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ABSTRACT

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KEY WORDS: Risk Management, Value at Risk, Stress Testing, Loss Cut Rule, Positive Feedback Trader, Macro Market Model, Concentration Problem, Systemic Risk, Macro Prudence Policy

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Dynamic Micro and Macro Stress Simulation

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Abstract

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[1] The views expressed in the paper are those of the authors and do not necessarily represent those of the Bank of Japan. Although the paper benefited from comments by the staff of the Institute for Monetary and Economic Studies of the Bank of Japan, the authors are solely responsible for any remaining errors.

I. Introduction

Remarkable progresses have been shown in the area of financial risk management recently. Individual institutions are more capable of measuring financial risks especially market risks than ever due to the recent innovations on the field both in theory and in practice. At the same time, the concern about macro market stability as a whole voiced by market participants and regulators has been growing. Systemic risk is our interest of research, though it is still relatively unexplored compared to other financial risks, such as market risk and credit risk.

Previous studies on systemic risk, such as the BIS "Promisel report" (1992) and Hentschel and Smith (1995) regarded default events and sequential domino effects as the main threat in systemic risk. While these can be said phenomena at the final stage of systemic stress, we focus more on sources of systemic risk. We assume that extreme jumps of prices of financial assets have potential to lead to systemic stress and are sources of systemic risk. A major disadvantage of using extreme price jumps as an indicator is that those are not observable well in advance of occurrence of systemic stress. Based on the following analysis of historical data, we assume that high volatility of prices can also be an indicator of systemic risk, though a highly volatile market does not always lead to extreme price jumps.

We examine daily data during the last eight years (from May 1987 to August 1995) in the Nikkei 225 market and the ¥/US$ exchange market, and measure daily percentage changes of the prices and standard deviations, i.e. volatility of price changes during 20-day sub-periods. Over the last eight years, both the Nikkei 225 index and the ¥/US$ exchange rate display a distribution with a greater frequency of extreme price changes than the normal distribution (see Charts 1 and 2).

Next, we pick up the ten sub-periods during which daily price changes presented the highest volatility and the ten days when the price changes were the highest during the eight years. As shown in Table 1 and Table 2, all of the ten most volatile periods in both the Nikkei 225 index and the ¥/US$ exchange rate include one or two days listed in the right hand column of the tables, figures in which represent the highest daily percentage changes during the period. This indicates that highly volatile periods have high probability of including extreme price jumps.

The goal of this study is to explore a macro mechanism that leads to market stress as an aggregated picture of individual micro risk management systems. We can point out three important advances made by our study as follows;

1. a more realistic description of micro structure than those in previous studies.
2. a direct connection of micro structures to a macro mechanism in order to bridge the gap between micro subsystems and a macro system.
3. development of a dynamic macro model, where a market price is determined endogenously.

Our paper will contribute to micro risk management by presenting a possible method for dynamic micro stress simulation. The most popular types of existing stress testing conducted within financial institutions have rather static analysis based on subjective scenarios or extend value-at-risk type model. However, human factors, such as decision making and trading behavior, will play a central role in a stress situation. Our dynamic micro simulation will present a better framework for assessing risks in a stress situation that can be used as a fire drill or exercise for senior managers when they set out to prepare for market stress.

The framework of micro dynamic simulation that models trading of a market participant is employed for a macro model. Market prices are determined endogenously as a result of trading behavior of all the participants in the market. By so designing, we have succeeded in developing a macro model which overcomes such shortcomings of previous models as too simple profiles of micro market structure, unrealistic rationality of price determining mechanism and the gap between micro risk management subsystems and a macro system. Since micro behavior is directly linked to a price determining mechanism in the macro system, we can easily explore what kind of micro structure will affect a macro system and how vulnerable the macro system is to changes in micro trading profiles.

This paper is structured as follows: we present micro stress simulations in Chapter II after explaining the framework of our model. We then depart from the micro world in Chapter III and explore a macro mechanism of market stress based on macro simulations by our model. Chapter IV concludes and suggests implications for stress testing and systemic risk.

Table 1 The Ten Most Volatile Periods and Days in Nikkei 225 since May 1987(%)

Rank	1st day of the period	Volatility	Date	Daily Change	
1	16/10/1987	78.3	20/10/1987	16.1	(10.8)
2	15/10/1987	78.1	2/10/1990	12.4	(8.3)
3	17/10/1987	78.1	21/10/1987	8.9	(5.9)
4	14/10/1987	76.0	31/ 1/1994	7.6	(5.0)
5	13/10/1987	75.3	10/ 4/1992	7.3	(4.9)
6	12/10/1987	75.2	2/ 4/1990	6.8	(4.6)
7	7/10/1987	74.8	19/ 8/1991	6.1	(4.1)
8	3/10/1987	74.7	21/ 8/1992	6.0	(4.0)
9	6/10/1987	74.7	23/ 8/1990	6.0	(4.0)
10	8/10/1987	74.6	27/ 8/1992	5.9	(4.0)
	Average Volatility	23.7			

The price jumps in the right column with shading occurred during the volatile period indicated in the left column with the same shading.
Figures in parenthesis indicate the ratio of a daily change to the average daily volatility.

Table 2 The Ten Most Volatile Periods and Days in ¥/US$ rate since May 1987(%)

Rank	1st day of periods	Volatility	Date	Daily Change	
1	15/12/1987	22.2	5/ 1/1988	4.0	(5.7)
2	8/ 6/1989	22.1	20/ 8/1993	4.0	(5.6)
3	7/ 6/1989	22.1	20/ 1/1992	3.3	(4.6)
4	6/ 6/1989	22.1	11/12/1987	3.0	(4.2)
5	16/12/1987	22.0	15/ 2/1994	2.9	(4.2)
6	5/12/1987	21.9	8/ 3/1995	2.8	(3.9)
7	8/12/1987	21.9	18/ 1/1988	2.6	(3.7)
8	1/12/1987	21.9	10/ 6/1989	2.5	(3.5)
9	3/12/1987	21.9	9/ 3/1995	2.4	(3.4)
10	17/12/1987	21.9	21/ 6/1993	2.4	(3.4)
	Average Volatility	11.2			

The price jumps in the right column with shading occurred during the volatile period indicated in the left column with the same shading.
Figures in parenthesis indicate the ratio of a daily change to the average daily volatility.

II. Micro Simulations

1. Summary of the Simulations

We examine effects of market stress on the risk profile of an individual institution through dynamic simulations. We model trading behaviors and introduce position adjustment in response to day-to-day market price fluctuations, incorporating trading strategies of the trader and internally-set risk management rules of the institution. This type of stress simulation which takes into account dynamic trading activities is very different from currently common methods of simulation where stress scenarios are applied to static trading positions. Through such static simulations, a gigantic figure of possible losses in a hypothetical stress event (sometimes equivalent to four or five times value at risk) is derived just for reporting purposes or to end up as an "imaginary monster" not seriously accepted by the senior management. By contrast, we believe that dynamic stress simulations give much more insight in designing effective risk management.

Simulations designed in this section are micro simulations in the sense that we focus on profits and losses (P/Ls) of one hypothetical trader and we assume that the trader's trades do not affect market prices.

We first model trading behavior of the hypothetical trader. Trading volumes of the trader are determined depending on such factors as the trader's view of market movements, the trader's aggressiveness as affected by the accumulated P/Ls and market price changes as of the trading date, and trading constraints set in the risk management perspectives. We simulate P/Ls with various assumptions about these parameters.

Next we define market price movements. We assume that there is only one financial product tradable and the simulation period is twenty trading days. Prices that the product can be traded at are acquired from historical market prices of an existing product. Both a stress period and a non-stress period are selected to enable us to compare simulated results under different circumstances of market price movement.

By setting various parameters in the model, we identify eight different types of trading, fortrend trading or contrarian trading (defined below), trading with risk management constraints or without them, and trading instruments with only linear risks or with linear and non-linear risks. For each of the trading types, two different simulation periods are used. With the total of sixteen assumption sets, we simulate P/Ls to explore effects of trading style, risk management practices and trading instruments with non-linear risks in a stress and a non-stress situation.

The results we get from simulations suggest that such behavioral information plays important roles in assessing an institution's risk profile in a stress situation.

2. The Model

In this section we describe how our model determines trading volumes of the trader each day incorporating its risk management practices and how profits and losses are brought about through trading.

<u>Trading Volumes</u>

We assume that trading volume (V) of each day is a function of the most recent percentage change in prices (dP/P) expressed by the following formula with four parameters (V1, V2, V3 and V4).

$$V = V1 * V2 * V3 * V4 * dP/P$$

V1 V1 is an indicator of the trader's view of market price movement. It is +1 if the trader believes that a price which has been rising will continue to rise and one which has been declining will continue to decline. We call such a trader a positive feedback trader or fortrend trader. It is -1 if the trader believes that a price which has been rising will decline and one which has been declining will rise. We call such a trader a negative feedback trader or contrarian trader.

V2 V2 is an indicator of the trader's aggressiveness. Faced with a certain percentage change in prices, the trader trades more (larger V2) if she/he is more aggressive.

V3 V3 is a coefficient which describes the effects of accumulated P/Ls on trading volumes. When P/Ls are positive, V3 is 1.0, and when they are negative, it is a figure expressed as a proportion to the volume that would be traded if they were positive. Throughout the simulation, it is 0.75 when P/Ls are negative since it is assumed that traders having accumulated profits transact more than those suffering accumulated losses.

V4 V4 is an indicator of the trader's trading constraints set by its risk management rules. If there is no such constraint, it is 1.0 and if there are constraints, it is the ratio defined below which we call the RM Ratio. Based on typical internal risk management rules of several major Japanese banks which we interviewed, we defined the RM Ratio as such. The basic idea of the RM Ratio, although more fully described below, is (i) to limit the trading position within a certain range, (ii) to reduce the range as net losses accumulate and (iii) to terminate trading when the accumulated losses reach a certain level.

Brief Description of Risk Management Rule

The maximum position limit and the loss limit are imposed on trading, which are set in advance with the following rule.

Maximum Position Limit (R1)

The outstanding trading position of each day is constrained by the maximum position limit. This limit (R1) is calculated as the position whose value at risk is the maximum that the trader can bear in one day.

Loss Limit (R2)

Trading volumes are also constrained by a loss limit. The loss limit is set with the intention of keeping losses accumulated during twenty trading days below this limit. As accumulated losses approach the limit, capacity for trading volumes is decreased by the ratio of consumed portion of the limit to the given limit. When accumulated losses reach the limit, trading volumes ought to be zero, so that no further loss can be realized.

Link between the two (R1 & R2)

We link the maximum position limit and the loss limit as the loss limit is twice the daily value at risk which is determined by the maximum position limit.

R2 = 2 * VaR = 2 * R1 * volatility of P * 99% Confidence Interval[2]

The rationale behind such a link is the idea that a trader should stop trading if she/he twice in twenty trading days suffers losses that might statistically happen only 1% of the time.

Reflecting such risk management rules, the RM Ratio is calculated as follows.

RM Ratio = Maximum Position Limit Ratio * Loss Capacity Ratio
= Min (A, R1) / A * Max (R2 - Accumulated losses, 0) / R2
A = V2 * V3 * dP/P

A is a volume that would be traded if there were not any limit on it. The Maximum Position Limit Ratio is imposed to limit the trading volume to R1 when it would exceed R1 and the Loss Capacity Ratio is imposed to reduce trading volumes when losses accumulate and to terminate trading when the accumulated losses reach the loss limit.

Interpretation

The above function of the trading volume (V) can be interpreted as follows.

If a trader is a positive feedback trader without risk management constraint and the most recent change in price is a rise of 1%, the trader goes for a position which is long by 1% of V2 unless the accumulated P/L position is in red. If the most recent price change is a decline of 3% instead, the trader goes for a short position of 3% of V2. If the accumulated P/L is in red, the trading volume is adjusted by the coefficient, V3, reflecting a change in the bullishness of the trader. If the trader is constrained by risk management rules, the trading volume is reduced when it exceeds the maximum position limit and as losses accumulate. If the trader is a negative feedback trader, selection of long and short positions is reversed.

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[2] We use 99% Confidence Interval to calculate VaR although other intervals such as 95% and 98% are also common among financial institutions.

Determination of profits and losses

The trader closes the outstanding trading position at the beginning of each day then decides on trading volume of the day so that the outstanding trading position of the day is always same as the traded amount at the beginning of the day. When the trading position is closed, daily profits and losses are calculated from the price change from the previous day, the trading volume of the previous day and the risk profile of the position. The risk profile is characterized by delta and gamma. If the traded instrument is an outright position of the trading product, the delta is 1 and the gamma is 0. If it is an option instrument, the delta ranges from -1 to +1 and the gamma has non zero value. The third or higher order risks are ignored. Profits and losses of the day are calculated by the following formula.

$$P/Ls = \text{Trading Volume (V)} * (\text{delta} * \text{price change(dP)} + 0.5 * \text{gamma} * \text{price change(dP)}^2)$$

3. Parameter Settings

Parameters are set as those in the following table in order to enable us to observe differences in effects of a fortrend trader and a contrarian trader, a trader with risk management constraints and without them, and trading instruments only with linear risks and with linear and non-linear risks. Other parameters are being kept constant.

Table 3

Parameters	V1	V2	V3		V4	R1	R2	delta	gamma
			P/L>0	P/L<0					
Type 1	1	10000	1.0	0.75	1	---	---	1.0	---
Type 2	1	10000	1.0	0.75	RM Ratio	500	2500	1.0	---
Type 3	-1	10000	1.0	0.75	1	---	---	1.0	---
Type 4	-1	10000	1.0	0.75	RM Ratio	500	2500	1.0	---
Type 5	1	10000	1.0	0.75	1	---	---	1.0	-0.2
Type 6	1	10000	1.0	0.75	RM Ratio	500	2500	1.0	-0.2
Type 7	-1	10000	1.0	0.75	1	---	---	1.0	-0.2
Type 8	-1	10000	1.0	0.75	RM Ratio	500	2500	1.0	-0.2

We set V1 = +1 or -1 to simulate with a fortrend trader or a contrarian trader, respectively. V2 is set as the basic trading volume per unit change in prices. To reflect bearishness of the trader when accumulated P/Ls are negative, V3 is set 75% of the base. V4 is +1 when trading is not constrained by risk management and it is RM Ratio defined in the previous section when trading is constrained by the maximum position limit (R1) and the loss limit (R2) set as 500 and 2500 respectively. V2 and V3 are identical in all cases.

For trading instruments, we first assume the trader trades instruments only with linear risks (gamma = 0), and afterwards we include non-linear risks (gamma = -0.2) for comparison. Linear risks expressed in delta are kept identical to highlight effects of non-linear risks.

4. Sample Periods

We simulated with the model with historical market prices of Yen/US$ exchange rates. In order to compare how P/Ls evolve under a stress situation and normal situation, we selected two representative sample periods. Table 2 exhibits the ten most volatile periods and the ten most extreme jumps in the last eight years. We selected June 1989 as a sample period with a stress situation, since the period shows both high volatility and a couple of extreme jumps.

Chart 3 enables us to take a closer look at the price movements of the period. The Yen/US$ exchange rate experienced a 2.45% rise on June 10th, which amounted to 3.55 yen. After experiencing such an extreme rise, it confronted several large declines in succession, which amounted to 2.40% on June 16th, 1.89% on June 22nd and 2.20% on June 23rd. The annualized volatility of the 20-day period is 22.1%, which is the second largest in the last eight years.

For comparison with the sample of a stress situation, we selected July 1989 as a sample period with a normal situation. As shown in Chart 4 the volatility was 11.9% during the period which is very close to the overall average of the eight years and the period experienced no major jumps.

5. Simulation Results

With eight different trading types, profits and losses were simulated using two different sets of historical market prices. Daily profits and losses of the fortrend trader and the contrarian trader are illustrated in Charts 5-1 and 5-2 respectively. From daily profits and losses we acquired statistics such as volatility (standard deviation) and maximum loss. Table 4 summarizes such statistics when trading instruments had only linear risks and Table 5 when trading instruments had both linear and non-linear risks.

Table 4 Without non-linear risks

Trader Type		Fortrend Trader		Contrarian Trader	
Risk Management Constraints		w/o(Type 1)	w/ (Type 2)	w/o(Type 3)	w/ (Type 4)
July 1989	volatility	63	61	65	65
	max. loss	109	109	150	148
	accumulated P/Ls	+25	+15	-125	-128
June 1989	volatility	236	236	177	154
	max. loss	335	335	435	398
	accumulated P/Ls	+1500	+1500	-1126	-992

Table 4 produces several findings. Both volatility and maximum loss are larger when simulated with the data of June 1989 than when simulated with those of July 1989, which is as expected. For the fortrend trader, no major differences are found in the volatility, the maximum loss and the accumulated P/Ls with the introduction of the risk management constraints because the fortrend trader was not faced with large losses in either a stress situation or a normal situation and the loss limit did not affect trading.

Similar results are exhibited for the contrarian trader in a normal situation. In a stress situation, however, the volatility, the maximum loss and the accumulated losses become smaller with the introduction of the risk management constraints. Since the contrarian trader made large losses during the stress period, the risk management constraints were effective in their role of reducing losses and volatility.

Table 5 With non-linear risks

Trader Type		Fortrend Trader		Contrarian Trader	
Risk Management Constraints		w/o(Type 5)	w/ (Type 6)	w/o(Type 7)	w/ (Type 8)
July 1989	volatility	65	64	69	68
	max. loss	94	94	172	167
	accumulated P/Ls	+79	+70	-177	-179
June 1989	volatility	259	256	215	190
	max. loss	454	455	571	550
	accumulated P/Ls	+1344	+1314	-1258	-1104

As shown in Table 5, in many cases both volatility and maximum loss are larger when trading instruments contain non-linear risks. However, differences between the fortrend trader and the contrarian trader, the stress situation and the normal situation, trading with the risk management constraints and trading without them are revealed as in the case of trading instruments without non-linear risks. The volatility and maximum loss reduction effect for the contrarian trader during the stress situation is as large as when trading instruments do not contain non-linear risks.

6. Implications

Dynamic micro simulations will help individual institutions exercise for a stress situation. As we present in this chapter, a dynamic stress simulation which uses market data in a stress situation and incorporates information on trading behaviors and risk management rules provides senior management with more insight into a stress situation than a static stress testing does. It is further notable that this type of simulation helps to develop effective risk management system within each institution.

III. Macro Simulations

1. Summary of the Simulations

In this section, we explore a macro mechanism of market stress by simulating market price movements endogenously determined by our macro model. We observe volatility of price movements and extreme price jumps during simulation sub-periods, which are prospective indicators of market stress. Since prices reflect aggregated information of micro behavior, we can examine how micro behavior affects the macro risk profile of the market as a whole by analyzing the relationship between micro structures and price movements. We are especially interested in the proposition that risk management of market participants is of some help for avoiding excess volatility and sudden market shocks. Effects of changes in three parameters in the model which reflect presence of positive feedback traders, micro risk management, and existence of non-linear risks are examined.

Our simulations show that micro trading behaviors have a great effect on macro market condition. The following hypotheses are examined in simulations.

a. When trading behavior is constrained by risk management rules, the market becomes less volatile and is less likely to experience extreme price jumps.

b. When the presence of positive feedback traders is dominant in a market, the market becomes more volatile and is more likely to experience extreme price jumps.

c. When trading portfolios have non-linear risks, the market becomes more volatile and is more likely to experience extreme price jumps.

d. Concentration is one of the triggers for an extreme price jump.

2. The Model

The same parameters are used in this simulation as in the micro simulations shown in the previous chapter. The major difference between micro and macro simulations is that for the macro simulation we model behaviors of all the market participants to enable us to determine market prices of the product endogenously within the model while these are given exogenously in the case of the micro simulation. In the following sections, we describe how market participants are categorized, how supply and demand in the market are derived and how market prices are determined.

Description of the Market Participants in Our Model

In our model we categorize market participants into three groups and discuss trading behaviors of each group. Group A is a group of traders who believe that the market tends to rise if it has been rising and tends to decline if it has been declining. They are known as positive feedback traders. The larger the rise or decline, the more bullish these traders are. Group B is a group of traders who believe that the market tends to revert from recent movement. They are known as negative feedback traders. These traders are more confident of their belief in reversion when the recent movements are larger. Group C is the group of everyone else. Although this group is a gathering of traders who have diverse views on market movements, when it is seen as a whole, it can be characterized as a random trader. Hence, the trading behaviors of the group are modeled so that their expectation on price changes is represented by a randomly generated number from a log-normal distribution. The real market, seen as a whole, confronting random price changes, can be characterized by Group C. Here we assume that we can extract two distinctive types of traders and represent these by Groups A & B and all the rest of traders by Group C.

Table 6 Categories of traders in our model

Group A	Positive feed back traders or Fortrend traders
Group B	Negative feed back traders or Contrarian traders
Group C	Random traders

In our model, we assume an efficient market at least in the semi-strong form where no one can constantly make profits without insiders' information. There are some previous studies developing macro market models which include fundamentalists and chartists as actors in the models[3]. With our assumption about the market efficiency, there is no difference between fundamentalists and chartists in that neither can constantly make profits. Fundamentalists form a part of Group C.

Supply and Demand Function

Our model provides us with a supply and demand function for each type of trader. Trading volume at time t (V_t) of a trader is a function of a price change from the price at the previous time (dP/P). Given any price change, trading volume of each group can be determined by the same formula below as in the micro simulation. V2 which is an indicator of the trader's aggressiveness in the micro model represents presence of each participant in the market in the macro model. This formula can be interpreted as the supply and demand function of each group. When V is positive, the figure indicates volumes that are demanded and if it is negative, it indicates volumes that are supplied.

$$\boxed{V=V1*V2*V3*V4*dP/P}$$

Trading characteristics are reflected in the supply and demand function. The four types of traders in the following simulation have supply and demand curves as shown in Chart 6. Fortrend traders' curves show an upward trend with rises in the market price and contrarian traders' curves have a downward trend. Whether trading is constrained by risk management rules or not is reflected in the shape of the curves; traders with no constraint in their trading decision process have supply and demand curves in straight lines (a solid line in Chart 6). Traders with constraint have supply and demand curves with a ceiling due to a position limit (R1=500 in Chart 6). Furthermore, their curves are bow-shaped when their accumulated P/Ls are negative, because they continuously change trading volumes according to changes in their accumulated losses. The observed kink in a broken line of a fortrend trader in Chart 6 reflects a step change in her/his trading aggressiveness (represented by V3 in the above formula.) If the market price goes down more than 2.4% from the previous day's price, his/her accumulated

[3] For example, see Jeffrey A. Frankel and Kenneth Froot (1986)

P/Ls will go below the break even point. At this point, his/her trading volumes are reduced discontinuously reflecting the change in V3 of the above formula.

By incorporating these various supply and demand curves, it becomes possible to develop a macro price determining mechanism. We can combine a micro trading profile and a macro market system by taking micro information from these supply and demand functions.

Price Determination

Supply and demand of the three groups corresponding to each price change are totaled. Traders submit buy/sell orders for each 0.1 % change from the previous day in the range of ± 5%, and these orders are aggregated so that an equilibrium is found among 101 prices. In other words, the price change for the following day is determined as the level at which total supply and demand are equal. The price change so determined is the equilibrium. Table 7 shows some of the trading orders when the previous day's price is 100 as an example, and supply and demand curves derived from the orders are shown in Chart 7.

Table 7

Market Price	Trading Orders (supply and demand)			
	Group A	Group B	Group C	Total
99.50	-500	1,000	5,500	6,000
99.60	-400	800	5,000	5,400
99.70	-300	600	4,500	4,800
99.80	-200	400	4,000	4,200
99.90	-100	200	3,500	3,600
100.00	-0	0	3,000	3,000
100.10	100	-200	2,500	2,400
100.20	200	-400	2,000	1,800
100.30	300	-600	1,500	1,200
100.40	400	-800	1,000	600
100.50	500	-1,000	500	0
100.60	600	-1,200	0	-600
100.70	700	-1,400	-500	-1,200
100.80	800	-1,600	-1,000	-1,800
100.90	900	-1,800	-1,500	-2,400
101.00	1,000	-2,000	-2,000	-3,000

3. Simulation Results

a. Effect of Micro Risk Management

We compare volatility of prices when participants trade with risk management constraint and when they trade without it.

Hypothesis 1

When trading behavior is constrained by risk management rules, the market becomes less volatile and is less likely to experience extreme price jumps.

Scenario A

Parameters	V1	V2	V3		V4	R1	R2	delta	gamma
			P/L>0	P/L<0					
Group A	1	10,000	1.0	0.75	1	---	---	1.0	-0.2
Group B	-1	10,000	1.0	0.75	1	---	---	1.0	-0.2
Group C	-1	100,000	1.0	0.75	1	---	---	1.0	-0.2

In Scenario A, no Groups have maximum position limits (R1) and loss limits (R2) as their risk management rules. Their trading aggressiveness (indicated by V3) is assumed to be reduced to 0.75 when their accumulated P/Ls become negative. All Groups have non-linear risks (negative gamma) in their portfolio. The reason for Group C's large V2 is that Group C represents all of the other participants in the market.

Scenario B

Parameters	V1	V2	V3		V4	R1	R2	delta	gamma
			P/L>0	P/L<0					
Group A	1	10,000	1.0	0.75	RM Ratio	500	2500	1.0	-0.2
Group B	-1	10,000	1.0	0.75	RM Ratio	500	2500	1.0	-0.2
Group C	-1	100,000	1.0	0.75	1	---	---	1.0	-0.2

In Scenario B, all parameters are the same as in Scenario A, except the risk management parameters (R1 & R2). The institutions in the three groups calculate the RM Ratio every day and control their trading volume based on the ratio.

Result

The hypothesis that micro risk management can be of any help to reduce market volatility and lessen the possibility of extreme price jumps is not supported by our simulation (see

Appendix). There is no doubt that micro risk management is effective to reduce an individual institution's P/L volatility as shown in the micro simulation. However, the simulation result shows that micro risk management does not necessarily guarantee macro market stability.

b. Effect of Positive Feedback Trading

We compare volatility of prices when the presence of positive feedback traders is dominant and when it is not.

<u>Hypothesis 2</u>

When the presence of positive feedback traders is dominant in a market, the market becomes more volatile and is more likely to experience extreme price jumps.

Scenario A

Parameters	V1	V2	V3		V4	R1	R2	delta	gamma
			P/L>0	P/L<0					
Group A	1	10,000	1.0	0.75	1	---	---	1.0	-0.2
Group B	-1	10,000	1.0	0.75	1	---	---	1.0	-0.2
Group C	-1	100,000	1.0	0.75	1	---	---	1.0	-0.2

This scenario is the same as Scenario A in the previous simulation.

Scenario C

Parameters	V1	V2	V3		V4	R1	R2	delta	gamma
			P/L>0	P/L<0					
Group A	1	**20,000**	1.0	0.75	1	---	---	1.0	-0.2
Group B	-1	10,000	1.0	0.75	1	---	---	1.0	-0.2
Group C	-1	100,000	1.0	0.75	1	---	---	1.0	-0.2

In Scenario C, Group A, positive feedback traders, have twice as much trading volume as Group B (indicated by doubled V2). This scenario describes a situation in which the presence of positive feedback players is more dominant in the market than in Scenario A.

Result

The hypothesis that the presence of positive feedback traders makes the market more volatile and more likely to experience extreme price jumps is supported by our simulation (see Appendix). This result is evidence of the negative effect of positive feedback traders on market volatility. However, this effect is reduced with a lower V3 according to the results of other simulations. This can be interpreted as showing that the negative effect of positive feedback traders is limited if they are sensitive to losses.

This result also implies that if there is a dominant player whose trading behavior has negative effect on market volatility, his/her dominant trading makes the market volatile and likely to generate extreme price jumps. This phenomenon is recognized as one aspect of the so-called "concentration problem."

c. Effect of Non-linear Risks

We compare volatility of prices when instruments with non-linear risks are traded and when those with only linear risks are traded.

Hypothesis 3

When trading portfolios have non-linear risks, the market becomes more volatile and is more likely to experience extreme price jumps.

Scenario A

Parameters	V1	V2	V3		V4	R1	R2	delta	gamma
			P/L>0	P/L<0					
Group A	1	10,000	1.0	0.75	1	---	---	1.0	-0.2
Group B	-1	10,000	1.0	0.75	1	---	---	1.0	-0.2
Group C	-1	100,000	1.0	0.75	1	---	---	1.0	-0.2

This scenario is the same as Scenario A in the previous simulation.

Scenario D

Parameters	V1	V2	V3		V4	R1	R2	delta	gamma
			P/L>0	P/L<0					
Group A	1	10,000	1.0	0.75	1	---	---	1.0	0.0
Group B	-1	10,000	1.0	0.75	1	---	---	1.0	0.0
Group C	-1	100,000	1.0	0.75	1	---	---	1.0	0.0

No Group has any non-linear risks in the portfolio in Scenario D. In other words, instruments such as options are not traded. All the other parameters are the same as those in Scenario A.

Result

The hypothesis that when trading portfolios have non-linear risks, the market becomes more volatile and is more likely to experience extreme price jumps is not supported by our simulation (see Appendix). Although this result may seem too obvious, it is important to recognize that non-linear risk itself does not harm market stability. Non-linear risks could have an indirect negative effect on market stability through channels of traders' responses to them such as dynamic hedging. Further survey will be necessary in this field to describe more details of trading behaviors in response to non-linear risks.

d. Effect of Concentration

Hypothesis 4

Concentration is one of the triggers for an extreme price jump.

As we followed how extreme price movements occurred in our simulations, we observed some cases where a dominant player's sudden disappearance causes an extreme price jump. In our simulation, such a disappearance is caused by risk management rules, when accumulated losses reach a loss limit. This can be interpreted as one aspect of the "concentration problem," which means that the price mechanism in a market becomes vulnerable to a dominant player's behavior. Although the phenomenon does not always occur when a dominant player disappears, we can point out that price movements tend to be amplified by a concentration problem, such as a dominant player's disappearance and position closing. Chart 8 shows such an amplification phenomenon caused by the disappearance of a dominant player. There is anyway a potential for a large decline in the price but it was greater with the disappearance.

IV. Conclusions

Our study shows that micro market structure, such as trading behaviors and risk management rules, affects a macro market risk profile and exposure to systemic risk. The results from our macro simulations help us towards evaluation of our hypotheses on linkage between micro market structure and market stress, such as the positive effect of micro risk management, the negative effect of the positive feedback trading, and the negative effect of non-linear risks on market stress. Our study supports only the second hypothesis, and cannot provide us with evidence for the other hypotheses. It is worth stressing particularly from a central bank' s point of view that an aggregation of well managed micro subsystems does not necessarily ensure macro market stability. This suggests that we need to explore a macro mechanism which reinforces the sustainability of a market as a whole. Adequate attention should be paid to micro market structure, such as positive feedback trading when we are concerned with macro market stability, although option trading's non-linear risk itself is not necessarily a cause of stress. We should take into account a concentration problem which is also observed when conducting simulations.

Our micro stress simulation is a possible method for meaningful stress testing within individual institutions. Since human factors, such as decision making and trading behaviors, will play a central role in a stress situation, a fire-drill-type simulation is effective and indeed indispensable for senior managers. Gathering micro information based on such a dynamic simulation can help central banks to prepare for systemic risk. In this process, our macro model, which provides them with an aggregated picture of micro subsystems, can be a useful tool to explore market risk profile.

We admit that our model is still too simple and cannot reflect other important factors existing in micro market structure. In future studies, we will extend the model to reflect more closely the reality of markets, incorporating such factors as trading behavior types and risk management rules.

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Chart 1

Distribution of Price Change Ratio (Nikkei 225)
1987～1995

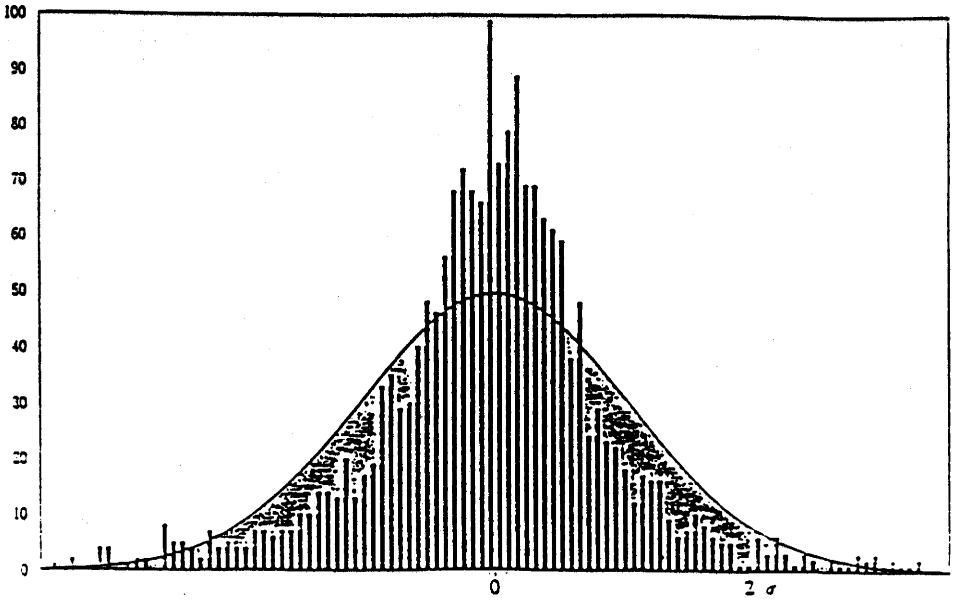


Chart 2

Distribution of Price Change Ratio (¥/$ rate)
1987～1995

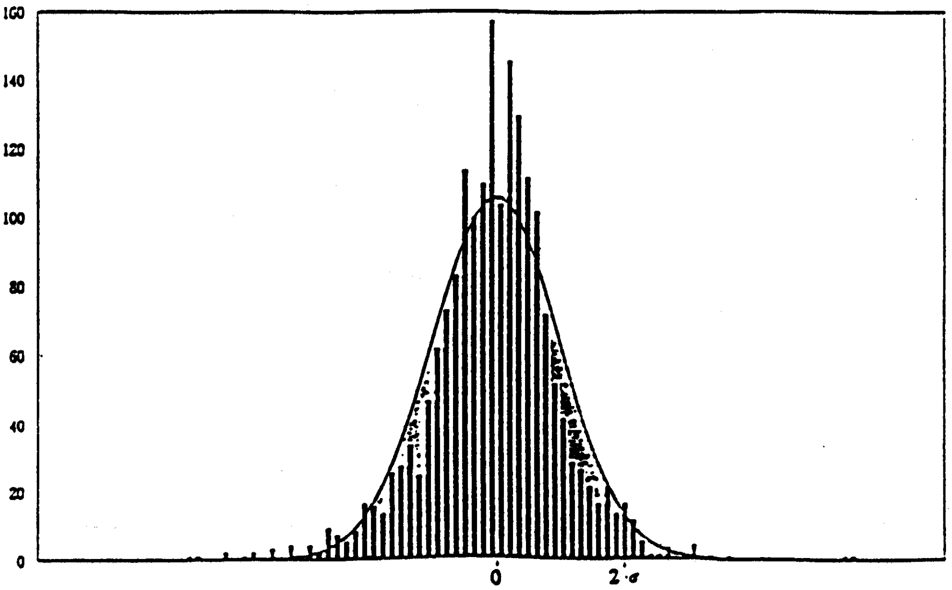


Chart 3

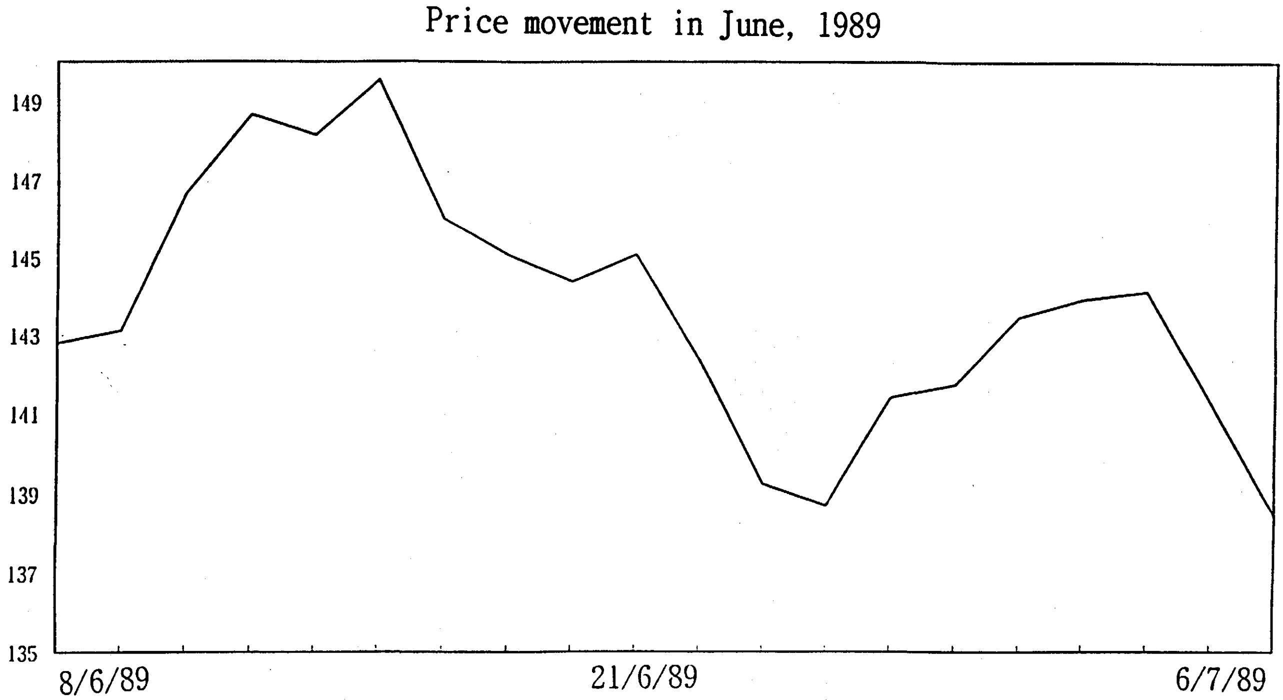


Chart 4

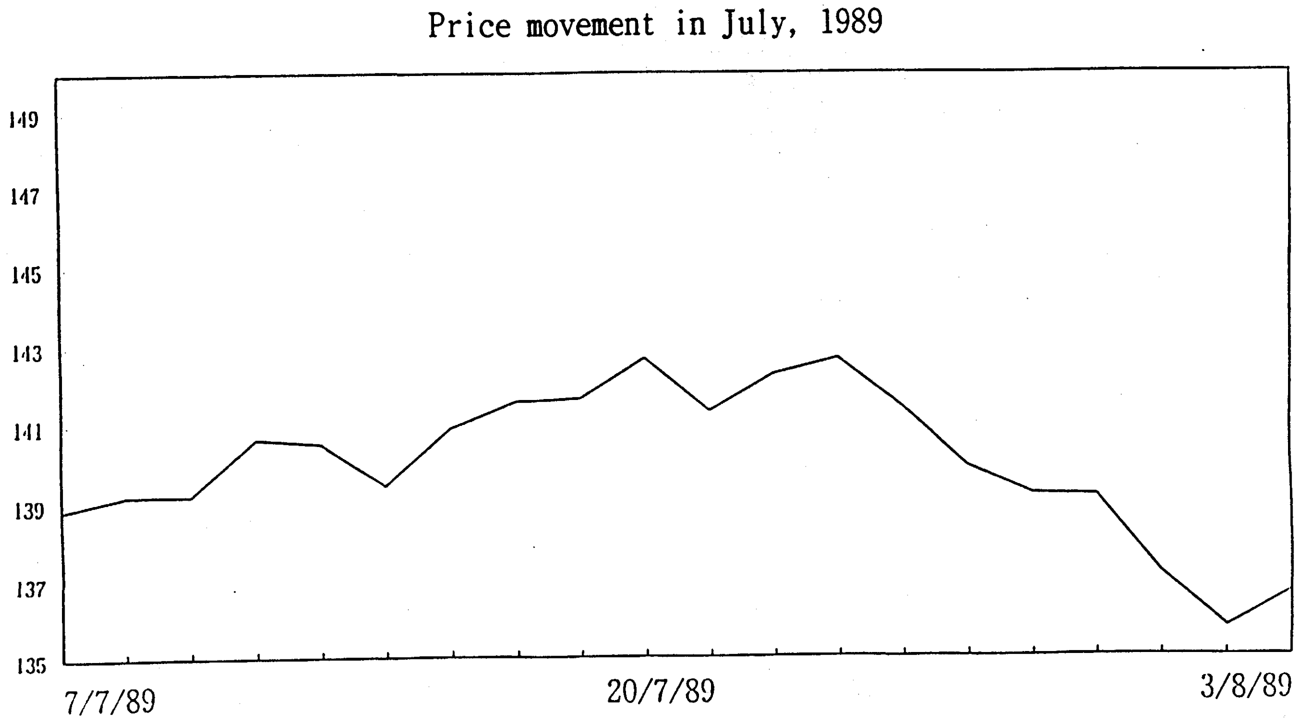
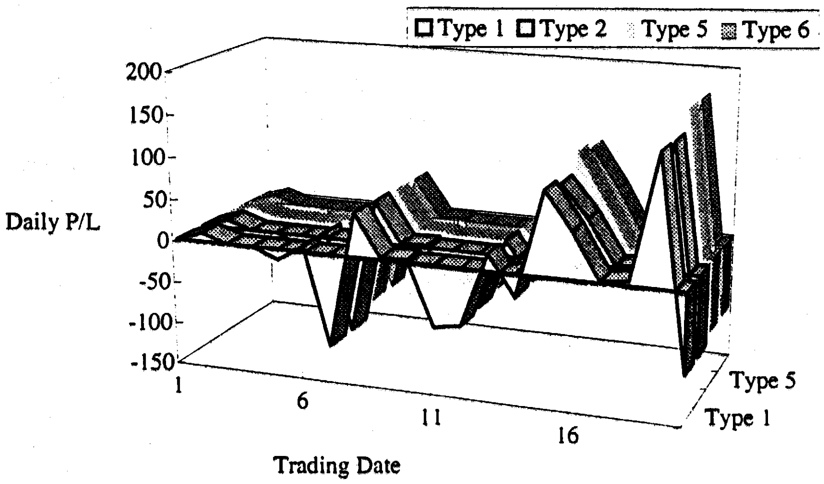


Chart 5-1

Fortrend Trader (July 1989)



Fortrend Trader (June 1989)

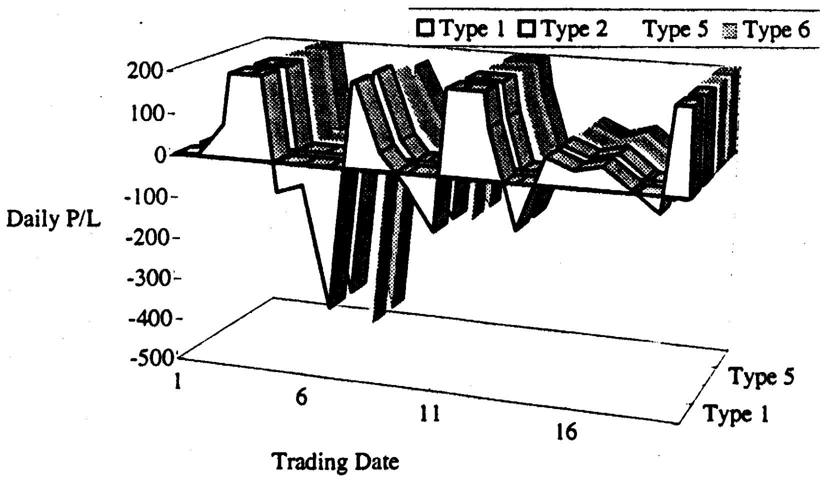
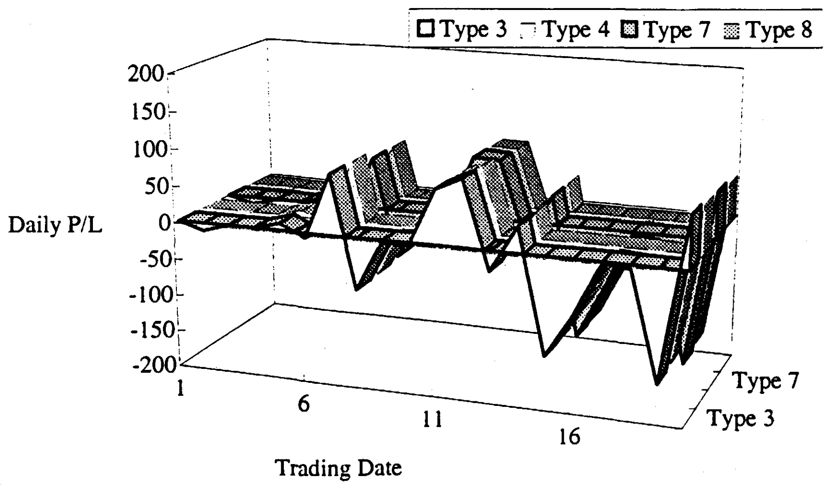


Chart 5-2

Contrarian Trader (July 1989)



Contrarian Trader (June 1989)

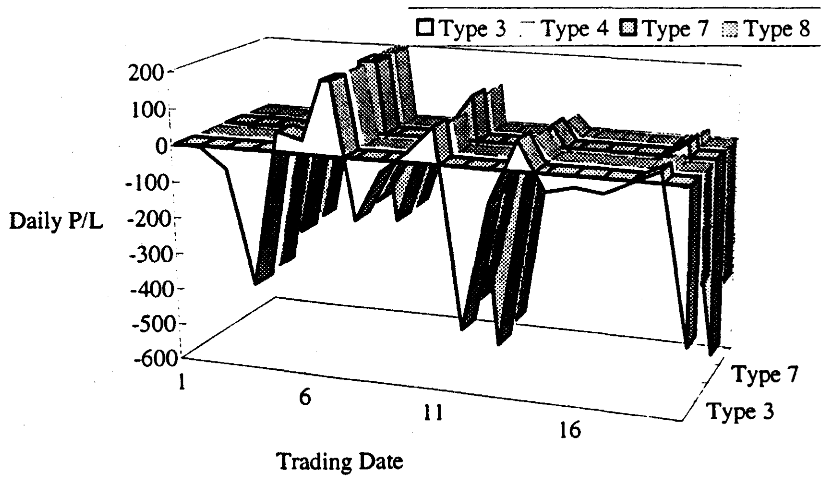


Chart 6

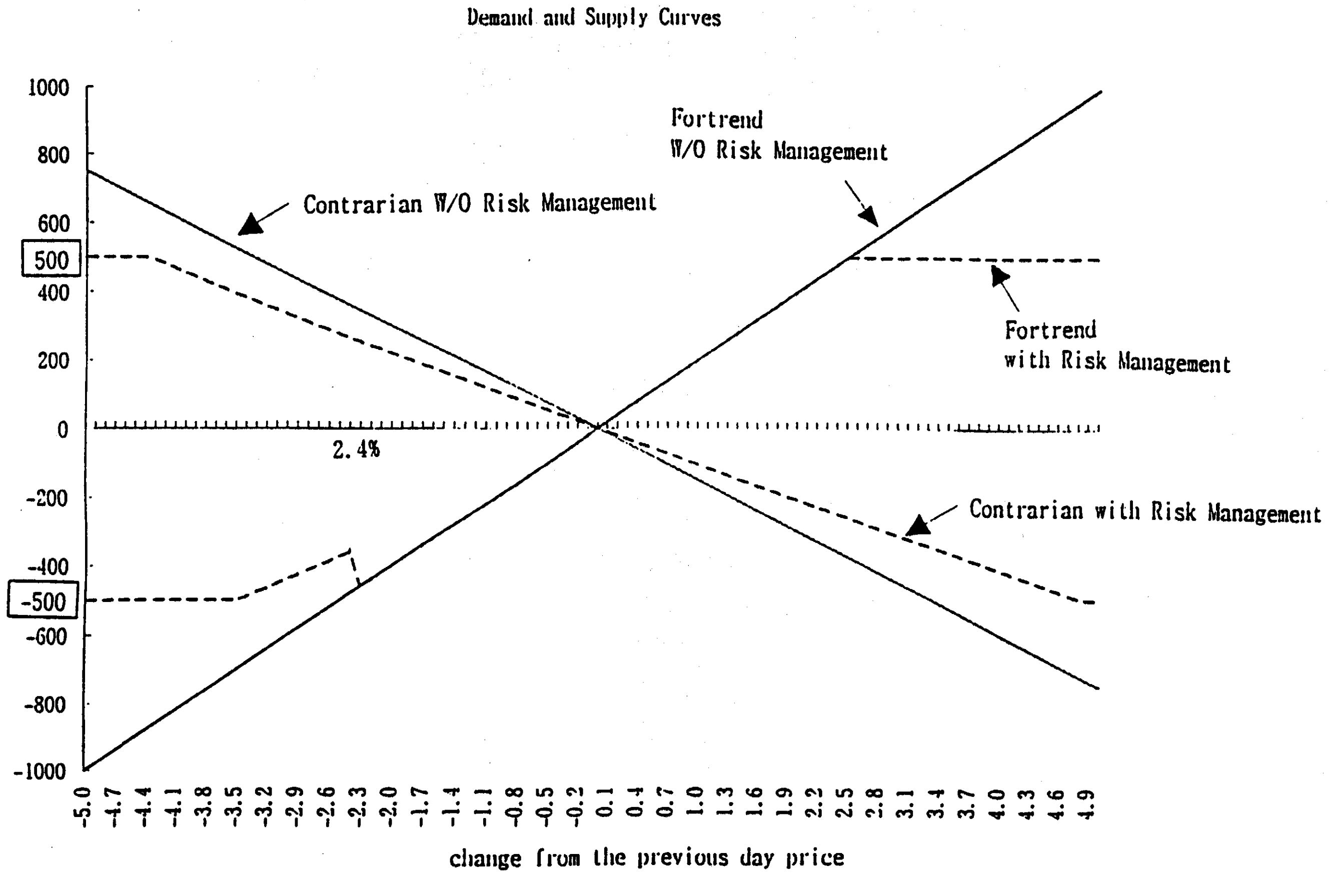

Demand and Supply Curves
1000
800
600
500
400
200
0
-200
-400
-500
-600
-800
-1000
Fortrend
W/O Risk Management
Contrarian W/O Risk Management
Fortrend
with Risk Management
2.4%
Contrarian with Risk Management
-5.0
-4.7
-4.4
-4.1
-3.8
-3.5
-3.2
-2.9
-2.6
-2.3
-2.0
-1.7
-1.4
-1.1
-0.8
-0.5
-0.2
0.1
0.4
0.7
1.0
1.3
1.6
1.9
2.2
2.5
2.8
3.1
3.4
3.7
4.0
4.3
4.6
4.9
change from the previous day price

Chart 7

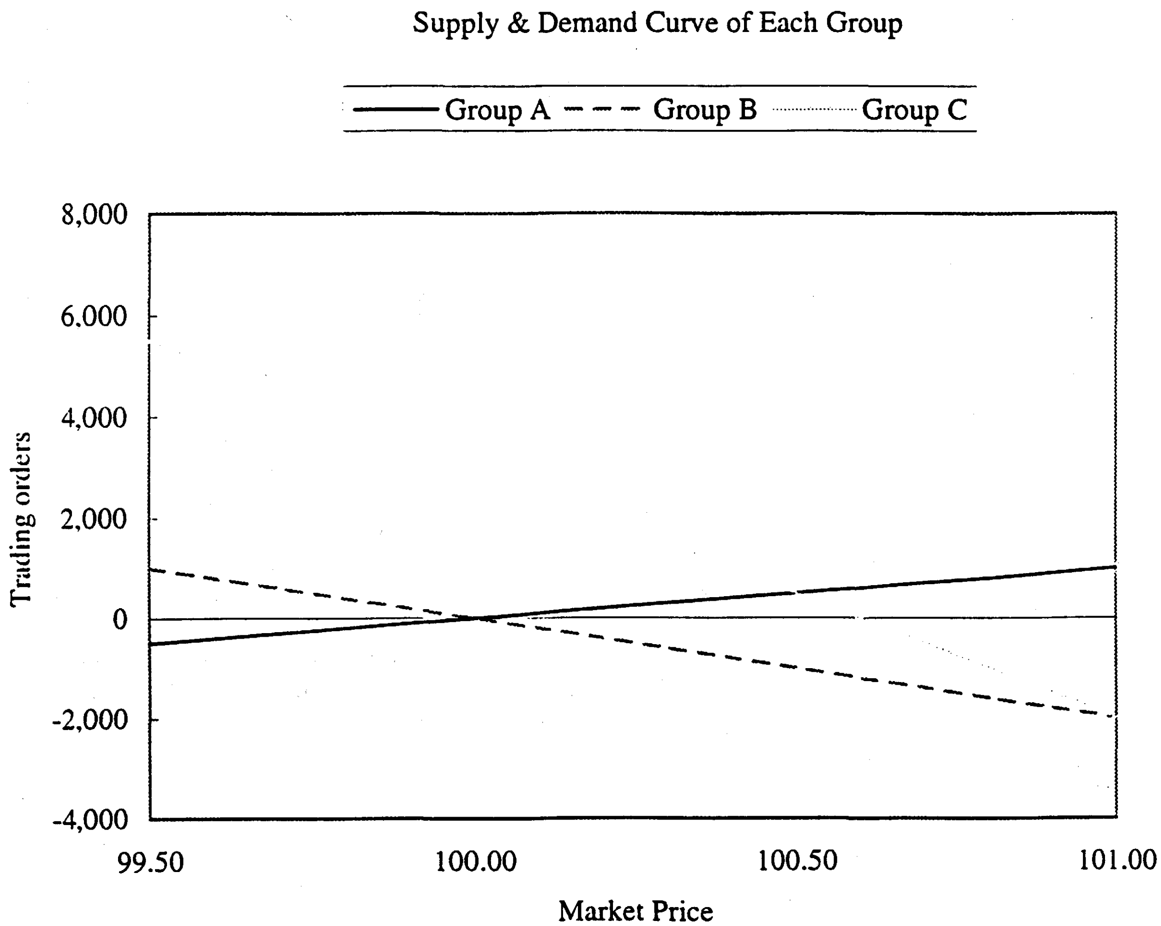
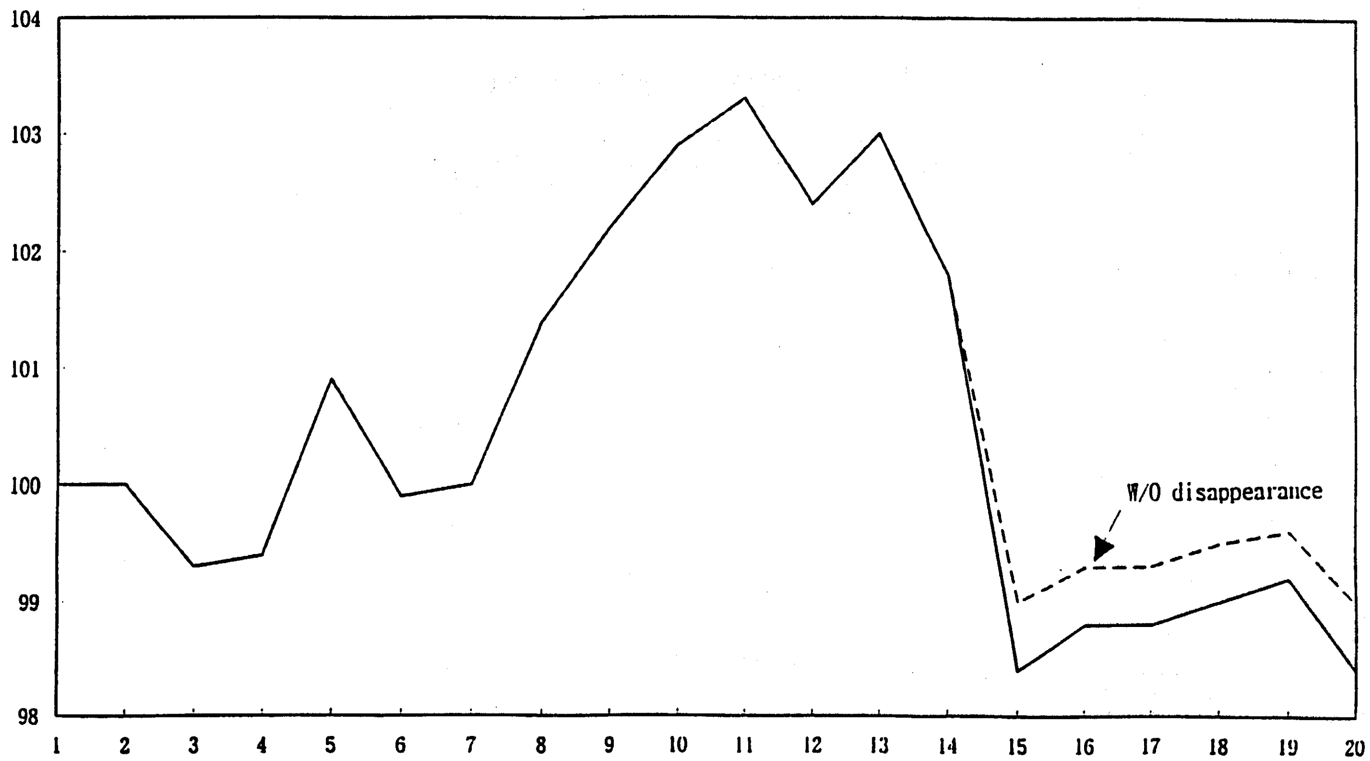

Supply & Demand Curve of Each Group
Group A
Group B
Group C
8,000
6,000
4,000
2,000
0
-2,000
-4,000
Trading orders
99.50
100.00
100.50
101.00
Market Price

Chart 8

Price Movements with a Dominant Player's Disappearnce



Appendix

(Hypothesis 1)

When trading behavior is constrained by risk management rules, the market becomes less volatile and is less likely to experience extreme price jumps.

Null hypothesis $\boxed{\sigma_a = \sigma_b}$

σ_a : volatility of realized prices in a market without micro risk management

σ_b : volatility of realized prices in a market with micro risk management

	Annualized Volatility	Maximum Daily Change
Scenario A	15.91%	-3.18%
Scenario B	15.95%	-3.18%

F score = 1.00 < 1.18 *

* The upper 5 percent point from the F-tables with degrees of freedom 379 and 379

Although volatility of realized prices in Scenario B is higher than that in Scenario A, the null hypothesis is not rejected by F-test. **Hypothesis 1 is not supported by our simulation.**

(Hypothesis 2)

When the presence of positive feedback traders is dominant in a market, the market becomes more volatile and is more likely to experience extreme price jumps.

Null hypothesis $\boxed{\sigma_a = \sigma_c}$

σ_a : volatility of realized prices in a market without dominant presence of positive feedback traders

σ_c : volatility of realized prices in a market with dominant presence of positive feedback traders

	Annualized Volatility	Maximum Daily Change
Scenario A	15.91%	-3.18%
Scenario C	17.48%	-3.20%

F score = 1.21 > 1.18 *

* The upper 5 percent point from the F-tables with degrees of freedom 379 and 379

Since the null hypothesis is rejected, **Hypothesis 2 is supported by our simulation.**

(Hypothesis 3)

When trading portfolios have non-linear risks, the market becomes more volatile and is more likely to experience extreme price jumps.

Null hypothesis $\boxed{\sigma_a = \sigma_d}$

σ_a : volatility of realized prices in a market with non-linear risks

σ_d : volatility of realized prices in a market without non-linear risks

	Annualized Volatility	Maximum Daily Change
Scenario A	15.91%	-3.18%
Scenario D	15.89%	-3.18%

F score = 1.00 < 1.18 *

* The upper 5 percent point from the F-tables with degrees of freedom 379 and 379

We cannot reject the null hypothesis by F-test, although volatility of realized prices in Scenario A is slightly higher than that in Scenario D. Therefore, **Hypothesis 3 is not supported by our simulation.**