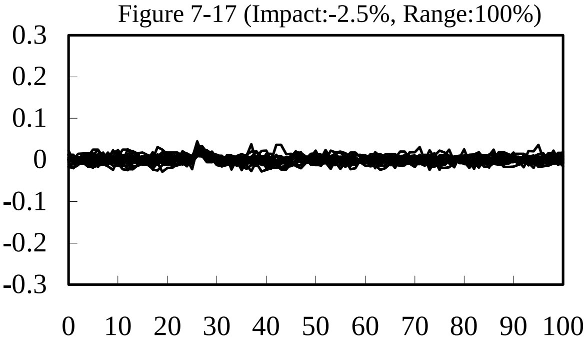



Figure 7-18 (Impact:-5.0%, Range:100%)

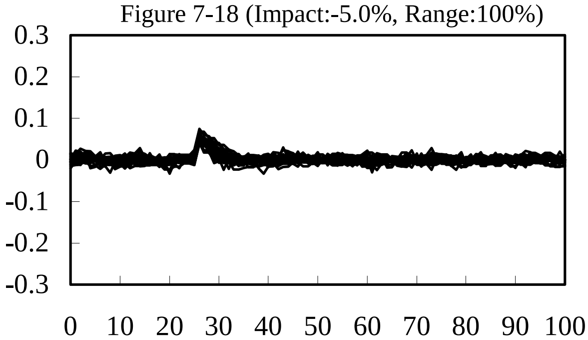


Figure 7. Developments in price overshoot ratio (Continued)

Figure 7-3 (Impact:-7.5%, Range:20%)

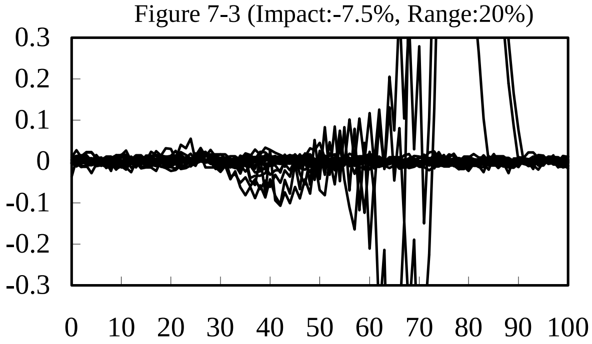



Figure 7-4 (Impact:-10.0%, Range:20%)

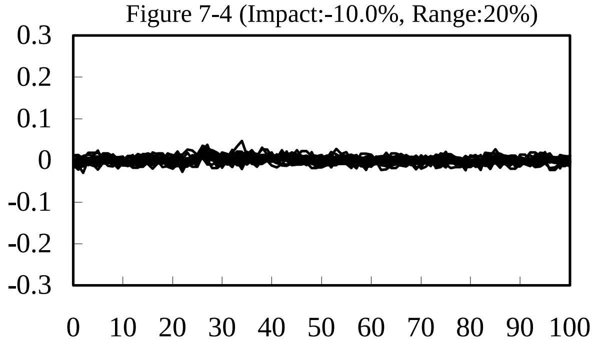



Figure 7-7 (Impact:-7.5%, Range:40%)

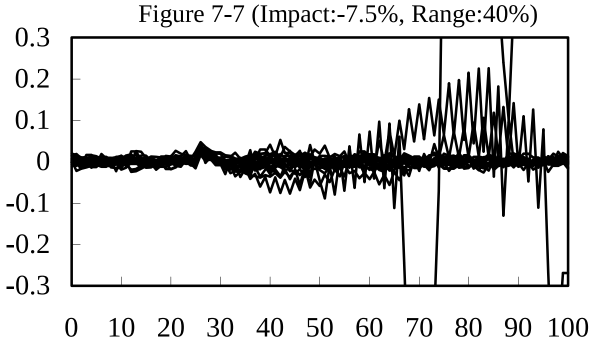



Figure 7-8 (Impact:-10.0%, Range:40%)

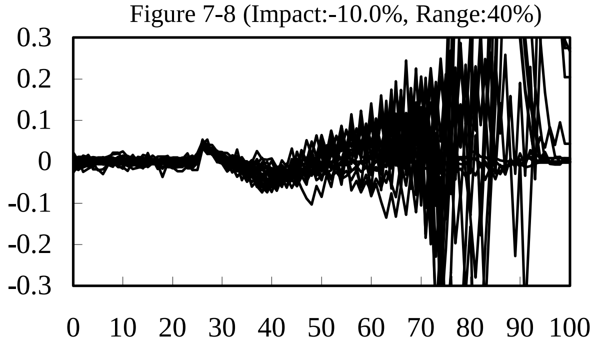



Figure 7-11 (Impact:-7.5%, Range:60%)

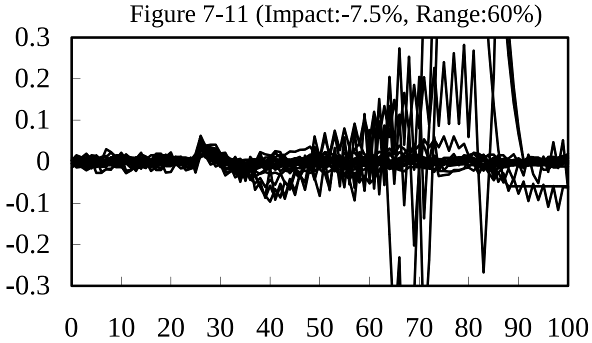



Figure 7-12 (Impact:-10.0%, Range:60%)

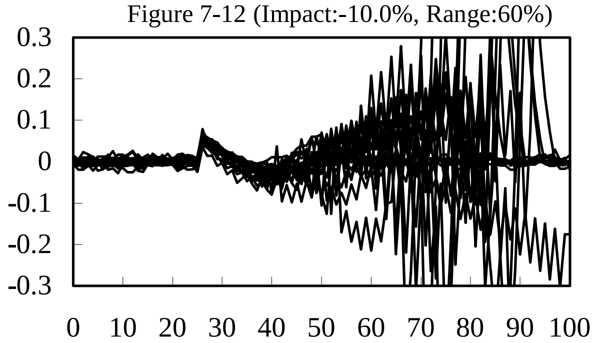



Figure 7-15 (Impact:-7.5%, Range:80%)

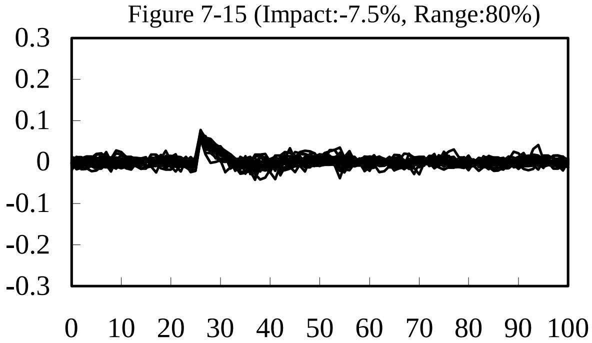



Figure 7-16 (Impact:-10.0%, Range:80%)

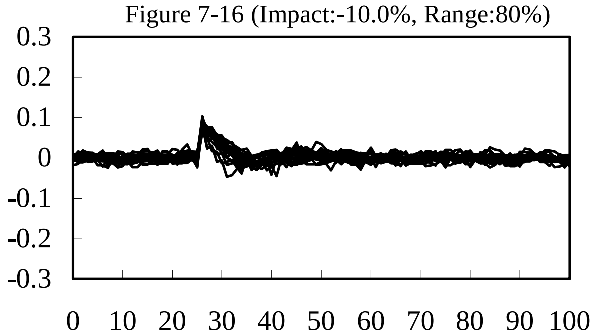



Figure 7-19 (Impact:-7.5%, Range:100%)

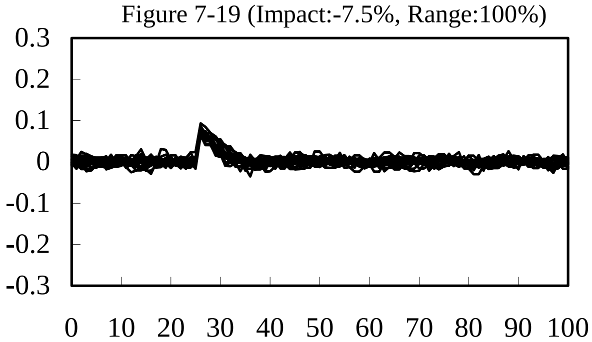



Figure 7-20 (Impact:-10.0%, Range:100%)

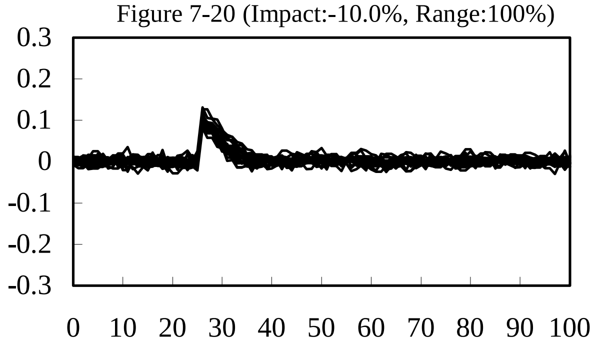
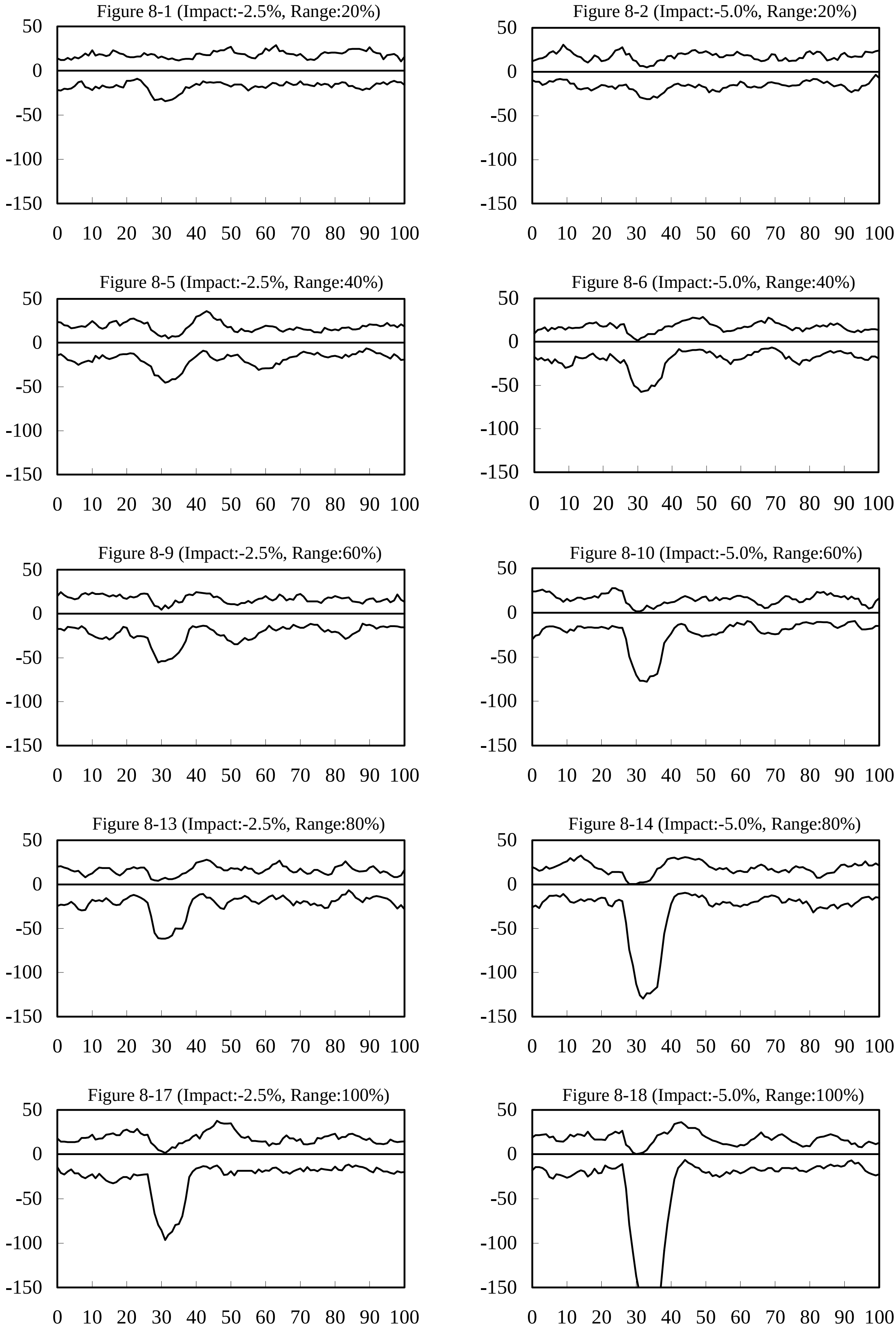
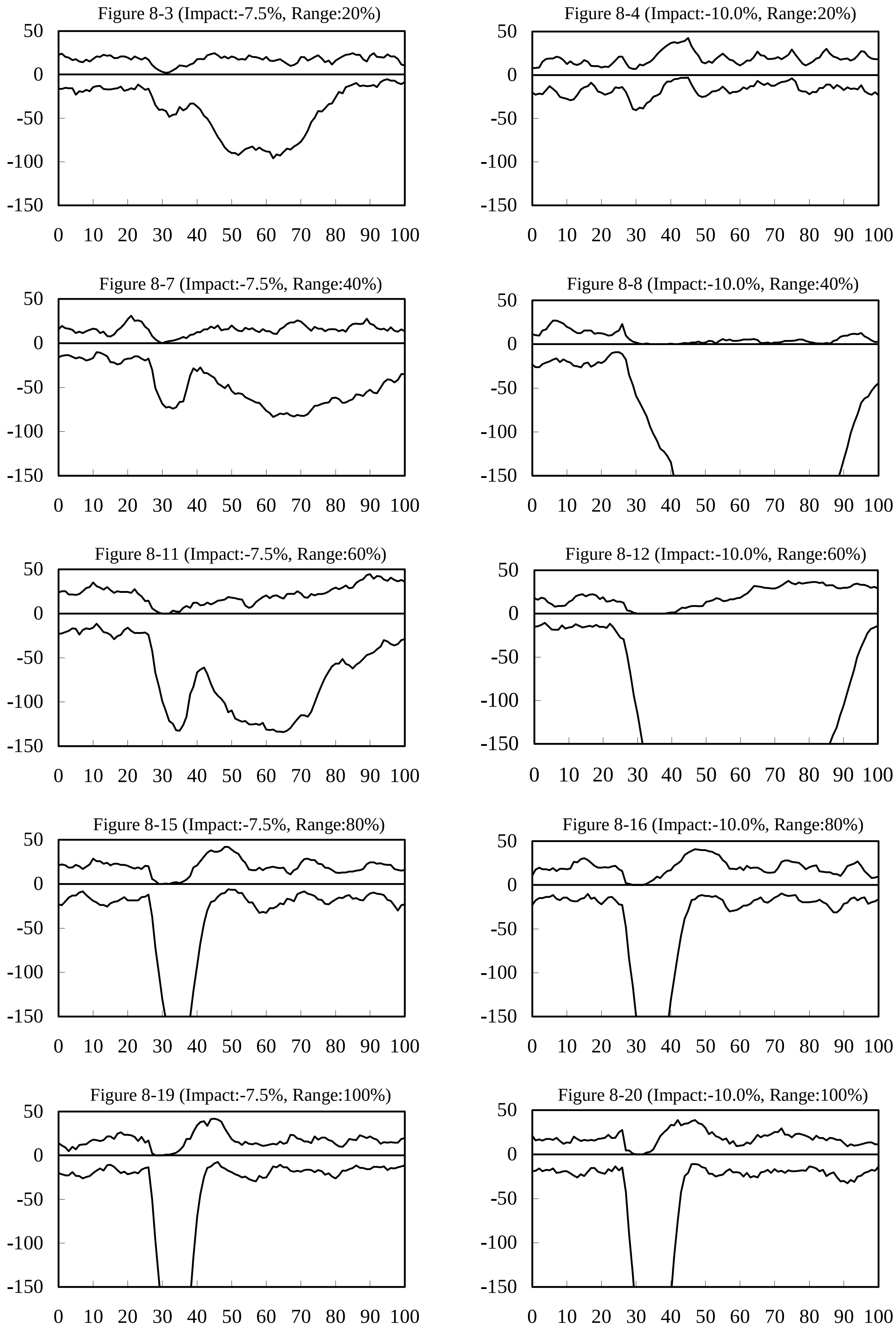


Figure 8. Developments in order imbalance (Feedback to expected value)*




*: What is plotted on the positive side of the vertical axis illustrates buying order volume, while selling order volume is plotted on the negative side.

Figure 8. Developments in order imbalance (Continued)*




*: What is plotted on the positive side of the vertical axis illustrates buying order volume, while selling order volume is plotted on the negative side.

Figure 9. Developments in market price (Feedback to confidence)

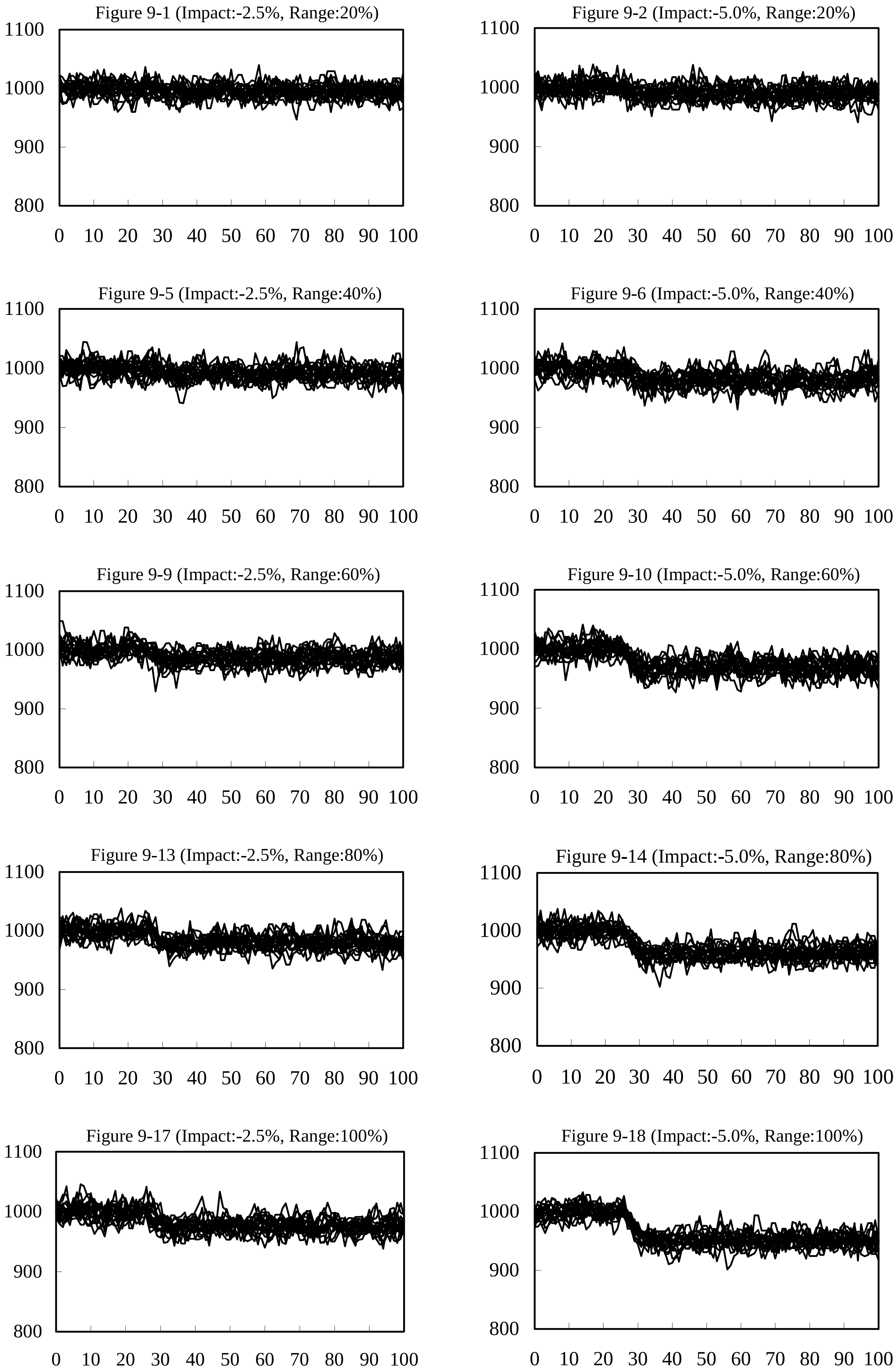


Figure 9. Developments in market price (Continued)

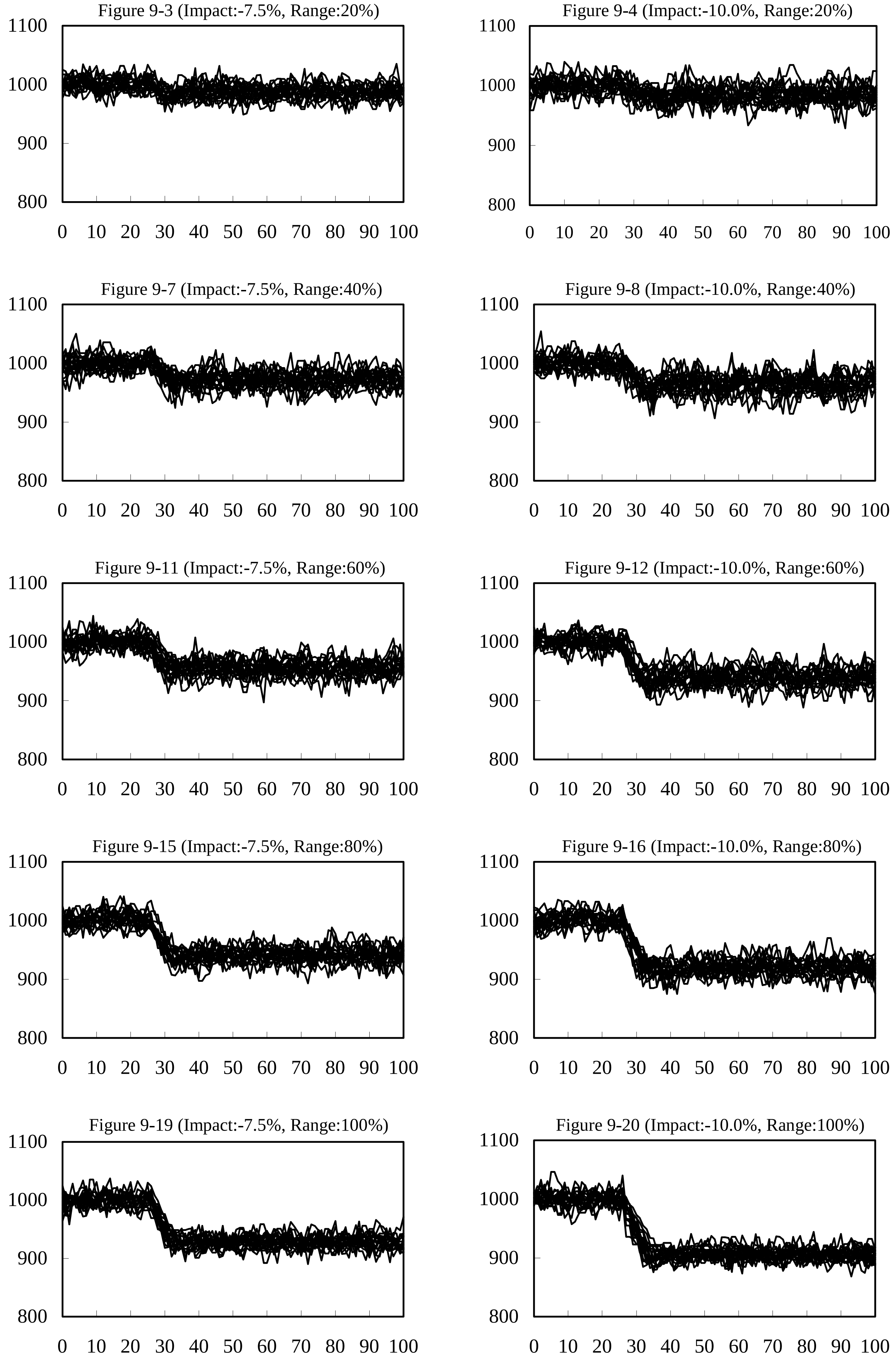


Figure 10. Developments in mean of traders' expected values (Feedback to confidence)

Figure 10-1 (Impact:-2.5%, Range:20%)

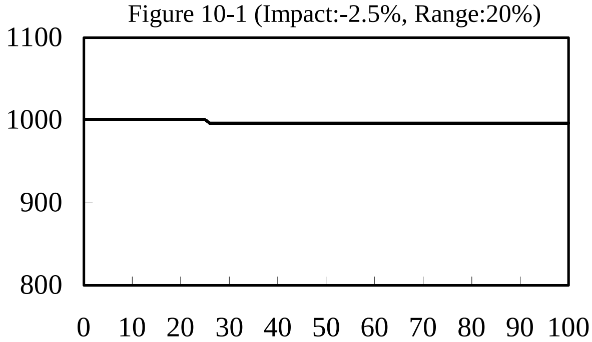



Figure 10-2 (Impact:-5.0%, Range:20%)

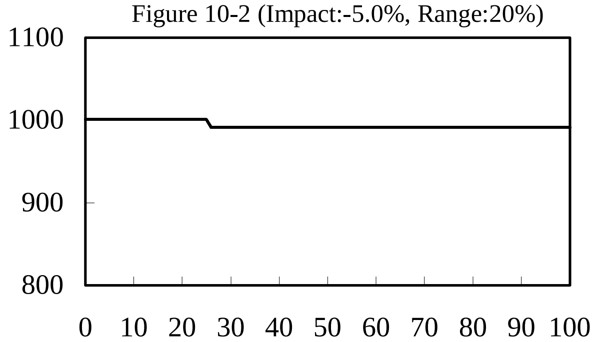



Figure 10-5 (Impact:-2.5%, Range:40%)

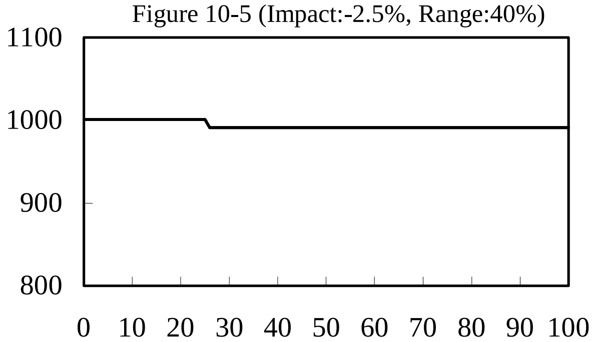



Figure 10-6 (Impact:-5.0%, Range:40%)

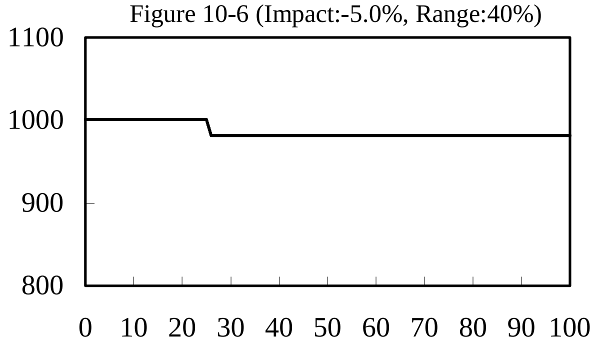



Figure 10-9 (Impact:-2.5%, Range:60%)

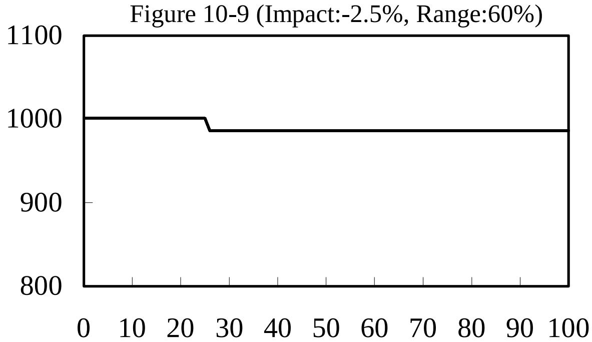



Figure 10-10 (Impact:-5.0%, Range:60%)

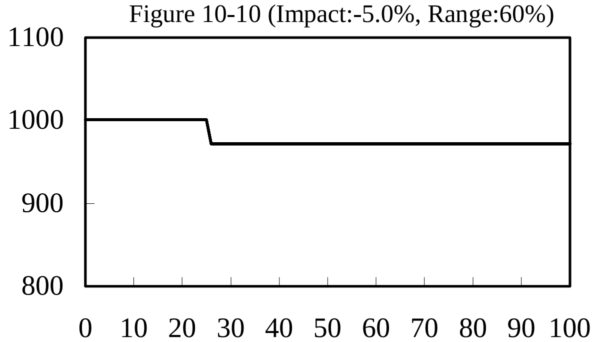



Figure 10-13 (Impact:-2.5%, Range:80%)

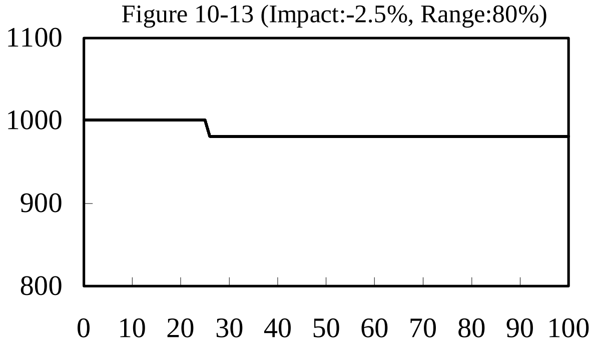



Figure 10-14 (Impact:-5.0%, Range:80%)

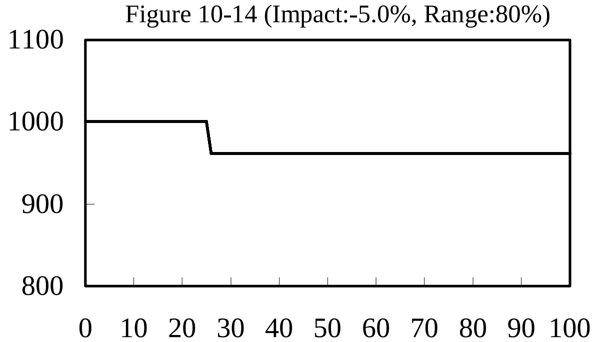



Figure 10-17 (Impact:-2.5%, Range:100%)

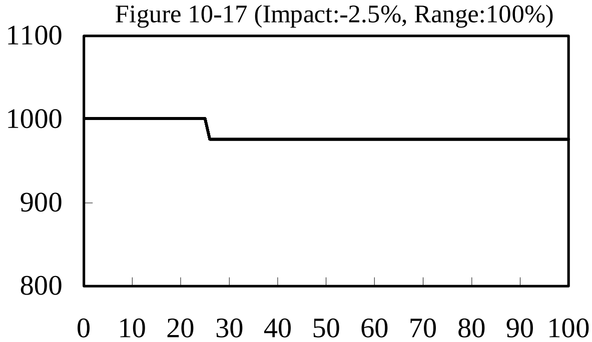



Figure 10-18 (Impact:-5.0%, Range:100%)

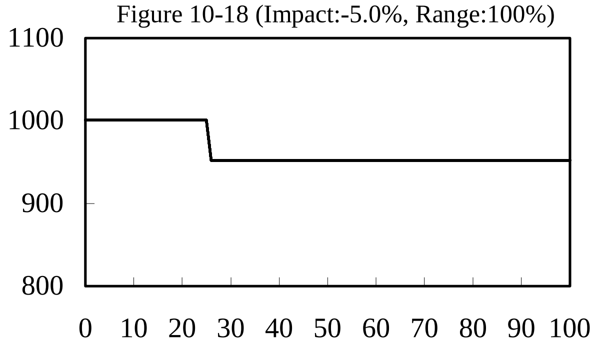


Figure 10.  Developments in mean of traders' expected values (Continued)

Figure 10-3 (Impact:-7.5%, Range:20%)

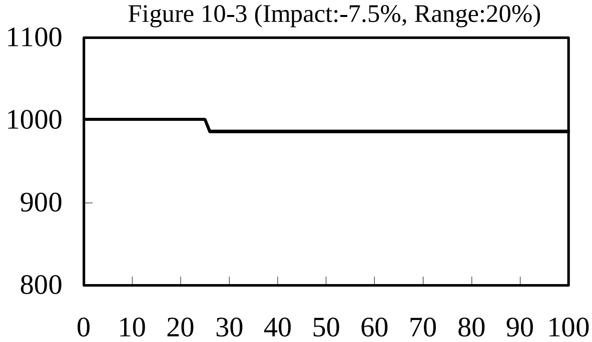



Figure 10-4 (Impact:-10.0%, Range:20%)

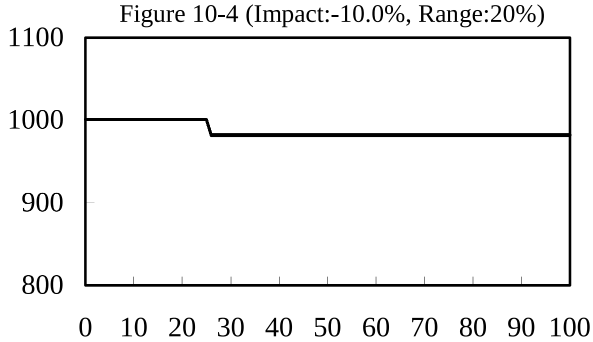



Figure 10-7 (Impact:-7.5%, Range:40%)

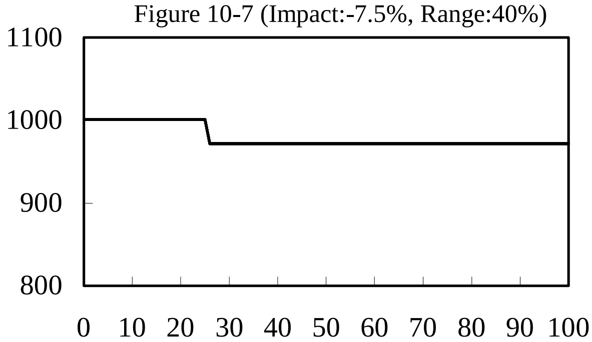



Figure 10-8 (Impact:-10.0%, Range:40%)

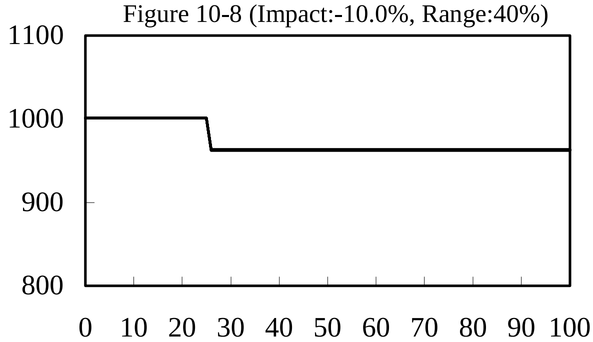



Figure 10-11 (Impact:-7.5%, Range:60%)

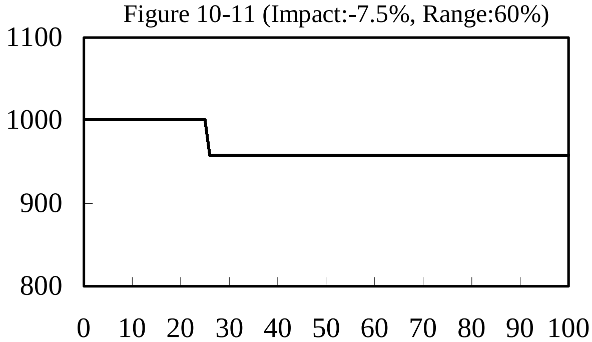



Figure 10-12 (Impact:-10.0%, Range:60%)

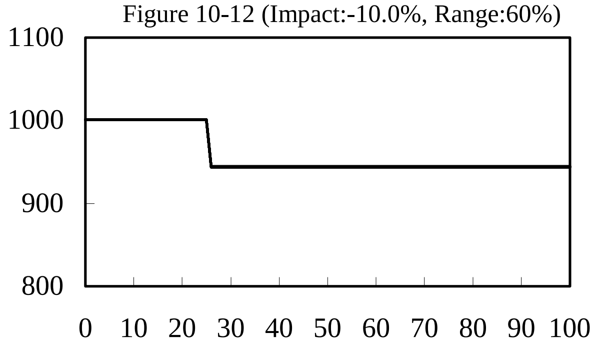



Figure 10-15 (Impact:-7.5%, Range:80%)

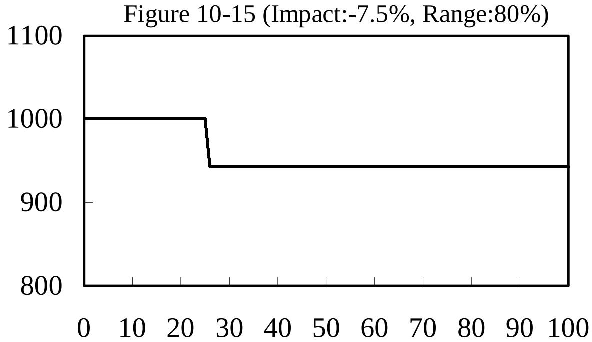



Figure 10-16 (Impact:-10.0%, Range:80%)

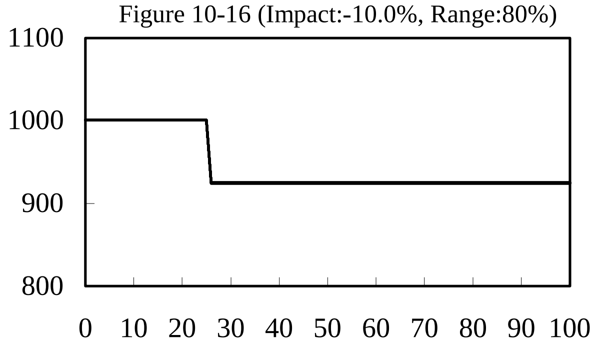



Figure 10-19 (Impact:-7.5%, Range:100%)

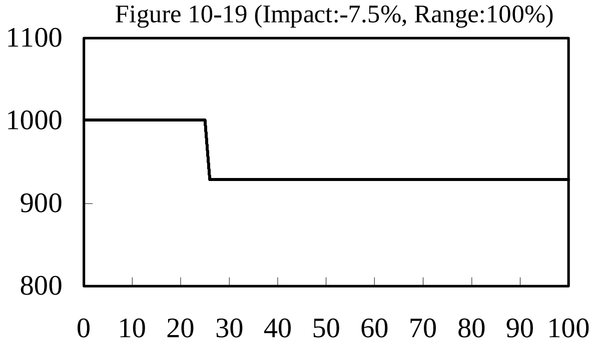



Figure 10-20 (Impact:-10.0%, Range:100%)

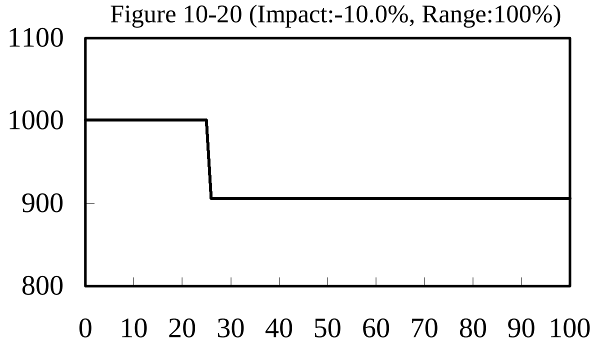


Figure 11. Developments in price overshoot ratio (Feedback to confidence)

Figure 11-1 (Impact:-2.5%, Range:20%)

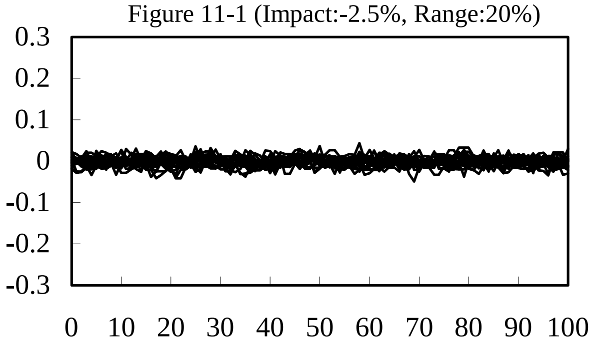



Figure 11-2 (Impact:-5.0%, Range:20%)

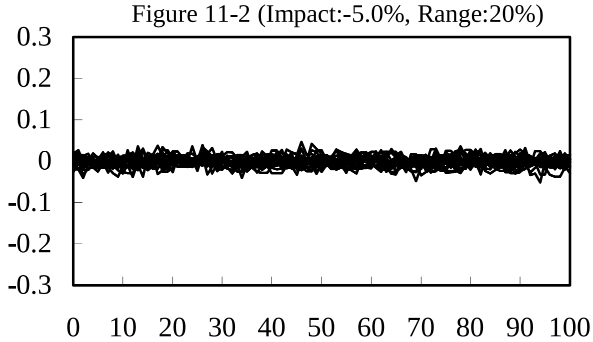



Figure 11-5 (Impact:-2.5%, Range:40%)

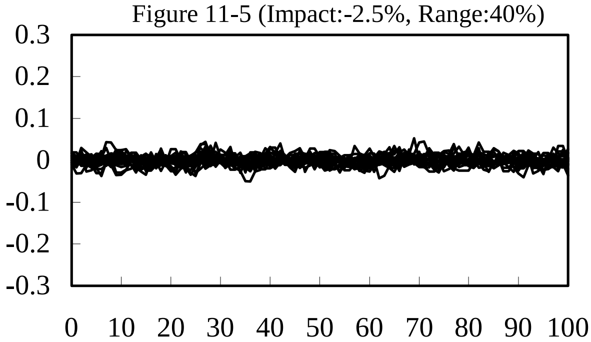



Figure 11-6 (Impact:-5.0%, Range:40%)

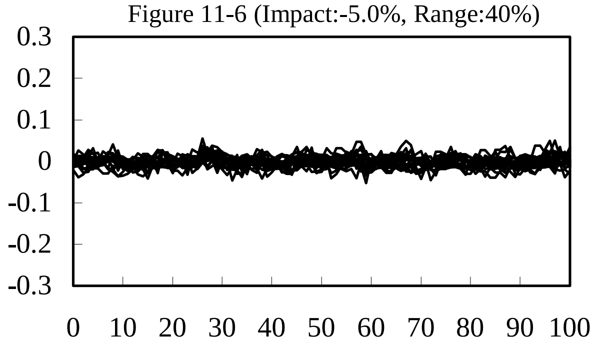



Figure 11-9 (Impact:-2.5%, Range:60%)

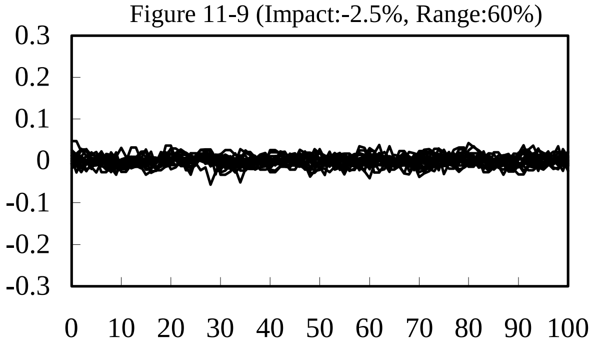



Figure 11-10 (Impact:-5.0%, Range:60%)

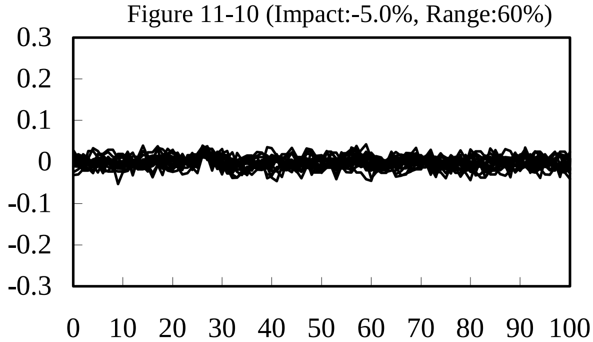



Figure 11-13 (Impact:-2.5%, Range:80%)

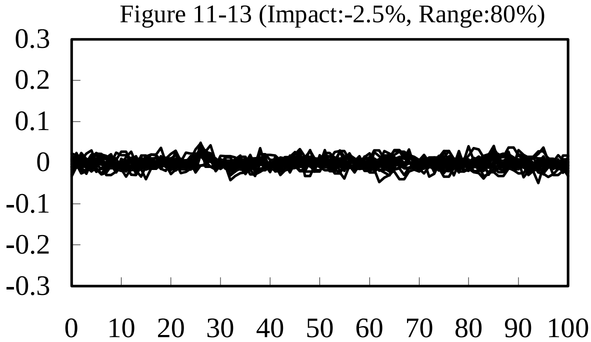



Figure 11-14 (Impact:-5.0%, Range:80%)

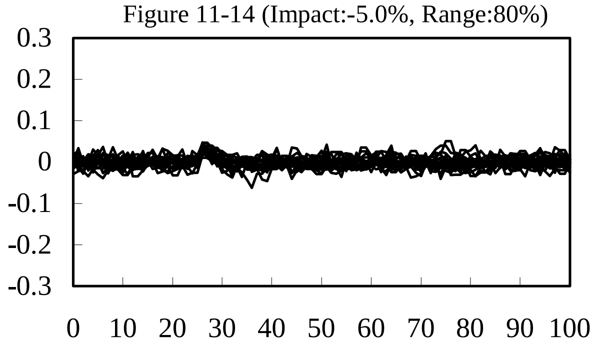



Figure 11-17 (Impact:-2.5%, Range:100%)

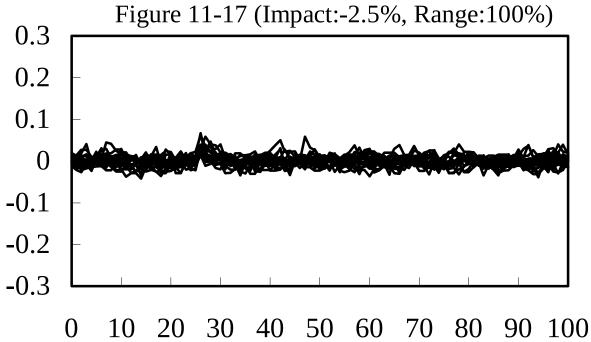



Figure 11-18 (Impact:-5.0%, Range:100%)

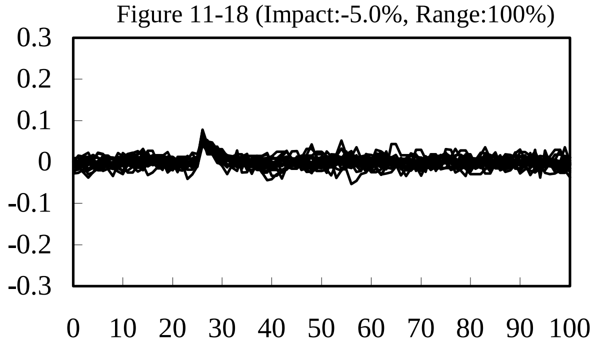


Figure 11. Developments in price overshoot ration (Continued)

Figure 11-3 (Impact:-7.5%, Range:20%)

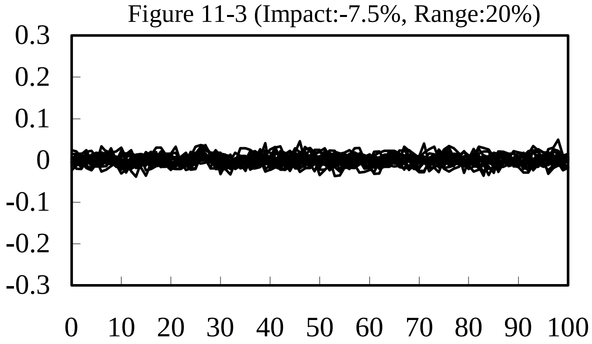



Figure 11-4 (Impact:-10.0%, Range:20%)

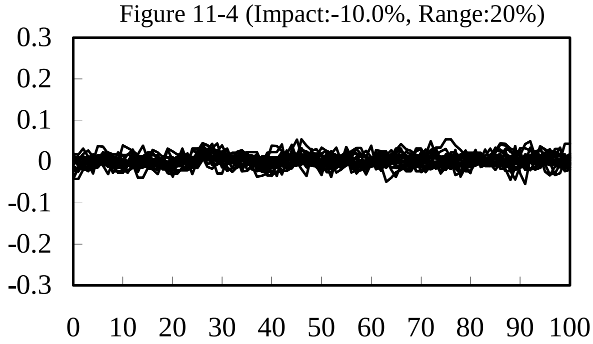



Figure 11-7 (Impact:-7.5%, Range:40%)

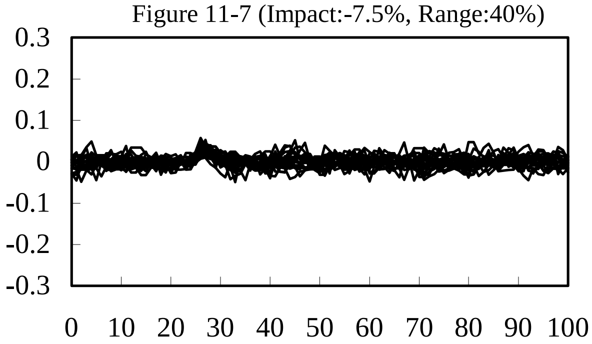



Figure 11-8 (Impact:-10.0%, Range:40%)

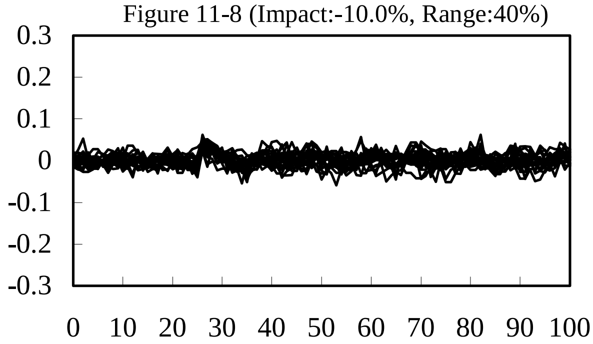



Figure 11-11 (Impact:-7.5%, Range:60%)

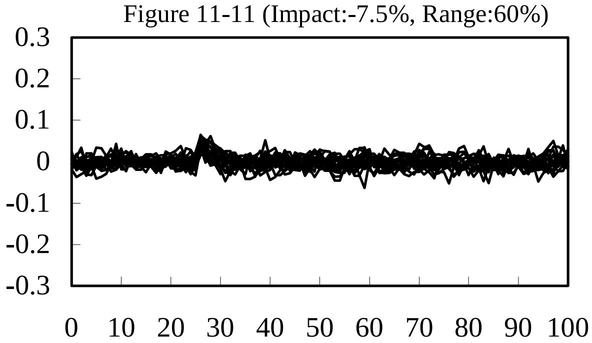



Figure 11-12 (Impact:-10.0%, Range:60%)

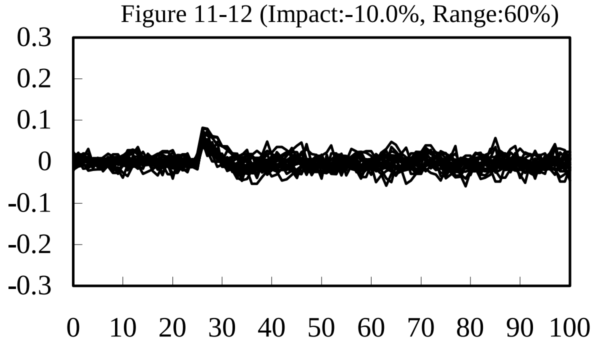



Figure 11-15 (Impact:-7.5%, Range:80%)

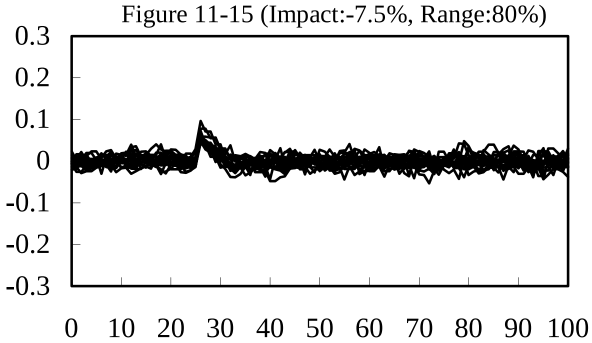



Figure 11-16 (Impact:-10.0%, Range:80%)

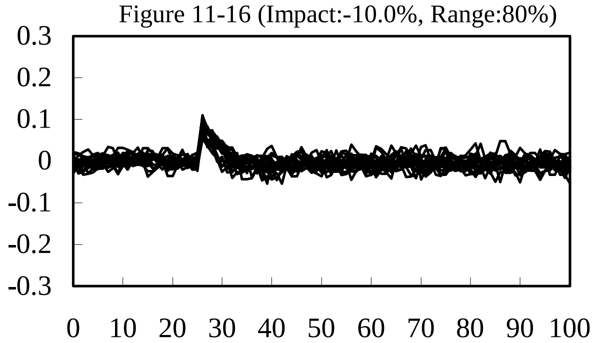



Figure 11-19 (Impact:-7.5%, Range:100%)

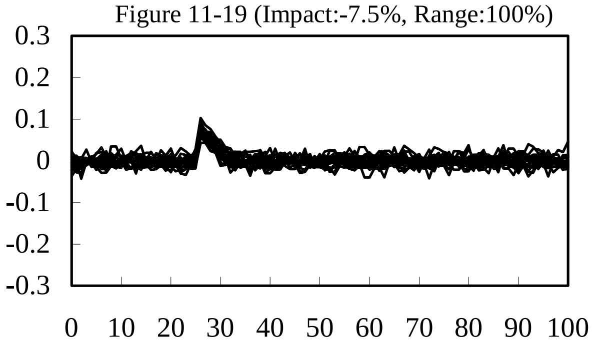



Figure 11-20 (Impact:-10.0%, Range:100%)

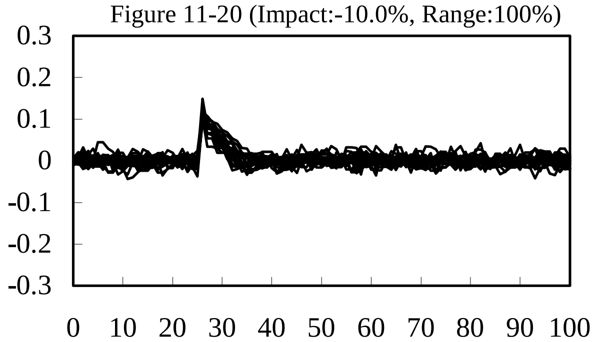
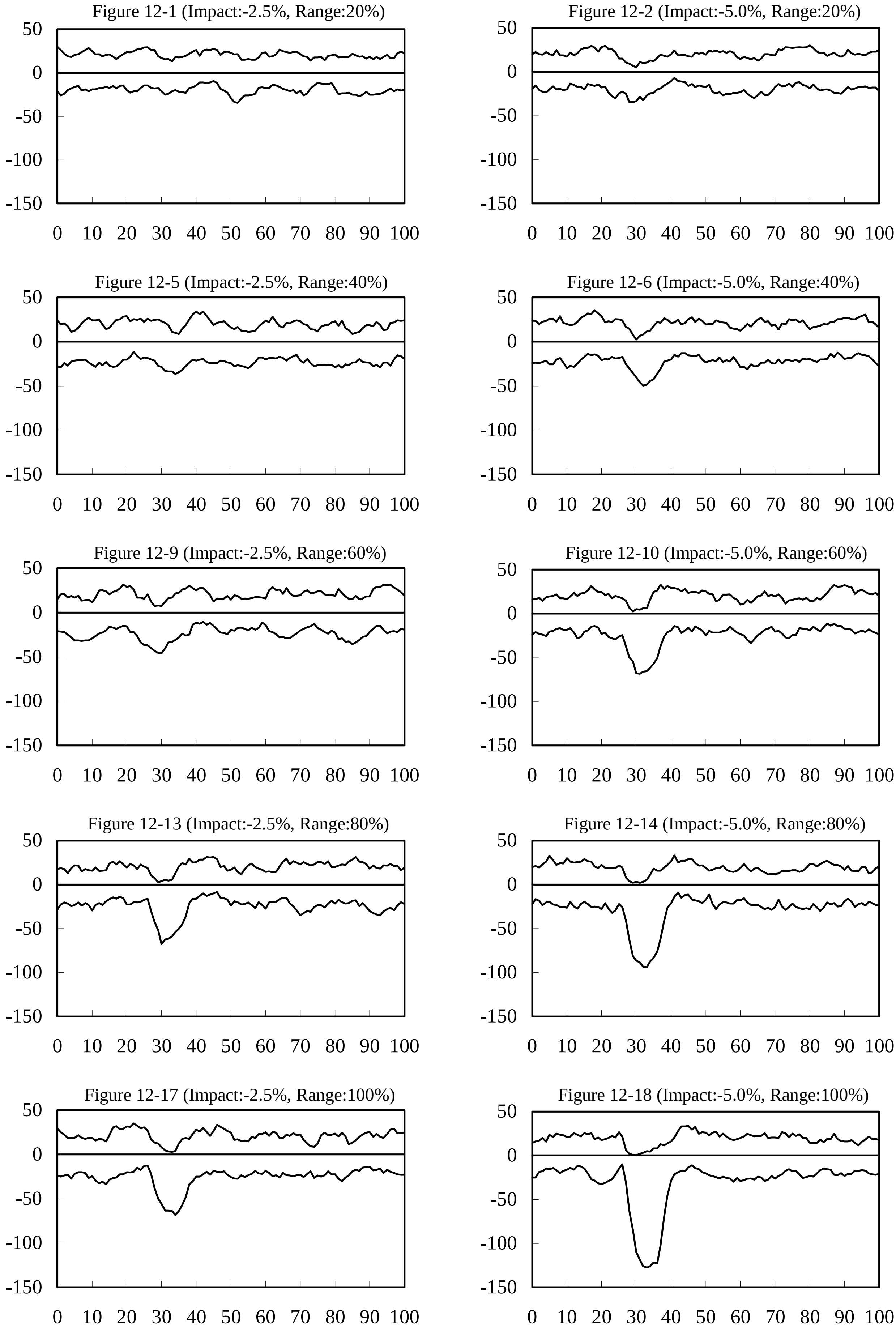


Figure 12.  Developments in order imbalance (Feedback to confidence)*




*: What is plotted on the positive side of the vertical axis illustrates buying order volume, while selling order volume is plotted on the negative side.

Figure 12. Developments in order imbalance (Continued)*

Figure 12-3 (Impact:-7.5%, Range:20%)

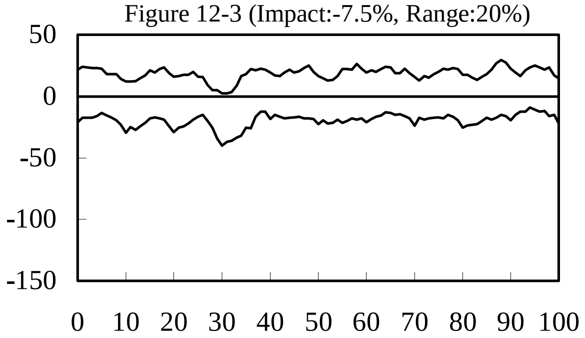



Figure 12-4 (Impact:-10.0%, Range:20%)

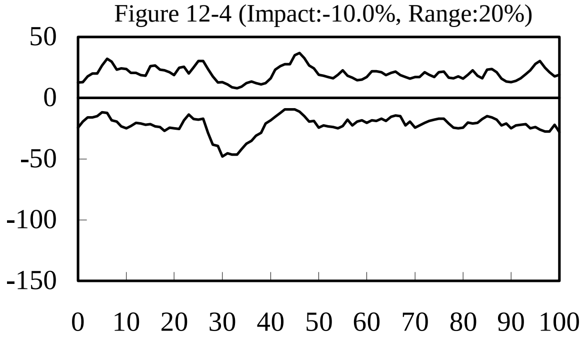



Figure 12-7 (Impact:-7.5%, Range:40%)

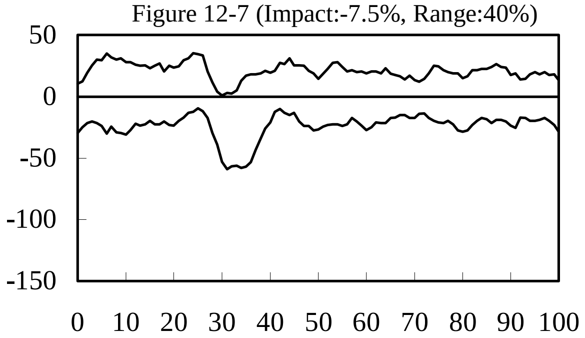



Figure 12-8 (Impact:-10.0%, Range:40%)

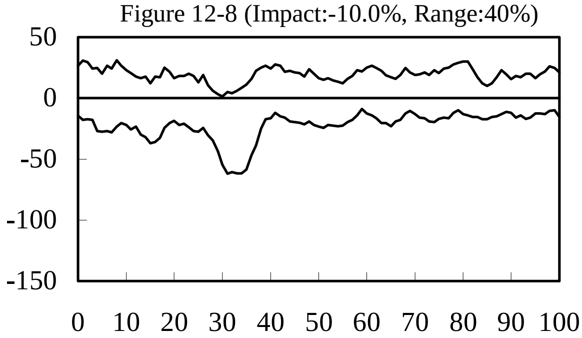



Figure 12-11 (Impact:-7.5%, Range:60%)

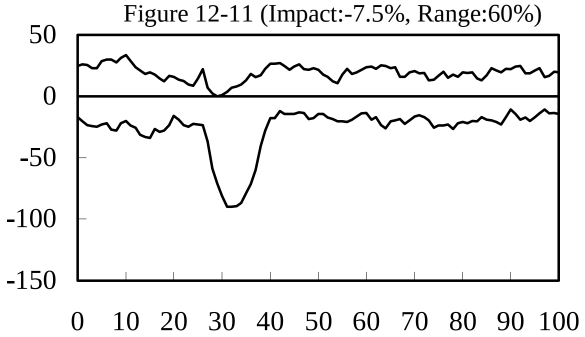



Figure 12-12 (Impact:-10.0%, Range:60%)

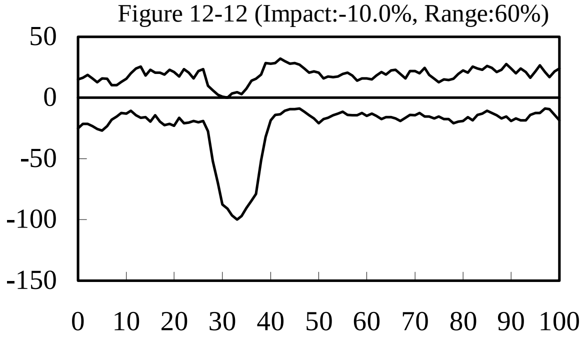



Figure 12-15 (Impact:-7.5%, Range:80%)

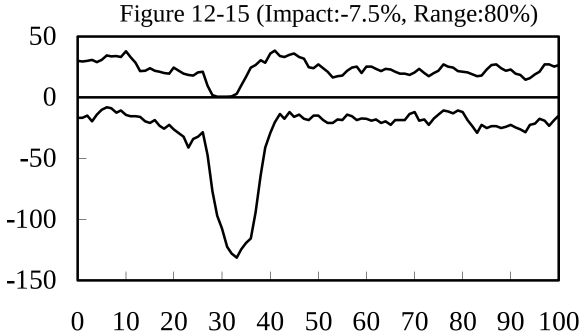



Figure 12-16 (Impact:-10.0%, Range:80%)

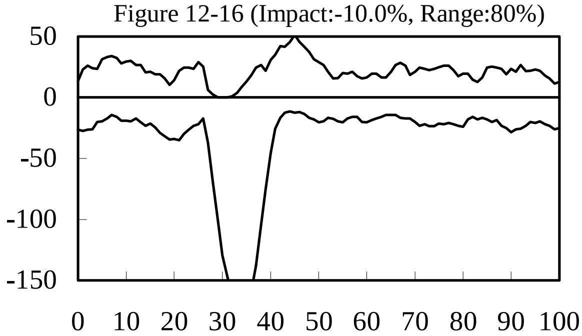



Figure 12-19 (Impact:-7.5%, Range:100%)

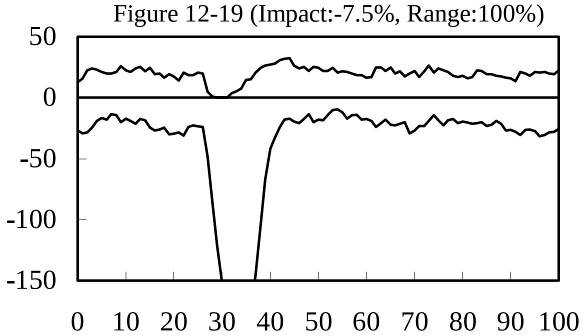
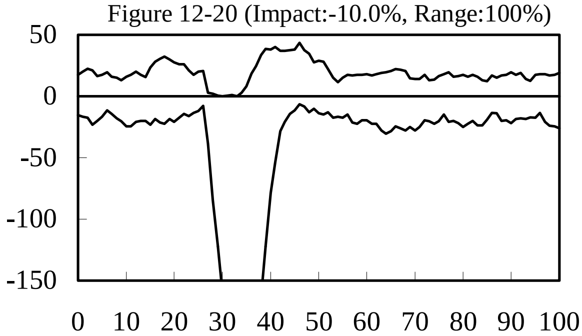



Figure 12-20 (Impact:-10.0%, Range:100%)




*: What is plotted on the positive side of the vertical axis illustrates buying order volume, while selling order volume is plotted on the negative side.

Figure 13. Developments in market price
(Feedback to expected value; with momentum traders)

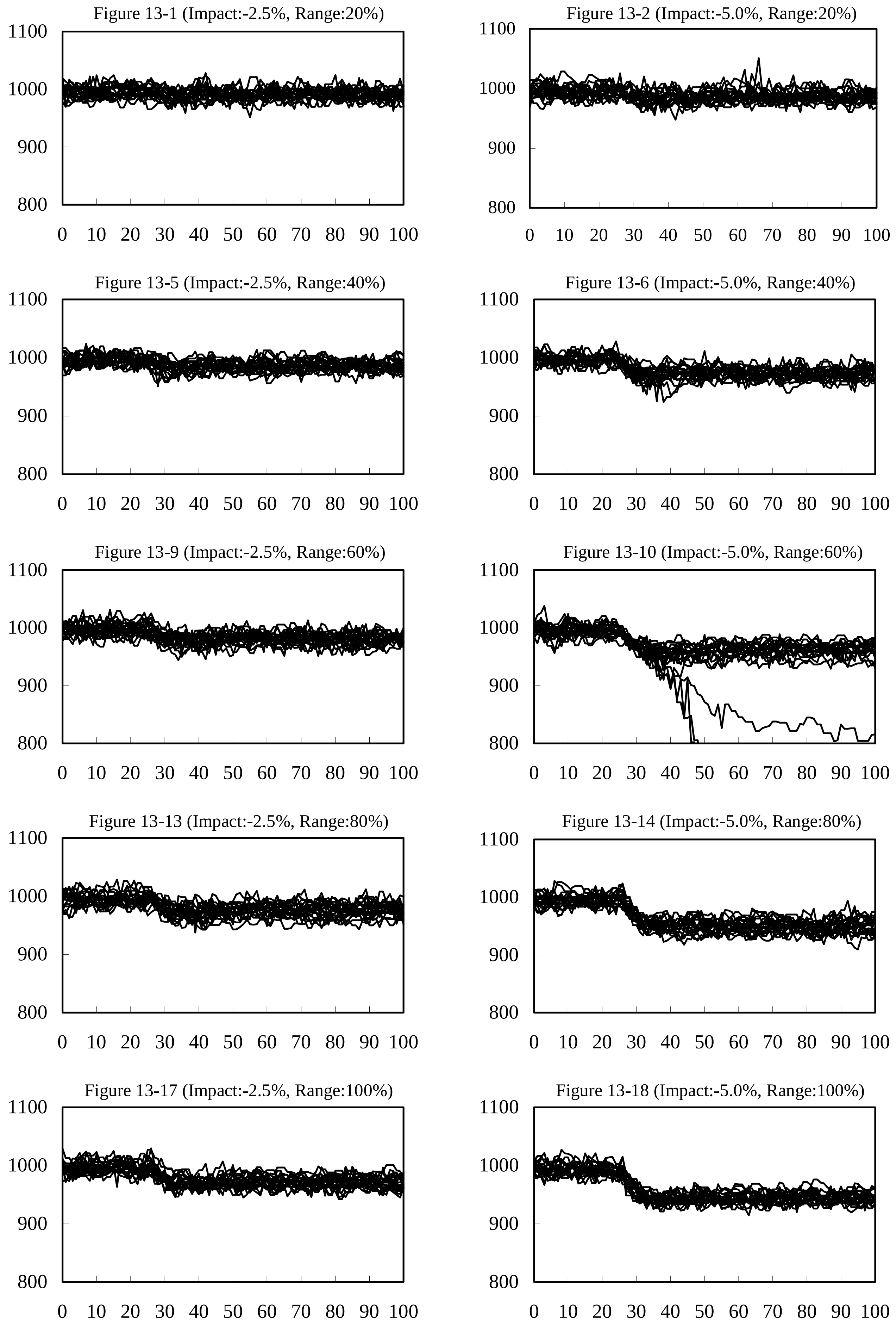


Figure 13. Developments in market price (Continued)

Figure 13-3 (Impact:-7.5%, Range:20%)

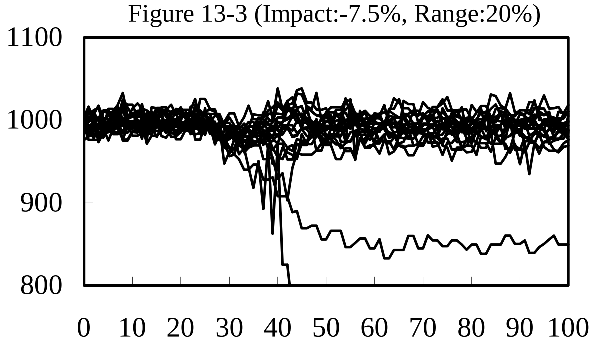



Figure 13-4 (Impact:-10.0%, Range:20%)

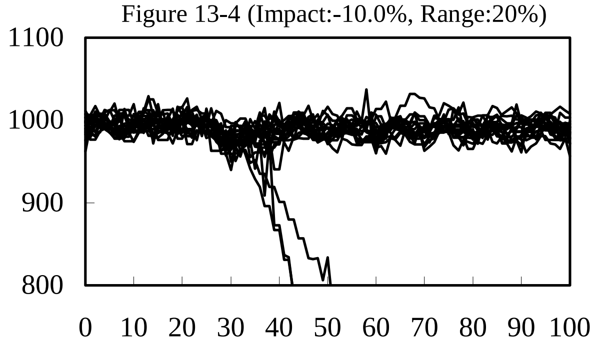



Figure 13-7 (Impact:-7.5%, Range:40%)

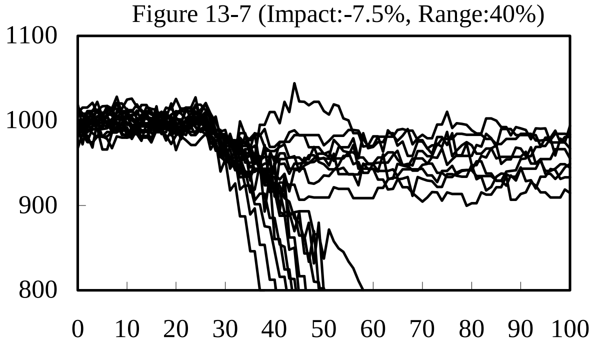



Figure 13-8 (Impact:-10.0%, Range:40%)

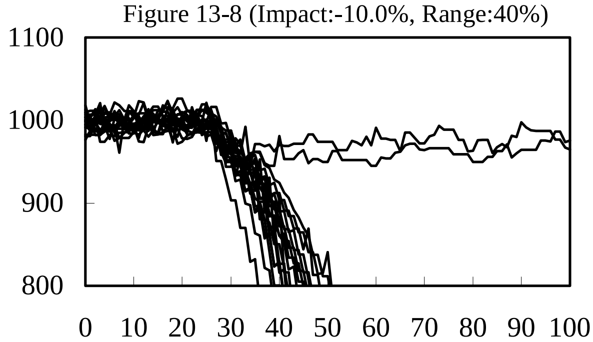



Figure 13-11 (Impact:-7.5%, Range:60%)

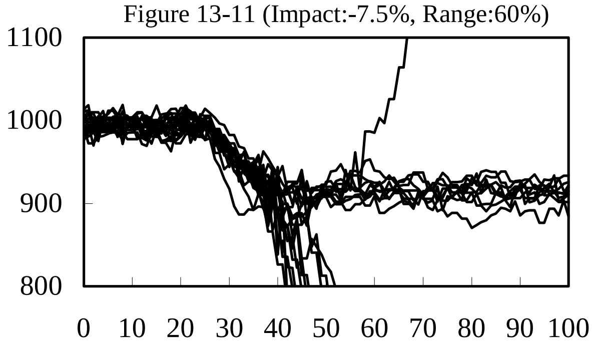



Figure 13-12 (Impact:-10.0%, Range:60%)

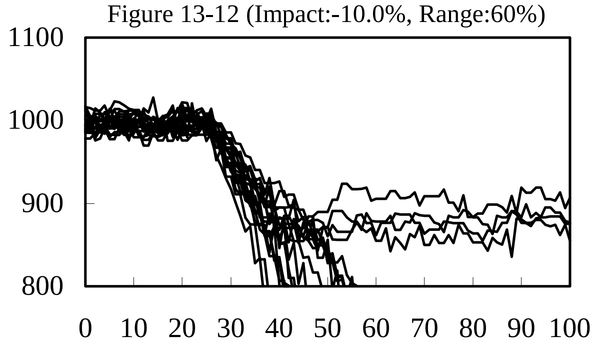



Figure 13-15 (Impact:-7.5%, Range:80%)

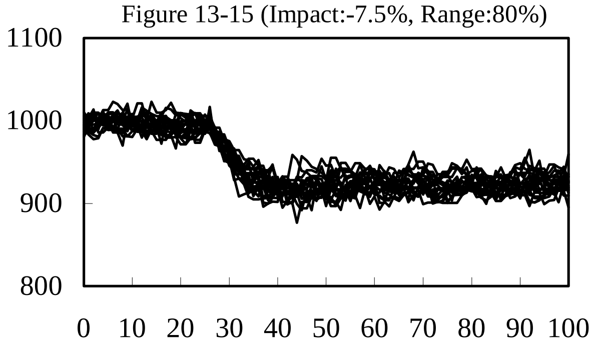



Figure 13-16 (Impact:-10.0%, Range:80%)

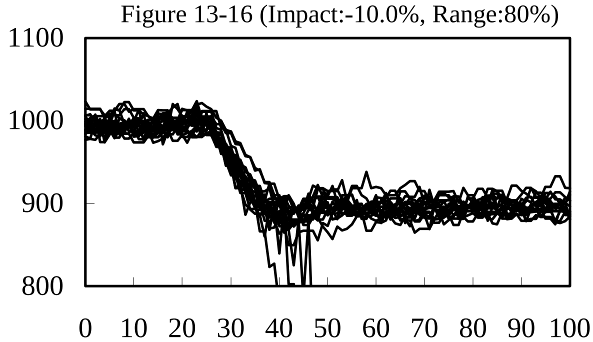



Figure 13-19 (Impact:-7.5%, Range:100%)

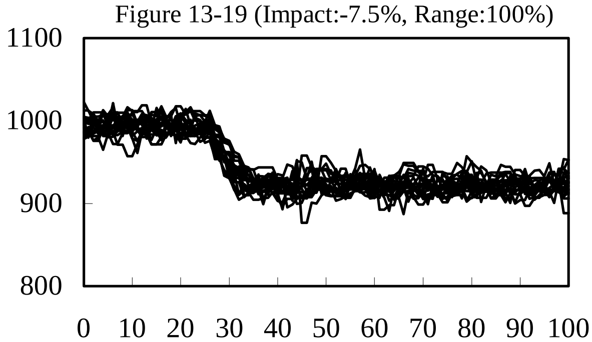



Figure 13-20 (Impact:-10.0%, Range:100%)

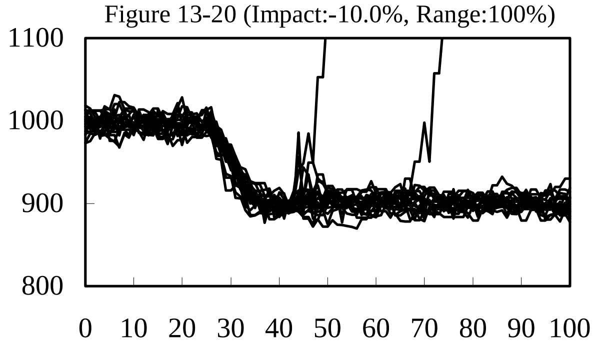


Figure 14. Developments in mean of traders' expected values
(Feedback to expected value; with momentum traders)

Figure 14-1 (Impact:-2.5%, Range:20%)

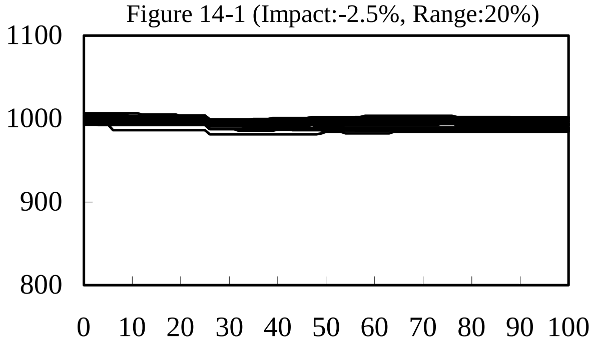



Figure 14-2 (Impact:-5.0%, Range:20%)

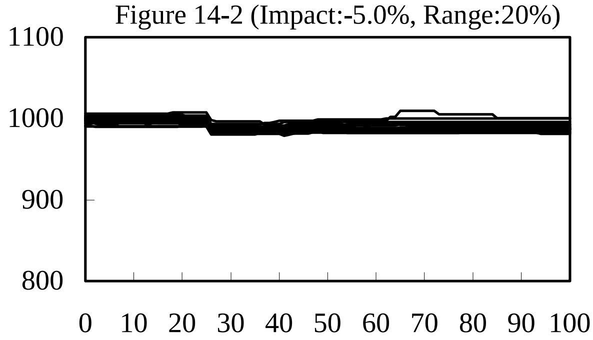



Figure 14-5 (Impact:-2.5%, Range:40%)

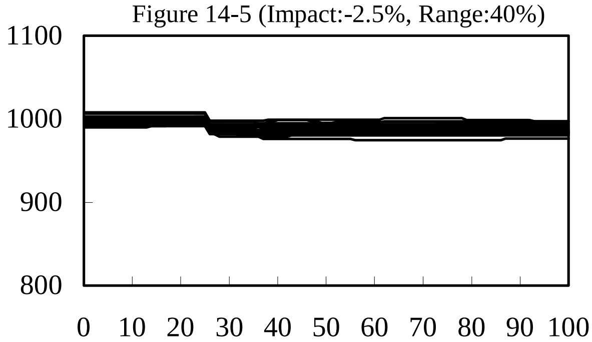



Figure 14-6 (Impact:-5.0%, Range:40%)

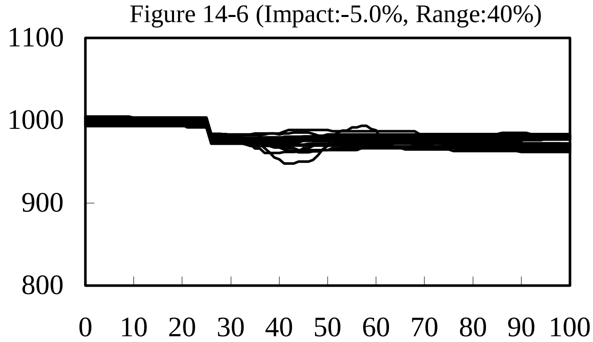



Figure 14-9 (Impact:-2.5%, Range:60%)

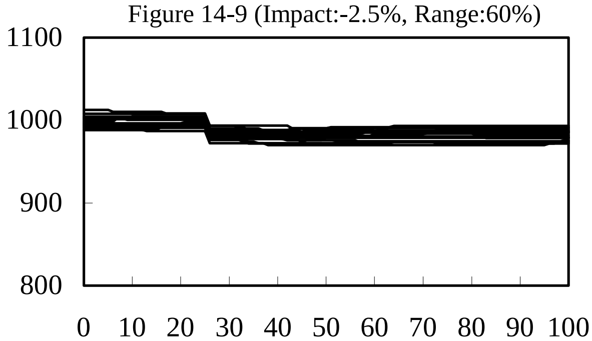



Figure 14-10 (Impact:-5.0%, Range:60%)

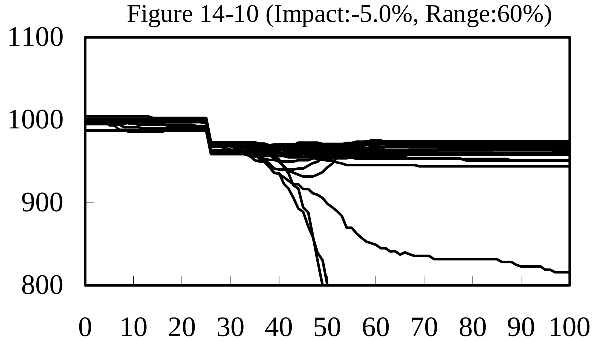



Figure 14-13 (Impact:-2.5%, Range:80%)

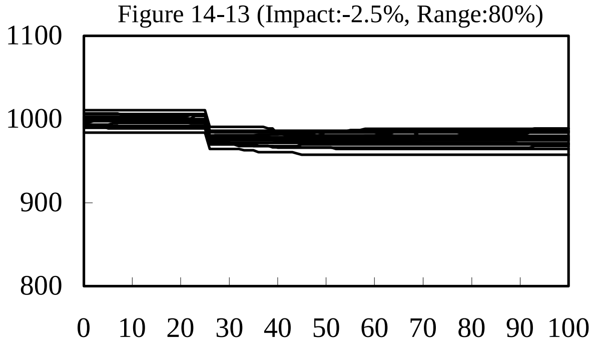



Figure 14-14 (Impact:-5.0%, Range:80%)

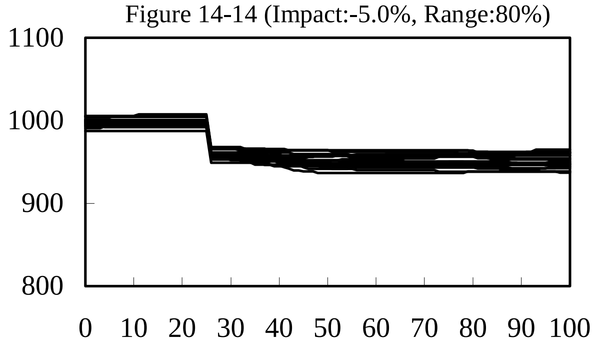



Figure 14-17 (Impact:-2.5%, Range:100%)

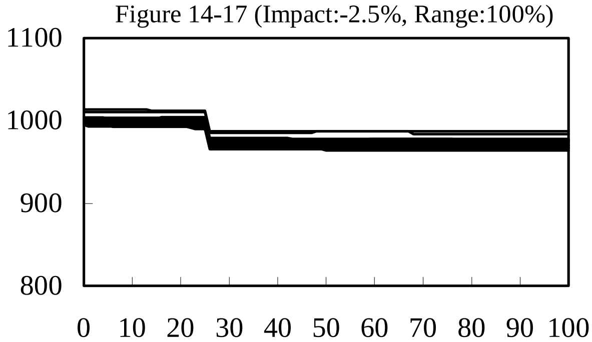



Figure 14-18 (Impact:-5.0%, Range:100%)

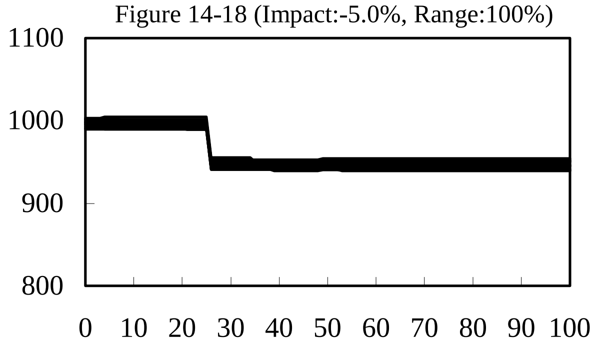


Figure 14.  Developments in mean of traders' expected values (Continued)

Figure 14-3 (Impact:-7.5%, Range:20%)

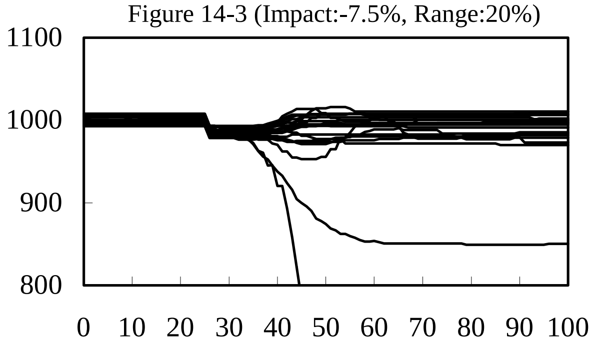



Figure 14-4 (Impact:-10.0%, Range:20%)

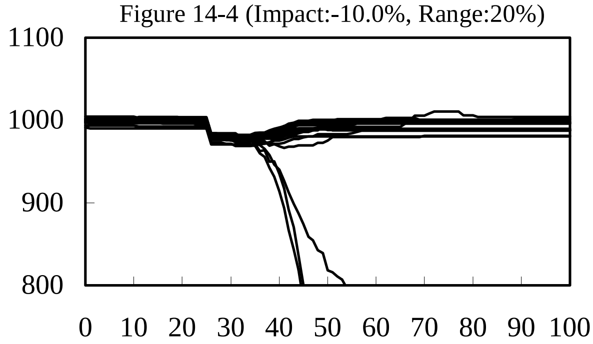



Figure 14-7 (Impact:-7.5%, Range:40%)

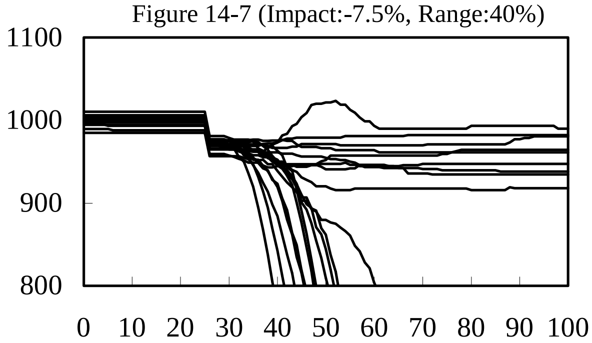



Figure 14-8 (Impact:-10.0%, Range:40%)

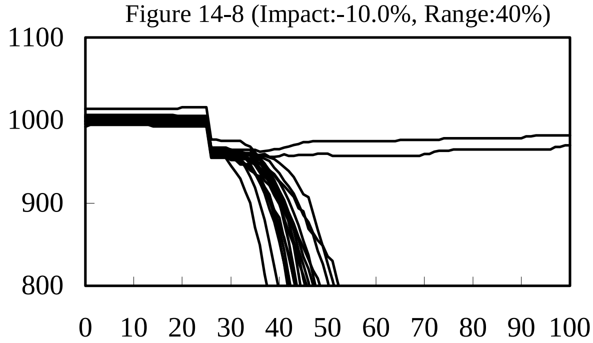



Figure 14-11 (Impact:-7.5%, Range:60%)

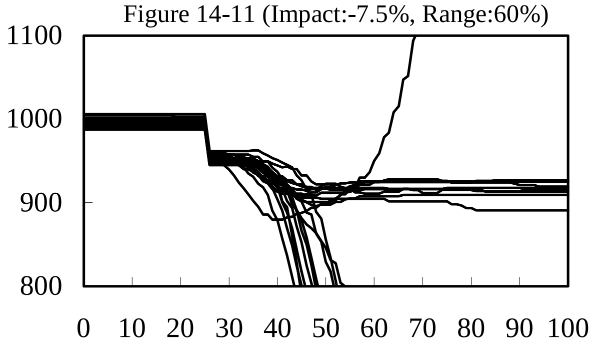



Figure 14-12 (Impact:-10.0%, Range:60%)

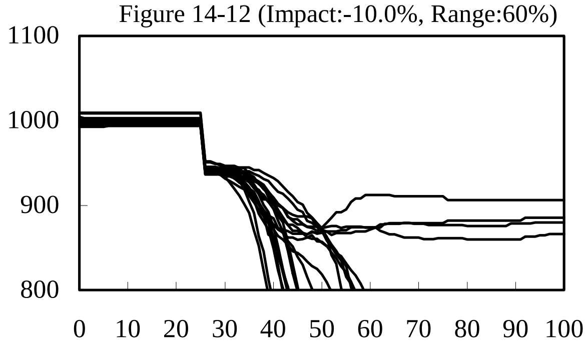



Figure 14-15 (Impact:-7.5%, Range:80%)

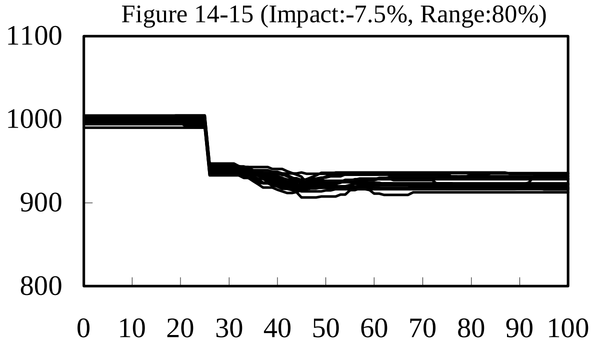



Figure 14-16 (Impact:-10.0%, Range:80%)

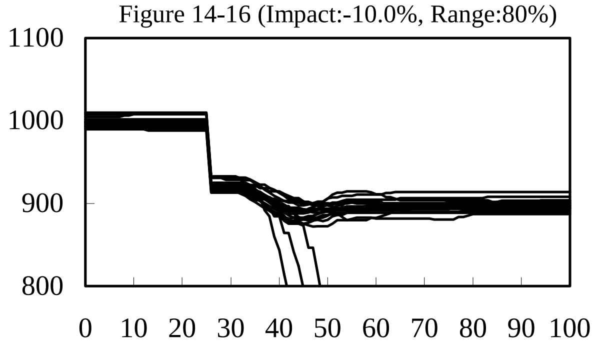



Figure 14-19 (Impact:-7.5%, Range:100%)

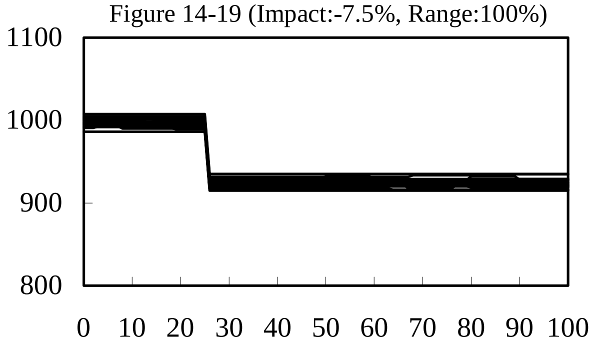



Figure 14-20 (Impact:-10.0%, Range:100%)

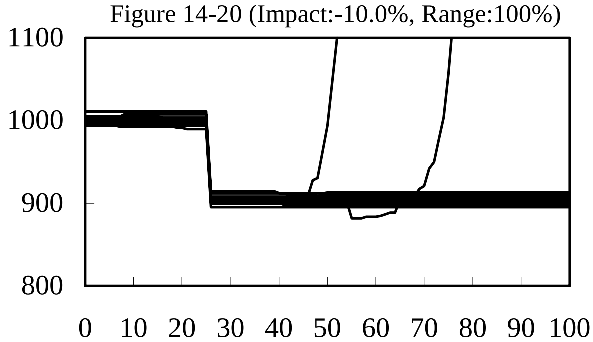


Figure 15. Developments in price overshoot ratio
(Feedback to expected value; with momentum traders)

Figure 15-1 (Impact:-2.5%, Range:20%)

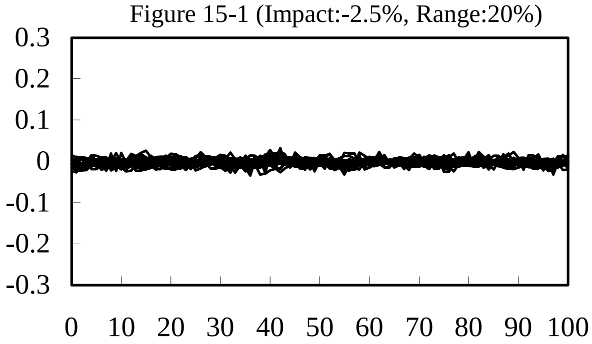



Figure 15-2 (Impact:-5.0%, Range:20%)

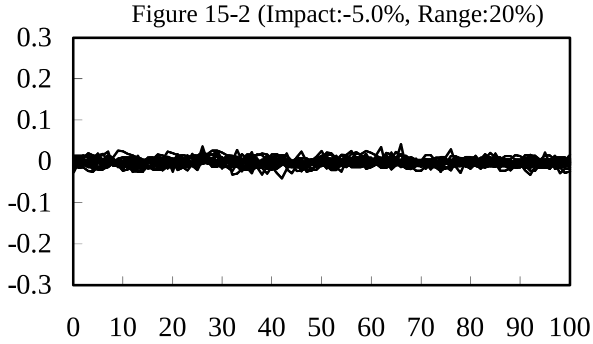



Figure 15-5 (Impact:-2.5%, Range:40%)

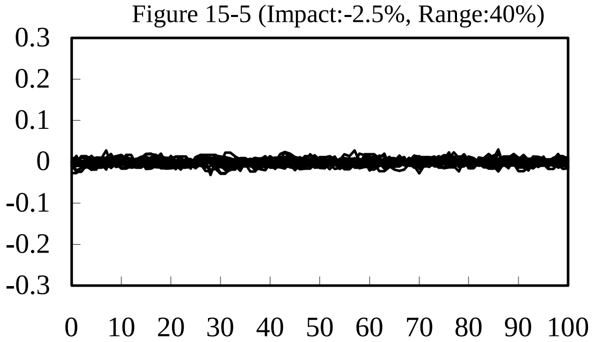



Figure 15-6 (Impact:-5.0%, Range:40%)

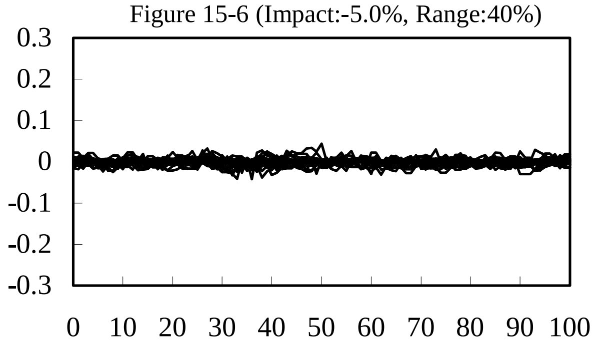



Figure 15-9 (Impact:-2.5%, Range:60%)

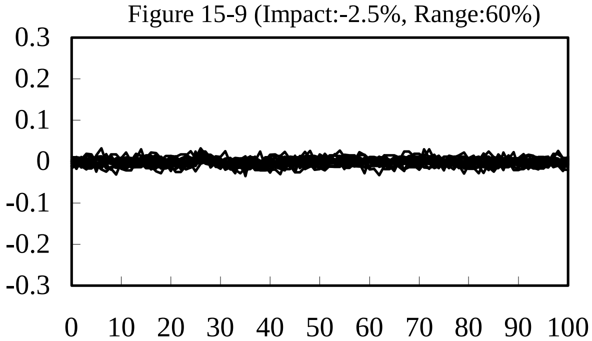



Figure 15-10 (Impact:-5.0%, Range:60%)

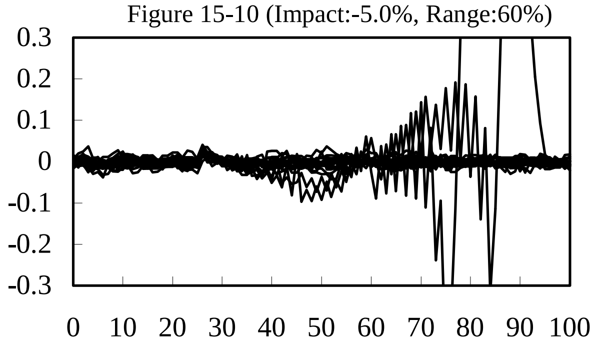



Figure 15-13 (Impact:-2.5%, Range:80%)

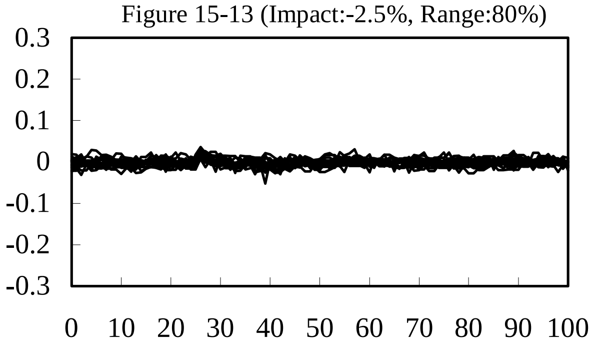



Figure 15-14 (Impact:-5.0%, Range:80%)

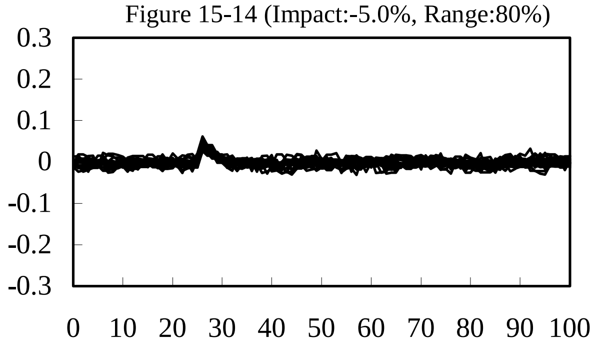



Figure 15-17 (Impact:-2.5%, Range:100%)

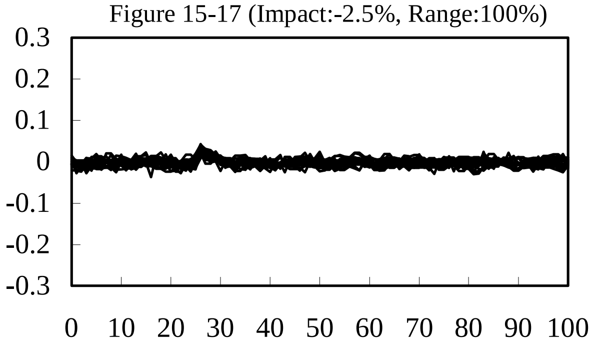
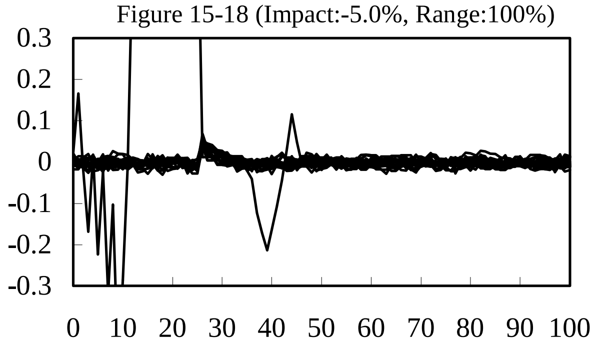



Figure 15-18 (Impact:-5.0%, Range:100%)



## Figure 15. Developments in price overshoot ratio (Continued)

Figure 15-3 (Impact:-7.5%, Range:20%)

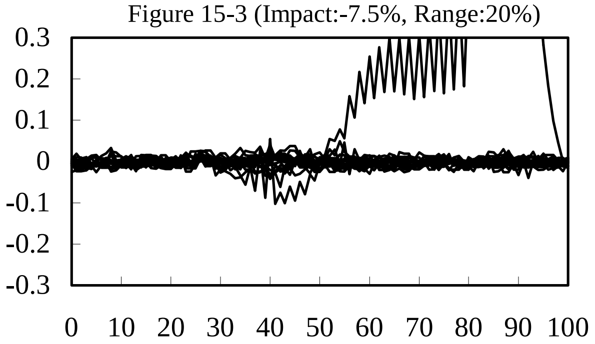



Figure 15-4 (Impact:-10.0%, Range:20%)

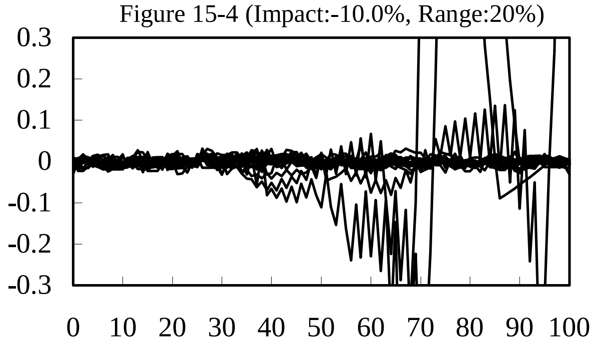



Figure 15-7 (Impact:-7.5%, Range:40%)

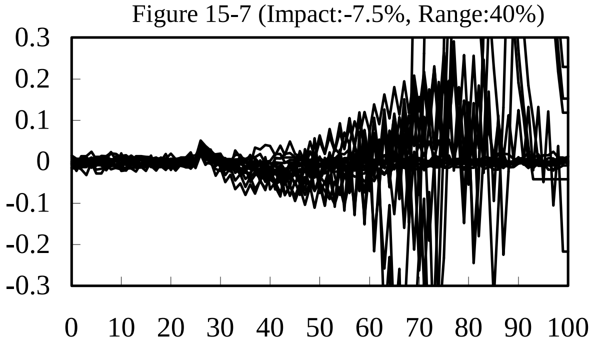



Figure 15-8 (Impact:-10.0%, Range:40%)

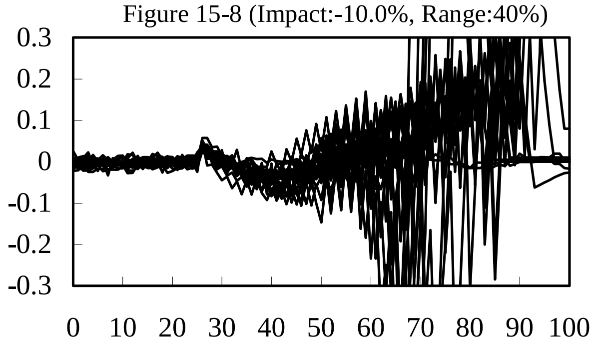



Figure 15-11 (Impact:-7.5%, Range:60%)

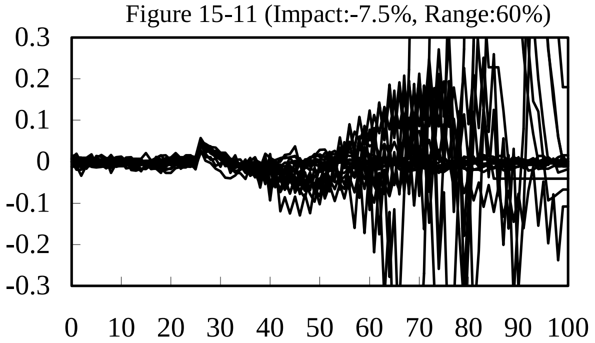



Figure 15-12 (Impact:-10.0%, Range:60%)

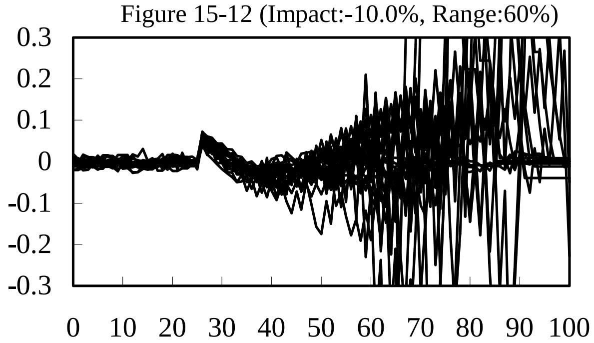



Figure 15-15 (Impact:-7.5%, Range:80%)

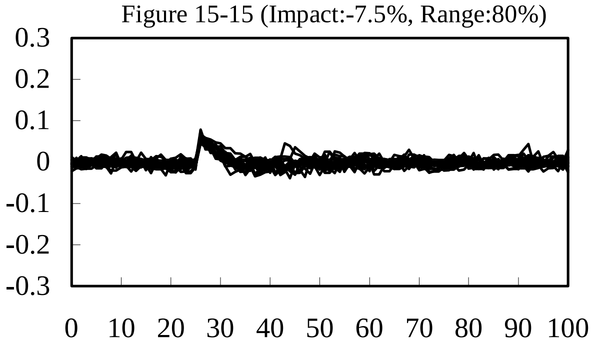



Figure 15-16 (Impact:-10.0%, Range:80%)

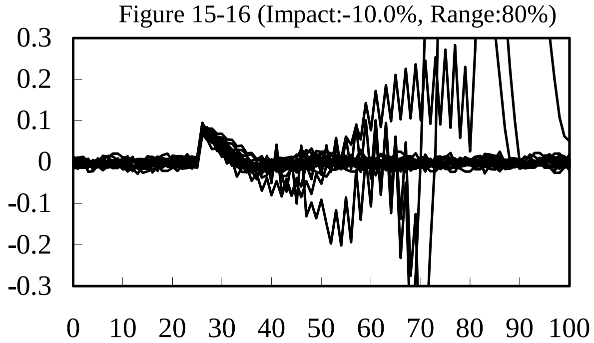



Figure 15-19 (Impact:-7.5%, Range:100%)

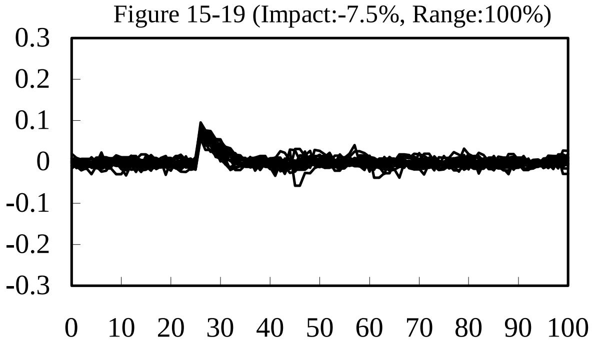



Figure 15-20 (Impact:-10.0%, Range:100%)

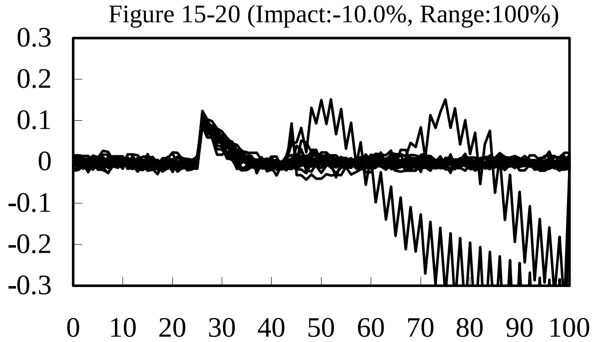
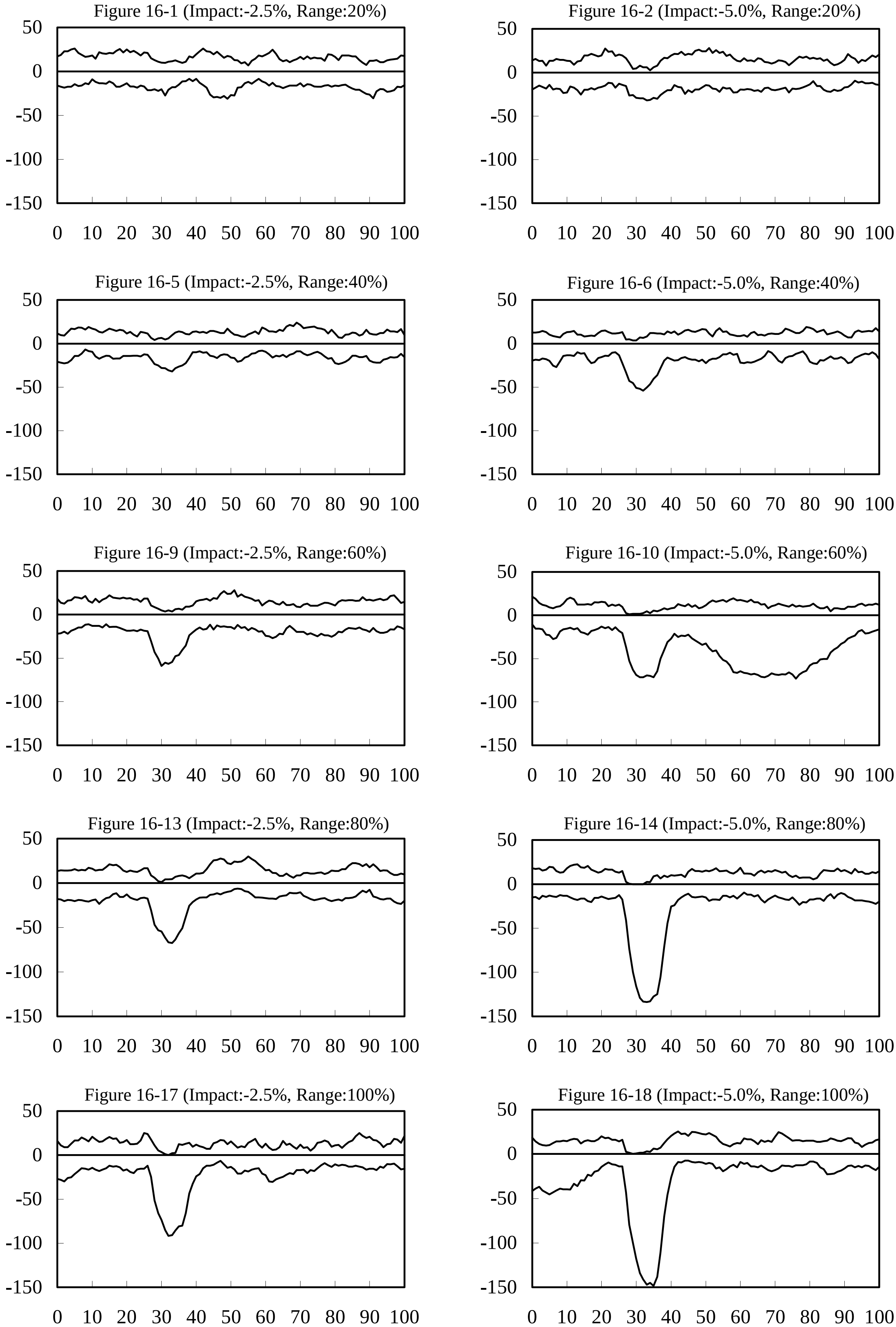


Figure 16. Developments in order imbalance*
(Feedback to expected value; with momentum traders)




*: What is plotted on the positive side of the vertical axis illustrates buying order volume, while selling order volume is plotted on the negative side.

Figure 16. Developments in order imbalance (Continued)*

Figure 16-3 (Impact:-7.5%, Range:20%)

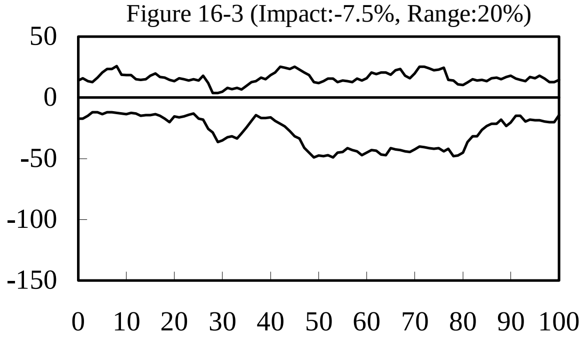



Figure 16-4 (Impact:-10.0%, Range:20%)

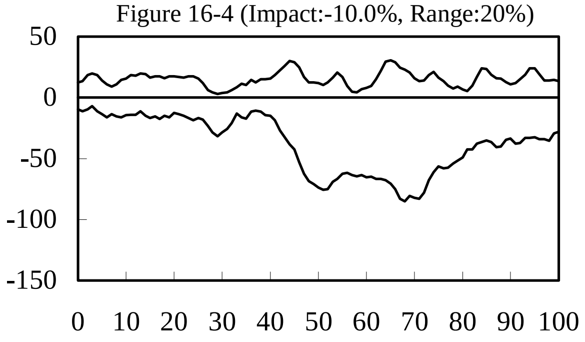



Figure 16-7 (Impact:-7.5%, Range:40%)

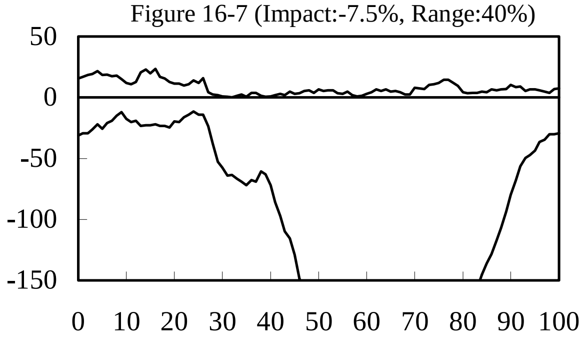



Figure 16-8 (Impact:-10.0%, Range:40%)

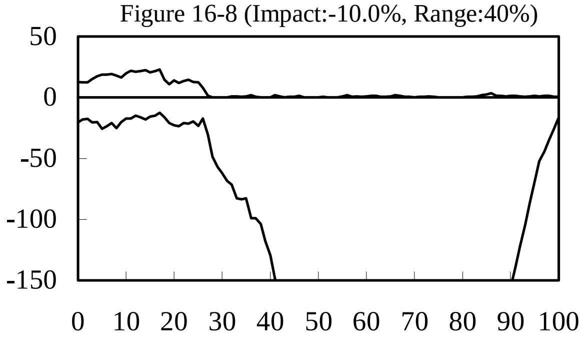



Figure 16-11 (Impact:-7.5%, Range:60%)

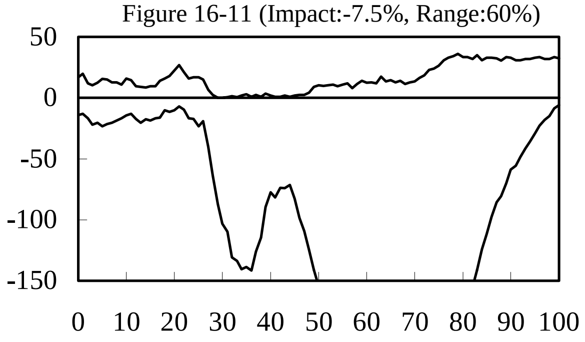



Figure 16-12 (Impact:-10.0%, Range:60%)

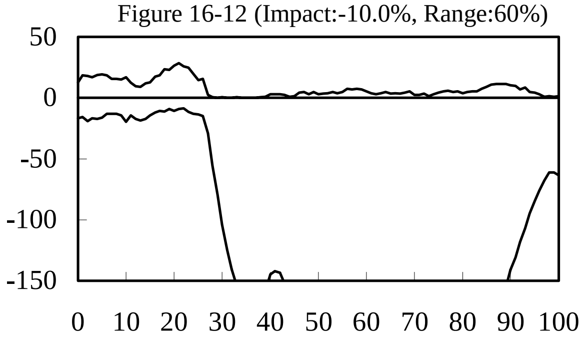



Figure 16-15 (Impact:-7.5%, Range:80%)

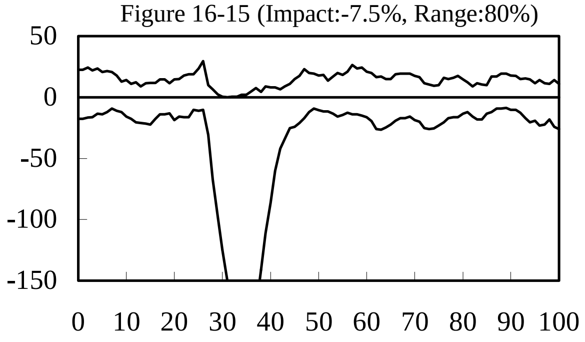



Figure 16-16 (Impact:-10.0%, Range:80%)

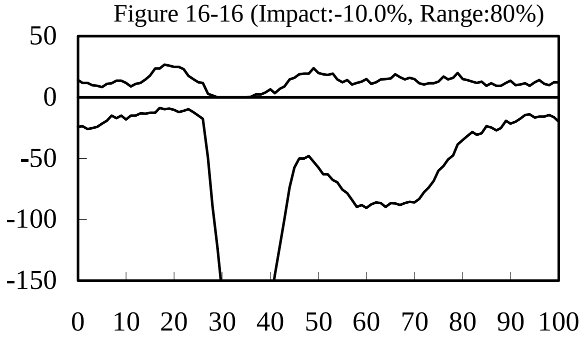



Figure 16-19 (Impact:-7.5%, Range:100%)

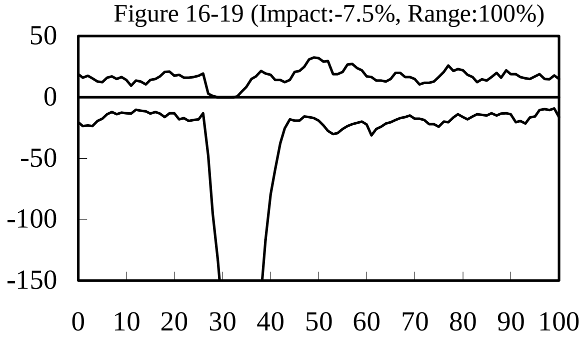
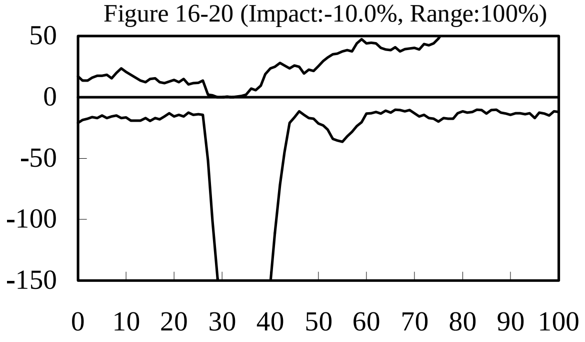



Figure 16-20 (Impact:-10.0%, Range:100%)




*: What is plotted on the positive side of the vertical axis illustrates buying order volume, while selling order volume is plotted on the negative side.

Figure 17.　Developments in market price
(Feedback to expected value; with momentum traders & a trading halt)

Figure 17-1 (without trading halt)

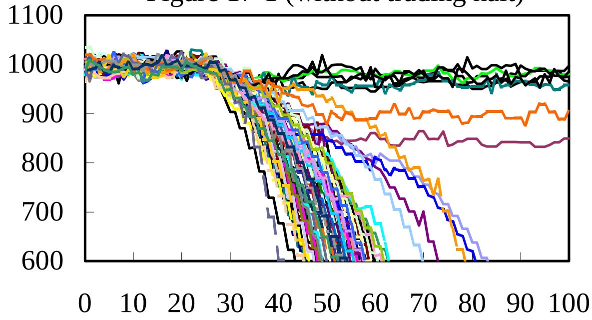



Figure 17-2
(Level: 900 yen, 5 periods  of halt)

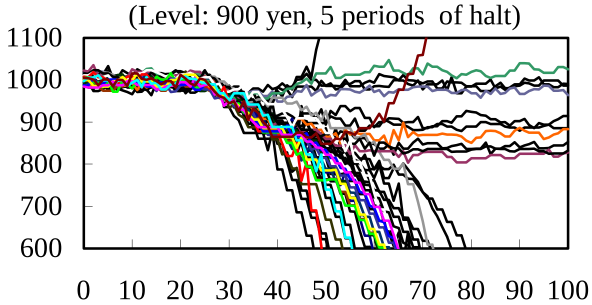



Figure 17-3
(Level: 900 yen, 10 periods of halt)

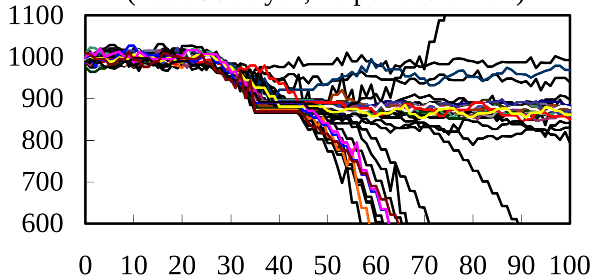



Figure 17-4
(Level: 900 yen, 15 periods of halt)

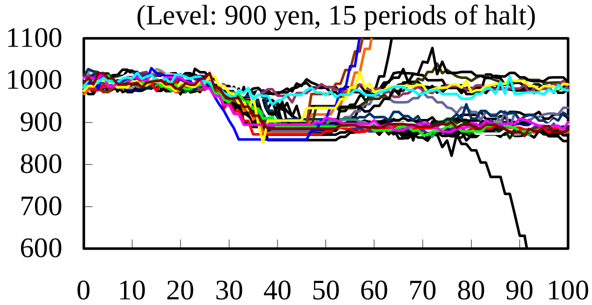



Figure 17-5
(Level: 900 yen, 20 periods of halt)

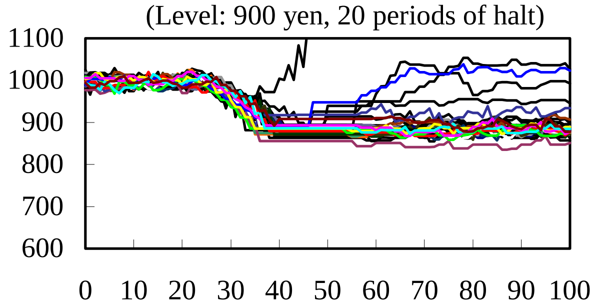



Figure 17-6
(Level: 800 yen, 5 periods of halt)

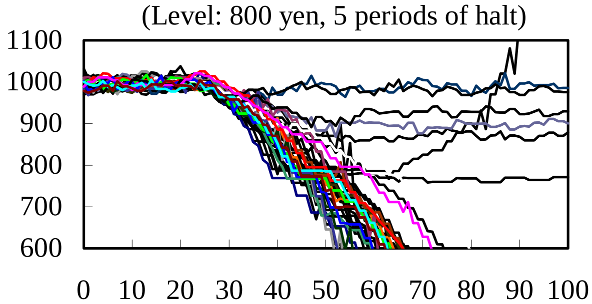



Figure 17-7
(Level: 800 yen, 10 periods of halt)

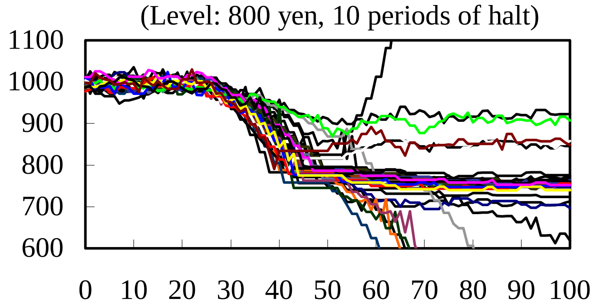



Figure 17-8
(Level: 800 yen, 15 periods of halt)

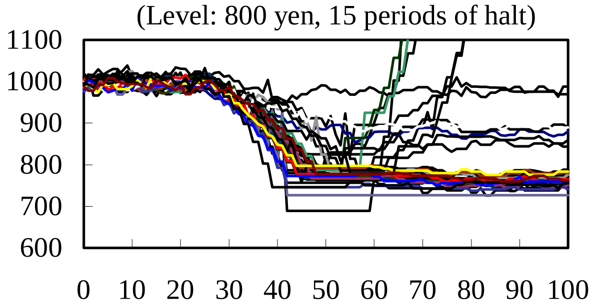



Figure 17-9
(Level: 800 yen, 20 periods of halt)

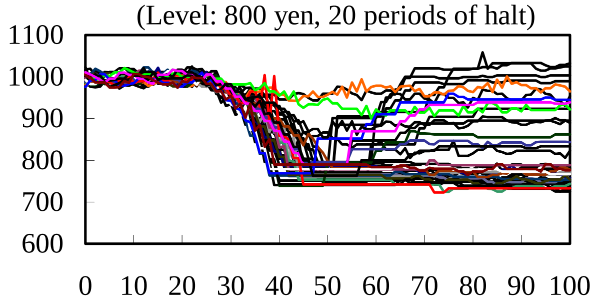


Figure 18. Developments in mean of traders' expected values
(Feedback to expected value; with momentum traders & a trading halt)

Figure 18-1 (without trading halt)

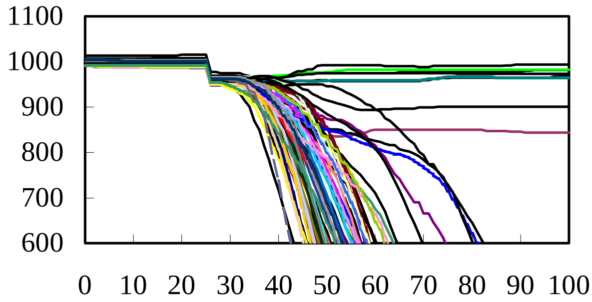



Figure 18-2
(Level: 900 yen, 5 periods of halt)

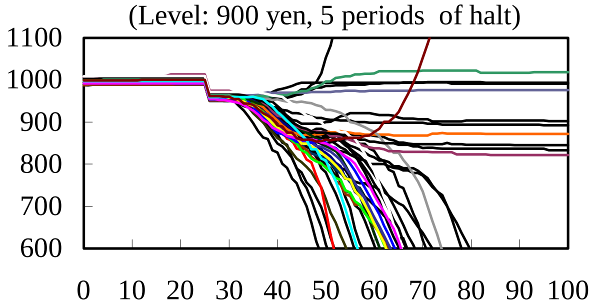



Figure 18-3
(Level: 900 yen, 10 periods of halt)

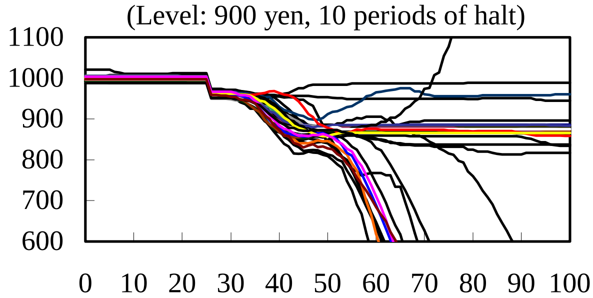



Figure 18-4
(Level: 900 yen, 15 periods of halt)

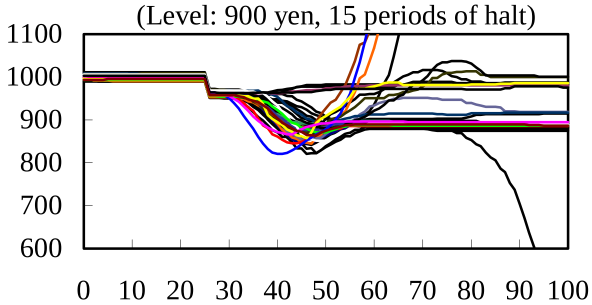



Figure 18-5
(Level: 900 yen, 20 periods of halt)

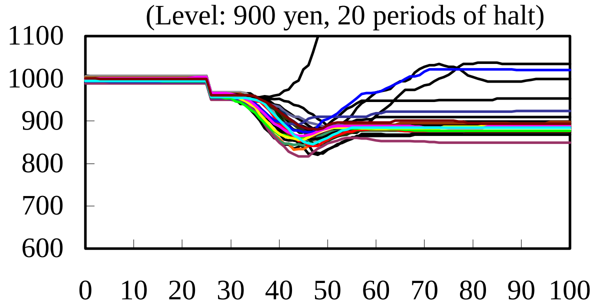



Figure 18-6
(Level: 800 yen, 5 periods of halt)

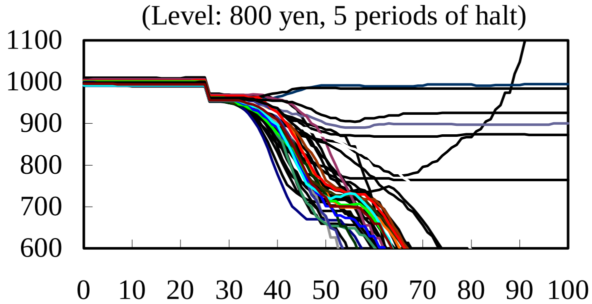



Figure 18-7
(Level: 800 yen, 10 periods of halt)

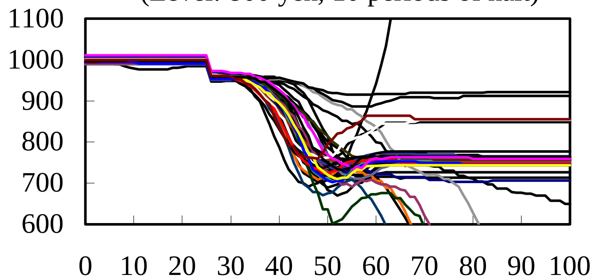



Figure 18-8
(Level: 800 yen, 15 periods of halt)

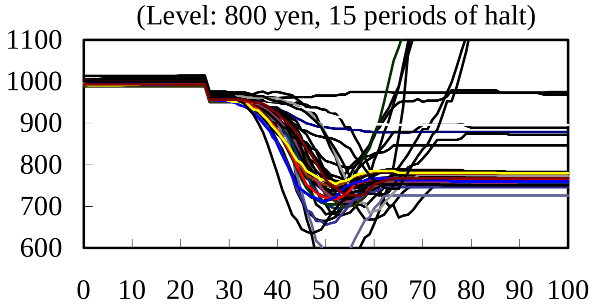



Figure 18-9
(Level: 800 yen, 20 periods of halt)

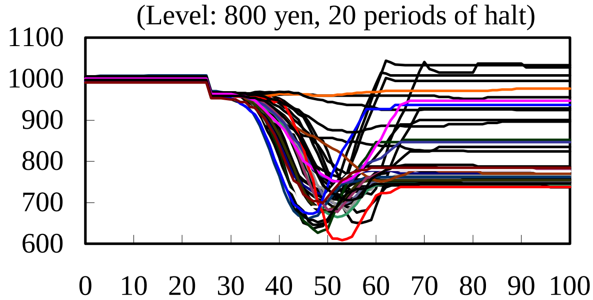


Figure 19. Developments in price overshoot ratio
(Feedback to expected value; with momentum traders & a trading halt)

Figure 19-1 (without trading halt)

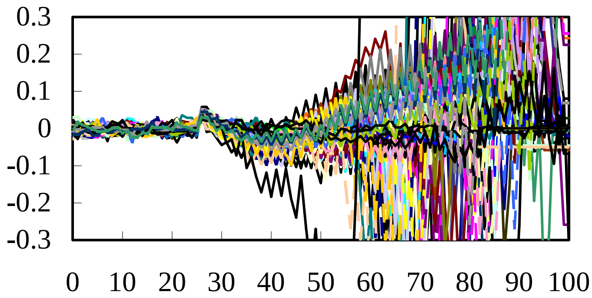



Figure 19-2
(Level: 900 yen, 5 periods of halt)

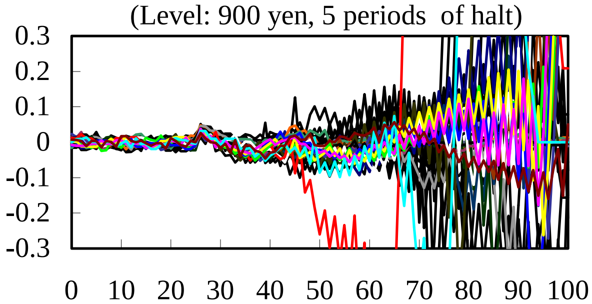



Figure 19-3
(Level: 900 yen, 10 periods of halt)

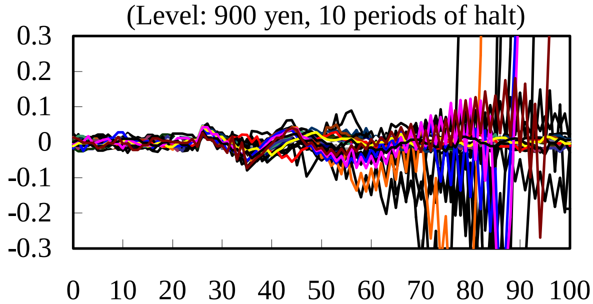



Figure 19-4
(Level: 900 yen, 15 periods of halt)

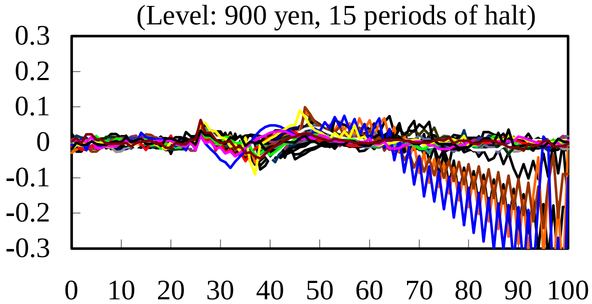



Figure 19-5
(Level: 900 yen, 20 periods of halt)

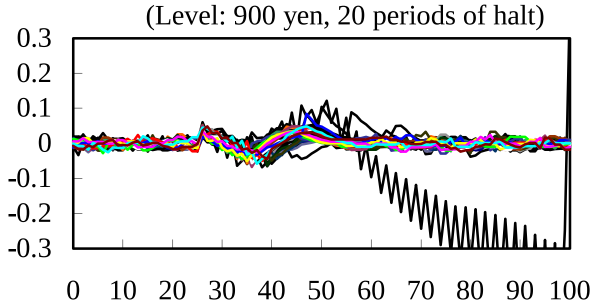



Figure 19-6
(Level: 800 yen, 5 periods of halt)

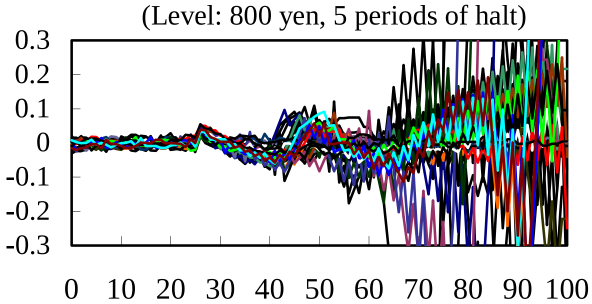



Figure 19-7
(Level: 800 yen, 10 periods of halt)

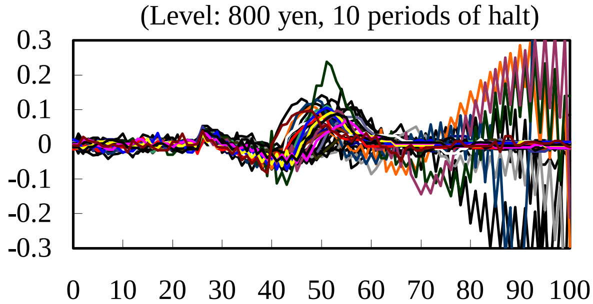



Figure 19-8
(Level: 800 yen, 15 periods of halt)

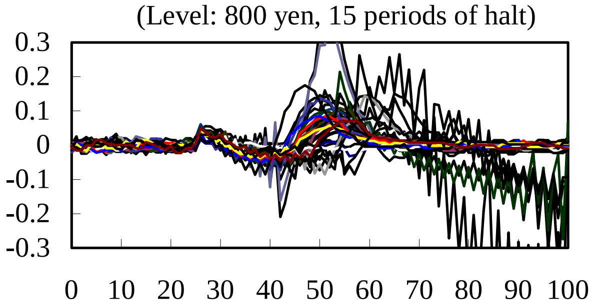



Figure 19-9
(Level: 800 yen, 20 periods of halt)

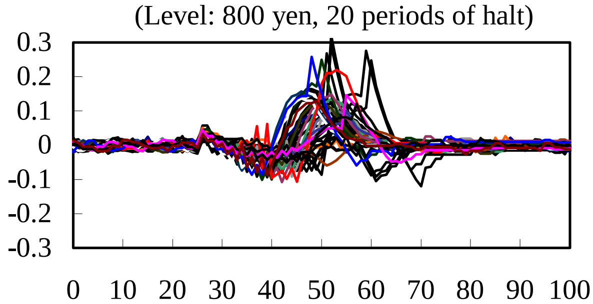
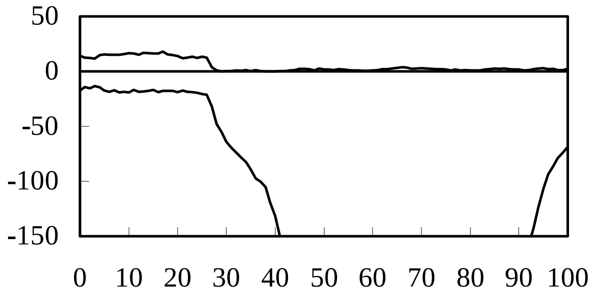


Figure 20. Developments in order imbalance*

(Feedback to expected value; with momentum traders & a trading halt)

Figure 20-1 (without trading halt)




*: What is plotted on the positive side of the vertical axis illustrates buying order volume, while selling order volume is plotted on the negative side.

Figure 20-2
(Level: 900 yen, 5 periods of halt)

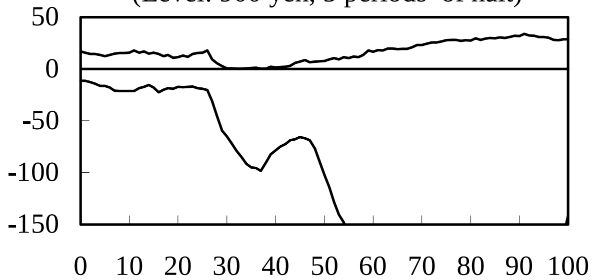



Figure 20-3
(Level: 900 yen, 10 periods of halt)

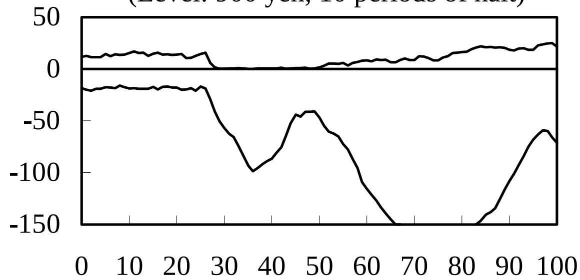



Figure 20-4
(Level: 900 yen, 15 periods of halt)

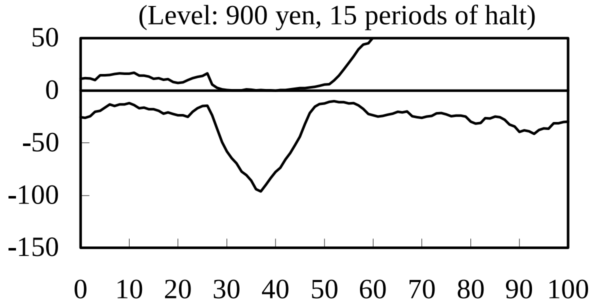



Figure 20-5
(Level: 900 yen, 20 periods of halt)

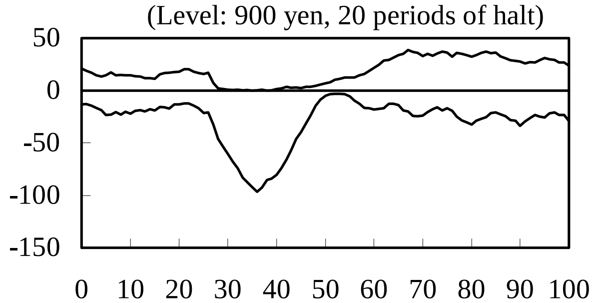



Figure 20-6
(Level: 800 yen, 5 periods of halt)

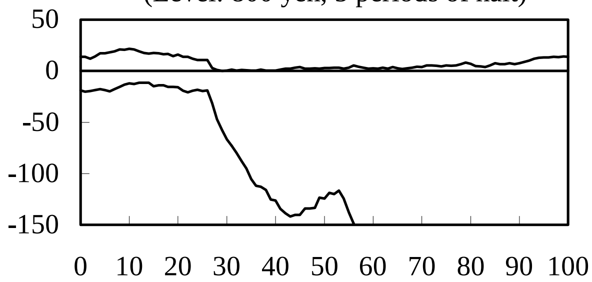



Figure 20-7
(Level: 800 yen, 10 periods of halt)

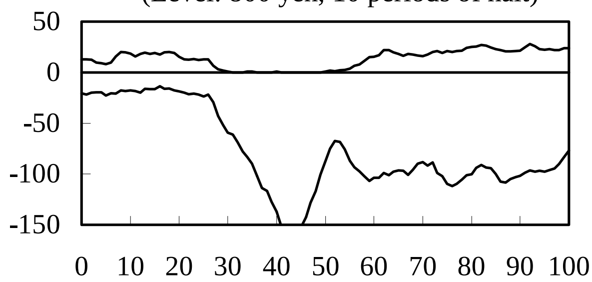



Figure 20-8
(Level: 800 yen, 15 periods of halt)

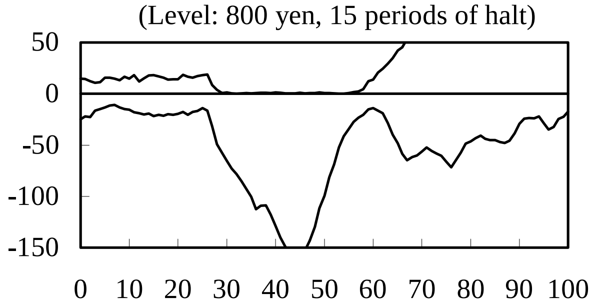



Figure 20-9
(Level: 800 yen, 20 periods of halt)

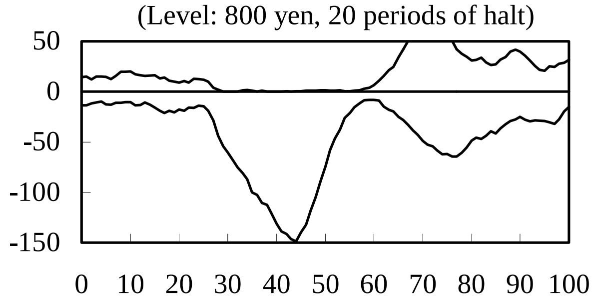
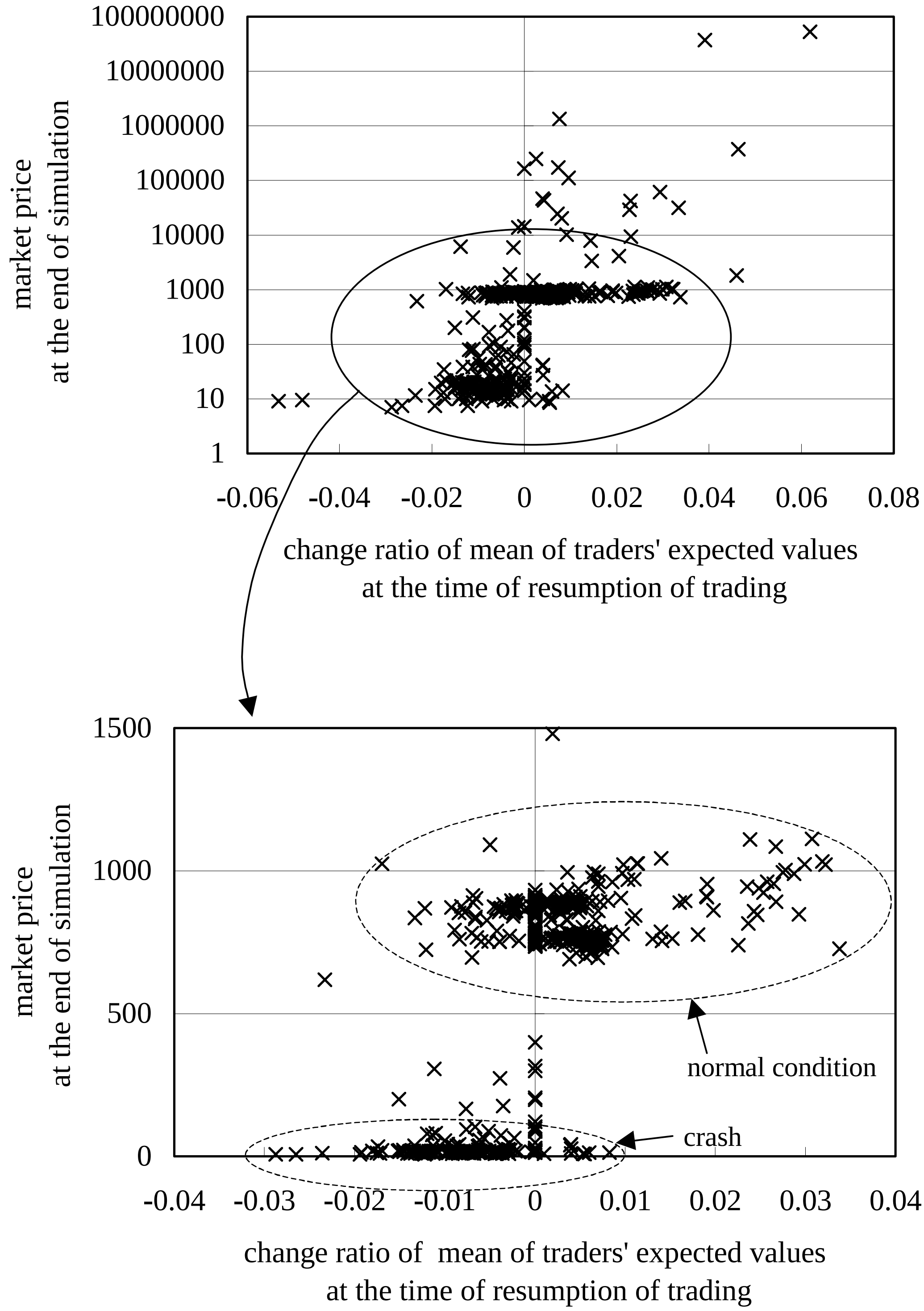


Figure 21. Change ratio of mean of traders' expected values upon resumption of trading and market behavior after the resumption



## Appendix 1

### Simulation flows and traders' decision making mechanism

In order to verify the decision making mechanism and to explore the possibility of quantitative analysis, we use a Monte Carlo simulation in our analysis. The reason for using this procedure is that when an analytical approach is adopted, it often results in solutions only being obtained in a relatively simple setting compared with that of actual market conditions. Since market microstructure theory, on which our analysis is based, formulates an individual trader's trading behavior at the micro level and aggregates the behavior of many such traders to analyze market behavior, a simulation approach becomes quite useful. By using the Monte Carlo simulation, which has developed rapidly in the field of finance theory, we can incorporate in our models traders who have complex decision making functions or conditions and analyze the market behavior patterns.

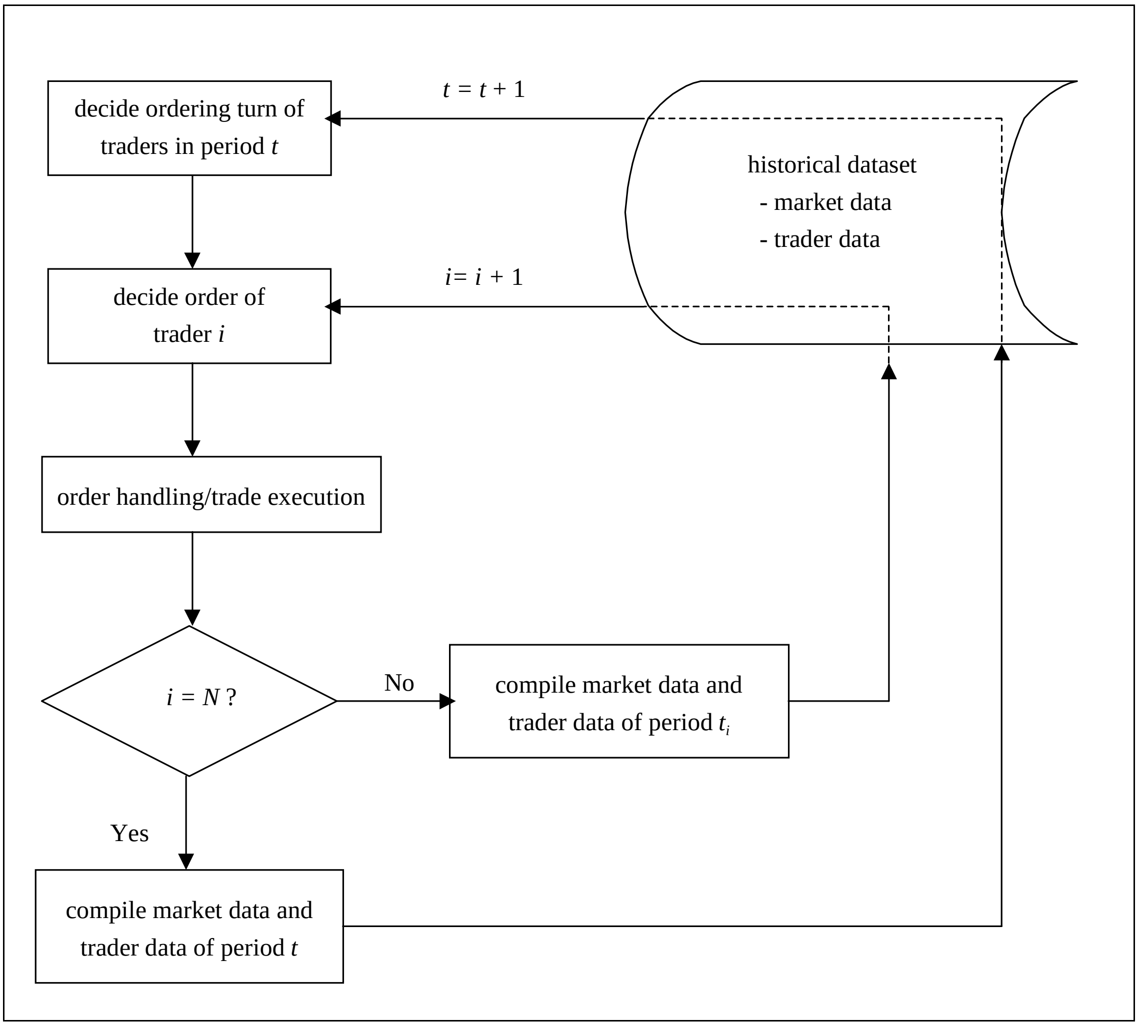
Our model consists of two major parts. The first part models an individual trader's decision making and ordering (micro stage), and the second part models order flow aggregation in the trade execution system (macro stage). Parameters incorporated in the model are those that are unique to each market participant, such as expected value, confidence in their forecasts, the extent of risk aversion, and sensitivity to feedback information obtained from the macro stage. Based on these parameters, a trader compares the benefit and cost (risk) of each trade, selects a trade which maximizes the net benefit, and places an order if the net benefit is consistent with the extent of risk aversion. Of the factors which affect trading behavior, we assume explicit trading costs to be zero. We employ a continuous auction system which allows market orders and limit orders (during continuous sessions only) based on the trade execution model of the Tokyo Stock Exchange (TSE).[11]

[11] In modeling a trade execution system, there are various methods, such as modeling a market maker system or modeling a market with a plural execution system for one product. Since this

### A1.1. Simulation flow

The structure of our model is as follows: in a TSE-type market composed of $N$ traders, we will conduct a simulation for $M$ periods. In period $t$ ($t$ =1, 2,…, $M$), all $N$ traders can place an order once. Ordering rotation is randomly decided in the starting period, and each trader's order will be executed based on the first-in rule, as in the TSE. The flow of the simulation is summarized in Figure A1-1.

Figure A1-1. Simulation flow

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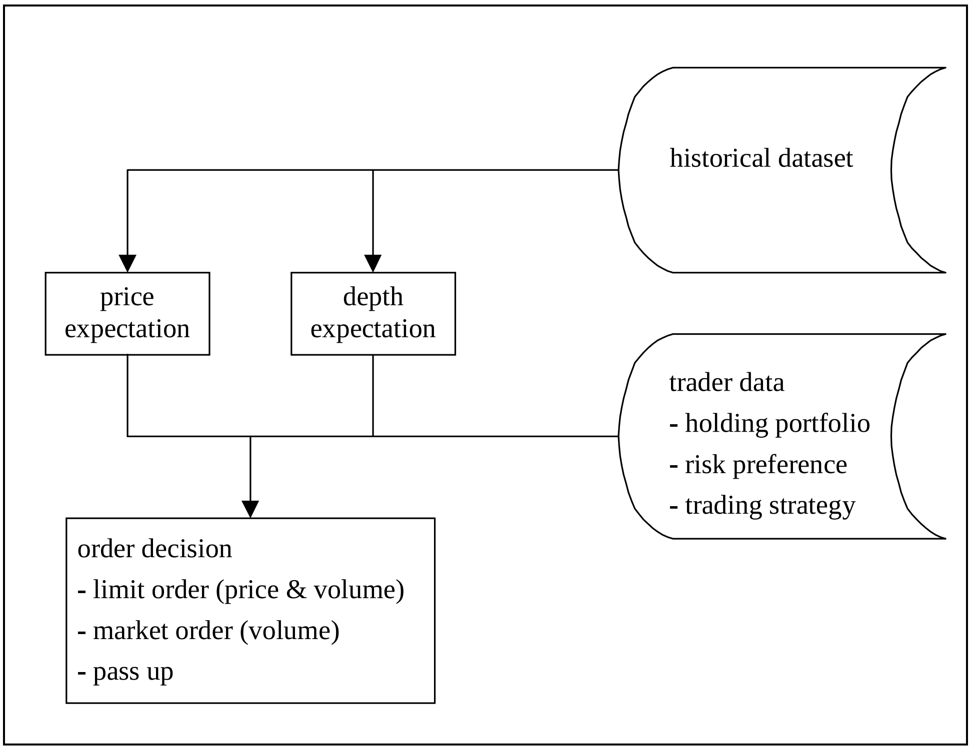
paper focuses on the micro stage, i.e. how the market microstructure affects an individual trader's decision making, we do not go as far as attempting various models of the execution system.

Figure A1-2 shows a rather detailed flow of the trader's order decision process. Based on historical data such as price, order-book, and indication, a trader will forecast future market price and market liquidity (depth), take into account his/her own portfolio composition and risk preference, and make decisions about the order (order/not order, limit order/market order, order volume, and order price in the case of a limit order). Except for adding external shocks,[12] traders are uninformed of security prices, and thus all market behavior can be regarded as endogenous.

Figure A1-2. Order decision of trader




[12] As a method of adding an external shock to the simulation, we plan to change the initial conditions in the middle of the simulation. For example, we are thinking of placing signals of future financial conditions (price, depth, price change ratio, etc.) which traders normally forecast by using their own unique forecasting models.

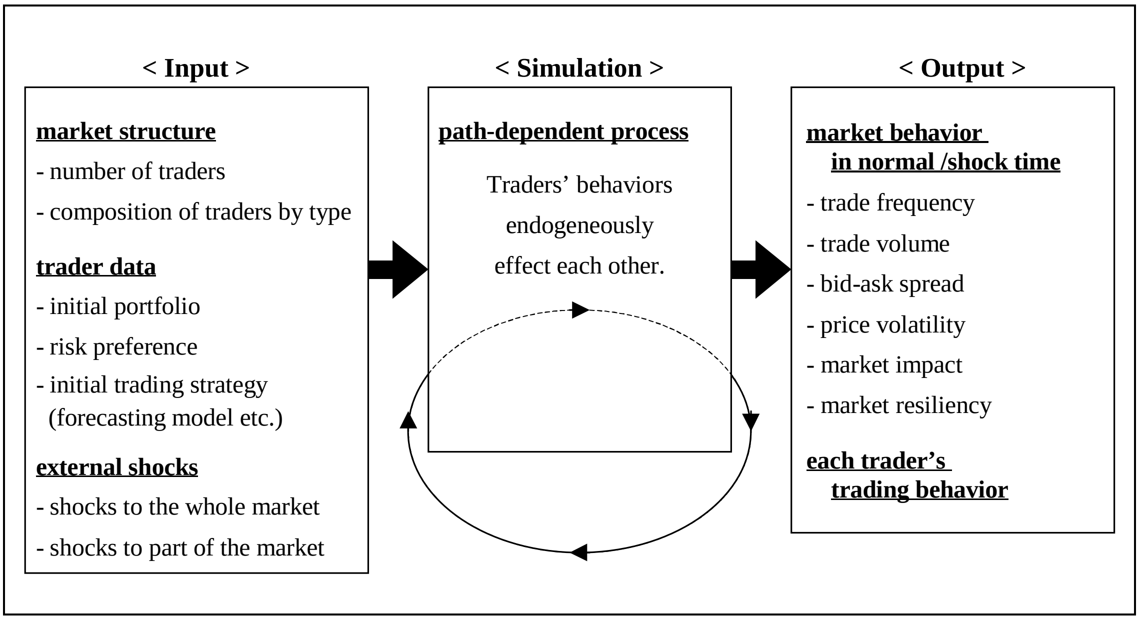
The format for accumulating market data is outlined in Figure A1-3. In period $t$, trader $i$ places an order, the order is executed in the trade execution system, and market data will be produced as output: market data forms a matrix of $N$ rows and 8 columns. In columns 1-4, the number of the trader whose limit/market order has been executed in the corresponding period (= period $t_i$), the trade execution price, the trade volume, and the timing of the order will be entered, while in columns 5-8, the trader number whose limit order is remaining on the order-book unexecuted, the buy/sell quote, the order volume, and the timing of the order will be entered according to price (from high to low) and time (first-in basis).

Figure A1-3. Market data for period $t_i$ (order book information)

| | col. 1 | col. 2 | col. 3 | col. 4 | col. 5 | col. 6 | col. 7 | col. 8 |
|---|---|---|---|---|---|---|---|---|
| row 1 | trader No. | trade execution price | trade volume | timing of order | trader No. | selling limit order | selling volume | timing of order |
| row 2 | • | • | • | • | • | • | • | • |
| • | • | • | • | • | • | • | • | • |
| • | • | • | • | • | • | • | • | • |
| • | • | • | • | • | trader No. | buying limit order | buying volume | timing of order |
| • | • | • | • | • | • | • | • | • |
| • | • | • | • | • | • | • | • | • |
| • | • | • | • | • | • | • | • | • |

The input (initial conditions) and the output (results) of the simulation are summarized as in Figure A1-4.

Figure A1-4. Input/output of the simulation




A1.2. Trader's decision making model

For our trade execution model we employ a continuous auction system patterned after that of the Tokyo Stock Exchange (TSE). There is no designated liquidity provider and market liquidity is only provided through trade orders from market participants. There are two traders in the market: 'value traders' who place limit orders based on their expected values, and 'momentum traders' who make market orders following short-term market trends.[13] The former maintain expected values about asset prices based on information other than market data, and place limit orders according to differences between market prices and their expected values. The latter make market orders

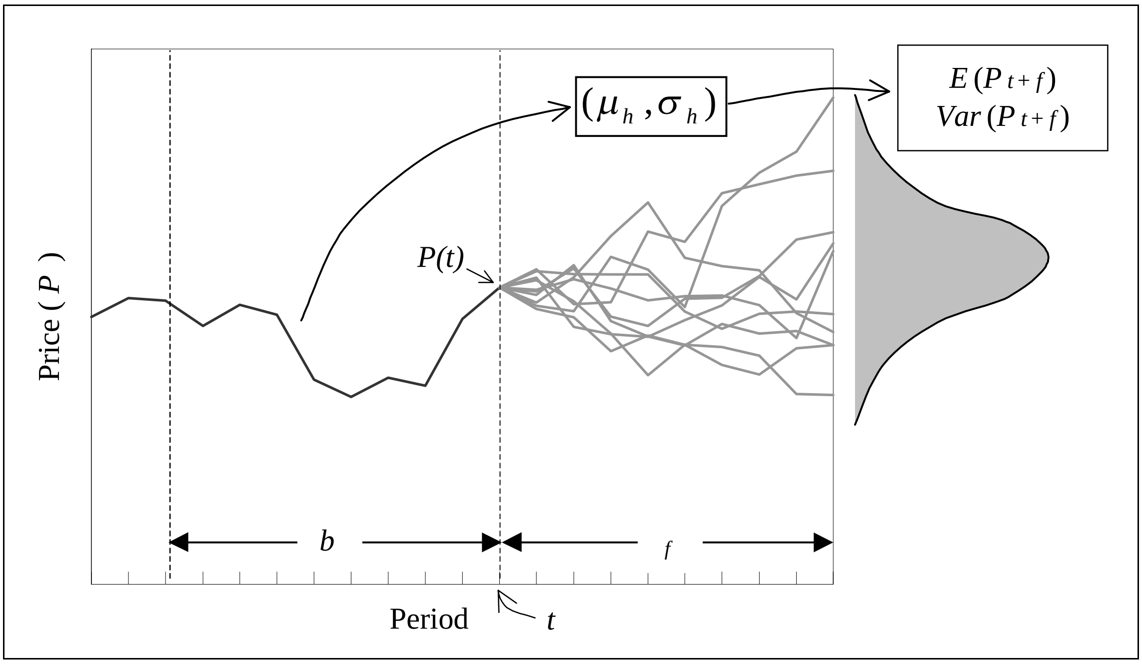
[13] The traders in this paper are of the simplest type. Other than these two types, there is a variety of traders in the actual market, such as 'gamma traders' who make delta hedges on their option positions, and 'noise traders' who have trading incentives which are irrelevant to market movements. It should be noted that we are not at all suggesting that actual traders can be neatly classified into the two types that we are using. Rather, it is reasonable to believe that the attributes of value traders and momentum traders coexist within a single trader.

following short-term trends in market prices, and, as a result, they buy when market prices are rising and sell when market prices are falling.[14] In the following, we first look at the short-term price forecasting model, which both trader types use, and explain the trading behavior patterns of both value traders and momentum traders.

### A1.2.1. Short-term price forecasting of the trader

In determining a trading order, a trader will make a short-term forecast of future market price based on historical market data.[15] The simplest pattern is shown in Figure A1-5. At period *t*, a trader monitors mean price movements during the period immediately before ( $b$ ), measures the trend ( $\mu_h$ ) and volatility ( $\sigma_h$ ) of mean price, and based on this data, forecasts the market price's expected value $E(P_{t+f})$ and variance $Var(P_{t+f})$ of the next trading opportunity, which is a period of *f* ahead.

Figure A1-5. Price forecast of the trader




[14] In the simulation, the size of trade orders is constant.

[15] 'Short-term' refers to the interval between the point in time when the trader accesses the market to decide on a trading order and the next trading opportunity.

### A1.2.2. Trading behavior of value traders

In addition to forecasting future short-term prices, value traders also maintain subjective information $V$ about the fundamental value of an asset. We assume that the expected values of all traders in the market will, when aggregated, follow lognormal distribution with a standard deviation of $\sigma_V$. Each trader individually forms his expected value; its initial value is exogenously provided in our simulation, although this initial value does not represent an asset's true value. The value trader will determine his/her order based on his/her expected value $V$ and expectation distribution of the short-term price $P_{t+f}$. In placing limit orders, the order price (selling: $P_{ask}$, buying: $P_{bid}$) will be established to allow for maximized expected return $E(R \mid P_{ask})$ or $E(R \mid P_{bid})$, which can be obtained by multiplying return of the order and the probability of being executed within the interval ($t$ to $t+f$) prior to the next ordering opportunity.

Selling limit order Maximum $E(R \mid P_{ask}) = \Pr(P_{t+f} \geq P_{ask}) \cdot (P_{ask} - V)$

Buying limit order Maximum $E(R \mid P_{bid}) = \Pr(P_{t+f} \leq P_{bid}) \cdot (V - P_{bid})$

Value traders will recognize their lack of confidence in their forecasts as the risk in submitting orders. When the expected return is substantially larger than the risk, the trader will place either a selling or buying order, which has a larger expected return. In our model, this lack of confidence is given as an expected dispersion (standard deviation) $\gamma$ of the aggregate of each value trader's expected values.[16]

$$E(R \mid P_{ask}) > E(R \mid P_{bid}) \text{ and } E(R \mid P_{ask}) / \gamma > A \quad \rightarrow \quad \text{Selling limit order } (P_{ask})$$

$$E(R \mid P_{ask}) < E(R \mid P_{bid}) \text{ and } E(R \mid P_{bid}) / \gamma > A \quad \rightarrow \quad \text{Buying limit order } (P_{bid})$$

where $A$ is a positive constant reflecting a trader's risk aversion.

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16 $\gamma$ represents each trader's forecast of the actual dispersion $\sigma_V$.

### A1.2.3. Trading behavior of momentum traders

Momentum traders are indifferent to the level of market prices and their trading is based on the trends and volatility of market prices. Namely, based on the short-term forecast by taking into account historical market data, they compare the expected earnings ratio with risks until the next trading opportunity. If the extent of their risk aversion allows, they make selling market orders (when market prices are falling), or buying market orders (when market prices are rising). The order of the momentum trader is:

$$\mu_h / \sigma_h < -B \quad \rightarrow \quad \text{Selling market order}$$

$$\mu_h / \sigma_h > B \quad \rightarrow \quad \text{Buying market order}$$

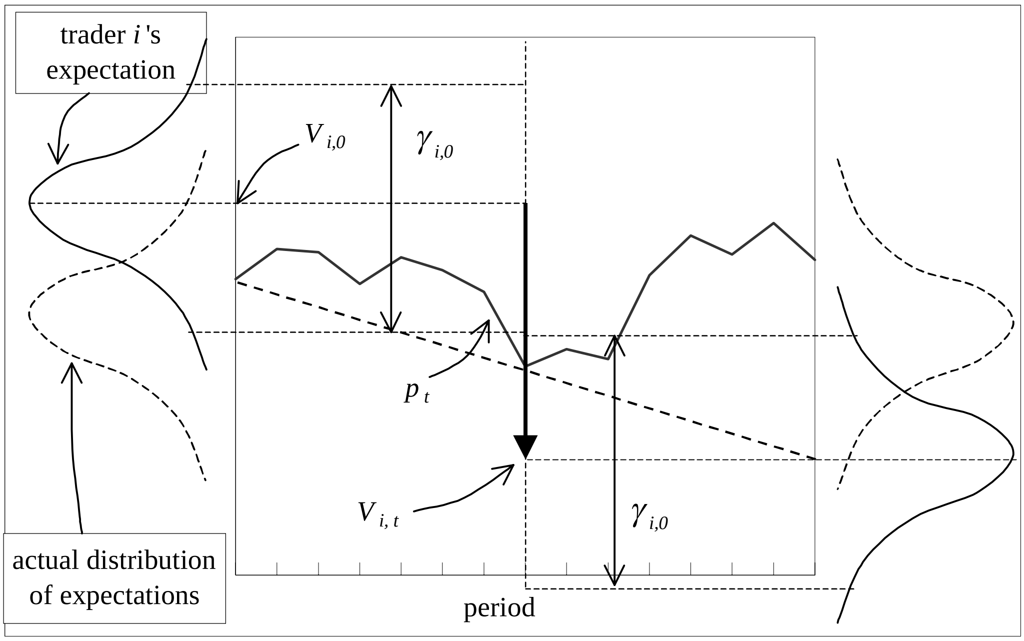
where $\mu_h$ and $\sigma_h$ are trend and volatility of mean price, respectively, and $B$ is a positive constant which reflects a trader's risk aversion.

**Appendix 2**

**Feedback effects on traders' expectations**

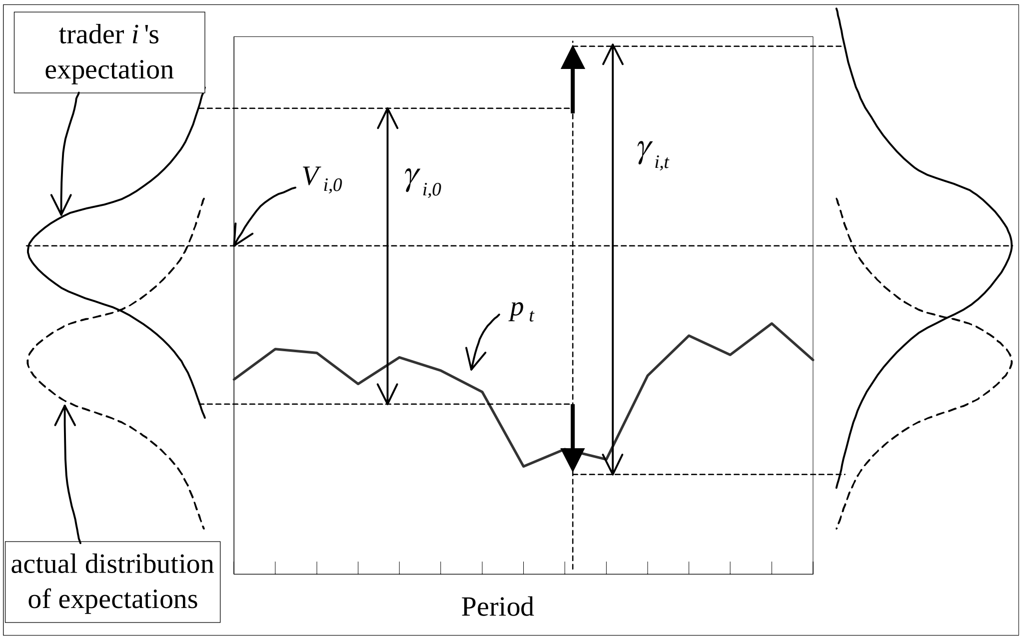
As shown in Figure A2-1, feedback mechanism to expected value is when a trader revises his/her own expected value based on market information he/she receives. Specifically, when trader *i*, who holds initial expected value $V_{i,0}$ , observes that the market price just before his/her order is below a certain confidence level of his/her expected distribution of *V*, he/she forecasts market equilibrium price based on the market trend and revises $V_{i,t}$, accordingly. Hereafter, we call the certain confidence level which causes such a revision, 'trigger.'

Figure A2-1. Feedback to expected value




As shown in Figure A2-2, feedback mechanism to confidence is when a trader revises his/her forecast on confidence, that is, variance of market participants' expected values based on market information he/she receives. Specifically, when trader *i*, who holds an initial expected standard deviation of $\gamma_{i,0}$, observes that the market price just before his/her order is below the 'trigger,' he/she revises $\gamma$ at time t to $\gamma_{i,t}$, so that the observed market price will fall within the range $\gamma_{i,t}$ above the trigger.

Figure A2-2. Feedback to confidence



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