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Circuit Breakers and Price Discovery

Theory and Evidence

A dissertation submitted in partial satisfaction of the

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by

Jong-Won Yoon

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The dissertation of Jong-Won Yoon is approved

John McCall

Keunkwan Ryu

Oliver Kim

David Levine, Committee Co-Chair

Axel Leijonhufvud, Committee Co-Chair

University of California, Los Angeles

1994

I dedicate this dissertation to my parents and to my wife, Soo-Hyang.

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VITA

December 4, 1960	Born, Milyang, Korea
1984	B.A., Economics Seoul National University Seoul, Korea
1984 - present	Deputy Director Ministry of Finance, Korea
1986	M.A., Public Administration Graduate School of Public Administration Seoul National University
1991 - 1994	Teaching Assistant Department of Economics University of California, Los Angeles
1994	Ph.D., Economics University of California, Los Angeles Los Angeles, California

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ABSTRACT OF THE DISSERTATION

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Professor Axel Leijonhufvud, Co-Chair

Professor David Levine, Co-Chair

This dissertation analyzes how circuit breakers affect stock price behavior. We present an auction-based asset market model in which traders with differential information about an unknown true value of an asset trade an indivisible share in a simple clearinghouse. Based on different trading rules which mimic the actual trading process in a market with and without circuit breakers, we investigate how the existence of circuit breakers makes a difference in the resulting price behavior. Our model suggests that in presence of circuit breakers, asset prices overshoot their equilibrium value that would have been achieved without circuit breakers. We identify this price overshooting as an institution-induced phenomenon, since the existence of circuit breakers themselves becomes a source of panic trading by enticing people to overreact

to an underlying shock.

In order to examine how circuit breakers have worked in actual stock markets, we investigate Korean stock market data which possess a large number of circuit breaker triggered observations. We test whether the price overshooting hypothesis suggested in the model is empirically valid. The test of price overshooting is based on the idea that stock price behavior would systematically differ if circuit breakers are triggered than if they are not. We find a significant negative (positive) bias after the upper (lower) circuit breaker bound is triggered, supporting the price overshooting hypothesis. We also examine how circuit breakers affect price volatility using a variant of the Autoregressive Conditionally Heteroscedastic (ARCH) model. We find that price volatility becomes greater after circuit breaker-triggered events compared to non-triggered events.

In sum, the existence of circuit breakers, aimed at reducing volatility in compensation for an efficiency loss, does not aid price discovery. Rather, the findings of price overshooting and increased volatility indicate that circuit breakers destabilize prices: exactly opposite of what this regulation intends to accomplish. This evidence suggests the need for more careful formulation in the design and implementation of circuit breaker mechanisms.

Chapter 1.

Introduction

Stock markets play a central role in a modern industrial economy, both as a harbinger and a facilitator of economic activities. Moreover, they are the primary engine of a nation's economic growth by providing means by which industries raise capital to finance innovative businesses and to provide employment opportunities. Given the importance of stock markets to the economy and to the public, it is critical that they be maintained in an effectively structured and well functioning manner. However, an event threatening their integrity occurred in October of 1987. Not only did this event bring about a one third price decline across the globe, but also significantly impaired people's confidence in the entire financial system. One of the institutional responses to this extraordinary event was to introduce circuit breaker mechanisms as a device to prevent unusual market breakdowns. This paper attempts to answer the following question: "What would have occurred in October of 1987 if there had been circuit breakers?"

Circuit breaker mechanisms, by themselves, are not new. As Grossman (1990) points out, stock markets experience a daily "circuit breaker" between the close of trading on one day and the opening of trading the following morning. However, the intraday programmed circuit breakers are different from regular market closings in the sense that the latter is perfectly *predictable*. Different stock markets have instituted their own intraday circuit breaker systems. For example, the New York Stock Exchange (NYSE) in the United States introduced trading halts after Black Monday in

The reasoning underlying price overshooting is explained as follows. In the model, price changes are driven by a fundamental shock to the asset as well as a supply shock. Since prices are not fully revealing due to the supply shock, traders supplement their private information with price information when available. In the presence of circuit breakers, price information is given to traders as a truncated distribution. This leads traders to guess that the underlying shock is so large that the equilibrium price is beyond the circuit breaker bound. Belief adjustment based on the truncated price information causes some traders (called *naive* traders) to overreact to the underlying shock since their reservation price becomes greater when it is conditioned on that information. Since they regard prices as exogenously given, they do not consider the possibility that their aggressive bidding results in a greater price than the equilibrium level. Recognizing the consequence of aggressive bids submitted by some traders, other traders (called *sophisticated* traders) behave conservatively and submit lower bids than their reservation prices. The resulting market clearing price as a function of both traders' bidding strategy is shown to be greater than the price determined in a market without circuit breakers. However, as more rounds of trading continue, prices converge to their equilibrium level.

While an once and for all shock is assumed throughout the analysis, we also discuss the presumed benefit of circuit breakers under the assumption that shocks arrive in the market each period. In this situation, circuit breakers may have a beneficial effect by preventing a sudden price change due to a temporary volume shock. A release of information about order imbalances while circuit breakers are in effect can make traders recognize that the price change is mostly due to a particular realization of a supply shock. Also, if circuit breakers can affect a realization of the supply shock by inducing more value traders to the market, they might contribute to moderate price volatility. However, price overshooting occurs even under this circumstance if there are some traders whose updated bids are based on the truncated price information. That is, in a situation where it is unknown whether a price decline is due to a fundamental or supply shock, a triggering of circuit breakers may cause traders to overreact and scare them away from the market rather than reassuring them. After all, whether circuit breakers are effective in moderating price volatility will depend on which effect dominates the other.

We rely on the real market data to see how circuit breakers have worked in reality. Korean stock market data are employed considering the advantage that they have in providing a large number of circuit breaker triggered observations. Identification of price overshooting in an empirical context is based on the idea that if price overshooting has occurred, successive stock returns after the circuit breaker-triggered events no longer follow a martingale which would have held otherwise. A significant negative (positive) bias in price movements is detected after the upper (lower) circuit breaker bound was triggered, suggesting that there is a substantial price overshooting. It is also found that price volatility is greater for the circuit breaker-triggered events compared to non-triggered events. This evidence of price overshooting and increased volatility indicates that circuit breakers did not facilitate price discovery. On the contrary, their very existence impairs price discovery and consequently destabilizes price movements.

However, there may be situations where circuit breakers would be beneficial. For example, while we analyze a situation where there is no system overload, the huge order flows beyond the limited capacity of exchanges may create bottlenecks in the order transmission process. Also, markets may have built-in amplifiers of feedback effects of price movements such as margin calls. In such situations, circuit breakers can help the price discovery process by preventing or retarding possible endogenous amplifying feedback effects. Although this study cannot deny such a rationale of circuit breakers, it suggests the need for more careful formulation in the design and implementation of circuit breaker mechanisms.

The remaining chapters of this dissertation are organized as follows. Chapter 2 briefly reviews the literature regarding the effects of circuit breakers on price behavior. Chapter 3 presents a theoretical framework to analyze the stock price behavior in the presence of circuit breakers. Chapter 4 provides a connection between the theoretical deductions and empirical inferences. It addresses the question of how to identify price overshooting if any, and also differences in price volatility caused by the triggering of circuit breakers. Chapter 5 describes the data set and its variables. Based on the reasoning suggested in Chapter 4, we present the empirical evidence about whether circuit breakers help facilitate price discovery in actual stock markets in Chapter 6. Besides providing descriptive statistics, we also test the price overshooting hypothesis and the volatility implications of circuit breakers. Chapter 7 discusses the existing arguments for circuit breakers and suggest their rationale based on our empirical results. The last chapter concludes this dissertation with several comments and a summary.

Chapter 2.

Literature Review

There have been extensive studies on intraday, programmed circuit breaker mechanisms since the market crash of 1987. The first line of studies on circuit breakers was initiated by stock market-related institutions. These studies include those made by the Federal government, and also by major stock exchanges such as the New York Stock Exchange (NYSE) and the Chicago Mercantile Exchange (CME).

In response to this extraordinary market break, a Task Force on Market Mechanisms was organized to examine what happened and why, and to provide guidance in helping to prevent such a break from happening again. *The Report of the Presidential Task Force on Market Mechanisms (1988,* known as the Brady Report) attributed much of the volatility associated with the crash to aspects of market microstructure and suggested circuit breaker mechanisms as a response to extreme market volatility. Identifying the need for circuit breaker mechanisms with the inherently limited capacity of markets to absorb massive, one-sided volume, the Brady Report stated the benefits to circuit breaker mechanisms as follows:

> *First, circuit breaker mechanisms limit credit risks and loss of financial confidence by providing a "time-out" amid frenetic trading to settle up and ensure that everyone is solvent.*
>
> *Second, they facilitate price discovery by providing a "time-out" to pause, evaluate, inhibit panic, and publicize order imbalances to attract value traders to cushion violent movements in the market.*

Finally, they counter the illusion of liquidity by formalizing the economic fact of life.... that markets have a limited capacity to absorb massive one-sided volume.

This report also recognized the disadvantages of circuit breakers mechanisms:

They hinder trading and hedging strategies. Trading halts may lock investors in, preventing them from exiting the market.

Also, they may hinder price discovery and may..... even contribute to the intensity of price declines by giving rise to a gravitational effect.[2]

Despite of the above perceived disadvantages, the Brady Report recommended the installation of circuit breaker mechanisms to cushion the impact of market movements which would otherwise damage market infrastructures, thereby protecting markets and investors. Following the recommendation of this report, major stock exchanges such as the NYSE and CME introduced circuit breakers mechanisms.

Subsequent studies initiated by other major institutions were made following the Brady Report. *Final Report of the Committee of Inquiry* (1989, CME) and the *Market Volatility and Investor Confidence Panel* (1990, NYSE) offer a comprehensive discussion of circuit breakers. Examining performances of the CME and its S&P 500 contract during the October crash, the *Final Report of the Committee of Inquiry* addressed key policy issues such as margins, circuit breakers and regulatory obstacles to market efficiency. After giving the main arguments for and against making the price limits the permanent feature of the futures contract, it states that "under the conditions of system overload, the Brady Report's call for the installation of circuit breakers is certainly understandable, and the possible need for circuit breakers has

[2]A gravitational effect occurs, for example, when traders, who are afraid of being locking into their position as prices approach the lower circuit breaker bound, expedite their selling activities.

been a concern of the exchanges themselves as well."

The *Market Volatility and Investor Confidence Panel* analyzed the issues of extreme short-term stock market volatility and made recommendations intended to help maintain a strong market for all participants. Reflecting their concerns to install circuit breaker mechanisms, the first among eight recommendations is stated as follows:

> *Recommendation 1: Coordinated "circuit breakers" should be introduced to halt or limit trading in times of market stress. These measures should be mandatory across all domestic equity and equity derivative markets. Enhanced price and trade information should be made available times when circuit breakers are triggered.*

In the Appendix of this report, they also illustrated some desirable features of circuit breakers which are only partly mentioned in the above recommendation.[3] Although the above three studies recognize perceived disadvantages of circuit breakers, they seemed to have reached the same conclusion that formal circuit breakers may have benefits over unplanned, *ad hoc* circuit breakers.

A more rigorous theoretical study was made by Greenwald and Stein (1988, 1991). Focusing on the immediate pricing decision of market makers, they argue that potential buyers in a real-world market, whose market makers are confronting an unexpectedly large surge of sell orders, cannot always be sure of the price at which their *market orders* to buy will be executed. This transaction price uncertainty may lead to deviations from Walrasian prices and allocations. In their stylized model, there are two periods that contain uncertainty about fundamentals and also about the

[3]See the Appendix E, prepared by Mann and Sofianos, of the Market Volatility and Investor Conficence Panel (1990) for the details about the desirable features of circuit breakers.

behavior of value buyers. An *informationless* supply shock occurs in the first period. Market makers must absorb the excess supply until value buyers arrive in the second period. Value buyers submit *market orders* at the beginning of the second period without knowing what their transaction price will be. This transaction price uncertainty affects the demand behavior of value buyers during period two and this in turn affects the inventory behavior of market makers during period one. They show that when a supply shock is large, the transmission of a supply shock into value buyers breaks down leading to a microstructure-induced crash. Rather than incorporating circuit breakers explicitly into the model, they offer a discussion that circuit breakers can reduce the uncertainty of value buyers by making the potential value buyers aware of the response of other traders to large shocks. Hence, the trade-off owing to circuit breakers, in their model, is between full information pricing and timeliness of execution.

On the contrary, Subrahmanyam (1993) suggests that circuit breakers may have the perverse effect of increasing price variability and exacerbating price movements. He focuses on the *ex ante* strategic trading decision of the discretionary trader with an exogenous demand, who can split his trades across two periods and also has the cost of not being able to trade in a period. When there is no circuit breaker, the discretionary trader splits his trades across periods rather than concentrating trades in period one or two in order to reduce the price impact of his trades. However, the introduction of a circuit breaker distorts his optimal trading behavior and causes him to concentrate his trading in an earlier period. In this model, he assumes that if the price in period one is outside the circuit breaker bound, trading in period two is halted while the period one trade goes through. In this situation, traders suboptimally advance their trades in time when the probability of a circuit breaker bound being crossed is high. The expected cost of not being able to trade in the second period dominates the advantages of splitting his trades. As a result, price variability increases and the probability of the period one price crossing the bound also increases.

Park (1990) analyzes traders' behavior in the presence of price limits. Unlike trading halts, price limits allow trading to take place at the limit price. For example, when the (upper) limit is triggered, the sell orders below the limit are executed at the limit price. Since the amount of buy orders are greater than sell orders at the upper limit, exchanges usually prespecify how selling orders below the upper limit are to be assigned to buyers. Assuming a random assignment, he shows that a trader with a reservation price lower than the upper limit has an incentive to submit his bid at the upper limit since it makes his expected payoff greater than the case when he submits his reservation price. He also suggests that a triggering of the upper price limit can make people increase their reservation prices.

While the above studies analyze the circuit breakers in the cash market, Brennan (1986) and Miller (1990) approached this issue by analyzing the futures market. They attempt to explain why price limits have long been a standard feature of futures contracts. Brennan interprets the existence of price limits in the futures market in the context of efficient contract design. In a futures market, the problem of contract enforcement is liable to arise whenever the absolute value of the change in the futures price from the previous settlement exceeds the margin requirement, for then one party to the contract may have an incentive to renege, which would make it costly or even impossible to enforce the contract. Based on the premise that margin requirements are costly for at least some market participants, he showed that price limits may act as a partial substitute for margin requirements in ensuring contract performance. Since the losing party's decision whether to renege depends on his expected loss, a daily price limit can alleviate or even eliminate the contract enforcement problem by limiting the information available to the losing party about the extent of his losses at the time he is required to make the daily settlement.

Miller (1990), focusing on the moral hazard problem, asserts that price limits typically exist in a futures market to assure clearinghouse solvency. The floor population of market makers in the trading pits consists primarily of "locals" trading for their own account, but whose settlements are guaranteed by a clearing firm, a member of the exchange's clearinghouse. Thanks to the zero-sum nature of futures trading, every large price move, whether up or down, leads to substantial losses for half the floor population. As guarantors the clearing firms protect their interests by imposing capital requirements on their locals enough to cover a normal day's potential trading losses. However, large sudden price moves not only can hamper this protection, but also create additional incentives for the locals that are adverse in the extreme to the clearing firm's interests. A local already wiped out has nothing more to lose and potentially much to gain from "double-or-nothing" strategies with what amounts to the clearing firm's money. He argues that price limits are a cost effective way to control clearing firm exposure, since a triggering of price limit gives the clearing firm time to remove potentially insolvent traders from the floor before they accumulate further losses.

Both studies attribute the existence of price limits in the futures market to the particular environment surrounding the futures market where sudden price changes might pose problems for its particular trading, clearing and settlement technology. Although they provide a rationale for circuit breakers in futures markets, the question of how the existence of price limits affects price behavior is not addressed.

Despite the controversial effect of circuit breakers on price movements, not many empirical studies have been made due to data limitations. Since circuit breakers are, by design, rarely triggered, it is inherently difficult to obtain sufficient evidence to evaluate their effectiveness. When circuit breakers were first triggered in October 1989 after their introduction, two separate empirical studies of this event appeared.[4]

McMillan (1990) gives a very thorough investigation of the impact of the circuit breakers in the futures market on October 13, 1989. Using S&P 500 future price series before and after the circuit breaker bound is triggered, he found that the dispersion (the average absolute value) of successive price changes increased after circuit breakers were lifted. He also found more price dispersion on October 13, 1989 than on October 13, 1987, another Friday on which the market fell by about 6 percent, but with no circuit breakers in place.

Kuhn, Kuserk and Locke (1990) also analyzed the same event employing several measures of volatility.[5] Their findings, similar to McMillan's, indicate that circuit breakers did not function as a calming device on October 13, 1993. Further, they found an evidence that a binding constraint in one market (S&P 500 futures) is associated with increased volatility in unconstrained markets (MMI futures). Hence, both studies found that circuit breakers impaired price discovery rather than facilitating it as Greenwald and Stein suggest.

Empirical studies based on a different approach were made by Roll (1989) and

[4]On October 13, 1989, stock prices declined precipitously after the announcement of the failure of the management of United Airlines to secure financing for their leveraged buyout. In the cash market, the Dow Jones Industrial Average fell 191 points (6.9 percent), which was not enough to trigger trading halts. However, the S&P 500 futures index fell to its 12-point limit and also subsequently hit the expanded 30-point limits. For details, see McMillan (1990) pp. 252-256.

[5]The volatility measures they employed are 'standard deviation of price change', 'average absolute log price change' and 'range'. They also tested whether the median level of volatility changed from one period to the next.

Bertero and Mayer (1990). Both studies investigate whether substantial variations in stock market performances across countries during the international crash in October 1987 can be attributed to their market microstructure. They employed cross-sectional data on market performances during the October and institutional structure variables over 23 countries.[6] Regressing the full October return on 10 institutional variables, Roll finds that none of the institutional market characteristics including a 'price limits' dummy were significantly associated with the October return. Bertero and Mayer ran similar regressions but used returns during the days immediately surrounding the crash (rather than the full month of October as in Roll) as a dependent variable. Contrary to Roll, they find that markets with circuit breakers in operation on average declined by between 7% and 9% less than those without circuit breakers.

Another evidence about the effect of circuit breakers is suggested by Mann and Sofianos (1990). In January 1988, the NYSE put restrictions on index arbitrage orders transmitted over the Exchange's SuperDot automated order routing system in an effort to reduce volatility. Although these restrictions, known as a "collar," made index arbitrage program trades more costly, it did not make them impossible. Using the seven collar-triggered events when the collar was in effect, they find that the collar was not effective in preventing a sharp price decline. The trades were simply executed manually at a higher cost by those firms with direct access to the floor. Due to its ineffectiveness, the collar restriction was eventually abandoned in October 1988. Their findings suggest that circuit breakers might bring inefficiency by creating spill-over effects into substitute instruments and markets.

Unlike other empirical studies which examined *formal* circuit breakers, Gerety

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[6]As dummy variables representing institutional structure, both studies commonly used "circuit breakers," "continuous trading,"' "computer-assisted trading," and "future trading," but also included a different set of other institutional variables.

Table 2.1: Major Arguments for and against Circuit Breakers

	benefits	costs
price discovery	**facilitate price discovery and reduce volatility** •provide a cooling-off period •reduce credit risk related to the margin calls •improve information about order imbalances • prevent bottlenecks due to the limited capacity of exchanges to absorb massive, one-sided volume	**may impede price discovery** •may scare investors away from markets rather than reassuring them •slow down the incorporation of new information into prices •gravitational effect (*i.e.*, traders expedite selling activities when price approaches the lower bound) •distort trading decision
efficiency	**welfare gain > efficiency loss** planned circuit breakers are better than unplanned, ad hoc ones	**incur inefficiency** •keep traders from completing mutually beneficial trades • spill-over effect

Chapter 3.

The Model

3.1. Overview and Characteristics of the Model

Overview We present an auction-based asset market model to analyze price behavior in response to a shock to an asset and examine how the existence of circuit breakers makes a difference in price behavior. In this model, risk-neutral traders who maximize the expected payoffs make a bidding decision based on a private signal which is positively correlated with the unknown value of a shock. In addition to a fundamental shock which affects the future dividend stream of the asset, traders are faced with another source of uncertainty, a supply (or demand) shock which represents order imbalances at a particular date. Assuming that there is no further shock, prices as a function of traders' bidding strategy depend not only on the fundamental shock but also on a random draw of the supply shock. Whereas a large price change is more likely to be driven by a fundamental shock, a large realization of a supply shock can also bring about a large price swing. Since traders cannot distinguish one shock from the other, they make a Bayesian inference about the true value of the asset based on their beliefs about the distribution generating the supply shock as well as their own private signal.

Prices in this auction model are given as an order statistic and the clearinghouse executes the transaction at this price. Since prices are partially revealing due to the supply shock, traders update their beliefs about the true value of an asset using price information when available. In order to analyze the consequences of this updating of beliefs, we consider two consecutive rounds of price determination following shocks to the asset. There are two types of traders, sophisticated and naive traders, who show different behavior in updating their bids. Whereas sophisticated traders make a bidding decision by fully utilizing all the available information, naive traders with limited ability to process information summarize the multi-dimensional information vector into a single dimension. That is, naive traders respond to price information by adjusting their private signal to reflect their updated beliefs about a shock and make a bidding decision based on the adjusted signal. Since the adjusted signal is not a sufficient statistic for the available information, there inevitably incurs an information loss.

When there are no circuit breakers, markets clear in each round and price information is released as a single point. Since the convex combination of the two points gives a value between these two points, the adjusted signals of naive traders do not affect the price determined in the first round. Under this circumstance, updated bids of sophisticated traders based on this price information also result in the same price as determined in the first round since it is already consistent with their beliefs.

On the other hand, a triggering of the (upper) circuit breaker bound provides price information in the form of a truncated distribution. Belief adjustment based on the truncated price information causes traders to hold more optimistic beliefs about the true value of the shock. The adjusted signals of naive traders will reflect their optimistic beliefs and therefore result in greater updated bids. While the updated bids of naive traders place an upward pressure on prices, sophisticated traders behave conservatively since they know that the price will become greater than the equilibrium level due to aggressive bidding by naive traders. That is, they submit bids which are smaller than their initial bids. The market clearing price which results from the bidding prices of both types of traders is shown to overshoot the equilibrium level. However, it eventually converges to the equilibrium level as further rounds of trading follow.

While we assumed an once and for all shock to focus on the psychological effect brought by the presence of circuit breakers, we also discuss their presumed benefits on the assumption that supply shocks impinge on the market each period.[7] A large volume shock in the first round can lead to a deviation of prices from the equilibrium level determined by the fundamentals. However, as more realizations of supply shocks are observed in successive rounds of auctions, traders can accurately calculate the true value of the asset and prices eventually approach their equilibrium level. In this situation, the presence of circuit breakers may be beneficial by preventing a sudden price change due to a temporary volume shock. A release of information about the order imbalances while circuit breakers are in effect may help traders to recognize that price change is mostly due to a particular realization of a supply shock. Also, circuit breakers can affect a realization of the supply shock in the second round if they help to induce more value traders into the market.

However, we cannot sure which way it will go. A triggering of circuit breakers may scare traders away from the market rather than reassuring them, making a realization of the supply shock move in the opposite direction. Also, price overshooting occurs even under this circumstance if there are some traders who bid aggressively due to a triggering of circuit breakers. After all, whether circuit breakers are effective in moderating price volatility depends on which effect dominates the other.

[7]There are other arguments for circuit breakers such as limiting credit risks related to margin calls and also preventing bottlenecks due to the limited capacity of exchanges. While our model does not incorporate such possibilities, we will discuss those arguments in Chapter 7.

Characteristics of the Model Our model has several distinctive features which distinguish it from other studies. First, auction mechanisms are employed as a trading rule and show an explicit price formation process. Whereas most studies of stock market behavior analyze a market where market makers exist, this paper seeks to model stock trading in a market without market makers. Trading in exchanges where market makers or specialists do not exist is best described as an auction market.[8] A desirable feature of auction models is that they capture many of the details of real stock markets. For example, in a typical stock transaction for a listed stock, a buyer places a limit order, *i.e.*, he instructs his broker to obtain the most favorable possible terms of trade but not to pay more than the suggested price. He expects to acquire the security whenever his bid is greater than the prevailing price. In this procedure, traders must make a bidding decision in ignorance of execution prices. In a rational expectations, Walrasian setting, on the other hand, agents behave as if they know the prices or submit demand schedules contingent on prices.[9] Although auction models have limitations such as a restriction on the amount each buyer can acquire, they provide a convenient device to address the question of how prices are formed.

Second, differential information among individuals is used as a basic motive for trading in this model. In order for trading to take place, some disparities in preferences, endowments and beliefs among individuals are needed. Trading in actual stock markets results from a mixture of the above factors. In this model, the motives of traders other than differential information are suppressed as large price swings accompanied by huge trading volumes are more likely to be an informational

[8]Their micro-structure is quite different from U.S or British exchanges in the sense that there do not exist traders who take their own positions as a market maker or a specialist does. On Japanese stock exchanges, for example, the members, called *saitori or nakadachi,* do not take their own positions. They simply execute orders according to a certain set of auction rules. See for details Takagi (1989).
[9]Milgrom (1981) points out that most rational expectations equilibrium models are not models of price formation and naive mechanisms leading to such equilibria can be severely manipulable.

phenomenon. This paper emphasizes the belief adjustment process of heterogenously informed traders facing both fundamental and supply shocks. In this sense, our model can be distinguished from other studies which focus on the transmission process of order flows (Greenwald and Stein, 1991) or choice of trade timing (Subrahmaynam, 1993).

Third, naive (noise) traders as well as sophisticated (rational) traders are present in the model. A recurring assumption in economic theory is that all individuals are fully rational. Questions have, however, been raised as to whether fully rational agents and the resulting rational expectations equilibrium can properly reflect economic reality.[10] There have been roughly two approaches to modelling agents better suited to explain actual economic phenomena. The first (the Bounded Rationality approach) is to assume boundedly rational agents by peeling off some degree of rationality from all the individuals in the model.[11] The alternative (Noise Trader approach) is to introduce a certain portion of "irrational" agents while allowing the others to maintain their full rationality.[12] Shleifer and Summers (1990) give a review on the noise trader approach. After defining noise traders as those whose *opinions* and *trading patterns* are subject to systematic biases, they illustrate three advantages of this approach as follows:

The noise trader approach provides tractable and more plausible theoretical

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[10]As shown in the 'no trade theorem', for example, fully rational traders are too sharp to trade solely based on differences in private information, which overrules common sense intuition. See Milgrom and Stokey (1982) for the no trade theorem. The logic underlying the no trade theorem is also well summarized in Sargent (1993).

[11]Among those who take this approach, Thomas Sargent states that "the rational expectations hypothesis has two key aspects, individual optimality and the mutual consistency of beliefs. We interpret a proposal to build models with 'bounded rational' agents as a call to retreat from the second piece of rational expectations by expelling rational agents from model environments..." See Sargent (1993) pp. 1-25.

[12]Kyle (1985) and De Long, Shleifer, Summers and Waldman (1990) are among those applying this approach.

> models..., yields a more accurate description of financial markets..., and yields new and testable implications about asset prices.... It is absolutely *not true* that introducing a degree of irrationality of *some* investors into models of financial markets "eliminates all discipline and can explain anything".[13]

In this paper, the second approach is applied and it is assumed that there are some portion of traders whose behavior is not fully rational due to the limited ability to process information.

The fourth characteristic of the model relates to the information content of prices. The recurrent idea in the rational expectations equilibrium models is that prices are fully revealing. The information conveyed by the equilibrium price is superior to any private information in the sense that price information is a sufficient statistic for diverse private information. It results in the following well-known paradox. If prices are fully revealing, an individual's optimal demand is independent of his private signal. Then, how can the equilibrium price system aggregate the individual's diverse private information and how can prices fully reveal all the diverse information? This paradox can be resolved if the price system aggregates information only partially. The price is fully revealing when there is only one source of uncertainty, namely, regarding the true value of the shock. In a typical auction model, price is given as an order statistic which is not fully revealing. However, as the number of traders becomes large as in this model, price converges to the unknown true value of the auctioned object. (Milgrom, 1979) Unlike typical auction models, our model has an additional source of uncertainty, that is, a supply shock.[14] Since prices are partially revealing in this situation, price information no longer swamps the information contained in private signals and traders supplement their private signals with the price information in

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[13]See Shleifer and Summers (1990) pp. 19-33. All italics and double quotation marks in the quoted paragraph are from their paper.
[14]See Huang and Litzenberger (1988) pp. 259-283 and also Sargent (1993) pp. 116-125.

making inferences about the unknown true value of a shock.

3.2. Framework

Market environment Consider a market where M *indivisible* shares of an asset are traded.[15] Each share pays a liquidating dividend at a known time in the future. The price of the asset is subject to change due to exogenous shocks to the asset which affect the future dividends stream. M *indivisible* shares are traded in a simple clearinghouse market by $n > M$ traders. There is a single share constraint so that each agent can obtain a maximum of one share. At any time in the market, therefore, there are M shareholders and $(n - M)$ non-shareholders. The number of shares M is an unknown random variable due to a supply shock. This assumption reflects the fact that the number of buyers and sellers participating in stock trading at a particular date varies over time.

Traders are assumed to be risk-neutral and make trading decisions based on differential information about the true value of a shock. There are two types of traders: sophisticated traders (denoted S) and naive traders (denoted N). Naive traders are present in the model as a proportion α of n traders and sophisticated traders as a proportion $(1 - \alpha)$. Trading behavior of each type is described later in this section.

Information structure Suppose there is a certain shock to the asset. The true value of the shock is unknown to the traders and denoted by V. Since we are focusing on

[15]Some kinds of circuit breakers like 'trading halts' on the NYSE are triggered when an overall market index hits the predetermined limit. To incorporate such cases, 'an asset' can be interpreted as a market portfolio.

price responses to one shock, we assume that successive shocks will come only after the trading procedures to resolve the effect of one shock have completed. People have a common prior on the distribution generating shocks. Its probability density function $\xi(\cdot)$ is given as follows:

$$\xi(v) = N(\mu, r_v) \tag{3.1}$$

where the precision parameter r_v is the reciprocal of the variance of V.

The traders, having access to different information sources, have different guesses about how much the shock to the asset is objectively worth. Each trader observes a real-valued random signal X_i in connection with the occurrence of a shock. Each private signal is treated as a random draw from a normal distribution with an unknown mean V and a (conditional) precision r_x. That is,

$$X_i = V + \varepsilon_i \qquad \text{where } \varepsilon_i \sim N(0, r_x), \tag{3.2}$$

We denote the conditional density of X by $f(\cdot)$.

Since price changes can be driven by a supply (or demand) shock as well as by a fundamental shock, we incorporate the possibility of a price decline due to a supply shock into the model by assuming that the number of shares M is a random variable. For example, a realization of large value of M indicates that there are more sellers than buyers in the market and vice versa. Since price is given as a order statistic in auction models, the M^{th} (highest) order statistic among n signals, denoted by $X^n_{(M)}$, plays an important role in the model. The distribution of $X^n_{(M)}$ depends not only on private signals but also on an exogenous random process governing the supply shock. Let us assume that M takes a value of m_k with a probability q_k where $k = 1,2,\dots,K$, $K \le n$ and $\sum_{k=1}^{K} q_k = 1$. Also define $m_k/n \equiv p_k$ and θ_k to be the $p_k{}^{th}$ quantile of *p.d.f.* of X. We borrow the following lemma about the asymptotic distribution of $X^n_{(m_k)}$, the $m_k{}^{th}$ order statistic among n signals.[16]

Lemma 1: Given the assumption on X in (3.2), $X^n_{(m_k)}$ is asymptotically distributed as a normal distribution with mean θ_k and variance $\sigma_{kk} \equiv q_k(1-q_k)/n[f(\theta_k)]^2$.

From the above lemma, it can be shown that a random variable $X^n_{(M)}$ is distributed with a mean $\sum_{k=1}^{K} q_k \cdot \theta_k$ and variance $\sum_{k=1}^{K} q_k^2 \sigma_{kk} + 2\sum_{k=1}^{K-1} \sum_{j=k+1}^{K} q_k q_j \sigma_{kj}$. Notice that θ_k can be expressed as $V + \lambda_k$ where λ_k is a fixed constant since θ_k is a given quantile of $f(\cdot)$ which has a mean V. Hence, $\sum_{k=1}^{K} q_k \cdot \theta_k = V + \lambda$ where $\lambda \equiv \sum_{k=1}^{K} q_k \cdot \lambda_k$. For simplifying calculation and notation, let us denote $Y = X^n_{(M)} - \lambda$. Then, Y is given as follows:

$$Y = V + \varepsilon_y \quad \text{where } \varepsilon_y \sim (0,\ r_y) \tag{3.3}$$

where r_y, a precision of ε_y, is equal to $(\sum_{k=1}^{K} q_k^2 \sigma_{kk} + 2\sum_{k=1}^{K-1} \sum_{j=k+1}^{K} q_k q_j \sigma_{kj})^{-1}$ and ε_i and ε_y are independent of each other. Since Y is a linear transformation of an order statistic, it follows that X_i and Y are independent conditional on V and also that Y has the monotone likelihood ratio property (MLRP).[17] We interpret Y as a market signal in

[16]Lemma 1 can be found in Mood, Graybill and Boes (1974), p. 257.
[17]MLRP is defined as follows: Y has the (strict) MLRP if the likelihood ratio function $f(y|v)/f(y|v')$ is nonincreasing (decreasing) in y whenever $v' > v$ and nondecreasing (increasing) whenever $v > v'$. This definition is from Milgrom (1981). Milgrom also provides a proof that an order statistic among n random variables has the MLRP if they are independent and identically distributed.

the sense that the price is a bid submitted by the M^{th} highest signal holder. Whenever prices are known to traders, they deduce a market signal Y from price information and update their beliefs about V based on (3.3).

The above information structure summarized by (3.1) to (3.3) suggests that large values for some of the variables make the other variables more likely to be large than small. For example, a buyer whose valuation is high will expect that the true value is more likely to be high and believe that others have a high valuation also. This approximates the reality of stock markets. When a shock of great significance to the asset has occurred, it is more likely that people have a signal which indicates that something substantial has happened.

Trading mechanism The trading mechanism we have in mind is a computerized exchange rather than a dealership market where market makers or specialists exist. In those exchanges, stock trading is conducted according to two types of auction methods: *a call auction* or *a continuous auction*. A call auction method is used to establish opening prices at the beginning of each day (more specifically, each session). It places all orders received during some specified period of time preceding the opening of trading and sets the opening price so as to clear the market. We assume that trading takes place once in a period and follows a call auction method. Using auction jargon, the trading rule in this model can be identified as a *common-value sealed-bid double auction.*[18]

See Milgrom (1981), pp. 925-929.

[18]It is natural to take the common-value assumption since the auctioned asset has a single objective market value to all traders once the true value of a shock is known. We use a sealed-bid auction rather than an open outcry model since the call auction method we are assuming is typically based on sealed bids. Also, stock markets are basically a double-sided market where buyers and sellers coexist. The major difference distinguishing this model from auction models is the fact that the number of shares is a random variable while auction models assume the number of auctioned objects as fixed and known to all traders. See McAfee and McMillan (1987) for a survey of the auction literature.

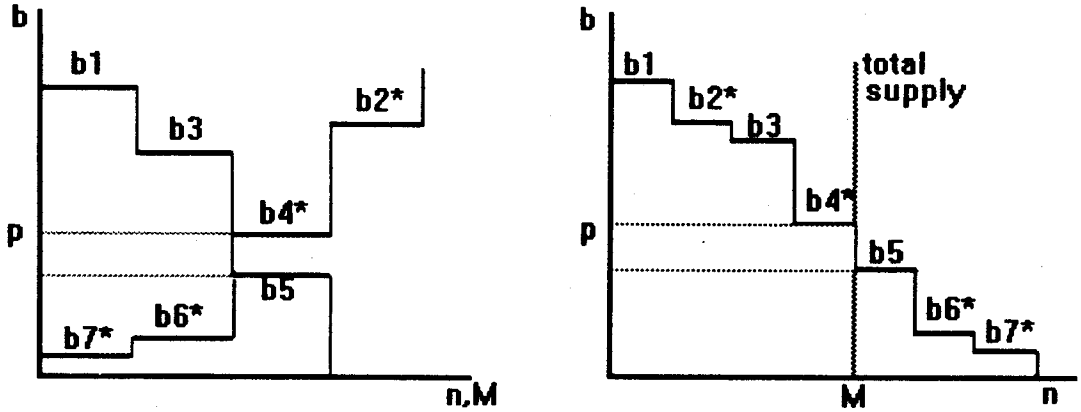
Trading proceeds as follows. Having received a private signal X with the occurrence of a shock, each trader submits a single "limit order" to the clearinghouse. For a shareholder, this order is an offer to sell his share at any price which is equal to or greater than his asking price. For a non-shareholder, it is a maximum bid below which he is willing to buy one share. The clearinghouse in the model plays the role of an auctioneer (like a computer in a computerized exchange system). It receives all bidding and asking orders from n traders, determines a market clearing price and executes a transaction under that price.

In order to find a market clearing price, the clearinghouse obtains the market supply schedule $S(p)$ by arranging asking orders by M shareholders in an ascending order and the demand schedule $D(p)$ by arranging $(n-M)$ non-shareholders' orders in a descending order. The market clears at a price where $D(p)$ and $S(p)$ intersect. There is a continuum of prices at which the market clears. For computational convenience, the market clearing price p^* is set at the highest intersection of $D(p)$ and $S(p)$, that is, $p^* = \sup \{p : D(p) = S(p)\}$. Alternatively, the clearinghouse arranges all bids in a descending order and find the M^{th} highest bid as a market clearing price.[19] We follow the latter method since it helps to find the equilibrium price more easily. The equivalence of the two methods is proven in the Appendix and intuitively described in Figure 3.1. At this price, orders are executed and the M highest bidders become the shareholders for the next period.

Whereas trading proceeds as described above when there are no circuit breakers, the existence of circuit breakers may keep prices from fully adjusting to the market clearing price in a round of the auction. Since the upper and lower limit up to which prices can change in a round are specified by circuit breakers, the determination

[19]This market clearing mechanism can be found in Friedman and Aoki (1992).

Figure 3.1: Market Clearing**



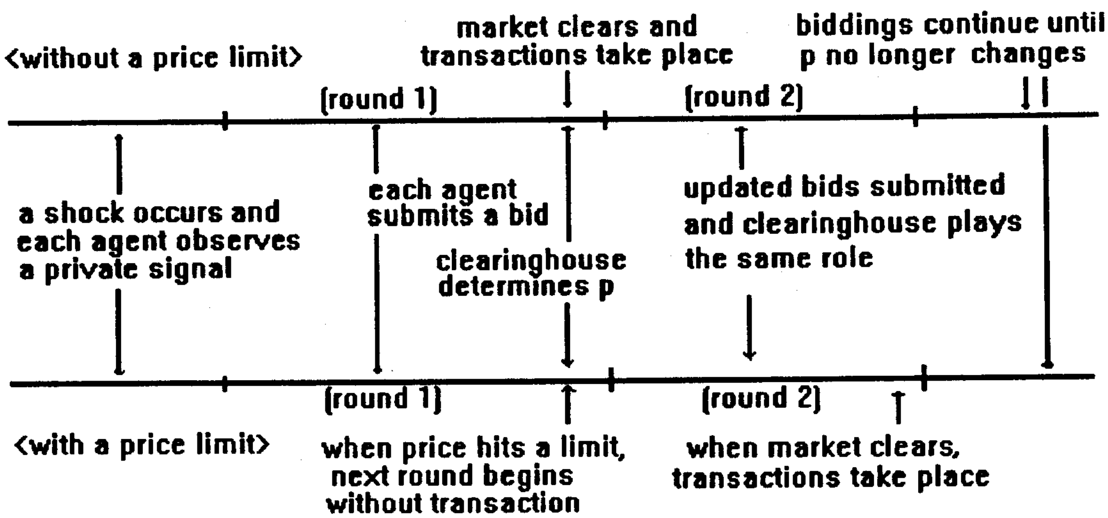
<Supply and Demand> <Order of bidding prices>

* denotes the seller ** when n=7 and M=4

of the market clearing price in response to an unexpected large shock may require repeated call auctions over several days. When there is a market excess demand at the first round (assuming a positive shock), *i.e.*, there are more than M traders who submit their bids at the upper limit, the clearinghouse announces that the market is not cleared and begins the second round of bidding without executing transactions at the upper limit.[20] The bidding procedure continues until traders with the M highest bids can be identified. When the market clears, the traders who have submitted higher (lower) bids than the market clearing price become the shareholders (non-shareholders). The

[20]Trading stops as soon as the price hits a predetermined limit in case of the 'trading halts' type of circuit breakers and no transaction takes place at the limit price although there are traders who are willing to trade even at the limit price. For example, in the New York Stock Exchange (NYSE), trading in all stocks is halted for one hour when the Dow Jones Industrial Average (DJIA) declines 250 points from the previous day's close, and for two hours when DJIA declines 400 points. See the Fact Book of the NYSE (1992). On the other hand, in the case of price limits, transactions take place between buyers and sellers who are willing to trade at the limit price. Although some shareholders (non-shareholders) become non-shareholders (shareholders) in the next period due to transactions at the limit price, such a change in traders' identities does not affect their bidding decisions.

Figure 3.2: Temporal Illustration of Trading Process



temporal illustration of the trading mechanisms with and without circuit breakers is provided in Figure 3.2.

Behavior of traders The objective of traders is to maximize the current expectation of final payoffs. A buyer acquires a share and pays the market clearing price p if his bid b is greater than p. On the other hand, a seller sells his share at p in case his bid is lower than p and keeps his share otherwise. Hence, when trader i tenders a bid b and the price is realized to be p, his payoff denoted by $U(V, X_i, b)$ is given as follows:

$$U(V,X_i,b) = \begin{cases} (V-p)\cdot 1_{\{p\le b\}} & \text{for buyer } i \\ V\cdot 1_{\{p\le b\}} + p\cdot 1_{\{p>b\}} & \text{for seller } i \end{cases} \qquad (3.4)$$

where $1_{\{e\}}$ is an indicator function, which takes the value one if the event e occurs and zero otherwise. Knowing that prices are partially revealing in this model, they supplement private information with price information whenever available.

There is a difference in the bidding behavior of the two types of traders. The sophisticated traders who are fully rational understand the entire model structure including the fact that there exists a portion α of naive traders. They also recognize that price determined in the auction is the M^{th} highest bid among n bids and make a strategic bidding decision considering how the others behave. Their strategies constitute a Nash equilibrium and are consistent with their beliefs.

On the other hand, the naive traders are assumed to have limited analytical capacity. First, they do not consider the strategic interaction among traders and take price as exogenously given.[21] Whereas sophisticated traders recognize the possibility that when everyone evolves (*e.g.*, adopts aggressive bidding strategies) price can change correspondingly, naive traders regard price as an exogenous function of Y, the market opinion on which they do not have an influence. Let us define a function mapping Y into p by $\phi{:}Y \to p$. Then, price is perceived as $p = \phi(Y)$ for naive traders.

The second assumption about the naiveté is related to their belief adjustment process. Having less capability to process information, naive traders adopt a relatively simple learning and adaptation strategy. They respond to the newly available information by adjusting their *signals* using the adjustment parameter γ, $0 < \gamma < 1$, which represents how much importance naive traders put on their own signal in updating beliefs about V.[22] In this game, information regarding the true value of a

[21]This assumption ignores the possibility that each trader's current bidding decision may affect other agents' contingent behavior and thus affect his own future trading opportunities. Friedman (1991) adopted this assumption and called it a "Game against Nature."

[22]The extreme case that $\gamma \approx 1$ implies that each trader considers his own private signal only. When $\gamma \approx 0$, on the other hand, people ignore their own signal completely. It is most probable that $0 < \gamma < 1$. When γ is such that $E[V|X = x, Y^*] = E[V|X' = \gamma x + (1-\gamma)Y^*]$, the adjusted signal x' well represents their reservation price given the available information.

shock is revealed at more than one stage. In the beginning of the first round when price information is not available, a trader makes a bidding decision solely based on his private signal x. When he obtains price information at the end of the first round, revealing that the best estimate of market signal Y is equal to Y^*, he adjusts his private signal x to $x' = \gamma \cdot x + (1-\gamma) \cdot Y^*$ and makes a bidding decision for the next round based on the new signal x'. That is, naive traders summarize a multi-dimensional information vector (private and price information) into a single dimension. When they have a proper adjustment parameter reflecting each variable's precision, the new signal x' may reflect the reservation value of V given the available information. However, since the adjusted signal is not a sufficient statistic for both private and price information, it inevitably entails ignoring information that would be useful in calculating the optimal decision. Such an information loss may cause them to make a mistake in their bidding decision.

When there is no circuit breaker, price information is given as a single point, that is, $Y^* = y$. The adjusted signal $x' = \gamma \cdot x + (1-\gamma) \cdot y$ summarizes the updated belief about V. Notice that x' is smaller than y for $x<y$ and greater than y for $x>y$. Even if they make a bidding decision based on the adjusted signal, it does not affect the price. The updated bids based on x' well represent their reservation price and result in the same price as determined in the first round.

However, this relationship breaks down when there are circuit breakers. A limit-triggering event results in price information in the form of a truncated distribution that the market clearing price is greater than the upper limit $\overline{\delta}$, that is, Y is greater than c where $c \equiv \phi^{-1}(\overline{\delta})$. Given this price information, the best forecast of Y is $E[Y|x, Y \geq c]$ and naive traders adjust their signal $x' = \gamma \cdot x + (1-\gamma) \cdot E[Y|x, Y \geq c]$. Although the proper γ makes the adjusted signal adequately represent their reservation price so that $E[V|x,Y \geq c] = E[V|x']$, their bids based on x' are not optimal from the perspective of sophisticated traders. Suppose that all traders submit bids based on x'. Since x' is greater than x for all x unlike the case without circuit breakers, it results in aggressive bidding causing prices to rise. If they are rational enough to recognize that a greater price occurs due to this aggressive bidding, they can deduce that the true y is smaller than $\phi^{-1}(p)$ and find that what they wanted to pay was more than what they are willing to pay. That is, $E[E[V|x']|Y = y] = E[V|x',y] > E[V|x,y]$. However, naive traders who regard price as exogenous given do not consider such a possibility and believe that a greater price is due to a greater Y. Consequently, their naiveté results in irrationally aggressive bids that put upward pressure on prices. The behavior of sophisticated and naive traders are summarized in Table 3.1.

Table 3.1 Behavior of Sophisticated and Naive Traders

	sophisticated	naive
price	the M^{th} highest bid $p = B_M$	an exogenous function of Y $p = \phi(Y)$
belief adjustment	Bayesian updating $E[V\|x,Y^*]$	signal adjustment using γ $E[V\|x'],\ x' = \gamma x + (1-\gamma)Y^*$
bidding strategy	$b_S = b_S(x,Y^*)$	$b_N = b_N(x')$

3.3. A Benchmark: The Case without Circuit Breakers

When there are no circuit breakers, traders can bid whatever price they want. The market clears in each round at the price of the M^{th} highest bid B_M. Any buyer (seller) who submits a bid higher (lower) than the market clearing price buys (sells) a share. Other buyers and sellers do not transact.

Before analyzing traders' strategies, we make a simplifying assumption that there are sufficiently large number of traders so that they ignore the difference between the M^{th} and the $(M+1)^{th}$ order signal. In this situation, it can be shown that the optimal bidding price for the buyer is the same as the one for the seller if and only if they have the same private signal.[23] This assumption not only allows us to analyze the strategy of one side of traders, but also offers an advantage that an ordering by bidding prices of traders is equivalent to an ordering by their private signals.

Since the bidding strategy of a sophisticated trader is different from a naive trader, we first analyze the sophisticated trader's strategy. (when all traders are rational $(\alpha = 0)$) We also see how it brings a different result if traders are naive $(\alpha = 1)$ and finally analyze the general case in which both traders are present.

Equilibrium with the Sophisticated Traders We identify competitive behavior with (non-cooperative) symmetric Nash equilibrium behavior. A pure strategy for a trader is a function converting his information into a bid. Let us denote the strategy of sophisticated trader i who has a signal $X_i = x$ by $b_{S,i}(x)$. Holding the other traders'

[23]Although this assumption reflects an aspect of real stock markets, it is made to simplify the analysis. The double auction imposes considerable difficulties in formalizing tractable models because the strategy of a buyer is different from that of a seller even if they have the same signal. However, as the number of traders becomes sufficiently large, the magnitude by which an individual trader can affect the price becomes trivial and the strategic differences between a buyer and seller vanish. A proof is provided in Appendix 2.

strategies as fixed, trader i may regard the M^{th} highest bid B_M as a random variable. His strategy $b_{S,i}$ is called an optimal response to the opposing strategies if

$$b_{S,i} \in \arg\max_{b} \; E[U(V,X_i,b) | X_i = x] \tag{3.5}$$

If each $b_{S,i}$ in an *n-tuple* $(b_{S,1}, b_{S,2}, \cdots)$ is an optimal response to the other strategies, it is called an equilibrium point.

Let us define a function $\varphi(x,y) = E[V | X_i = x, Y = y]$, which is increasing in both arguments since X_i and Y have the (strict) monotone likelihood ratio property. Since traders are assumed to be risk-neutral, $\varphi(x,y)$ is the reservation price for trader i if he were able to observe $Y = y$. For example, buyer i would be willing to pay any price less than $\varphi(x,y)$ to acquire a share but would not do so at any higher price.

Theorem 1: Let $b_S(x) = \varphi(x,x)$. Then the n-tuple of strategies $(b_S, b_S, \cdots, b_S)$ is an equilibrium point in a market without a price limit.[24]

Proof: Let us show that the optimal bidding strategy of trader i, as a solution to (3.5), is equal to $b_S(x)$ when all the other traders follow the strategy $b_S(x)$. Since $b_S(x)$ is increasing in x, traders with higher private signals tend to submit higher bidding prices at equilibrium. Since the market clearing price is the M^{th} highest bid submitted by the M^{th} highest signal holder, it follows that $p = B_M = b_S(Y)$. Then trader i's maximization problem is as follows:

[24]This derivation of the equilibrium strategy follows the one used in Milgrom and Weber (1982). Whereas there is a fixed number of buyers in their model since they analyze the typical one-sided auction market, the number of the auctioned object M is a random variable and also both buyers and sellers are present in this model.

$$
\begin{aligned}
\underset{b}{Max} \quad & E[\ (V-p)\cdot 1_{\{p\le b\}} \mid X_i = x] \\
&= E[(V-B_M)\cdot 1_{\{B_M\le b\}} \mid X_i = x] \\
&= E[\ E[(V-B_M)\cdot 1_{\{B_M\le b\}} \mid X_i, Y] \mid X_i = x] \\
&= E[\ E[(V-b_S(Y))\cdot 1_{\{(b_s(Y)\le b\}} \mid X_i, Y] \mid X_i = x] \\
&= E[\ (E[V \mid X_i = x, Y] - E[V \mid Y, Y])\cdot 1_{\{b_s(Y)\le b\}} \mid X_i = x] \\
&= \int_{-\infty}^{b_s^{-1}(b)} \{(\varphi(x,\omega)-\varphi(\omega,\omega)\}\ h_{Y/X}(\omega)\ d\omega
\end{aligned}
\tag{3.6}
$$

where $h_{Y/X}(\cdot)$ is a conditional density of Y given x. The second equality comes from the law of iterated expectations. The maximum is achieved by integrating over $\{\omega\text{: } \varphi(x,\omega)-\varphi(\omega,\omega)\ge 0\}$. Since $\varphi(x,\omega)-\varphi(\omega,\omega)$ is positive for $\omega < x$ and negative for $\omega > x$, (3.6) is maximized when $b_S^{-1}(b) = x$. Hence, $b = b_S(x)$. *Q.E.D.*

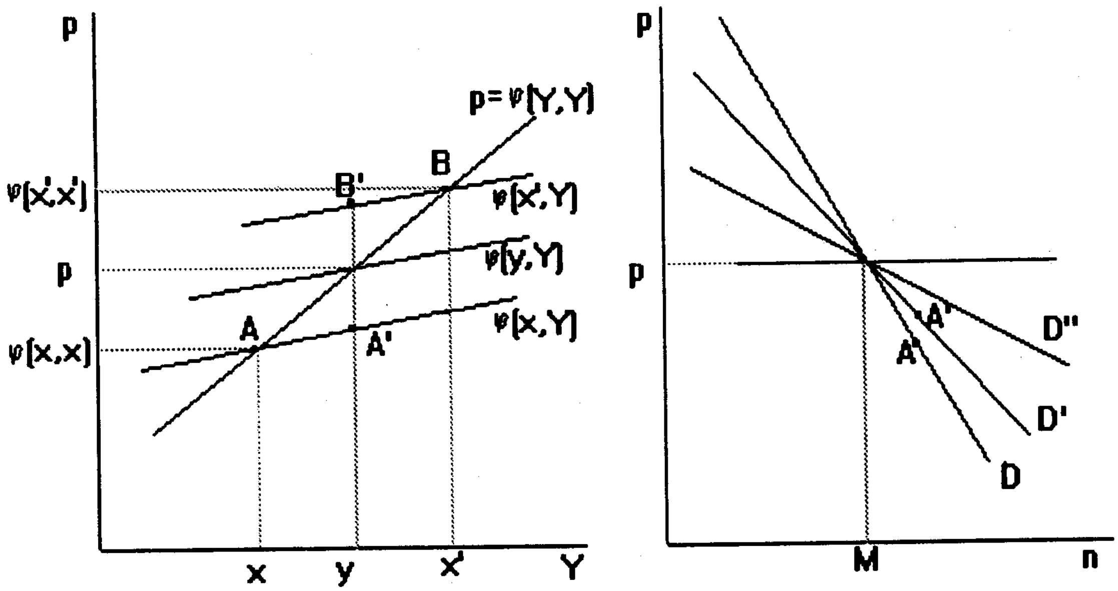
Theorem 1 states that it is optimal for each trader to submit his reservation price as if Y were equal to his own signal x. The optimal strategy $b_S(x)$ can be explained by Figure 3.3. Remember that $\varphi(x,y)$ is the reservation price of a trader given that his signal is x and $Y = y$. Since Y is an unknown random variable until the market is cleared, $\varphi(x,Y)$ denotes his reservation price function. The optimal bid for a trader who has a signal $x < y$ is indicated by point A in the figure. The strategy $\varphi(x,x)$ guarantees that whenever the market clearing price p is greater than his bid, his reservation price conditional on p is smaller than p. He sells (does not acquire) a share if he is a shareholder (non-shareholder), which is what he wants to do at p. The same logic applies to a trader with $x > y$. Since price is the M^{th} highest bid,

$$p = \varphi(Y,Y) \qquad (3.7)^{25}$$

---

[25]When ε_y in (3.3) follows a normal distribution, (3.7) is equal to $p = \dfrac{r_v\cdot\mu + (r_x + r_y)\cdot Y}{r_v + r_x + r_y}$.

Figure 3.3: Price Determination in the Benchmark Model



When the market clearing price in the first round is known to all, traders update their beliefs about the true value of the shock using price information and tender a new bid for the next round. We prove in the Appendix, however, that the updated bids do not change the price. Consider again Figure 3.3. After Y is realized to be equal to y, a trader with the initial signal x will submit a new bid $\varphi(x,y)$ for the next round, which is indicated by A' in the figure. Notice that A' is greater than A but still smaller than p. Also, the updated bid for a trader with $x' > y$, indicated by B', is smaller than his initial bid but still higher than p. The updated bid stays the same for a trader whose initial bid is equal to p. The right-hand side of Figure 3.3, showing the market demand schedule, describes that updated bids do not change the market clearing price although the slope of the schedule changes.[26] Hence, the price given in (3.7) remains the same for successive rounds unless further shocks arrive.

Bidding Strategy of the Naive Traders Since naive traders regard price as $p = \phi(Y)$, we require explicit knowledge about ϕ in order to analyze their strategy. We shall impose a restriction on ϕ so that ϕ is consistent with their understanding of the information structure. Suppose a trader's bid is realized to be equal to the market clearing price p. Then, he would believe that the average market opinion is the same as his belief about the true value of a shock and submit the same bid for the next period. That is, his reservation value of the shock conditional on p would be equal to p. On the other hand, any trader who submits a bid lower (higher) than p would think that his signal is smaller (larger) than the market player's signal. Hence, the price function ϕ is restricted to satisfy the following:

$$E[V \mid X_i = Y, p = \phi(Y)] = \phi(Y) \text{ and increasing in } X_i \tag{3.8}$$

Let $\phi(Y) = \varphi(Y,Y)$. Then, it can be shown that $\phi(Y)$ is a unique function satisfying (3.8).[27] However, the qualitative results of the paper do not change due to the choice of ϕ and $\phi(Y)$ can be understood as a normalization.

Let us denote a bidding strategy of the naive traders by b_N. The optimal bid of naive trader i who has a private signal $X_i = x$ is a solution to the following:

---

[26]In the figure, D'' is drawn to be more elastic than D'. The precision of Y assumed in D'' is greater than the one assumed in D'. It indicates that the slope of market demand schedule based on the updated bids becomes more elastic as traders believe that market information is more informative than their private information. In the extreme case when $r_x / r_y \cong 0$, the schedule becomes horizontal at the market clearing price.

[27]A proof is provided in Appendix 4.

$$b_{N,i} \in \arg\max_b E[(V - \phi(Y)) \cdot 1_{\{b \geq \phi(Y)\}} | X_i = x] \tag{3.9}$$

Theorem 2: Suppose that naive traders' beliefs on price is given as $\phi(Y) = \varphi(Y,Y)$. *Then, the optimal bid of naive trader i whose signal* $X_i = x$ *is* $\varphi(x,x)$.

Proof: Since $p = \phi(Y) = \varphi(Y,Y)$, the maximization problem for trader i is as follows:

$$\begin{aligned} &\underset{b}{Max}\ E[(V - \phi(Y)) \cdot 1_{\{b \leq \phi(Y)\}} \mid X_i = x] \\ &= E[\ E[(V - \phi(Y) \cdot 1_{\{b \leq \phi(Y)\}} \mid X_i, Y] \mid X_i = x] \\ &= \int_{-\infty}^{\phi^{-1}(b)} \{\varphi(x,\omega) - \varphi(\omega,\omega)\}\ h(\omega / x)\ d\omega \end{aligned}$$

The maximum is achieved when $\phi^{-1}(b) = x$. Hence, the optimal bid for naive trader i is equal to $b_{N,i} = \phi(x)$. *Q.E.D.*

Notice that the optimal bid for a naive trader is the same as that of a sophisticated trader as long as they have the same private signal. However, it no longer holds when there are circuit breakers as will be shown later.

The market clearing price as the M^{th} highest bid is equal to $\varphi(Y,Y)$, which is the same as in (3.7). After the market clearing price is known, naive traders adjust their signal x into $x' = \gamma \cdot x + (1-\gamma) \cdot y$ where $y \equiv \phi^{-1}(p)$ and make a bidding decision based on x' for next period.[28] However, the updated bids based on these new signals do not change the equilibrium price since the updated signal x' is a convex combination of x and y which takes on a value between x and y. An updated bid by a trader whose

[28]When ε_y follows a normal distribution and $\gamma = r_x/(r_x + r_y)$, it can be shown that $\varphi(x,y) = \phi(x')$.

private signal is smaller (bigger) than y is still smaller (bigger) than the market clearing price determined in the first round. Hence, the market clearing price remains the same.

Equilibrium with Both Types of Traders When both types of traders are present in the model ($0 < \alpha < 1$), sophisticated traders behave strategically knowing how naive traders behave. They treat the naive traders' strategy as given. The equilibrium strategy of the sophisticated traders and the resulting market clearing price depend on the portion α of the naive traders. The sophisticated trader i's problem is given as follows:

$$\underset{b}{Max}\ E[(V-p)\cdot 1_{(b\geq p)} \mid X_i = x]$$

subject to (3.10)

$$b_N(x) = \varphi(x,x)$$

$$n\cdot\{\alpha\cdot(1-G_N(p))+(1-\alpha)\cdot(1-G_S(p))\} = M$$

where $G_N(\cdot)$ and $G_S(\cdot)$ is the cumulative distribution function of the bidding prices for each type of traders. The last equation in (3.10) represents the market clearing condition that the number of bids higher than the market clearing price is equal to the number of shares offered for sale. The optimal bidding strategy and the resulting equilibrium price must satisfy the above three equations simultaneously since the market clearing depends on the strategy of sophisticated traders whose bidding decisions in turn are based on the price being determined.

Suppose that the sophisticated traders except i follow the strategy $b_S(x) = \varphi(x,x)$. Since the market clearing price is again equal to $\varphi(Y,Y)$ given the naive trader's bidding strategy $\varphi(x,x)$, the maximization problem for sophisticated trader i becomes the same one as given in (3.6). Hence, it is optimal for him to submit

$\varphi(x,x)$, which results in the same market clearing price as in (3.7).

In the second round, traders update their bids using price information. However, the updated bids do not change the market clearing price p determined in the first round since the updated bids submitted by traders whose initial bids were lower (greater) than p are still smaller (greater) than p. As far as the market clearing in the first round provides price information as a signal point, which is the case when there is no price limit, the presence of naive traders does not change the market clearing price determined in the first round.

3.4. The Existence of Circuit Breakers and Price Overshooting

When there are circuit breakers, traders should choose their bids within the prespecified upper and lower price limit. Since the possible limit-triggering provides further information on the true value of the shock, their strategy in presence of circuit breakers might differ from the strategy without circuit breakers. Throughout the analysis, we assume that the market is cleared in the second round for simplicity. Since we assumed that transactions do not take place until the market is cleared, the optimal strategy for the first round is the same as the one without circuit breakers except that traders with greater or smaller bids than the limit price should submit the upper or lower limit bid. Hence, we focus on the bidding strategy of traders for the second round.

Suppose that the upper limit $\overline{\delta}^1$ is triggered in the first round. This limit-triggering provides information that the market clearing price is equal to or greater than the upper limit. From the information $p \geq \overline{\delta}^1$, they can deduce that Y is greater than c. If we define $f(Y|v)$ to be the conditional probability density function of Y, then people have the following belief regarding $f(Y|v)$ after the first round.

$$f(Y|v) = \begin{cases} 0 & \text{for} \quad Y < -c \\ \int_{-\infty}^{-c} f(Y|v)\, dy & \text{for} \quad Y = -c \\ f(Y|v) & \text{for} \quad -c < Y < c \\ \int_{c}^{\infty} f(Y|v)\, dy & \text{for} \quad Y = c \\ 0 & \text{for} \quad Y > c \end{cases} \tag{3.11}$$

When people update their beliefs about V using (3.11), they have greater reservation prices for the asset. That is,[29]

$$E[V|X_i = x,\ Y \geq c] > E[V|X_i = x,\ Y] \tag{3.12}$$

Based on the information given in (3.11), traders make a bidding decision for the second round. We first analyze how rational traders respond to the price information provided by limit-triggering. In the following, we denote the bidding strategies of traders when there is a price limit by $\bar{b}_S$ and $\bar{b}_N$ to distinguish them from the case without circuit breakers. (An upper bar in the notation indicates the case with a price limit and we delete the superscript in traders' bidding strategy denoting the second round since we focus on the second round.)

Equilibrium with the Sophisticated Traders Given the market information $Y \geq c$, an

[29]This inequality can be proven using the monotone likelihood ratio property. For every nondegenerate prior distribution ξ on v and every y and y' in the range of Y with $y'>y$, the posterior distribution $\xi(v|Y=y')$ dominates $\xi(v|Y=y)$ in the sense of first-order stochastic dominance. Since higher values of V are integrated with a higher density, the posterior mean takes on a greater value.

optimal bidding strategy $\bar{b}_{S,i}$ of sophisticated trader i in the second round is given as

$$\bar{b}_{S,i} \in \underset{\underline{\delta}^2 \le b \le \bar{\delta}^2}{\arg\max}\ E[\ U(V, X_i, b) |\ X_i = x,\ Y \ge c] \tag{3.13}$$

Although traders have greater reservation prices due to the limit-triggered event, the equilibrium price is the same as the one determined in a market without circuit breakers, as shown in the following theorem.

Theorem 3: Let $\bar{b}_S(x) = \begin{cases} \bar{\delta}^2 & \text{if} \quad \varphi(x,x) \ge \bar{\delta}^2 \\ \varphi(x,x) & \text{if} \quad \underline{\delta}^2 < \varphi(x,x) < \bar{\delta}^2 \\ \underline{\delta}^2 & \text{if} \quad \varphi(x,x) \le \underline{\delta}^2 \end{cases}$ (3.13)

Then the n-tuple of strategies $(\bar{b}_S, \bar{b}_S, \ldots, \bar{b}_S)$ *is an equilibrium point in a market where there is a price limit.*

Proof: Suppose all other traders follow the strategy in (3.13). Since $\bar{b}_S(Y) = \varphi(Y,Y)$ when the market is cleared, $\bar{p} = B_M = \varphi(Y,Y)$. Trader i's maximization problem is given as follows:

$$\begin{aligned} &\underset{\underline{\delta}^2 \le b \le \bar{\delta}^2}{Max}\ E[(V - \bar{p}) \cdot 1_{\{\bar{p} \le b\}} \mid X_i = x,\ Y \ge c] \\ &= E[\ E[(V - B_M) \cdot 1_{\{B_M \le b\}} \mid X_i, Y] \mid X_i = x,\ Y \ge c] \\ &= E[\ E[(V - \bar{b}_S(Y)) \cdot 1_{\{\bar{b}_S(Y) \le b\}} \mid X_i, Y] \mid X_i = x,\ Y \ge c] \qquad (3.14) \\ &= E[\ (E[V \mid X_i = x, Y] - E[V \mid Y, Y]) \cdot 1_{\{\bar{b}_S(Y) \le b\}} \mid X_i = x,\ Y \ge c] \\ &= \int_c^{\bar{b}_S^{-1}(b)} \{\varphi(x,\omega) - \varphi(\omega,\omega)\}\ h(\omega / x, \omega \ge c)\ d\omega \end{aligned}$$

where $h(\omega / x, \omega \ge c)$ is a conditional density of Y given $X_i = x$ and $Y \ge c$. Since $\varphi(x,\omega) - \varphi(\omega,\omega)$ is monotonically decreasing in ω and zero for $\omega = x$, the maximum is achieved when $\bar{b}_S^{-1}(b) = x$. Suppose trader i's signal x is smaller than c. Since (3.14) is always negative, it is optimal for him to submit the lowest bid allowed by the stock exchange, that is, $b = \underline{\delta}^2$. When $x \geq c$, on the other hand, the maximum can be found by integrating until $\bar{b}_S^{-1}(b) = x$. Hence, $\bar{b}_{S_i} = \varphi(x,x)$. If $\varphi(x,x) \geq \bar{\delta}^2$, he should submit $\bar{\delta}^2$ which is the maximum bid available in the second period. When $\underline{\delta}^2 < \varphi(x,x) < \bar{\delta}^2$, the optimal strategy is to submit $\varphi(x,x)$. Hence, $\bar{b}_S$ is the optimal strategy for trader i. *Q.E.D.*

Notice that the optimal bidding strategy $\bar{b}_S(x)$ is equivalent to the strategy $b_S(x)$ for the case without circuit breakers, except that bids greater or lower than the limit price are transformed into the upper or lower limit bid. Although the price information provided by the limit triggering affects those whose initial bids are smaller than the lower limit $\underline{\delta}^2$, their updated bids are still lower than $\underline{\delta}^2$. Hence, they should submit the lowest bid $\underline{\delta}^2$. On the other hand, those whose initial bids are greater than $\underline{\delta}^2$ will find it optimal to behave as if they ignore the market information provided by the limit-triggered event. This is because a market clearing in the second round will provide price information as a point which dominates the previous range information, $Y \geq c$.

To see why, suppose that traders bid more aggressively due to limit-triggered event. Then, the market clearing price p' will be greater than p given in (3.7). In this situation, a trader who has submitted p' as his bid will realize that he is the M^{th} highest signal holder and will regret his aggressive bidding since his reservation value $\varphi(y,y)$ is smaller than his bid p'. Cleverly recognizing the sequential nature of this game, sophisticated traders follow the same strategy as before. As a result, the market clearing price is the same as the one determined in a case without circuit breakers.

Behavior of the Naive Traders Given the price information $p \geq \overline{\delta}^1$, naive traders adjust their signal into $x' = \gamma \cdot x + (1-\gamma) \cdot E[Y|x,\ Y \geq c]$ where $c \equiv \phi^{-1}(\overline{\delta}^1)$ and make a bidding decision based on x'. Since $E[Y|x,\ Y \geq c]$ is greater than x for all x, the adjusted signal is greater than the initial signal for all traders. That is, the information $Y \geq c$ provided due to limit-triggering causes them to hold more optimistic beliefs about the true value of a shock. Given x', the optimal bid of naive trader i for the second round is a solution to the following:

$$\overline{b}_{N,i} \in \underset{\underline{\delta}^2 \leq b \leq \overline{\delta}^2}{\arg\max}\ E[(V - \phi(Y)) \cdot 1_{\{b \geq \phi(Y)\}} |\ X_i = x'] \tag{3.15}$$

Compare (3.15) to the optimal bidding strategy of sophisticated traders given in (3.13). Whereas sophisticated traders fully utilize the available information $X = x$ and $Y \geq c$, naive traders' bidding decision is based on the adjusted signal x'. Since the maximization problem in (3.15) is equivalent to (3.9) except a change in signal, the optimal bid $\overline{b}_N$ for naive trader i as a solution to (3.15) can be shown to be as follows:

$$\overline{b}_N(x) = \begin{cases} \overline{\delta}^2 & if \quad \varphi(x',x') \geq \overline{\delta}^2 \\ \varphi(x',x') & if \quad \underline{\delta}^2 < \varphi(x',x') < \overline{\delta}^2 \\ \underline{\delta}^2 & if \quad \varphi(x',x') \leq \underline{\delta}^2 \end{cases} \qquad (3.16)[30]$$

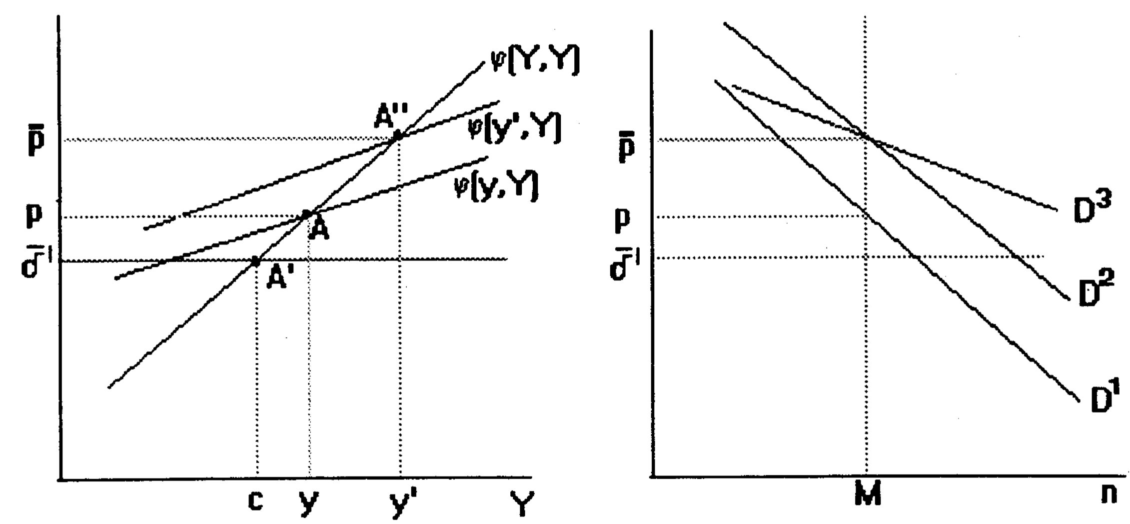
Since $\varphi(x',x')$ is greater than $\varphi(x,x)$, the market clearing price $\varphi(y',y')$ is greater than the one determined in a market without circuit breakers. After the market is cleared in the second round, traders adjust their signal x' into $x'' = \gamma \cdot x' + (1-\gamma) \cdot y'$ where y' is $y' = \phi^{-1}(\overline{p})$. However, the updated bids based on x'' do not affect the price

[30] A proof is given in Appendix 5.

determined in the second round since the updated signal y'' of the M^{th} highest signal holder stays the same as y'.

The behavior of naive traders is explained in Figure 3.4. Suppose a trader whose signal is equal to y, the M^{th} highest among n signals. The reservation price functions based on his initial and updated signal are drawn as $\varphi(y,Y)$ and $\varphi(y',Y)$. In the first round, he should submit $\overline{\delta}^1$, indicated by point A', although he wants bid higher. A triggering of the upper limit shifts his reservation price function upward. An updated bid A'' in the second round is greater than A which would have been submitted without circuit breakers. The figure on the right describes the market demand schedules. The market demand schedule D^1 in the first round shifts into D^2 reflecting the change in traders' beliefs due to the limit-triggered event. We also see that the schedule D^3 for the third round does not change the price determined in the

Figure 3.4: Naive Trader's Bidding Strategy



second round although its slope changes due to the adjustment of beliefs after market clearing.

Notice that this adjustment behavior results in price overshooting when there are circuit breakers. Compared to the case when the price information is released as a point, the limit-triggered event provides price information in the form of a truncated distribution. Whereas the adjusted signal takes a value between their own signal and market signal Y in a case without circuit breakers, the adjusted signals take greater values than their initial signals when circuit breakers are triggered. Signal adjustment reflecting more optimistic beliefs about V due to a limit-triggering makes traders bid more aggressively, and consequently the market clearing price $\bar{p}$ becomes greater than the price which would have been determined without circuit breakers.

Equilibrium with Both Types of Traders When both types of traders are present, sophisticated traders behave strategically knowing that naive traders follow the bidding strategy of (3.16). The maximization problem for sophisticated trader i is given as follows:

$$\underset{\underline{\delta}^2 \le b \le \bar{\delta}^2}{Max} \; E[(V - \bar{p})1_{(b \ge \bar{p})} | X = x, Y \ge c]$$

subject to (3.17)

$$\bar{b}_N(x) = \varphi(x', x')$$

$$n \cdot \{\alpha \cdot (1 - G_N(\bar{p})) + (1 - \alpha) \cdot (1 - G_S(\bar{p}))\} = M$$

If we define $F(\cdot)$ as the cumulative distribution function of private signals, the market clearing condition in (3.17) becomes as follows:[31]

[31]Since $\bar{b}_N(\cdot)$ is a monotonically increasing function, $G_N(\bar{p}) = \text{Prob}(\bar{b}_N(X) \le \bar{p})$ $= \text{Prob}(X \le \bar{b}_N^{-1}(\bar{p})) = F(\bar{b}_N^{-1}(\bar{p}))$. It can also be shown that $G_S(\bar{p}) = F(b_S^{-1}(\bar{p}))$.

$$\alpha \cdot \{1 - F(\bar{b}_N^{-1}(\bar{p}))\} + (1-\alpha) \cdot \{1 - F(\bar{b}_S^{-1}(\bar{p}))\} - F(Y) = 0 \qquad (3.18)$$

where $F(Y) = M/n$. From (3.18), we can define an implicit function $\bar{p} = r(\bar{b}_S, Y)$.[32] Any combination of $\bar{p}$, $\bar{b}_S$ and Y satisfying $\bar{p} = r(\bar{b}_S, Y)$ gives (3.18) the status of an identity. Given the sophisticated traders' strategy $\bar{b}_S$, the market clearing price can be expressed as a function of Y:

$$\bar{p} = \pi(Y) \qquad (3.19)$$

where $\pi' > 0$. Given (3.19), the optimal bidding strategy of the sophisticated trader $\bar{b}_S$ is defined as follows:

$$\bar{b}_s \in \underset{\underline{\delta}^2 \le b \le \bar{\delta}^2}{\arg\max}\ E[(V - \pi(Y)) \cdot 1_{\{b \ge \pi(Y)\}} | X_i = x, Y \ge c] \qquad (3.20)$$

The optimal strategy $\bar{b}_S$ as a solution to (3.20) is consistent with the market clearing condition since $\pi(Y)$ is a function satisfying (3.18). Since it is difficult to derive the optimal strategy of the sophisticated traders as an explicit function, we shall analyze the qualitative properties of the equilibrium.

The equilibrium of this game is summarized by the strategies of each type of trader, $\bar{b}_S$, $\bar{b}_N$, and the resulting market clearing price. The equilibrium strategy of the sophisticated trader should be the one which guarantees the condition that his bid is

[32]Let us denote (3.18) by $R(\bar{p}, \bar{b}_S, Y) = 0$. Since R has continuous partial derivatives $R_{\bar{p}}$, $R_{\bar{b}_s}$ and R_Y and also $R_{\bar{p}}$ is nonzero for every point of $\bar{p}$ ($R_{\bar{p}} = -\alpha g_N(\bar{p}) - (1-\alpha) g_N(\bar{p}) < 0$), the condition under which the implicit function theorem holds are satisfied. This condition is sufficient for the existence of an implicit function. For the implicit function theorem, see Chiang (1974), pp. 216-227.

greater than the market clearing price p if and only if his reservation price on V is greater than p. Hence, for any value of x and Y, $\bar{b}_S$ should satisfy the following:

$$E[V \mid X_i = x, \bar{p} = \pi(Y)] \begin{cases} > \pi(Y) & \text{iff} \quad \bar{b}_S > \bar{p} \\ = \pi(Y) & \text{iff} \quad \bar{b}_S = \bar{p} \\ < \pi(Y) & \text{iff} \quad \bar{b}_S < \bar{p} \end{cases} \tag{3.21}$$

Lemma 2: Suppose that the price $\bar{p} = \pi(Y)$ is greater (smaller) than $\varphi(Y,Y)$. Then, it is optimal for sophisticated trader i to submit a bid which is smaller (greater) than $\varphi(x,x)$. When $\pi(Y) = \varphi(Y,Y)$, the optimal bid is equal to $\varphi(x,x)$.

A proof is provided in the Appendix. The above lemma can be explained as follows. Suppose that the market clearing price $\bar{p}$ is greater than $\varphi(Y,Y)$. If a sophisticated trader submits a bid $\varphi(x,x)$ and his bid happens to be equal to $\bar{p}$, he will realize that his reservation price $\varphi(x,y)$ is smaller than $\varphi(x,x)$ since $y = \pi^{-1}(\bar{p}) < \varphi^{-1}(\bar{p}) = x$. Recognizing this, he will find it optimal to submit a bid which is smaller than $\varphi(x,x)$.

Based on Lemma 2, we can characterize the equilibrium as follows.

Theorem 5: When both types of traders are present, the optimal bid of sophisticated trader i as a solution to (3.20) is smaller than $\varphi(x,x)$. Also, the market clearing price $\bar{p}$ determined in a market with circuit breakers is greater than p, the one determined in a market without circuit breakers.

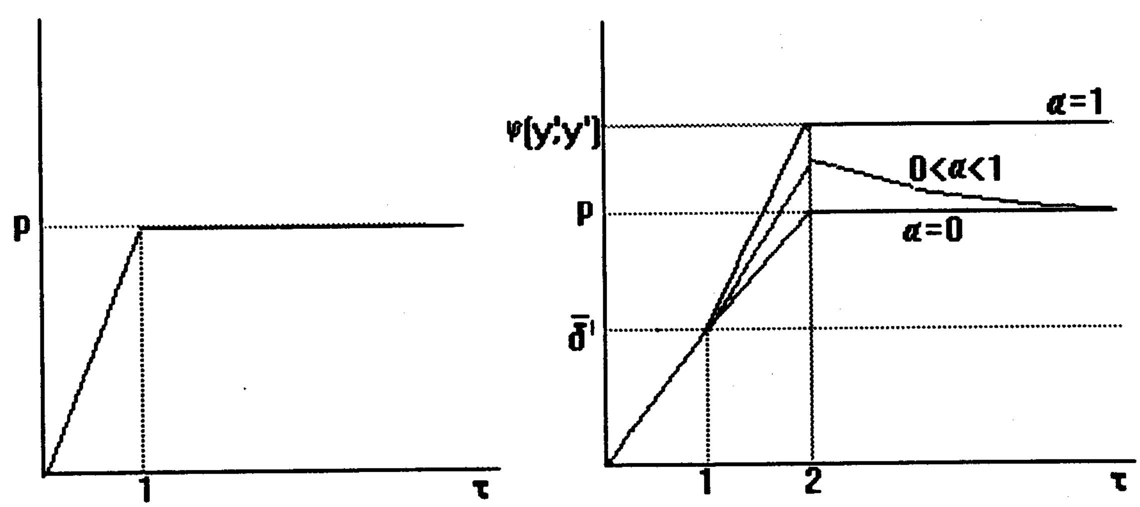
Proof: The market clearing price in (3.18) is an increasing function of both $\bar{b}_S$ and $\bar{b}_N$. Notice that $\bar{b}_N = \varphi(x',x') > \varphi(x,x)$ since $x' > x$. First, suppose $\bar{b}_S(x) \geq \varphi(x,x)$. Then the market clearing price is greater than the one determined in a market without a limit. Given that $\bar{p} > p$, the strategy $\bar{b}_S$ which is greater than $\varphi(x,x)$ is not optimal considering Lemma 2. Second, suppose that $\bar{b}_S(x) < \varphi(x,x)$ and $\bar{p} = p$. Given that $\bar{p} = p$, the optimal bid of the sophisticated trader should be equal to $\varphi(x,x)$, which contradicts $\bar{b}_S(x) < \varphi(x,x)$. Third, suppose that $\bar{b}_S(x) < \varphi(x,x)$ and $\bar{p} < p$. Given that $\bar{p} < p$, the optimal bid $\bar{b}_S(x)$ should be greater than $\varphi(x,x)$, which is a contradiction. Finally, when $\bar{b}_S(x) < \varphi(x,x)$ and $\bar{p} > p$, $\bar{b}_S$ is consistent with the resulting price $\bar{p}$ $(> p)$. *Q.E.D.*

The market clearing price overshoots the equilibrium level which would have been determined without circuit breakers. After the market is cleared in the second round, traders update their beliefs on V using price information. Since the sophisticated traders can deduce y from price information, their bidding price for the next round is equal to $\varphi(x,y)$. On the other hand, the naive traders deduce Y using $Y = \phi^{-1}(\bar{p})$ and adjust their signal x' into $x'' = \gamma x' + (1-\gamma)\phi^{-1}(\bar{p})$. Since we are focusing on price behavior, it is enough to only look at the bidding price of a naive trader whose initial signal is y. His updated signal for the third round is equal to $y'' = \gamma y' + (1-\gamma)\phi^{-1}(\bar{p})$. Since $\phi^{-1}(\bar{p}) < y'$, y'' is smaller than y' and the resulting price in the third round is smaller than the price in the second round. In subsequent rounds, his updated signal becomes smaller as $\bar{p}$ decreases and this process continues until the price reaches $\bar{p} = \phi(y)$. When $\bar{p} = \phi(y)$, his updated signal stays at y and the price does not change unless further shocks arrive.

Figure 3.5 summarizes the results. When there is no circuit breaker, the price immediately jumps to its equilibrium level, irrespective of the existence of naive traders. On the other hand, price overshoots its equilibrium level when there are circuit breakers. How much price overshoots depends on the portion α of naive traders and the precision of Y. When traders believe that Y is more informative than their own signal, the price information released by the limit-triggering event makes them bid higher. Also, when there are more people who make a bidding decision based on the optimistic beliefs due to the limit-triggering event, the magnitude of the price overshooting becomes greater.

We identify this price overshooting as an institution-induced phenomenon since it would not have occurred except for the presence of circuit breakers. When there is no limit on price movements, the market emits price signals as a single point. Since a convex combination of any two points gives a value between these two points, traders' updated bids based on price information do not cause prices to overshoot even with naive traders. On the other hand, the existence of circuit breakers provides price information as a truncated distribution. Belief adjustment based on the truncated price information causes some traders to hold more optimistic beliefs about the true value of

Figure 3.5: Comparision of Prices with and without Circuit Breakers



<without circuit breakers> <with circuit breakers>

the shock. That is, the existence of circuit breakers itself becomes a source of panic trading by enticing otherwise 'well-behaved' traders to bid aggressively and consequently brings about price overshooting. In this situation, the existence of circuit breakers not only delays the incorporation of new information into prices, but also impairs the price discovery process.

3.5. Discussion

Throughout the analysis, we have examined the effect of circuit breakers under the simplifying assumption that there is no further shock until the effect of one shock is fully resolved. While we assumed a once and for all shock in order to focus on the psychological effect brought about by the presence of circuit breakers, shocks continuously impinging on actual stock markets. Under such circumstances, the arrival of a positive shock following a negative shock may partially offset the latter when there are circuit breakers. However, such offsetting due to opposing fundamental shocks does not seem to be the presumed benefits of circuit breakers suggested by their proponents. They are concerned the adverse effect of a large price swing caused by informationless panic trading. The potential benefits of circuit breakers can be incorporated into our model as follows.

To focus on large price changes which are not justified by fundamentals, let us assume that supply shocks arrive in each period whereas a fundamental shock comes only in the first round. In this model, successive supply shocks can be represented by realizations of a random variable M^{τ} in each period, where M^{τ} is a number of shares offered for sale at round τ.[33] A relatively large realization of M^{τ} indicates that there are more sellers than buyers and the M^{th} highest signal Y at round τ takes a lower value. Since traders submit their bids in ignorance of what supply shock is realized, prices depend on not only private signals on which their bids are based, but also on realizations of M^{τ}. For example, although traders follow the same strategy, different realizations of supply shock result in different prices.

Suppose that a large volume shock hits the market in the first round, that is, the number of shares M^1 offered for a sale at the first round takes on an extremely large value so that prices fall away from their equilibrium level which is determined by fundamentals. Since traders cannot tell whether the lower value of Y is due to a fundamental shock or a supply shock, they submit updated bids for the next round using their beliefs about the distribution of Y. As more buyers come to the market in the second round so that M^2 is realized as a moderate value, which is likely considering its randomness, the market clearing price becomes higher and approaches the equilibrium price. As auction procedures continue, traders get more accurate information about V from large number of observations of supply shocks and prices eventually converge to their equilibrium level. That is, a large, temporary volume shock can lead to a deviation of prices from their equilibrium level.

In this situation, the presence of circuit breakers may be beneficial in facilitating the price discovery process. First, release of information about order imbalances in the first round while circuit breakers are in effect can prevent large fluctuations of prices due to the supply shock. If information about the number of shares offered for a sale at the first round is released to traders, they can recognize that

[33]There is a possibility that supply shocks are functionally dependent on the fundamental shock and have the same sign. However, if a functional relationship between two shocks is known to traders, they will respond by adjusting their bids considering such a relationship.

price declines are mostly due to the supply shock. When they submit updated bids based on this information, price approaches the equilibrium level.[34] Second, if circuit breakers can restore investors confidence and induce more value buyers to the market, this results in a lower realization of M^2. Then, the resulting price in the second round will be closer to the equilibrium level.

However, it might be too optimistic to believe that the above positive feedback loop of circuit breaker mechanisms will be effective in reality. Since tradings are halted or limited during short periods of time (for example, one hour in case of 'trading halts' on the NYSE), there may not be enough time for exchanges to process and release information in time to get a response from the public. Even if information about order imbalances is available, it is hard to distinguish information-based trading from noise. Also, it may take longer time for the stock market's natural long-term investors to step in and take a position when the market is undervalued. They might feel safe by waiting and watching the market rather than reacting quickly.

In addition, a triggering of circuit breakers can scare traders away from the market rather than reassuring them. Then, the realization of M^2 would become even larger, causing price to drop further. Also, even under the assumption of continuous shocks, price overshooting may occur if there are some traders who bid aggressively due to a triggering of circuit breakers. Hence, whether circuit breakers are effective in moderating price volatility depends on which effect dominates the other. Although the benefits of circuit breakers seem to exceed the costs in the case of price changes due to a supply shock, it should also be noted that circuit breakers are blunt instruments which, once introduced, are triggered upon the prespecified price change regardless of

[34]As shown in a typical auction literature where a fixed number of auctioned objects is assumed, prices converge to the unknown true value as the number of bidders becomes large. See, for example, Milgrom (1979).

whether price changes are due to a fundamental or supply shock.

Chapter 4.

Identification of Price Overshooting

4.1. Price Overshooting

The empirical test of the price overshooting hypothesis is based on the idea that stock price behavior might be different if circuit breakers are triggered than if they are not. In order to capture systematic differences in price behavior which may arise due to the existence of circuit breakers, we first need to specify a stochastic process governing price movements. In the model described in Chapter 3, price fluctuations are modeled as driven by fundamental shocks which affect future dividend streams of an asset and also by supply shocks. We analyzed the effect of circuit breakers under the simplifying assumption that further shocks will not arrive until the effect of one shock is fully resolved. To accommodate the actual stock market where shocks are continuously coming to the market, we need to know a stochastic process governing the occurrence of shocks.

Instead of specifying such a process which is difficult to identify, we employ the following martingale model which is frequently used as a characterization of equilibrium in financial markets.[35]

$$p_t = (1+\rho)^{-1} E[p_{t+1} + d_{t+1} | \Phi_t] \tag{4.1}$$

[35]For a review of martingale models in financial markets, see LeRoy (1989).

where d is dividends, ρ is the discount rate and Φ_t denotes information available at time t. Equation (4.1) states that the stock price today equals the sum of the expected future price and dividends, discounted back to the present at rate ρ. Although the above martingale model holds under certain assumptions such as risk neutrality, it has long been considered to be a reasonable approximation to actual stock price behavior and used to test capital market efficiency. If the market is efficient, any systematic discrepancies between p_t and $(1+\rho)^{-1}E[p_{t+1}+d_{t+1}|\,\Phi_t]$ will disappear through the intertemporal arbitrage activities of traders.

Since we are concerned with a relatively short time interval, say, a day, we can ignore dividends and discount rate terms. Then, (4.1) can be written as:

$$E[p_{t+1}|\,\Phi_t] = p_t \tag{4.2}$$

That is, the best forecast of p_{t+1} that can be constructed based on current information Φ_t would just equal the current price p_t. From (4.2),

$$p_{t+1} = p_t + e_{t+1}, \tag{4.3}$$

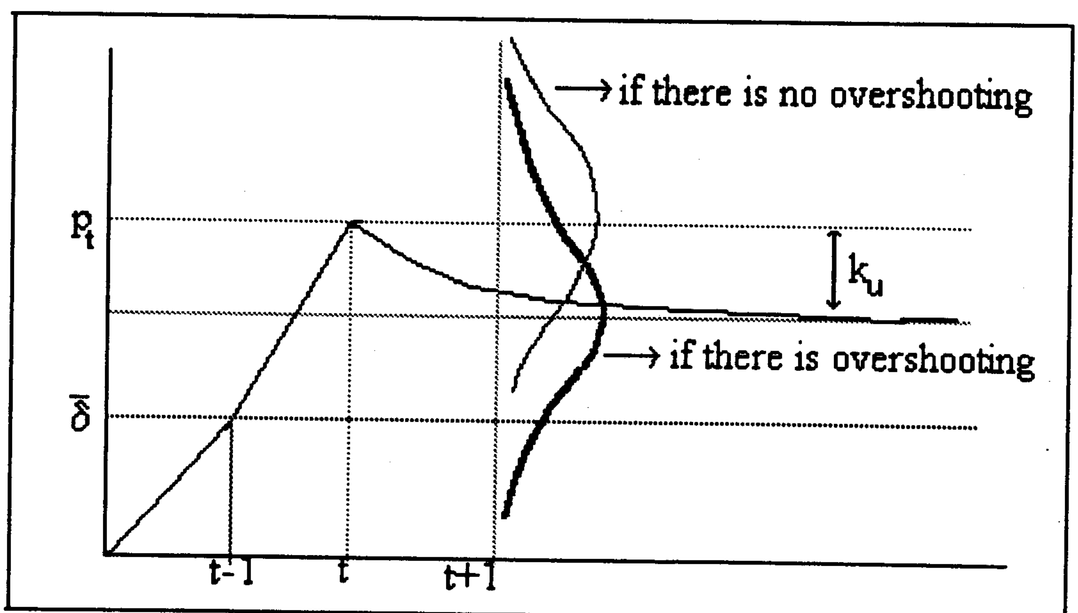
where e_{t+1} is the unexpected component of the one period return on stock. That is,

$$e_{t+1} \equiv p_{t+1} - E[p_{t+1}|\Phi_t] \tag{4.4}$$

Based on (4.2)-(4.4), we can empirically identify price overshooting, if any, as follows. Consider Figure 4.1, which describes the price behavior after triggering circuit breakers as predicted in Chapter 3. Suppose that the upper circuit breaker bound is triggered in period *t-1* and also that the market has cleared in period *t*. If the existence of circuit breakers helps facilitate a price discovery process, then the price will jump to the equilibrium level as soon as circuit breaker bound is expanded and no longer binds. Since p_t is the equilibrium price which fully resolves the effect of previous shocks, p_t should be the best forecast of p_{t+1}. Let us define $\Delta p_{t,\,t+1}$ to be the price difference between period *t* and *t+1* in growth terms. Then, we can model $\Delta p_{t,\,t+1}$ as white noise, as shown in Figure 4.1.

On the other hand, if price overshooting has occurred after the circuit breaker bound is triggered, the market clearing price at period *t* would be higher than the price which would have been determined without circuit breakers. Since the overshot price

Figure 4.1: Identification of Price Overshooting[a]



[a] It describes the case for a positive shock. The upper price limit is indicated by $\bar{\delta}$ and k_u is the magnitude by which price overshoots the equilibrium level when the upper limit is triggered. The case for a negative shock can be construed by reversing the figure upside down.

converges to the equilibrium level as time passes, price behavior after the circuit breaker is triggered will be systematically different from one with no triggering of circuit breakers. In this situation, the best forecast of p_{t+1} is no longer p_t as it has a systematic bias reflecting the magnitude of price overshooting. If we denote it by k_u (k_l) for the upper (lower) limit-triggered case, as drawn in Figure 4.1, we have $\Delta p_{t,\,t+1} = e_{t+1} + k_u(k_l)$, where k_u (k_l) is negative (positive).[36] That is, if price overshooting has occurred, $\Delta p_{t,\,t+1}$ no longer follows a fair game and (4.3) should be adjusted to the following.[37]

$$E[\Delta p_{t,t+1}|\Phi_t] = \begin{cases} k_u & \text{after the upper bound is triggered} \\ k_l & \text{after the lower bound is triggered} \\ 0 & \text{after no triggering} \end{cases} \qquad (4.5)$$

As empirical counterparts of $\Delta p_{t,\,t+1}$, we use three price difference series measured at different time intervals, that is, intraday, daily and weekly returns (denoted by *IR*, *DR* and *WR*). Since p_t is the opening price on the day when the circuit breaker bound is lifted, the intraday return denotes the difference between the opening and closing price, and the daily (weekly) return denotes price differences over one day (one week), all in growth terms. That is,

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[36]The magnitude of overshooting may vary depending on the particular circumstances in which the price limits were triggered. The size of a shock, the width of the circuit breaker bounds and the proportion of naive traders are among other factors which may cause bias. Since we can hardly identify these factors, we treat the magnitude of overshooting as constant by interpreting it as '*on the average*'.

[37]A stochastic process $\{y_t\}$ is a fair game if it has the property that $E[y_{t+1}|\Phi_t] = 0$. The martingale and fair game models are two names for the same characterization of equilibrium in financial markets.

$$
\begin{aligned}
IR_t &= (CLOSE_t - OPEN_t) / OPEN_t \\
DR_t &= (OPEN_{t+1} - OPEN_t) / OPEN_t \\
WR_t &= (OPEN_{t+6} - OPEN_t) / OPEN_t
\end{aligned}
\tag{4.6}
$$

where $OPEN_t$ and $CLOSE_t$ denote the opening and closing price at day t.

If price overshooting has occurred, all measures would show a significant negative (positive) bias for the upper (lower) bound triggered events compared to those when circuit breakers were not triggered. The magnitude of the bias will also depend on the speed of convergence. If it converges rapidly, say, within a day, the bias will be similar for all three measures. If not, the bias will be larger for the weekly return than for the intraday or daily returns.

4.2. Volatility Effect of Circuit Breakers

Besides price overshooting, we also examine how the existence of circuit breakers affects price volatility. Proponents of circuit breakers have asserted that circuit breakers can reduce price volatility by preventing panic trading, enabling traders to condition their trading decision on better information and attracting more traders to the market (see the Brady Report (1988), Greenwald and Stein (1990)). If so, the distribution of successive price changes after circuit breakers are triggered should be less dispersed than the one without triggering. On the other hand, circuit breakers may increase price volatility by bringing additional uncertainty into the market (Gerety and Mulherin (1990), McMillan (1991)) or distorting trading decisions (Subrahmanyam (1993)).[38]

[38]For example, Gerety and Mulherin (1990) state that "to the extent that circuit breakers increase the uncertainty regarding the ability to exit the market, an environment with circuit breakers may be *less*

We employ two volatility measures: conditional standard deviation and conditional average dispersion.[39] Comparison of those measures between the circuit breaker triggered events and non-circuit breaker triggered events will show how the existence of circuit breakers affects price volatility. If the existence of circuit breakers impaired the price discovery process and brought additional uncertainty into the market, a greater volatility would be observed after circuit breakers were triggered and vice versa.

First, the conditional standard deviation of successive price changes is defined as follows:

$$\begin{aligned}\{Var(p_{t+1}-p_t\,|\Phi_t)\}^{1/2} &= \{E[(p_{t+1}-E[p_{t+1}|\Phi_t])^2\ |\Phi_t]\}^{1/2} \\ &= \{E[e_{t+1}^2|\Phi_t]\}^{1/2}\end{aligned} \tag{4.7}$$

Note that the conditional standard deviation does not include the volatility effect brought about by price overshooting. Since the magnitude of price overshooting is reflected in both p_{t+1} and $E[p_{t+1}|\Phi_t]$, comparison of the conditional standard deviation between circuit breaker triggered events and non-circuit breaker triggered events will show the pure volatility effect of circuit breakers.

The second measure of volatility employed is the average absolute error of successive price changes (abbreviated as *average dispersion* for brevity), which is defined as follows:

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stable than an environment without circuit breakers." (pp. 1765-1766)

[39]In a study of the mini-market crash in the United States on October 13, 1989, Kuhn, Kuserk and Locke (1990) examine whether circuit breakers moderated price volatility by employing several measures of volatility for price changes of one-minute intervals. The volatility measures they employed are "standard deviation of price change," "average absolute log price change" and "range." The first two measures correspond to the ones employed in this study. On the other hand, we did not use the 'range' measure since the maximum price change is determined by the price limit itself.

$$avg.\ dispersion = E[\ |e_{t+1}|\ |\Phi_t\ ] \tag{4.8}$$

where the forecasting error e_{t+1} is price changes adjusted by the magnitude of price overshooting, that is, $e_{t+1} = \Delta p_{t,t+1} - k_u(k_l)$. The bias which may be introduced by price overshooting is also excluded in the average dispersion as in the conditional standard deviation. Compared to the conditional standard deviation which is sensitive to a few observations of large price changes, the average dispersion measure has the advantage that it is less affected by those observations. Consideration of the two volatility measures above will tell us whether market uncertainty has increased or decreased due to the existence of circuit breakers.

Chapter 5.

Data

5.1. The Korean Stock Market and Price Limits

Korean stock market data were used to evaluate the effect of circuit breakers on price behavior. As mentioned in the literature review (Chapter 2), the existing empirical studies of circuit breakers have been limited by data problems. In this context, use of Korean stock market data has the substantial advantage that it has relatively abundant observations of circuit breaker triggered events.

The Korean Stock Exchange (the Exchange) is the only stock exchange authorized in Korea. The Exchange market operates on an order-driven system and is best described as an auction market.[40] Its micro-structure is quite different from American or British exchanges where there are specialists who act as market makers. All bids and offers are brought to the Exchange, but it plays no role in market making. All orders are executed on the market according to a certain set of auction rules based on the principles of "price," "time" and "size" priority. The time priority principle is that the highest bid and the lowest offer have the precedence over all others. When bids and offers are made at the same price, the earliest one takes priority over those delivered later. Among simultaneous bids and offers at the same price, precedence is given to the largest order. Trading is conducted during two sessions each day (a morning session from 09:40 to 11:40, and an afternoon session from 13:20 to 15:20)

[40]For details of the Korean stock market including its price limits system, see Korea Stock Exchange (1992).

and according to two types of auction method, a call and continuous auction. Once the opening price in each session is established by the call auction, stocks are traded on a continuous basis during the remainder of the session.

The Exchange introduced a price limit system in the early 1960s. To avoid excessive price fluctuation and to foster an orderly market, the Exchange sets a maximum daily price change based on the previous day's closing price. Unlike the circuit breakers in the United States such as trading halts in the NYSE and price limits in the CME which are triggered based on the prespecified change in the *overall market index*, price limits in the Korean Stock Exchange are applied to each individual stock. Also, both upward and downward movements are subject to price limits.

The width of the price limits varies depending on the price level. Rather than specifying the maximum price change as a certain percentage of closing price, the Exchange sets a maximum amount of change for each price level.[41] Price limits become narrower in percentage terms as stock prices become greater. Also, price limits depend on whether an issue is under special supervision by the Exchange. When an issue falls under some delisting criteria, the Exchange may designate this issue as an *administrative* issue in order to warn the investing public of its exposure to risk. Among several restrictions imposed on trading administrative issues, the Exchange establishes more restrictive price limits for their price movements. Table 5.1 summarizes the current regulation on price limits. Compared to circuit breakers in other countries, the width of the price limits is very narrow.[42] For normal issues, it ranges from 2 to 7% as a percentage of the previous day's closing price and amounts

[41]Whereas Taiwan or Thailand sets price limits by a certain percentage, price limits in Japan are prespecified as a certain amount which varies depending on the price level.
[42]Among countries in which price limits apply to individual stocks, the width of the price limits is 16% (Japan, average figure), 7% (Taiwan) and 10% (Thailand). On the other hand, trading halts in NYSE are triggered when the Index (DJIA) declines by 250 points which amount to 6-7%.

to 4.6% on the average. And it ranges from 1 to 2 percent for most administrative issues.

5.2. Description of the Data and Variables

Since price limits apply to each individual stock, we selected 30 firms out of 374 firms which were in business since Dec. 15, 1986. Table 5.2 shows the name and characteristics of each firm. They represent different industries (1 mining, 11 manufacturing, 5 construction, 9 financial services and 4 other services) and different price levels, and also include 5 administrative issues.

The sample period covers Dec. 15, 1986 to Dec. 28, 1992, giving a total of 1761 daily observations. The starting point is chosen because the current structure of price limits has been maintained since Dec. 15, 1986. Each observation consists of daily price and trading volume. As a minimum requirement for the analysis, opening and closing price series were selected. The opening price is necessary since it represents the market clearing price first determined after the price limits were triggered. The closing price series is needed to identify the price limit-triggered events. When the price difference between successive closing prices is equal to the maximum daily change specified by price limits, those trading days are recorded as a limit-triggered event.

Among the limit-triggered events, there are cases in which the price limits are triggered not only in a single day but in successive days. In the latter cases, we can identify price overshooting only after the last limit-triggered day since the others dictate the next day to be a limit-triggered event whose opening price may not be a market clearing one. To differentiate one from the other, we define a dummy variable *UPLIM (LOLIM)* to indicate the single upper (lower) limit-triggered event or the last event when the upper (lower) limit is triggered in successive days. The other events among successive limit-triggered events are denoted by *UPLIM2 (LOLIM2)*. Let us temporarily denote the limit-triggered day as one and zero otherwise. Suppose, for example, data show {0, 1, 1, 1, 0, 1, 0} for a series of trading days, indicating that price limits were triggered on day 2, 3, 4 and day 6. In this case, the limit-triggered events for day 4 and 6 are recorded as *UPLIM (LOLIM)* and those for day 2 and 3 are as *UPLIM2 (LOLIM2)* if it is the upper (lower) limit that is triggered.

There are also cases where price changes are not subject to price limits. For example, when a firm pays a dividend or raises its capital by issuing new shares which typically entails a large price swing, price limits do not apply and prices can jump freely to their market clearing level. To indicate those events, we employed a dummy variable BAD which takes a value of one whenever the daily price change is greater than the maximum specified by the price limits.[43]

[43]To be precise, we need to identify those events by investigating the past record of business activities for each individual firm. Since the BAD variable is included for the purpose of controlling outliers, we followed the above simple convention.

Chapter 6.

Empirical Findings

Based on the reasoning suggested in Chapter 4, we examine how the existence of circuit breakers affects price behavior using Korean stock market data. After providing descriptive statistics, we test the price overshooting hypothesis and also volatility implications due to circuit breakers.

In the interest of brevity, we report the results for 8 firms whose names are shown in bold characters in Table 4.2 although all 30 individual firms have been analyzed.[44] They include 1 from mining, 3 from manufacturing (including 1 administrative issue), 1 from construction and 3 from financial and other services.

6.1. Descriptive Statistics

6.1.1. Frequency of Limit Triggering

To see how frequently price limits were triggered, we first calculated the number of trading days that price limits were triggered for each individual firm during the sample period. Table 6.1 summarizes the proportion of trading days that the upper and lower limit were triggered. Due to the narrowness of price limits, the proportion of limit-triggered events for the normal issues averages out to 13.4 percent, ranging from 7.9 to 16.9 percent of 1761 daily observations. For the administrative issue (I.D.:

[44]We obtained similar results for all 30 firms although there are minor differences between industries. The results for the firms which are not reported here are available upon request.

42010), the proportion amounts to 60 percent, most of which were triggered consecutively. This indicates that price movements were severely restricted due to price limits for more than half of the sample period.

Among those limit-triggered events, the upper limits were triggered roughly twice as much as the lower limits were. This can partly be explained by the fact that the Korean stock market experienced upward price movements during the sample period with large price swings. The Korean Stock Index which was 277 on Dec. 15, 1986 ended up at 669 at the end of 1992 after reaching its highest point of 1007 on April 1989.

Certain industries such as construction (75100) and securities (88010) show a higher percentage of limit-triggered events. They are often called *leading issues* by investors in the sense that they move faster than others in response to a marketwide shock. As a result, their price movements are more volatile than others as shown later in Table 6.3 and 6.4. In order to see how the frequency of limit-triggering is related to the responsiveness to a marketwide shock, we report the market beta at the bottom of the table. Betas are frequently used to measure the sensitivity of stock prices to overall fluctuations in the market portfolio.[45] Figure 6.1 plots the proportion of the limit-triggered events and beta values for all sample firms excluding the administrative issues. As expected, the firms with bigger beta values show the higher percentage of the limit-triggered events.

We also examined whether the frequency of limit-triggering is affected by stock prices. As a stock price becomes higher, a greater proportion of limit-triggering is expected since price limits become narrower in percentage terms. Figure 6.2 shows

[45]Due to difficulties in obtaining beta estimates of each firm, I used as a proxy the industry betas to which each firm belongs from the U.S. stock market. Data are from the Value Line Industry Review which releases betas monthly estimated using the weekly data over a period of 5 years. Since changes over time are minor, I used betas released in Dec., 1993.

the stock prices and the proportion of the limit-triggered events. The administrative issues are excluded since their high percentage of limit-triggering is due to narrowly specified price limits. The result shows that the proportion of limit-triggering tends to increase as stock prices become higher, although they are dispersed.

6.1.2. Price Overshooting

In order to examine the price overshooting hypothesis, successive price changes after the limit-triggered events are calculated and compared to events where limits were not triggered. We calculated sample means of successive price changes defined in (4.6) for three events: *UPLIM*, *LOLIM* and *NO* (the event that price limits were not triggered). Table 6.2 shows how much price overshoots its equilibrium level after price limits were triggered. Significant differences in sample means between the limit-triggered events and the other events indicate that a substantial price overshooting has occurred. In the case when price limits were not triggered, sample means of successive price changes take values which are close to zero. On the other hand, the mean of successive price changes shows a significant negative bias after the upper limits were triggered and a positive bias after the lower limits were triggered. In most cases, the magnitude of price overshooting ranges from 1 to 3 percent which is substantial considering that average maximum price change is 4.6 percent. Among the limit-triggered events, the magnitude of overshooting turned out to be greater for the lower limit-triggered events than for the upper limit-triggered events.

Compared to normal issues, the administrative issue (42010) shows a smaller amount of overshooting. However, it is partly due to the more restrictive nature of price limits applied to the administrative issue. Considering that the maximum daily price change for the administrative issue is 1~2 percent for most cases, the overshooting magnitude of 0.5 percent for the daily return cannot be said to be small.

We also examined how responsiveness to a marketwide shock affects the magnitude of price overshooting. Figure 6.3 plots the sample mean of the intraday return after the limit-triggered events and market betas for each firm except the administrative issues. Greater price overshooting is observed for stocks with high betas, suggesting that prices tend to overshoot more when due to a marketwide shock.

6.1.3. Increased Volatility

To examine how the existence of price limits affects price volatility, we calculated the conditional standard deviation defined in (4.7) and the average dispersion in (4.8) after the limit-triggered events and compared those with the events where price limits were not triggered. We found the increased volatility in both measures, which suggests that volatility has substantially increased after price limits were triggered.

Table 6.3 reports the conditional standard deviation of successive price changes after each event. Reflecting the fact that variances are an increasing function of time intervals, the conditional standard deviation was shown to be greater with longer time interval.[46] In all cases except the administrative issue, standard deviations of intraday, daily and weekly returns are greater after the limit triggered events. Roughly speaking, price volatility increased more than 20 percent after price limits were triggered. One exception is the administrative issue (42010), for which volatility

[46]When a discrete-time process $\{X_t\}$ follows a random walk (with drift), its variance is an increasing function of time intervals. That is, $Var(X_t) = t \cdot \sigma^2$ where σ^2 is the variance of random errors. The best-known examples of time series which behave like random walks are share prices on successive days, as is the case for this study.

becomes smaller in the case of the daily and weekly return. However, less volatility for the administrative issue after the limit-triggered events is mainly due to the fact that price limits are consecutively triggered in most cases as shown in Table 6.1. The very restrictive nature of price limits for the administrative issues dictates successive price movements in the same direction, which brings a decrease in volatility.[47]

Among the limit-triggered events, the lower limit-triggered events are found to be associated with greater volatility than the upper limit-triggered events. This indicates that people become more worried when they are confronted with a negative shock. Alternatively, we can interpret it as being due to the gravitational effect. When price approaches the lower limit, those who are liquidity-constrained will be afraid of being locked into their position and expedite their selling activities. Such an increase in noise-based trading will bring additional uncertainty since value traders find it more difficult to disentangle signal from noise, resulting in greater volatility after the lower limit-triggered events.

Average dispersion for intraday, daily and weekly returns is reported in Table 6.4. In order to exclude bias due to price overshooting, we deducted the bias reported in Table 6.2 from the original successive price change series and calculated the mean absolute error for the adjusted series.[48] Similar patterns to those of the conditional standard deviation are exhibited. Average dispersion for the limit-triggered events are more than 30 percent greater than the case when price limits were not triggered. And also, lower limit-triggered events showed greater dispersion than upper limit-triggered events.

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[47]For example, consider the extreme case when a maximum price change is close to zero. Price limits will be triggered in most trading days and one can observe decreased volatility after the limit-triggered event.

[48]By doing this, we can guarantee a zero mean for a successive price change series. We also calculated the average absolute value for the original price difference series. Reflecting the bias due to price overshooting, the dispersion was slightly greater in all events than the one reported in Table 4.6.

We plot the conditional standard deviations and market betas to see how the responsiveness to a marketwide shock affects price volatility. The vertical axis represents the ratio of the conditional standard deviations of the limit-triggered events compared to those of non-limit triggered events for the intraday return. Figure 6.4 tells us that price volatility has no clear relation to betas.[49] Although the absolute magnitude of conditional volatility is greater for limit-triggered events, its relative magnitude compared with non-triggered events is not affected by betas. Also, it can be easily confirmed from the figure that price volatility for lower limit-triggered events is greater than that for upper limit-triggered events.

6.1.4. Distribution of Price Changes

The above evidence of increased volatility together with price overshooting can be more clearly identified by relying on the figure. We chose three firms which represent different industries, one from manufacturing (28550), one from construction (75100) and one from financial services sector (88010). Figure 6.5a, 6.5b and 6.5c exhibit the distribution of daily returns after each event for three firms. When price limits were not triggered, daily returns are distributed symmetrically around zero. However, a significant negative (positive) bias in mean is observed in all three cases after the upper (lower) limit-triggered events. Also, it can be easily observed that the limit-triggered events are associated with greater volatility.

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[49]When the conditional volatility itself rather than the ratio is plotted on the vertical axis, a positive relation between volatility and beta is observed.

6.2. Estimation Method and Results

6.2.1. Test of Price Overshooting

To test the empirical validity of the price overshooting hypothesis more formally, we run several regressions based on (4.5). It follows from (4.5) that

$$R_t = \beta_0 + \beta_1 \cdot UPLIM_{t-1} + \beta_2 \cdot LOLIM_{t-1} + \varepsilon_t \tag{6.1}$$

where R_t denotes successive price changes in percentage terms. If price overshooting has occurred, the coefficient on the *UPLIM* dummy will take a significant negative sign while the coefficient will be positive for the *LOLIM* dummy.

Several explanatory variables are included in (6.1) to control for other effects besides circuit breakers. The dummy variables indicating the consecutive limit triggered events and the events where price limits do not apply (*UPLIM2, LOLIM2* and *BAD*) are included. We included lagged return variables considering the empirical evidence that short-horizon returns for individual securities are negatively autocorrelated. (Lo and MacKinlay (1988) and Conrad, Kaul and Nimalendran (1991)) Trading volume is included to control for its possible effect on returns. The expanded equation is given as follows:

$$\begin{aligned} R_t = {} & \beta_0 + \beta_1 \cdot UPLIM_{t-1} + \beta_2 \cdot LOLIM_{t-1} + \beta_3 \cdot UPLIM2_{t-1} + \beta_4 \cdot LOLIM2_{t-1} \\ & + \beta_5 \cdot BAD_t + \beta_6 \cdot VOL_t + \sum_{j=1} \gamma_{t-j} R_{t-j} + \varepsilon_t \end{aligned} \tag{6.2}$$

Based on (6.2), the intraday, daily and weekly returns are regressed on the above set of explanatory variables, which generates three separate equations. The same explanatory variables are used except for some minor changes in the lagged return and volume series. In a regression with *IR* (Intraday Return) as a regressed variable, lagged return variables include *OR* (Overnight Return) which is the immediate past return and IR_{t-1}. For equations with *DR* (Daily Return) and *WR* (Weekly Return) as dependent variables, we included the first lag of the dependent variable.[50] Whereas daily trading volume series (*VOL*) are included in the regression of *IR* and *DR*, the weekly moving average of trading volume series (*WVOL*) is used in the regression for weekly return. The three regression equations being run for the test of price overshooting are given as follows:

$$\begin{aligned} IR_t = \beta_0 + \beta_1 \cdot UPLIM_{t-1} + \beta_2 \cdot LOLIM_{t-1} + \beta_3 \cdot UPLIM2_{t-1} + \beta_4 \cdot LOLIM2_{t-1} \\ + \beta_5 \cdot BAD_t + \beta_6 \cdot IR_{t-1} + \beta_7 \cdot OR_{t-1} + \beta_8 \cdot VOL_t + \varepsilon_t \end{aligned} \tag{6.3a}$$

$$\begin{aligned} DR_t = \beta_0 + \beta_1 \cdot UPLIM_{t-1} + \beta_2 \cdot LOLIM_{t-1} + \beta_3 \cdot UPLIM2_{t-1} + \beta_4 \cdot LOLIM2_{t-1} \\ + \beta_5 \cdot BAD_t + \beta_6 \cdot DR_{t-1} + \beta_7 \cdot VOL_t + \varepsilon_t \end{aligned} \tag{6.3b}$$

$$\begin{aligned} WR_t = \beta_0 + \beta_1 \cdot UPLIM_{t-1} + \beta_2 \cdot LOLIM_{t-1} + \beta_3 \cdot UPLIM2_{t-1} + \beta_4 \cdot LOLIM2_{t-1} \\ + \beta_5 \cdot BAD_t + \beta_6 \cdot WR_{t-6} + \beta_7 \cdot WVOL_t + \varepsilon_t \end{aligned} \tag{6.3c}$$

where $OR_t = (OPEN_{t+1} - CLOSE_t) / CLOSE_t$ and $WVOL_t = \sum_{i=0}^{5} VOL_{t+j}$.

If the price overshooting hypothesis is true, *UPLIM* and *LOLIM* will have significant negative and positive coefficient in all of the above equations. Since *UPLIM2* (*LOLIM2*) are dummies indicating the events that the upper (lower) limits

[50]It is possible that returns are autocorrelated with lags of order higher than one. However, in the estimated equations, coefficients at higher lags than one turn out to be insignificant in most cases. Although there are cases where coefficients at higher lags are significant, those lags are different for each individual firm. Since omission of higher lags did not change the results significantly, only the first lag of the dependent variable is included in the regression equation.

are triggered both today and the next day, their coefficients will be positive (negative). The coefficients on the past return variables are expected to have a negative sign if negative autocorrelation in short-horizon return exists.

Tables 6.5a, 6.5b and 6.5c report the regression results for the equations (6.3a) to (6.3c). Whereas (6.3a) and (6.3b) are estimated by OLS, the regression equation for weekly return, (6.3c), is estimated by Cochrane and Orcutt's iterative procedure.[51] Since we used daily data for individual stock, R^2 is relatively small in the intraday and daily returns. However, the better fit is obtained in the regression of weekly returns.

Similar to the results shown in the descriptive statistics, coefficients on *UPLIM* and *LOLIM* have the expected and significant signs in all equations. Although the magnitude of price overshooting differs for individual firms, it does range from one to two percent in most cases, which is a substantial amount. Even for the administrative issues where price limits are narrowly specified, the price overshooting phenomenon is observed to hold although its magnitude is smaller.

The coefficients for *UPLIM2 (LOLIM2)* for the intraday and daily returns also have positive (negative) sign, which is dictated by its nature, and all of them are statistically significant. On the other hand, it can be observed that the coefficients for weekly returns have the opposite sign compared to those for intraday and daily returns. Note that *UPLIM2* (*LOLIM2*) is a dummy indicating the event that the upper (lower) limit is consecutively triggered for two days or more. Consecutive triggering of the price limit may cause people to hold more optimistic beliefs than for the single limit-triggered event and the magnitude of overshooting may be greater. Although the *UPLIM2* (*LOLIM2*) dummy dictates the *next day's* price to move in the same

[51]We conducted the Lagrange multiplier test suggested by Breusch-Godfrey (1978) to detect the possible autocorrelation. Whereas we could not reject the null hypothesis of no autocorrelation for Eq. (6.3a) and (6.3b), severe first order autocorrelation was found for Eq. (6.3c).

direction, greater overshooting for the successive limit-triggered events dominates the first day's effect as time passes, which causes the above reversion in signs.

The negative coefficients of the contemporaneous dummy *BAD* for intraday and daily return indicate that price declines due to issuance of new shares or payoff of dividends are not completely reflected in the daily opening price, but those coefficients are not significant for daily returns. For weekly returns, it takes on a positive sign indicating there was a tendency for price change due to those events to move toward the initial prices as time passes.

The negative significant coefficients of the immediate past returns suggest the possibility of mean reversion in short-horizon expected returns. This is consistent with the empirical findings by Lo and MacKinley (1988) and Conrad, Kaul and Nimalendran (1991). These authors find that whereas the weekly and monthly *portfolio* returns are strongly positively autocorrelated, *individual security* returns are negatively autocorrelated.[52]

Trading volume is found to have a positive correlation with successive price changes in all equations. This indicates that price tends to rise when trading volume is heavy.

6.2.2. Convergence Pattern

We also examined how rapidly the overshot price converges to an equilibrium by employing an unrestricted, finite distributed lag model. Lagged values of the *UPLIM* and *LOLIM* dummies are included in (6.3b), the regression equation for daily

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[52]To explain the different time-series properties of portfolio and individual securities, Lo and MacKinley (1988) suggest that idiosyncratic market microstructure effects causing a negative autocorrelation are diversified away and dominated by a positively autocorrelated common component in the case of portfolios.

returns. Appropriate lag length is chosen to be 7 for both dummies, which shows how the overshot price converges over about one week.[53]

$$DR_t = \beta_0 + \sum_{i=1}^{7} \beta_i \cdot UPLIM_{t-i} + \sum_{j=1}^{7} \gamma_j \cdot LOLIM_{t-j} + \lambda_1 \cdot UPLIM2_{t-1} + \lambda_2 \cdot LOLIM2_{t-1} + \lambda_3 \cdot BAD_t + \lambda_4 \cdot DR_{t-1} + \lambda_5 \cdot VOL_t + \varepsilon_t \qquad (6.4)$$

Table 6.6 summarizes the regression results based on OLS. The results including the first lag of *UPLIM* and *LOLIM* are almost the same as those reported in Table 6.5b. Regarding the distribution of lag coefficients for *UPLIM* and *LOLIM*, the coefficients of lags higher than 2 are statistically insignificant in most cases. This suggests that the overshot price nearly approaches its equilibrium level within one or two days. Also, it is found that the overshot prices converges more rapidly for the lower limit-triggered event than for the upper limit-triggered event.

In order to compare convergence patterns of the upper and lower limit-triggered events, we averaged the coefficients of 8 individual firms at each lag. Figure 6.6 presents the distribution of lag coefficients for the upper and lower limit-triggered events. The vertical axis refers to the average coefficients for each lag of *UPLIM* and *LOLIM* dummies. In the case of the upper limit-triggered events, price converges smoothly to the equilibrium level but it takes almost one week. On the other hand, the lower limit-triggered events converges relatively quickly but with fluctuation. Although the convergence patterns shown in Figure 6.6 are based on the average value of 8 individual firms, they are representative of individual stocks shown in Table 6.6.

[53]We applied Akaike's information criterion (AIC) and also the Schwarz criterion to determine the appropriate lag length. Although it turned out to be 2 to 3 in many cases, it differs for each individual firm. Since we have a large number of observations, we chose a lag length of 7, which allows us to see the convergence pattern over about a week.

6.2.3. Volatility Test

A variant of the Autoregressive Conditional Heteroscedastic (ARCH) model is employed to examine how the existence of price limits affects price volatility. It has long been recognized that speculative asset prices have the characteristic of time-varying volatility.[54] For example, large and small forecast errors appear to occur in clusters, suggesting a form of heteroscedasticity where the variance of the forecast errors depends on the size of the preceding disturbances. The ARCH model introduced in Engle (1982) explicitly recognizes this type of temporal dependence. According to the ARCH model, the conditional error distribution is normal, but with conditional variance equal to a linear function of past squared errors. Thus, there is a tendency for extreme values to be followed by other extreme values, but of unpredictable sign.

To analyze the volatility effect of circuit breakers, we first introduce a simple version of the ARCH model which is given as follows:[55]

$$\begin{aligned} R_t &= \beta' X_t + \varepsilon_t \\ E[\varepsilon_t^2 | \Phi_{t-1}] &= \alpha_0 + \alpha_1 \cdot \varepsilon_{t-1}^2 \end{aligned} \qquad (6.5)$$

where the first equation in (6.5) is a replication of (6.3a) to (6.3c). Equation (6.5) says that *conditional on an information set* Φ_{t-1}, ε_t is heteroscedastic.

In addition to the preceding disturbances, limit-triggered events would be another source of heteroscedasticity if circuit breakers affect price volatility. That is, if

[54] For an application of an ARCH model to analyze speculative asset prices, see Bollerslev (1987).
[55] To guarantee positivity of conditional variances, the second equation of (6.5) can be modelled as an exponential function, that is, $E[\varepsilon_t^2 | \Phi_{t-1}] = e^{\alpha_0 + \alpha_1 \cdot \varepsilon_{t-1}^2}$. Considering the estimation results shown in Table 6.7a to 6.7c, positive conditional variances are achieved also by the specification in (6.5).

price volatility has increased after price limits were triggered, then the conditional variance will have a positive correlation with the dummy variables indicating limit-triggered events. The systematic difference in conditional variances due to triggering the price limit can be captured by including the dummy variables indicating limit-triggered events into the second equation in (6.5).

$$E[\varepsilon_t^2 | \Phi_{t-1}] = \alpha_0 + \alpha_1 \cdot UPLIM_{t-1} + \alpha_2 \cdot LOLIM_{t-1} + \alpha_3 \cdot \varepsilon_{t-1}^2 \tag{6.6}$$

Both the *UPLIM* and *LOLIM* dummies are included since price volatility after the upper limit-triggered events may differ from price volatility after lower limit-triggered events. Equation (6.6) gives the following regression equation.

$$e_t^2 = \alpha_0 + \alpha_1 \cdot UPLIM_{t-1} + \alpha_2 \cdot LOLIM_{t-1} + \alpha_3 \cdot e_{t-1}^2 + u_t \tag{6.7}$$

where u_t is white noise and e_t^2 is the squared residual from the regressions of (6.3a) to (6.3c).

We run equation (6.7) for intraday, daily and weekly returns.[56] The regression results are reported in Table 6.7a, 6.7b and 6.7c. First of all, the ARCH effect is detected in all three equations. The coefficient on the previous squared residuals is positive and significant for most individual firms, suggesting that large forecast errors tend to be followed by other large forecast errors. This result is consistent with other empirical findings based on ARCH models. For example, Bollerslev (1987), using several stock price indices and foreign exchange rate data, also found a significant positive coefficient of the previous squared residuals.

[56] In estimating Eq. (6.7) for weekly return, we used e_{t-6}^2 instead of e_{t-1}^2 since e_{t-6}^2 corresponds to the squared residual of the previous disturbance in the case of weekly return.

Regarding the effect of price limits on price volatility, the results show that price volatility has increased after either price limit was triggered. Almost all the coefficients on the *UPLIM* and *LOLIM* dummies turned out to be positive although there are cases where they were insignificant. The exception is for the administrative issue (42010). The coefficients on the limit-triggered events for the administrative issue take a negative sign for the case of daily and weekly volatility. However, they are all insignificant.[57]

Also, it is found that price movements become more volatile after lower limit-triggered events than upper limit-triggered events. This is possibly due to the gravitational effect caused by the existence of circuit breakers. Or it may be caused by the selling activities of traders who need to meet margin requirements. Compared to upward price movements where there would be no "involuntary" counterparts, price declines are inevitably associated with more noise-based trading, thereby adding uncertainty to the market.

We conducted an F-test for the following hypothesis that price limits do not affect price volatility.

$$H_0\colon \alpha_1 = \alpha_2 = 0$$

The 5% critical value from the F-table with 2 and 1750 degrees of freedom is about 3.0 and the observed F is higher than 3 in about half of all the cases. This indicates that the existence of price limits impairs the price discovery process rather than facilitating it. Additionally, *t*-tests reveal that at least one of two dummies is significant in most of the cases.

[57]This result is consistent with what we observe in the descriptive statistics.

In sum, we conclude that price limits do not moderate price volatility. On the contrary, the above evidence of increased volatility together with price overshooting suggests that price limits introduce another source of uncertainty and confusion to the market, casting doubt on the presumed role and rationale of circuit breakers.

6.3. Discussion

We examined how the existence of circuit breakers affects price behavior based on Korean stock market data. The results indicate that price behavior after circuit breakers were triggered is systematically different from price behavior when circuit breakers were not triggered. Significant negative (positive) bias in price movements are detected after the upper (lower) circuit breaker bound was triggered, which is consistent with the price overshooting hypothesis suggested in Chapter 3. We also found that price volatility increased after circuit breakers were triggered. In sum, the existence of circuit breakers aimed at reducing price volatility destabilizes price movements, which contrasts with intentions of this type of regulation.

The evidence of increased volatility after limit-triggered events is consistent with the findings made by McMillan (1990) and Kuhn, Kuserk and Locke (1990). Using an episodic event of the mini-market crash in October 1989, both studies find that price volatility increased after circuit breakers were triggered. Compared to their studies, our findings provide more general evidence on the effect of circuit breakers. Whereas they analyzed a single historical event, this study has the advantage of being based on a large number of limit-triggered observations. Also, the price overshooting phenomenon was identified, which was not suggested by other existing studies.

Moreover, Korean stock market data allows us to examine the effect of circuit breakers not only for the lower limit-triggered event but also for the upper limit-triggered one. It is observed that the former is associated with greater overshooting and volatility than the latter, suggesting that the lower limit-triggered event may bring about further uncertainty.

The Korean stock market is different from other stock exchanges in its institutional characteristics. First, the Korean stock exchange does not have market makers. It may be possible that market makers with superior access to market information can stabilize price movements from an unexpected large shock by invoking circuit breakers. However, if people hold more optimistic (pessimistic) beliefs owing to the triggering of circuit breakers and submit orders based on such beliefs, it inevitably causes large price changes. Not only can market makers indistinguish noise trading from information-based trading, but also any attempt to maintain stable prices in such a situation may exhaust their capital.

Empirical evidence reported by Roll (1989) indicates that it makes no difference whether or not there are market makers. He investigates whether institutional market characteristics, including the existence of official specialists, affected market performance during the international market crash in 1987 and found that none of the institutional market characteristics remains even marginally significant. Also, note that the findings made by McMillan (1990) and Kuhn, Kuserk and Locke (1990) are based on a market where market makers exist. Their findings of increased volatility after the triggering of circuit breakers are consistent with the results of this study.

Another important difference is that the price limits in the Korean stock market are applied to each individual stock whereas circuit breakers in other exchanges such as the NYSE are triggered upon the prespecified change in the overall market index. However, the triggering of circuit breakers in the latter case may cause more uncertainty in the market since people may become more skittish when large price declines are observed for all other stocks as well as stocks they hold. Since large price changes of the market portfolio are more likely due to a marketwide shock, we examined whether a marketwide shock makes a difference in price behavior after the limit-triggered events by comparing each firm's "beta" to its performance. Our results show that greater price overshooting occurs with higher "beta" stocks. Although this evidence is only indirect, it suggests that the adverse effect of circuit breakers found in this study also applies to the case where their triggering depends on changes in the market index.

Chapter 7.

Policy Implication: Why Do We Need Circuit Breakers?

The evidence of the previous chapters casts doubt on the rationale for circuit breakers. We should reexamine the presumed benefits and costs of circuit breakers based on the above results. The existing arguments for circuit breakers can be broken down into the following although they are related to each other.

The first argument addresses psychological reasons. That is, circuit breakers may provide a cooling-off period and thereby prevent panic trading from spreading into the market. If circuit breakers help to restore investor confidence and prevent panic trading, a lower level of price volatility would be observed after circuit breakers are triggered. However, our results do not support such an argument. On the contrary, price movements became more volatile after circuit breakers are triggered. Moreover, the price overshooting phenomenon suggests that the existence of circuit breakers itself caused otherwise well-behaved traders to hold more optimistic or pessimistic beliefs. Evidence against circuit breakers can also be found from the October market crash (NYSE) in 1987. Following Friday, October 16 when the market fell by 6 percent, there was a natural circuit breaker (the weekend of October 17 and 18) which might have provided a cooling-off period. However, when the market reopened on October 19, massive selling pressure left the market with a 23 percent drop on that day. Two days of cool reflection only intensified the selling panic rather than reassuring investors.[58] This evidence together with our findings suggest that the

[58]For a detailed description of the October market crash, see the Brady Report (1988), pp. 141-172.

purely psychological arguments for circuit breakers are at best tenuous.

The second argument for circuit breakers is that they reduce credit risks which can amplify feedback effects of price movements. Most exchanges allow traders to purchase securities by putting up only a portion of the amount purchased, and also require them to maintain the margin requirements.[59] If a customer's margin account equity falls below these requirements, the customer is required to put up more margin or securities are sold either by the customer or by the broker. In cases of large, sudden price drop, margin calls may force traders to dump their shares on the market, causing prices to drop further. Similar to the argument of bank runs, acceleration of such a process can lead to further credit risks and loss of financial confidence, which may result in frenetic trading. In the presence of such built-in market amplifiers, circuit breakers can prevent or retard the endogenous amplifying feedback effects by providing time for intraday margin calls to be made and for margin payments to be collected.

Since our empirical findings are based on the case where circuit breakers are narrowly specified, the beneficial effect of circuit breakers due to credit risks may not be ruly appraised. However, the evidence of greater volatility after the lower limit-triggered event compared to the upper limit-triggered event may suggest that the adverse effects related to margin requirements are present in the market. Compared to upward price movements where there would be no "involuntary" counterpart, price declines cause traders to adjust their positions, thereby putting further downward pressure on price movements. In this context, the second argument for circuit breakers

[59]Margin, in popular usage, is the amount put up by the investor using credit to buy securities. Different stock exchanges maintain their own margin requirements. For example, the NYSE sets requirements for the maintenance of margins so that a customer's margin account equity may at no time be less than 25% of the current market value of the stocks or marginable convertible bonds carried. For details, see the Fact Book of the NYSE (1992) pp. 68-69.

is considered to be strongly grounded. However, if the motive for trying circuit breakers is to break this amplifying feedback loops, there seems to be little reason to have circuit breaker bound so narrow. Circuit breaker bounds as narrow as the Korean ones are more likely to do harm than good.

The third argument comes from the possibility of failure of market making in response to a large (informationless) volume shock. In a market where market makers exist, selling orders are first absorbed by market makers who eventually transfer these orders to the ultimate value buyers. Proponents of circuit breakers argue that whereas this transmission mechanism works smoothly in normal situations, it can break down when the volume shock is large. They propose that circuit breakers might reduce this transactional risk by stimulating buyer responsiveness through a release of the market information to the public and also by relying on a batch auction to determine the opening price after a trading halt.

In evaluating this market microstructure argument, one can consider two possible cases of large price changes which are either information-based or noise-generated.[60] If price movements are based on new information, prices will approach a new equilibrium as time passes whether or not there are circuit breakers. In this situation, circuit breakers at best delay the incorporation of news into prices. Price volatility will also be pushed into later periods when circuit breakers are lifted. On the other hand, suppose that price changes are driven by uninformed panic trading. When huge orders come from one side of the market, prices will move away from what should be the equilibrium level based on fundamentals. Price movements become volatile until the panic subsides. Under such circumstances, circuit breakers might have beneficial effects on the price discovery process. For example, if panic selling is driven

[60]Such a decomposition of source of price decline is suggested by Grossman (1990) and also by Kuhn, Kuserk and Locke (1990).

by rumors which cannot be justified by fundamentals, arrival of correct information while circuit breakers are triggered can help stabilize price movements. Also, information processed while circuit breakers are in effect might induce more value traders to come into the market. If these processes help reduce transactional risks, a lower level of price volatility should be observed after circuit breakers are lifted and the market reopens.

It is possible to rely on real market data to evaluate the effectiveness of circuit breakers. Contrary to what their proponents expect, the results of price overshooting and increased volatility indicate that circuit breakers were not effective in reducing transactional risks. While this study examined a market where market makers do not exist, other findings (McMillan (1990) and Kuhn, Kuserk and Locke (1990)) which analyzed the market maker setting also provide evidence of increased volatility after circuit breakers are triggered. Although the proponents have an *informationless* volume shock in mind, it is difficult to imagine a situation in which a large price change triggering a circuit breaker bound occur without a change in fundamentals. In fairness, it is more likely that panic trading mixed with an informational shock causes large price changes. However, it is hard for traders to distinguish one motive of trading from the other. The opening of order books does not tell traders whether one-sided orders are due to noise or information. Under such circumstances, circuit breakers can make people second-guess what is going on in the market, possibly frightening them from the market rather than reassuring them. The evidence presented in this dissertation suggests that this situation is likely to occur although we cannot conclusively refute the third argument for circuit breakers.

The fourth argument is related to the limited capacity of exchanges to cope with an unexpected large volume of orders. While the market infrastructure of exchanges is designed to operate effectively for most trading volumes, peak loads exceeding the maximum capacity of exchanges are likely to occur. For example, during the October market crash of 1987, an unprecedented traffic of orders overwhelmed the existing capacity of the exchanges, creating congestion such as crossed markets, lost orders, unanswered telephones and so on. Such congestion can easily bring about additional uncertainty and confusion to the market participants, possibly precipitating further declines. In addition to the market infrastructure, the limited capital positions of market makers may provide another source of bottlenecks. The NYSE gives its specialists a monopoly franchise to trade particular stocks in return for their commitment to set a fair and orderly market such as maintaining price continuity.[61] When massive orders come from one side of the market, any attempt by a specialist to keep prices from changing more than an eighth at a time can quickly deplete his capital so that he is unable to perform his function. As noted in the Brady report (pp. 128-129), liquidity sufficient to absorb the limited selling demands of investors became an illusion of liquidity when confronted by massive selling, which ironically led traders to adopt strategies calling for liquidity far in excess of what the market could supply.

When the limited capacity of exchanges creates a bottleneck in the order flow transmission process, the market becomes closed *de facto*, which is tantamount to invoking an *ad hoc, informal* circuit breaker. Although our results showed the adverse effects of *formal* circuit breakers, such effects may become even worse when the market is closed unexpectedly. An abrupt, unexpected closing of the market due to exchange bottlenecks can make people speculate about even worse possible scenarios

[61]A measure of price continuity is the size of the price variation from one trade to the next in the same stock. According to the Fact Book of the NYSE (1992), more than 95% of all transactions occurred with no change or an 1/8 point variation in 1990 and 1991. It is one business strategy adopted by the NYSE in an effort to reduce transaction price uncertainty and thereby inducing more customers. See for details the Fact Book of the NYSE (1992) and also Stoll (1985).

than the one where the new market clearing price is just above the circuit breaker triggered point.[62] Although expansion of a system's capacity including a specialist's capital position is one possible solution, it is quite likely inefficient to set aside extra resources only to absorb the very largest volume shocks if that capital is unnecessary most of the time. In this context, an argument for circuit breakers based on the potential for institutional breakdowns seems strongly credible.

The fifth argument for circuit breakers comes from a futures market perspective in that they contribute to the efficient functioning of the exchange. Brennan (1986) shows that price limits may act as a partial substitute for margin requirements in ensuring contract performance. Also, Miller (1990) asserts that price limits exist typically in a futures market to assure clearinghouse solvency. That is, in a situation where a large sudden price change can create moral hazard for "locals," a price limit gives the clearing firm time to remove potentially insolvent traders from the floor before they accumulate further losses.[63] These arguments give a clue to why price limits have long been a standard feature of futures contracts.

The possible adverse effect of circuit breakers analyzed in this study would be smaller for futures market since the price of a derivative asset is closely related to that of its primary asset. Although the presence of price limits may prevent the price of futures from approaching its equilibrium level, the market clearing price determined in a cash market provides information about what the equilibrium price in the futures market should be. In this sense, a futures market where large sudden price changes

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[62]Hong Kong's experience during the market crash in 1987 may provide an indication of the above argument. While the Hong Kong stock market is not equipped with a formal circuit breaker, the exchange was closed from Tuesday (Oct. 20) through the end of the week. When the market reopened after the *ad hoc* market closing, prices fell dramatically by almost 28 percent on that day, making Hong Kong the worst performer during the international market crash in 1987. See Roll (1989) for the comparative performance of major stock markets in 1987.

[63]The more detailed explanation is provided in the Literature Review (Chapter 2).

might pose problems for its particular trading, clearing and settlement technology appears to have its own different rationale for instituting price limits.

The above reexamination of the existing arguments based on our results reveals that justification of circuit breakers (at least in the cash markets) is more or less related to the organizational needs of exchanges to cope with huge order flows beyond the system's capacity. The bottom line is that if circuit breakers are triggered in any way, the *formal* and *recognizable* triggering would be much better than an *ad hoc, unexpected* one in a sense that the former makes people prepared and less frightened than the latter.

Then, the question narrows down to whether circuit breakers help facilitate price discovery in other situations. The answer to this question, although vague, depends on the beliefs about the effectiveness of market mechanisms. For example, the prices revealed in a market, even one highly stressed, may offer a better inducement for counterparts to assemble than do any reopening indications issued during the trading halt (Grossman, 1990). On the other hand, there may be a situation in which government intervention can bring about a better result as proponents of circuit breakers have asserted. The existence of circuit breakers can possibly prevent market breakdown by bolstering investors confidence and breaking the negative feedback loop caused by credit risks and the possibility of clearinghouse and bank failures. However, our findings indicate that circuit breakers are, on the average, more likely to impair the price discovery process than aid it. Moreover, inefficiencies such as not being able to complete mutually beneficial trades will further increase the cost of circuit breakers. Although this evidence does not conclusively refute the potential benefits of circuit breakers, it suggests the need for more careful formulation in instituting circuit breaker mechanisms so as to minimize their disadvantages.

Chapter 8.

Summary and Concluding Remarks

After Black Monday, concerns about market breakdowns have increased and the need for circuit breakers as a device to avoid extreme short-term stock market volatility has been taken for granted. As a consequence, major exchanges including the NYSE instituted several circuit breakers to halt or limit trading in times of market stress. However, it is not clear whether the existence of circuit breakers indeed stabilize price movements. Existing studies show mixed results.

This dissertation analyzed how the existence of circuit breakers affects price behavior. Using an auction-based asset market model, we showed that in the presence of circuit breakers, prices may overshoot their equilibrium level which could have been achieved in the absence of circuit breakers. Differential information about a shock is used as the basic motive for trading and the call auction method is employed as the trading mechanism. The reasoning underlying the above price overshooting phenomenon can be summarized as follows. When there is no limit on price movements, traders receive price information as a single point. The updated beliefs based on this price information do not affect the equilibrium price. However, when the market does not clear due to the existence of circuit breakers, people deduce that the equilibrium price is beyond the circuit breaker bound. This price information causes some traders to overreact to the underlying shock and submit more aggressive bids. Although the other rational traders recognize and exploit this irrational, aggressive bidding strategy, the market clearing price as a function of both traders' bidding strategies overshoots the equilibrium value that would have been determined without circuit breakers.

We employed Korean stock market data to test whether the price overshooting hypothesis is empirically valid. Use of Korean stock market data brings a substantial advantage over other studies in the sense that it has a large number of the limit-triggered observations. Due to the narrowness of price limits, the proportion of the limit-triggered trading days amounts to about 13 percent during the sample period. The results showed that a significant negative (positive) bias in price movements are detected after the upper (lower) circuit breaker bound was triggered, suggesting that there is a substantial price overshooting. It was also found that price volatility is greater for the limit-triggered events compared to the events that price limits were not triggered. Together with price overshooting, the above evidence of increased volatility after the limit-triggered events suggests that the existence of circuit breakers aimed at facilitating the price discovery process may actually destabilize price movements.

Although our findings provide evidence against circuit breakers, they do not completely refute the presumed benefits of circuit breakers. For example, they can help reduce excess volatility in cases where price changes are caused by large supply shocks. They may also prevent possible negative externalities caused by a sudden, large price drop such as clearinghouse or bank failures. Besides, in a situation where capital markets are underdeveloped so that illegal insider trading is frequently committed and prices are easily manipulable by a few transactors, the existence of circuit breakers may be beneficial in preventing such manipulation by disseminating insider information to the public.

However, the existence of circuit breakers inevitably brings about inefficiencies into stock markets. They prevent traders from completing what they perceive to be mutually beneficial trades. Moreover, when institution-induced price overshooting occurs, the existence of circuit breakers may cause inefficient outcomes without contributing to price stability. Although there may be particular situations where circuit breakers would be beneficial, it should be noted that they are blunt instruments which, once instituted, are triggered at a prespecified price change regardless of what causes the price to change.

The results presented in this dissertation suggest that we should be more cautious in accepting the presumed benefits of circuit breakers and should fairly assess their costs. If a decision is made to institute circuit breaker mechanisms, they should be designed so as to guarantee that they are triggered only if the potential benefits are considered to well exceed their costs. This study reveals one such possibility: circuit breakers as a substitute for *ad hoc, informal* market closings.

Table 5.1: Daily Price Limits in the Korean Stock Market[a]

previous day's closing price (in Korean currency, won)	a maximum daily price change[b]			
	normal issue		administrative issue	
below 500	100	(6.7%)	10	(4.0%)
500 to 990	100	(6.7%)	20	(2.7%)
1,000 to 1,990	100	(6.7%)	30	(2.0%)
2,000 to 2,990	100	(6.7%)	40	(1.6%)
3,000 to 4,990	200	(5.0%)	50	(1.3%)
5,000 to 6,990	300	(5.0%)	100	
7,000 to 9,900	400	(5.0%)	100	
10,000 to 14,900	600	(4.8%)	100	
15,000 to 19,900	800	(5.0%)	100	
20,000 to 29,900	1,000	(4.0%)	100	
30,000 to 39,900	1,300	(3.7%)	100	
40,000 to 49,900	1,600	(3.6%)	100	
50,000 to 69,900	2,000	(3.3%)	100	
70,000 to 99,900	2,500	(2.9%)	100	
100,000 to 149,900	3,000	(2.4%)	100	
150,000 to 199,900	4,000	(2.3%)	100	
200,000 to 299,900	6,000	(2.4%)	100	
300,000 to 399,900	8,000	(2.3%)	100	
400,000 to 499,900	10,000	(2.2%)	100	
500,000 or more	12,000		100	

[a] There have been many revisions in price limits and the above describes these limits as of the end of 1992.

[b] Values in parentheses are the ratio of a maximum price change to the mid-price of each corresponding price range.

Table 5.2: A List of 30 Sample Firms[a]

Name	I.D. #	Industry	Price[b]	Others
Shinla Trading	10320	Services	23462	
Yungpung Mining	**13010**	**Mining**	**13221**	
Cheil Steel	18520	Manuf.	30100	
Doosan Foods	23010	Manuf.	14873	
Bakyang	25000	Manuf.	37360	
Taekwang Inc.	**28550**	**Manuf.**	**69545**	
Daechun Leathers	33000	Manuf.	12557	
Daedong Chemicals	33550	Manuf.	4983	Administrative
Dongsan Oil & Fat	**42010**	**Manuf.**	**6313**	Administrative
Korye Steel	54060	Manuf.	32220	
Samsung Electrics	**64530**	**Manuf.**	**36319**	
Hankook Electronics	64540	Manuf.	28316	
Hyundai Auto Inc.	67510	Manuf.	24740	
Daelim Inc.	75060	Constru.	21598	
Hanshin Construction	**75100**	**Constru.**	**11917**	
Samik Housing	75130	Constru.	4260	Administrative
Life Housing	75160	Constru.	6744	Administrative
Hanil Development	75380	Constru.	17055	
Samsung Trading	**78020**	**Services**	**21350**	
Sebang Enterprise.	82020	Services	23894	
Seyang Shipping	83030	Services	13068	
Long-Term Credit Bank	85000	Financial	20760	
First Bank of Korea	85520	Financial	12300	
Chunbuk Bank	86000	Financial	16159	
Daehan Investment Bank	87030	Financial	19203	
Donghae Investment Bank	87070	Financial	20263	
Daeshin Securities	88000	Financial	26254	
Daewoo Securities	**88010**	**Financial**	**28586**	
Anguk Insurance	**90540**	**Financial**	**44385**	
Auto Insurance	91000	Financial	9970	Administrative

[a] Firms in bold characters indicate those whose results are reported.

[b] Mean price during the sample period, expressed in Korean currency.

Table 6.1: Frequency of Limit Triggering[a]
(Proportion of Trading Days That Price Limits Were Triggered)

(%)

	10320	28550	64530	75100	78020	88010	90540	42010	Avg[b]
Upper Limit	6.3	10.2	6.8	9.8	5.5	11.6	10.8	30.3	8.7
UPLIM	3.6	4.2	4.8	6.9	3.9	8.1	6.0	9.4	5.4
UPLIM2	2.7	6.0	2.0	2.9	1.6	3.5	4.8	20.9	3.3
Lower Limit	4.2	6.3	3.5	5.2	2.5	5.3	5.4	30.5	4.7
LOLIM	3.2	3.2	3.0	4.2	2.0	4.3	3.6	9.7	3.4
LOLIM2	1.0	3.1	0.5	1.0	0.5	1.0	1.8	20.8	1.3
Total	10.5	16.5	10.3	15.1	7.9	16.9	16.2	60.8	13.4
(# of days)	185	291	181	265	139	298	285	1070	235
price (won)	13221	69545	36319	11917	21350	28586	44385	6313	
beta[c]	1.11	1.01	1.14	1.42	1.08	1.57	1.12	1.26	

[a] Values are the proportion of each event over 1761 observations.

[b] The administrative issue (42010) is excluded.

[c] This indicates the market beta of the industry to which each firm belongs. Data are from the Value Line Industry Review (1993).

Table 6.2: Magnitude of Price Overshooting[a]
(Sample Mean of Price Changes)

(%)

	Intraday Return			Daily Return			Weekly Return		
	uplim	lolim	no	uplim	lolim	no	uplim	lolim	no
13010	-2.11	1.85	0.09	-2.30	2.57	0.10	-1.35	3.53	0.50
28550	-0.68	1.21	0.06	-1.18	1.28	0.05	-0.83	2.76	0.50
64530	-1.06	1.21	0.24	-1.31	1.13	0.00	-1.33	1.04	0.00
75100	-1.57	2.30	-0.10	-1.67	3.33	0.08	0.03	4.65	0.69
78020	-0.93	0.70	0.24	-1.35	1.57	0.05	-1.72	3.82	0.26
88010	-1.50	1.20	-0.09	-1.29	1.87	0.00	-0.40	3.40	0.17
90540	-0.92	1.54	0.24	-1.09	1.53	0.00	-1.09	1.48	0.50
42010[b]	-0.08	0.04	0.00	-0.49	0.45	0.03	-0.77	0.91	0.43
Average[c]	-1.11	1.26	0.08	-1.32	1.72	0.04	-0.93	2.70	0.38

[a] 'No' indicates events where price limits were not triggered. It does not include the '*BAD*' events.

[b] Administrative issue. [c] Arithmetic average of 8 firms.

Table 6.3: The Conditional Standard Deviation of Successive Price Changes

(%)

	Intraday			Daily			Weekly		
	uplim	lolim	no	uplim	lolim	no	uplim	lolim	no
13010	2.56	3.98	2.18	3.41	4.85	3.10	8.92	10.31	6.94
28550	1.57	1.87	0.78	2.65	2.65	1.54	7.11	7.55	5.00
64530	2.27	2.17	1.69	2.94	3.06	2.39	7.64	5.60	5.31
75100	2.78	4.46	2.33	3.83	5.34	3.28	9.13	11.48	8.00
78020	2.09	2.44	1.85	2.85	3.86	2.54	6.14	6.09	5.16
88010	2.37	2.45	1.76	2.96	3.34	2.71	8.29	7.86	6.62
90540	2.30	2.23	1.63	3.08	3.17	2.52	9.13	7.72	6.43
42010[a]	0.50	0.29	0.13	1.36	1.34	1.88	5.04	4.99	6.34
Average	2.06	2.49	1.54	2.89	3.45	2.50	7.68	7.70	6.23
(ratio)[b]	1.34	1.62	1.00	1.16	1.38	1.00	1.23	1.24	1.00

[a] Administrative issue.

[b] Ratios are calculated by dividing each average value by the one when price limits were not triggered.

Table 6.4: The Conditional Average Dispersion of Successive Price Changes[a]

(%)

	Intraday Return			Daily Return			Weekly Return		
	uplim	lolim	no	uplim	lolim	no	uplim	lolim	no
13010	1.97	3.15	1.58	2.75	3.71	2.32	6.55	7.21	4.98
28550	1.11	1.57	0.25	1.98	2.12	0.80	5.11	5.42	3.15
64530	1.67	1.67	1.22	2.17	2.35	1.73	5.58	4.24	3.94
75100	2.09	3.00	1.66	2.85	3.85	2.37	7.02	9.04	5.59
78020	1.57	1.83	1.38	2.18	3.20	1.85	4.57	4.70	3.80
88010	1.87	1.92	1.28	2.23	2.67	1.89	6.25	6.44	4.87
90540	1.77	1.89	1.11	2.31	2.64	1.75	6.26	5.89	4.37
42010[b]	0.18	0.09	0.02	1.09	1.08	0.98	3.85	3.56	4.11
Average	1.53	1.89	1.06	2.20	2.70	1.71	5.65	5.81	4.35
(ratio)[c]	1.63	1.78	1.00	1.29	1.58	1.00	1.30	1.34	1.00

[a] Average dispersion is measured by the mean absolute error defined in (4.8).

[b] An administrative issue.

[c] Ratios are calculated by dividing each average value by the one when price limits were not triggered.

Table 6.5a: Test of Price Overshooting (Intraday Return)[a]

	13010	28550	64530	75100	78020	88010	90540	42010
Constant	-0.28	0.05	-0.05	-0.46	-0.15	-0.15	0.03	0.02
	(-4.31)	(2.14)	(-1.13)	(-5.90)	(-2.80)	(-2.71)	(0.66)	(0.65)
Uplim(-1)	-2.10	-0.51	-1.08	-1.27	-0.72	-1.13	-0.78	-0.09
	(-8.76)	(-4.82)	(-5.63)	(-5.24)	(-3.35)	(-6.29)	(-4.84)	(-4.80)
Lolim(-1)	1.12	1.02	0.60	1.54	0.36	1.01	1.14	0.05
	(3.69)	(8.84)	(2.66)	(5.16)	(1.26)	(4.51)	(5.86)	(2.73)
Uplim2(-1)	1.56	0.88	2.06	1.79	2.36	1.43	1.63	0.06
	(4.60)	(8.92)	(7.17)	(4.90)	(7.14)	(5.38)	(8.65)	(3.72)
Lolim2(-1)	-3.12	-0.90	-2.11	-2.03	-3.37	-1.43	-2.24	-0.03
	(-5.95)	(-7.36)	(-3.75)	(-3.48)	(-5.76)	(-3.22)	(-7.91)	(-2.22)
BAD	-3.73	-0.89	-3.39	-4.69	-3.62	-1.27	-5.96	0.06
	(-1.76)	(-2.08)	(-5.18)	(-2.79)	(-3.77)	(-1.47)	(-7.40)	(0.27)
IR(-1)	0.03	-0.01	0.03	-0.10	-0.02	-0.04	0.08	0.01
	(1.35)	(-0.67)	(1.26)	(-4.02)	(-1.04)	(-1.37)	(3.81)	(0.71)
OR(-1)	-0.44	-0.24	-0.48	-0.31	-0.56	-0.20	-0.46	-0.02
	(-15.0)	(-15.1)	(-18.6)	(-9.45)	(-22.7)	(-6.29)	(-20.3)	(-4.71)
VOL	0.04	0.01	0.02	0.01	0.03	0.001	0.04	-0.01
	(9.77)	(0.64)	(7.23)	(8.00)	(8.22)	(2.01)	(4.02)	(-1.56)
R**2	0.20	0.19	0.21	0.14	0.25	0.10	0.25	0.04
D-W	2.00	1.72	1.99	2.02	2.01	1.99	1.95	1.98

a Coefficient estimates of equation (6.3a) by OLS.
Values in parentheses are respective t-statistics.

Table 6.5b: Test of Price Overshooting (Daily Return)[a]

	13010	28550	64530	75100	78020	88010	90540	42010
Constant	-0.39	0.05	-0.23	-0.45	-0.31	-0.05	-0.05	-0.03
	(-4.10)	(1.00)	(-3.30)	(-4.09)	(-3.98)	(-0.56)	(-0.75)	(-0.46)
Uplim(-1)	-2.70	-1.21	-1.21	-1.93	-0.92	-1.28	-1.41	-0.44
	(-7.64)	(-5.84)	(-4.14)	(-5.59)	(-2.82)	(-4.67)	(-5.09)	(-3.42)
Lolim(-1)	1.63	1.20	0.67	2.53	0.68	1.81	1.32	0.33
	(3.65)	(5.26)	(1.96)	(5.95)	(1.57)	(5.31)	(3.96)	(2.62)
Uplim2(-1)	3.60	2.65	3.23	2.95	3.76	2.72	3.00	0.64
	(7.27)	(13.7)	(7.39)	(5.73)	(7.52)	(6.80)	(9.47)	(6.11)
Lolim2(-1)	-4.78	-2.08	-3.40	-3.54	-3.51	-1.67	-3.23	-0.57
	(-6.21)	(-8.66)	(-3.98)	(-4.32)	(-3.95)	(-2.47)	(-6.66)	(-5.48)
BAD	1.53	-0.16	-1.56	-5.15	-1.92	2.12	-0.34	-0.79
	(0.49)	(-0.18)	(-1.57)	(-2.15)	(-1.32)	(1.77)	(-0.26)	(-0.54)
DR(-1)	-0.12	-0.01	-0.14	-0.11	-0.25	-0.01	-0.06	0.25
	(-4.42)	(-0.61)	(-5.45)	(-4.41)	(-10.3)	(-0.38)	(-2.20)	(9.39)
VOL	0.06	0.03	0.03	0.01	0.03	0.001	0.04	0.10
	(9.17)	(1.00)	(6.24)	(7.86)	(7.26)	(0.78)	(2.90)	(2.34)
R**2	0.15	0.19	0.08	0.12	0.11	0.07	0.11	0.23
D-W	1.98	1.98	2.00	2.01	2.01	1.98	1.97	1.80

a Coefficient estimates of equation (6.5b) by OLS.
Values in parentheses are respective t-statistics.

Table 6.5c: Test of Price Overshooting (Weekly Return)

	13010	28550	64530	75100	78020	88010	90540	42010
Constant	-2.45	0.86	-1.67	-2.72	-1.83	-0.91	0.07	-0.23
	(-3.80)	(0.83)	(-3.46)	(-3.28)	(-4.14)	(-1.14)	(0.09)	(-0.21)
Uplim(-1)	-1.64	-0.65	-1.66	-1.65	-1.22	-1.45	-1.66	-0.13
	(-5.27)	(-3.13)	(-6.50)	(-5.36)	(-4.08)	(-6.43)	(-6.57)	(-1.01)
Lolim(-1)	2.66	1.16	1.16	2.23	2.76	1.68	1.31	0.06
	(6.55)	(4.95)	(3.77)	(5.68)	(6.84)	(5.72)	(4.13)	(0.51)
Uplim2(-1)	-3.11	-0.85	-2.14	-2.20	-0.94	-2.49	-0.88	-0.46
	(-5.25)	(-2.48)	(-4.62)	(-3.90)	(-1.64)	(-5.72)	(-2.14)	(-2.80)
Lolim2(-1)	0.61	0.92	2.76	1.59	3.13	3.35	1.41	0.39
	(0.80)	(2.45)	(3.30)	(1.76)	(3.24)	(4.81)	(2.68)	(2.39)
BAD	8.66	1.16	1.04	0.56	-1.20	4.57	3.64	-0.77
	(3.01)	(1.23)	(1.16)	(0.25)	(-0.73)	(4.49)	(3.08)	(-0.54)
WR(-6)[b]	-0.43	-0.45	-0.44	-0.39	-0.46	-0.40	-0.43	-0.40
	(-20.2)	(-20.9)	(-20.9)	(-17.4)	(-22.1)	(-18.1)	(-19.5)	(-17.9)
WVOL[c]	0.33	0.35	0.17	0.06	0.22	0.01	0.19	1.26
	(10.5)	(1.84)	(7.41)	(8.92)	(9.04)	(3.46)	(2.05)	(4.07)
R**2	0.74	0.86	0.72	0.75	0.69	0.78	0.79	0.90

a Coefficient estimates of equation (6.5c) by the Cochrane-Orcutt iterative procedure.
Values in parentheses are respective t-statistics.
b WR(-6) indicates the weekly return over the immediate past week.
c WVOL is a weekly moving average of the daily trading volume.

Table 6.6: Convergence Pattern for Overshooting Prices (Estimation of An Unrestricted Finite Lag Model)

	13010	28550	64530	75100	78020	88010	90540	42010
Constant	-0.31	0.03	-0.19	-0.41	-0.28	-0.08	-0.06	0.05
	(-3.08)	(0.62)	(-2.53)	(-3.45)	(-3.40)	(-0.85)	(-0.67)	(0.64)
Uplim(-1)	-2.71	-1.24	-1.17	-1.97	-0.99	-1.31	-1.38	-0.47
	(-7.66)	(-5.91)	(-3.96)	(-5.62)	(-2.99)	(-4.74)	(-4.95)	(-3.68)
Uplim(-2)	-1.23	-0.25	-0.34	-0.54	-0.51	0.25	-0.34	-0.03
	(-3.71)	(-1.23)	(-1.24)	(-1.63)	(-1.60)	(1.00)	(-1.27)	(-0.24)
Uplim(-3)	-0.30	-0.14	0.10	-0.66	-0.82	-0.31	0.21	0.12
	(-0.92)	(-0.71)	(0.37)	(-2.02)	(-2.60)	(-1.25)	(0.81)	(0.97)
Uplim(-4)	-0.18	-0.03	-0.60	-0.32	-0.90	0.08	0.09	0.16
	(-0.55)	(-0.14)	(-2.20)	(-0.97)	(-2.89)	(0.31)	(0.38)	(1.37)
Uplim(-5)	-0.62	-0.01	-0.54	0.10	-0.40	-0.19	-0.04	-0.14
	(-1.93)	(-0.03)	(-1.98)	(0.31)	(-1.27)	(-0.76)	(-0.17)	(-1.17)
Uplim(-6)	0.31	0.45	-0.09	0.30	-0.15	0.36	-0.24	-0.24
	(0.97)	(2.18)	(-0.34)	(0.92)	(-0.49)	(1.46)	(-0.93)	(-2.05)
Uplim(-7)	-0.35	0.21	0.06	-0.44	-0.14	0.10	0.48	-0.13
	(-1.07)	(1.02)	(0.23)	(-1.38)	(-0.44)	(0.40)	(1.83)	(-1.07)
Lolim(-1)	1.70	1.17	0.72	2.51	0.74	1.72	1.33	0.23
	(3.80)	(5.03)	(2.08)	(5.85)	(1.70)	(4.90)	(3.95)	(1.83)
Lolim(-2)	0.64	0.16	0.39	0.53	0.75	-0.34	-0.25	-0.13
	(1.50)	(0.70)	(1.14)	(1.29)	(1.76)	(-1.01)	(-0.74)	(-0.81)
Lolim(-3)	-0.03	-0.26	-0.09	0.30	0.06	0.12	-0.34	0.02
	(-0.08)	(-1.13)	(-0.25)	(0.71)	(0.13)	(0.35)	(-1.02)	(0.15)
Lolim(-4)	-0.12	-0.08	-0.33	-0.13	0.75	0.50	-0.13	-0.09
	(-0.27)	(-0.36)	(-0.98)	(-0.32)	(1.75)	(1.48)	(-0.38)	(-0.77)
Lolim(-5)	0.60	0.05	-0.11	0.64	0.26	0.60	0.32	-0.04
	(1.40)	(0.22)	(-0.33)	(1.54)	(0.61)	(1.78)	(0.95)	(-0.31)
Lolim(-6)	0.07	0.53	0.26	-0.25	0.62	-0.02	0.34	0.08
	(0.16)	(2.30)	(0.76)	(-0.61)	(1.44)	(-0.06)	(1.01)	(0.66)
Lolim(-7)	-1.18	-0.01	0.25	-0.67	-0.77	-0.02	0.05	0.05
	(-2.79)	(-0.04)	(0.75)	(-1.62)	(-1.78)	(-0.06)	(0.14)	(0.40)
Uplim2(-1)	3.55	2.61	3.31	2.90	3.66	2.67	3.00	0.47
	(7.14)	(13.4)	(7.52)	(5.50)	(7.24)	(6.61)	(9.43)	(4.43)
Lolim2(-1)	-4.42	-2.15	-3.40	-3.61	-2.97	-1.61	-3.31	-0.45
	(-5.71)	(-8.61)	(-3.96)	(-4.35)	(-3.29)	(-2.36)	(-6.74)	(-4.31)
Bad	1.22	-0.11	-1.68	-5.08	-2.04	2.23	-0.42	-1.08
	(0.39)	(-0.14)	(-1.69)	(-2.11)	(-1.41)	(1.85)	(-0.31)	(-0.76)
DR(-1)	-1.14	-0.02	-0.16	-0.13	-0.27	-0.003	-0.07	0.36
	(-4.94)	(-0.80)	(-5.82)	(-4.80)	(-10.6)	(-0.09)	(-2.37)	(12.8)
Volume	0.06	0.03	0.03	0.01	0.04	0.001	0.04	0.06
	(9.75)	(0.95)	(6.50)	(8.20)	(8.01)	(0.57)	(2.78)	(1.48)
RBAR**2	0.16	0.18	0.09	0.12	0.12	0.07	0.10	0.26
D-W	1.94	1.97	1.99	1.99	2.00	1.99	1.95	1.94

Table 6.7a: Volatility Test (Intraday Return)[a]

	13010	28550	64530	75100	78020	88010	90540	42010
Constant	3.76	0.58	2.20	3.53	2.59	2.88	2.03	0.02
	(18.5)	(7.52)	(18.9)	(19.0)	(20.3)	(18.4)	(16.6)	(1.73)
Uplim(-1)	1.22	1.40	1.05	0.66	0.27	1.42	1.54	0.22
	(1.57)	(3.81)	(2.12)	(0.92)	(0.46)	(2.67)	(3.28)	(5.39)
Lolim(-1)	5.76	2.12	0.34	1.26	1.63	2.01	0.88	0.06
	(5.60)	(5.16)	(0.55)	(1.30)	(1.95)	(2.89)	(1.51)	(1.44)
Ressqr(-1)	0.08	0.02	0.08	0.09	0.02	0.05	0.03	-0.01
	(3.35)	(0.72)	(3.04)	(3.41)	(0.73)	(1.86)	(1.23)	(-0.50)
R**2	0.03	0.02	0.01	0.01	0.01	0.02	0.01	0.02
F statistic	16.13	19.60	2.29	1.11	1.93	6.69	6.20	14.92

a Coefficient estimates of equation (6.7) by OLS.
Values in parentheses are respective t-statistics.

Table 6.7b: Volatility Test (Daily Return)[a]

	13010	28550	64530	75100	78020	88010	90540	42010
Constant	8.00	1.98	5.07	7.23	5.49	7.16	5.98	1.52
	(17.5)	(10.8)	(16.6)	(16.5)	(17.1)	(12.8)	(12.9)	(6.60)
Uplim(-1)	2.40	3.39	2.05	4.78	0.75	1.05	3.17	-0.87
	(1.38)	(4.03)	(1.58)	(2.85)	(0.50)	(0.55)	(1.77)	(-1.22)
Lolim(-1)	8.74	3.91	2.88	4.02	5.32	3.35	3.22	-0.98
	(3.79)	(4.15)	(1.81)	(1.78)	(2.57)	(1.33)	(1.42)	(-1.41)
Ressqr(-1)	0.12	0.20	0.08	0.09	0.09	0.03	0.04	0.31
	(4.71)	(8.44)	(3.37)	(3.75)	(3.78)	(1.03)	(1.60)	(15.9)
R**2	0.03	0.06	0.01	0.02	0.02	0.01	0.01	0.13
F statistic	7.69	16.04	2.70	5.21	3.37	0.99	2.43	1.57

a Coefficient estimates of equation (6.7) by OLS.
Values in parentheses are respective t-statistics.

Table 6.7c: Volatility Test (Weekly Return)[a]

	13010	28550	64530	75100	78020	88010	90540	42010
Constant	12.12	3.42	7.11	12.39	8.10	8.97	8.19	2.68
	(18.9)	(11.7)	(18.6)	(13.1)	(17.9)	(13.5)	(13.5)	(8.83)
Uplim(-1)	3.20	0.88	-0.29	7.71	1.48	2.07	0.29	-1.09
	(1.32)	(0.66)	(-0.18)	(2.32)	(0.72)	(0.93)	(0.13)	(-1.21)
Lolim(-1)	12.65	1.28	3.72	12.34	-0.84	4.50	7.96	-0.74
	(4.01)	(0.85)	(1.91)	(2.92)	(-0.29)	(1.70)	(2.74)	(-0.85)
Ressqr(-6)	0.07	0.27	0.08	0.19	0.08	0.12	0.14	0.34
	(2.94)	(12.7)	(3.46)	(8.29)	(3.14)	(4.93)	(5.68)	(15.1)
R**2	0.02	0.09	0.01	0.06	0.01	0.02	0.02	0.12
F statistic	8.50	0.60	1.87	6.38	0.31	1.75	3.75	0.99

a Coefficient estimates of equation (6.7) by OLS.
Values in parentheses are respective t-statistics.
Ressqr(-6) indicates the squared residual over the immediate past week.

Figure 6.1

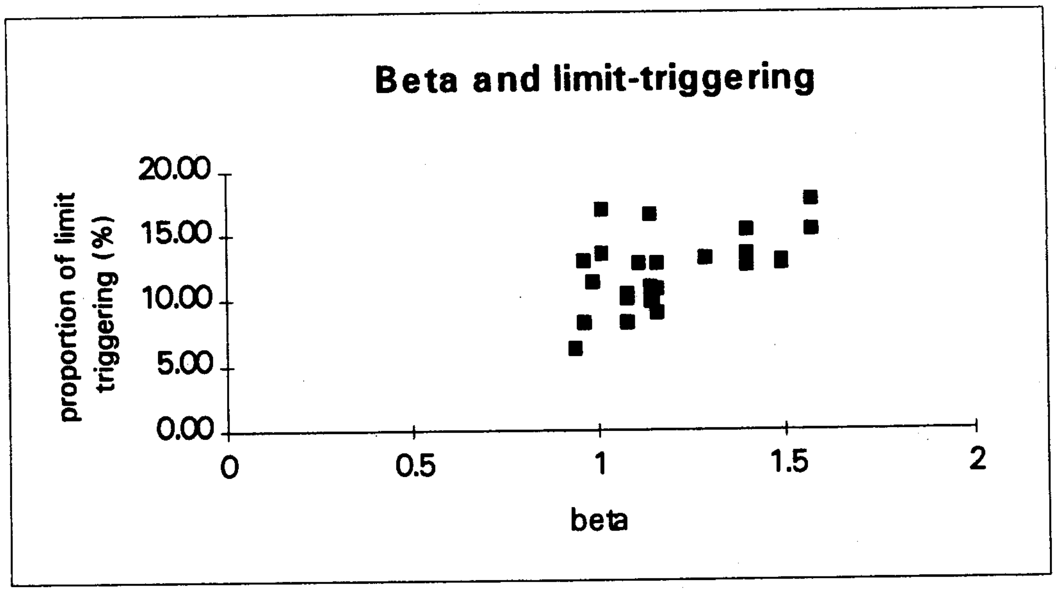


Figure 6.2

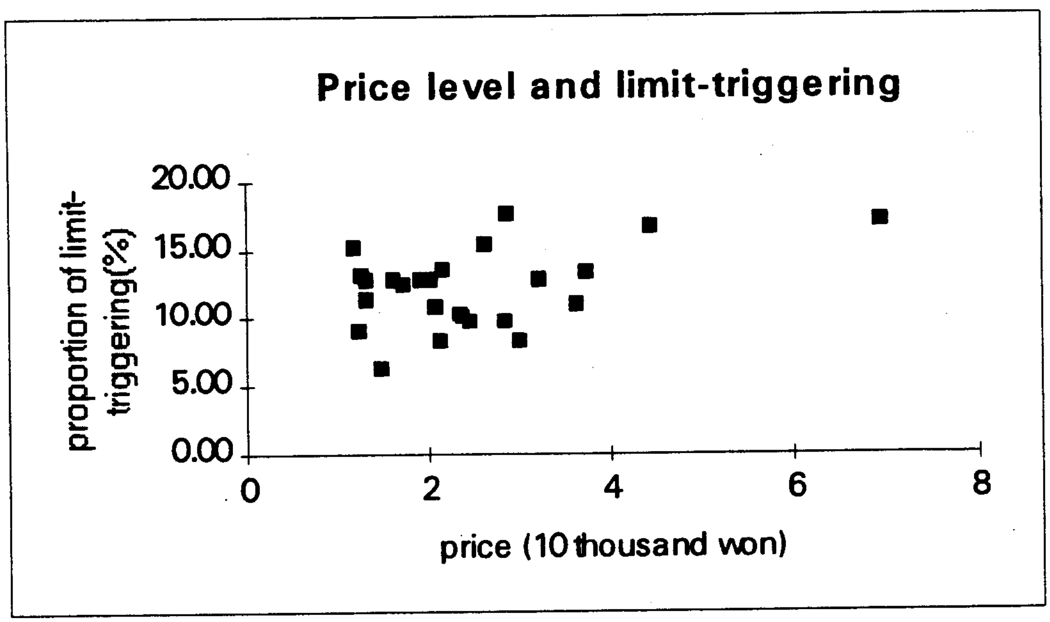


Figure 6.3

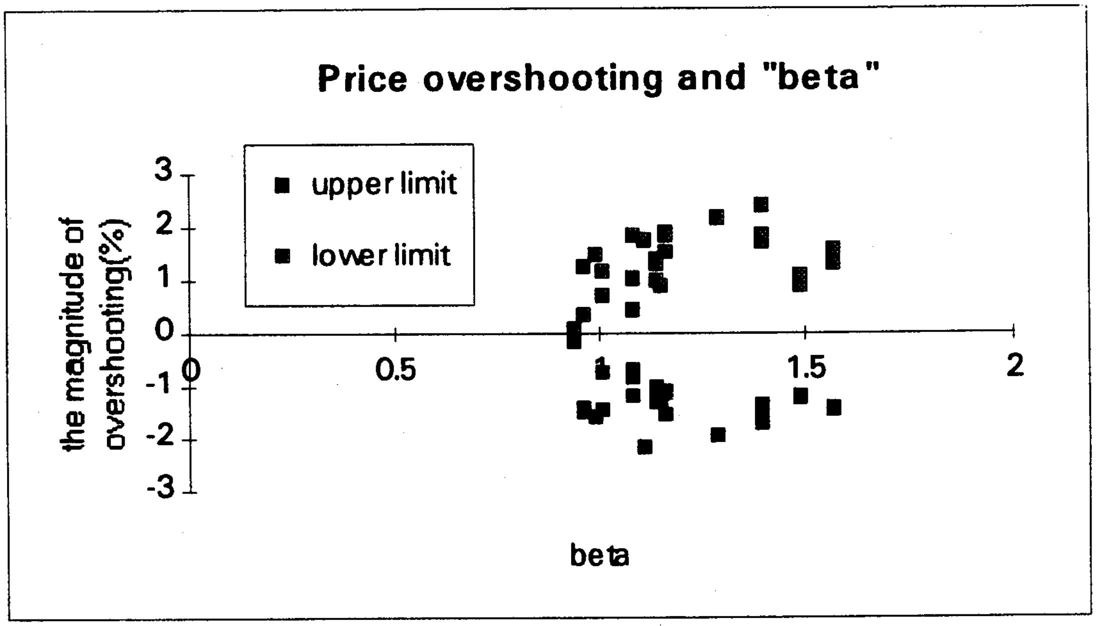


Figure 6.4

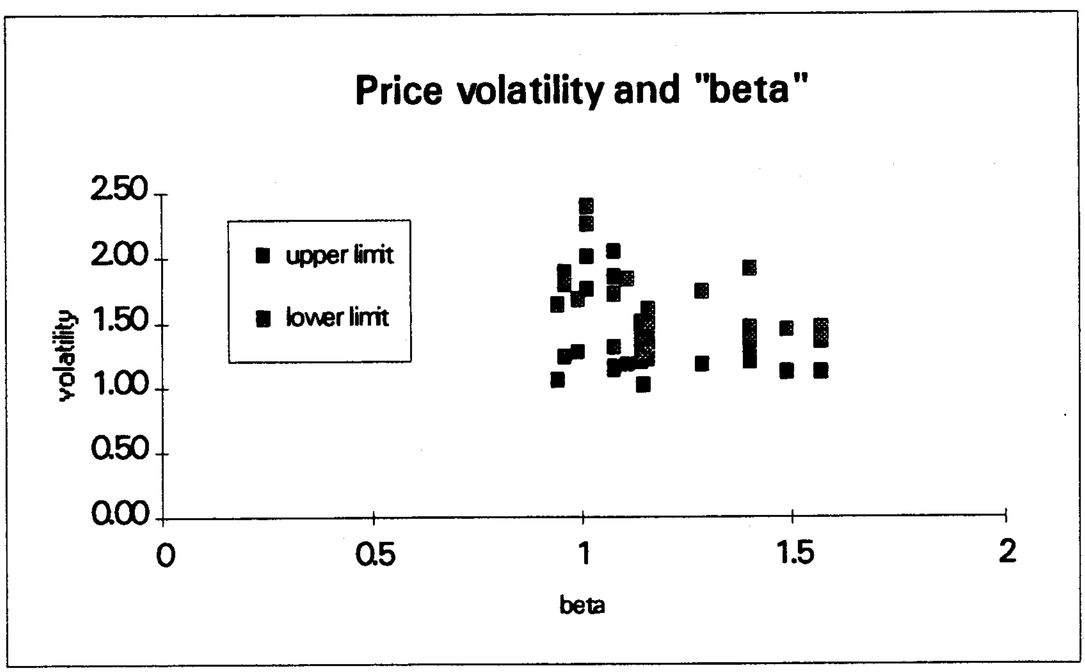


Figure 6.5a: Distribution of Daily Price Changes (Taekwang Industry (I.D. 28550))

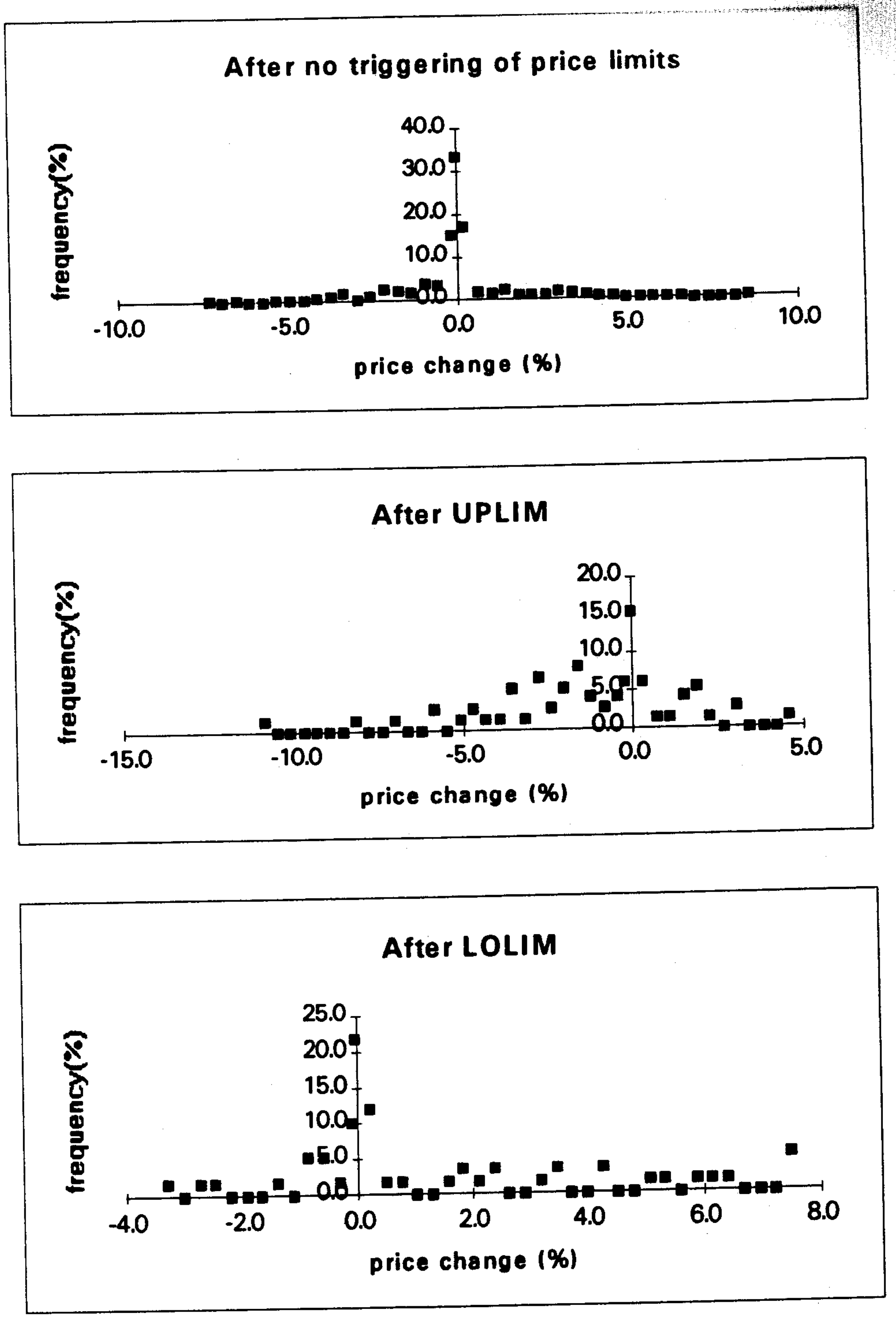


Figure 6.5b: Distribution of Daily Price Changes (Hanshin Construction (I.D. 75100))

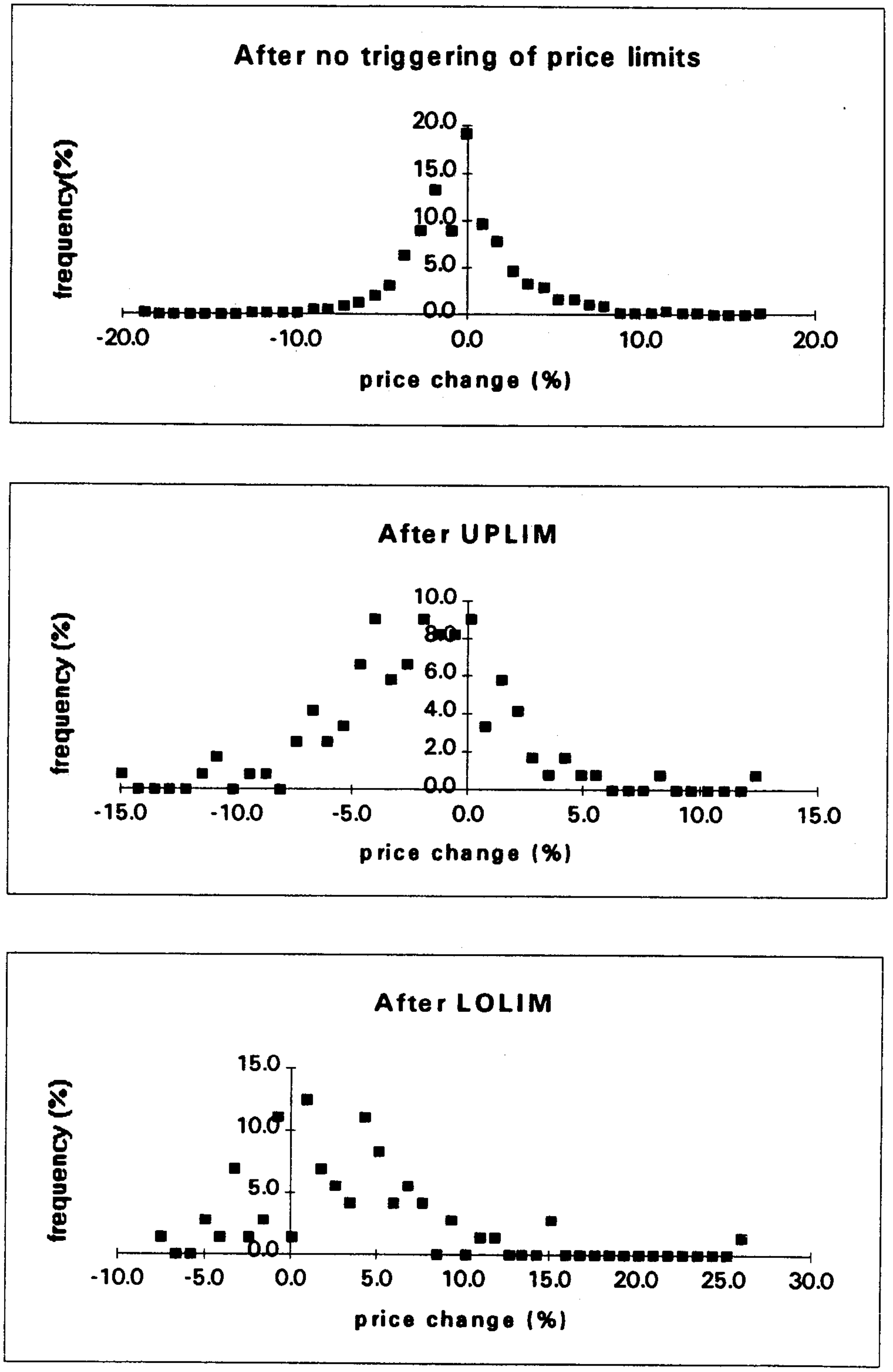


Figure 6.5c: Distribution of Daily Price Changes (Daewoo Securities (I.D. 88010))

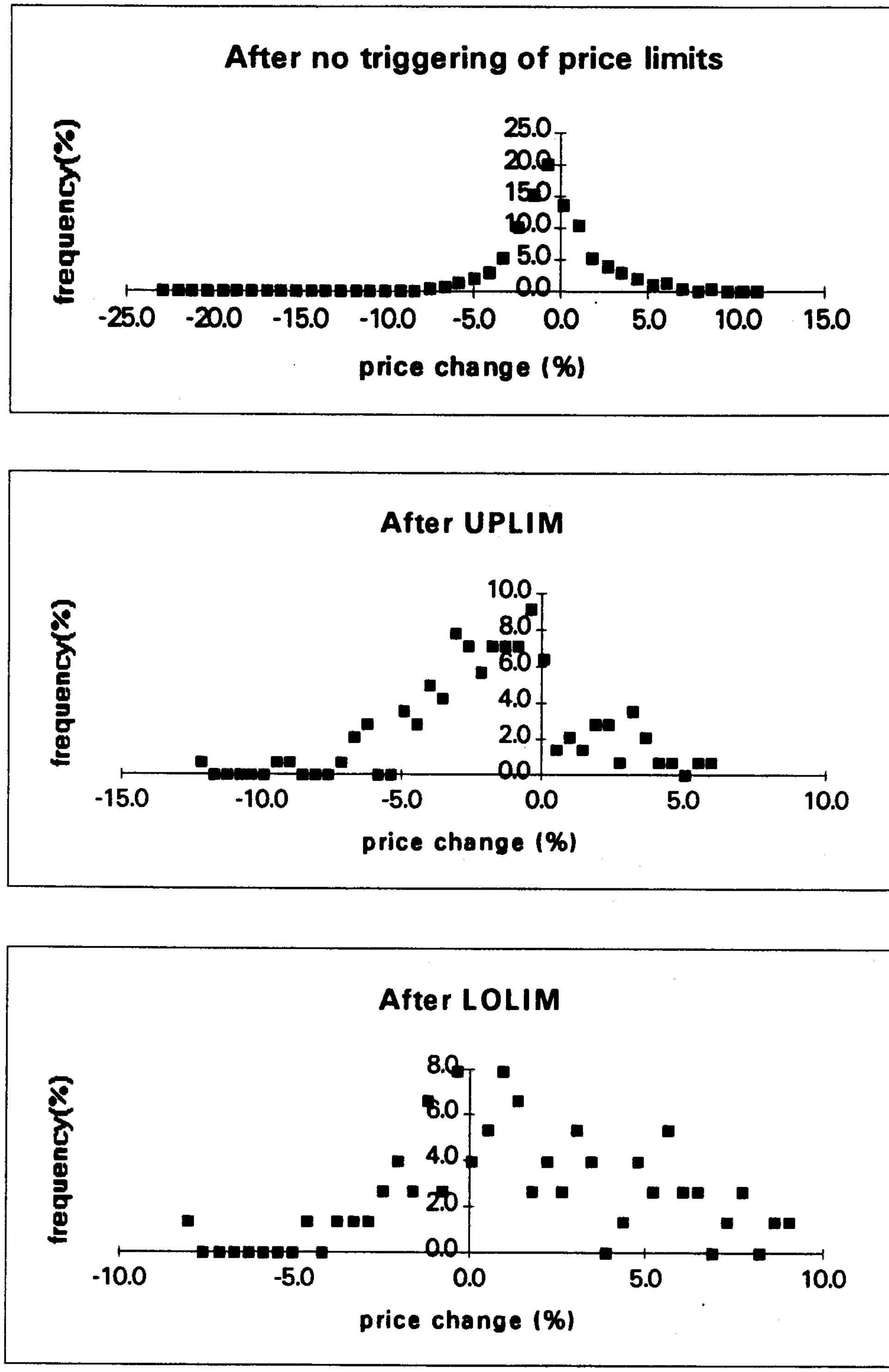
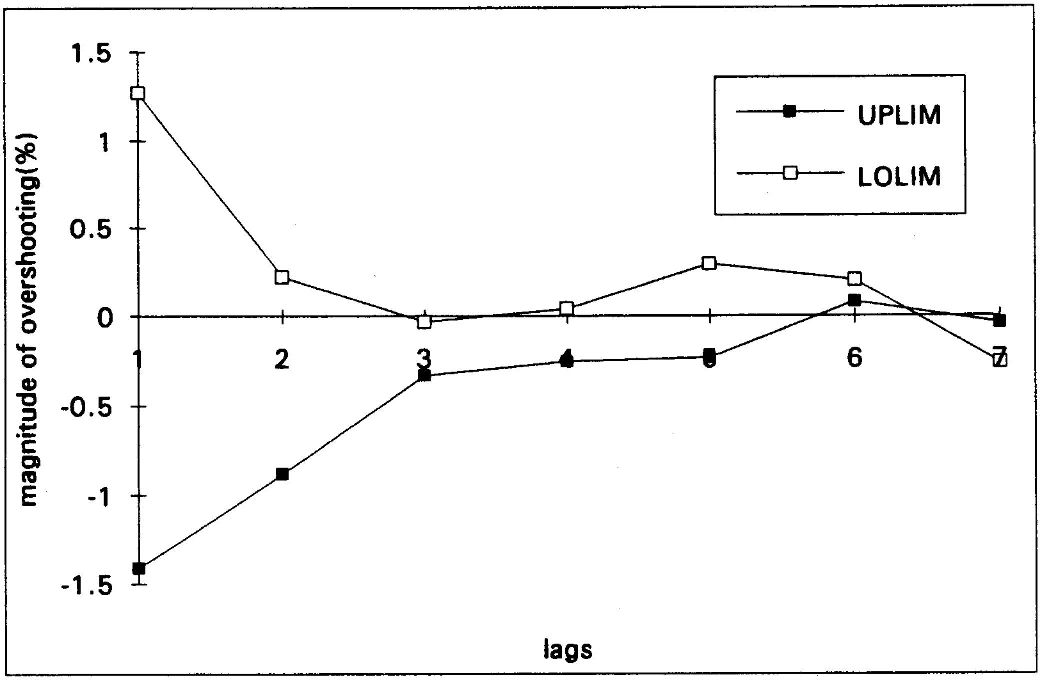


Figure 6.6: Convergence Pattern
(Distribution of Lag Coefficients for Limit-Triggered Events)



Appendix

Appendix 1 (Equivalence of the market clearing rules): Let us denote the number of shareholders (sellers) and non-shareholders (buyers) who have submitted a bid higher than the market clearing price p^* by n_s and n_b. It follows then that

	# of shareholders	# of non-shareholders
higher bids than p^*	n_s	n_b
lower bids than p^*	$M - n_s$	$n - M - n_b$
total	M	$n - M$

When the clearinghouse follows the first approach, *i.e.*, $p^* = \sup\ \{p : D(p) = S(p)\}$, market excess demand at p^* is equal to zero. That is, $n_b - (M - n_s) = 0$. When it follows the alternative approach, *i.e.*, arranging all bids in a descending order, the market clearing price is equal to the M^{th} highest bid. Since there should be M bids higher than p^*, $n_s + n_b = M$. Both approaches result in the same equation for market clearing. *Q.E.D.*

Appendix 2 (Equivalence of the buyer's and seller's strategy under price taking):
The optimal bid for buyer i in round τ given his private signal and market information Y^* is a solution to the following:

$$\underset{b}{Max}\, E[(V - p)\cdot 1_{\{b \geq p\}} \mid X_i = x, Y^*] \tag{A.1}$$

The maximization problem for seller i is

$$\underset{b}{Max}\, E[V \cdot 1_{\{b \geq p\}} + p \cdot 1_{\{b<p\}} \mid X_i = x, Y^*] \tag{A.2}$$

Since $V \cdot 1_{\{p \leq b\}} + p \cdot 1_{\{p>b\}} = V \cdot 1_{\{b \geq p\}} + p \cdot (1 - 1_{\{b \geq p\}}) = (V - p) \cdot 1_{\{b \geq p\}} + p$, it becomes

$$\underset{b}{Max}\; E[(V-p) \cdot 1_{\{b \geq p\}} \mid X_i = x, Y^*] + E[p \mid X_i = x, Y^*] \tag{A.3}$$

Since $E[p \mid X_i = x, Y^*]$ is not affected by their bid, a maximization problem (A.3) for seller i is equivalent to that for buyer i given in (A.1). Hence, the optimal bid for trader i is the same irrespective of the identity as a buyer or a seller. *Q.E.D.*

Appendix 3 (Updated bids do not change the equilibrium price): Suppose that each trader, observing the market clearing price p^*, submits an updated bid in the next round. The problem faced by a trader i who has signal x and price information p^* is to find a bid to solve the following:

$$\underset{b}{Max}\;\; E[U(V, X_i, b) \mid X_i = x, p^*]$$

Since they can infer Y from price information, their updated bid is equal to $\varphi(x,y)$. Traders who submit a bid higher than the market clearing price are those whose signal x is greater than y. Since the updated bid $\varphi(x,y)$ is still higher than the market clearing price $\varphi(y,y)$, this does not change a price determined in the first round. The same argument applies for traders whose signals are smaller than y. That is,

$$\varphi(x,x) < \varphi(x,y) < p^* \qquad \text{for} \quad x < y$$
$$p^* < \varphi(x,y) < \varphi(x,x) \qquad \text{for} \quad x > y$$
$$\varphi(x,y) = \varphi(x,x) = p^* \qquad \text{for} \quad x = y$$

A trader who tendered a bid higher (lower) than p^* will find it optimal to submit a new bid which is smaller (higher) than his initial bid but still higher (lower) than the market clearing price p^*. Price information does not affect a trader whose initial bid is p^*. Hence the updated bids do not change the market clearing price determined in the first round.

Appendix 4 ($\phi(Y) = \varphi(Y,Y)$ is a unique function satisfying (3.8)):
When $\phi(Y) = \varphi(Y,Y)$, $E[V|X_i = Y, p = \phi(Y)]$ is equal to $\phi(Y)$ since $E[V|X_i = Y, p = \phi(Y)] = \varphi(Y, \phi^{-1}(p)) = \varphi(Y,Y)$. Since $E[V|X_i = x, p = \phi(Y)]$ is increasing in x, $E[V|X_i = x, p = \phi(Y)] > (<)\ \phi(Y)$ for $x > (<)\ Y$.

Next, let us prove that the function satisfying (3.8) is unique. Suppose that it is not and there is another function $q(Y)$. Then, there should exist at least one point of $Y=y'$ such that $q(y') \neq \varphi(y',y')$. Since $q(Y)$ satisfies (3.8), $E[V|X_i = y', p = q(y')]$ should be equal to $\phi(y')$. It contradicts $q(y') \neq \varphi(y',y')$ since $E[V|X_i = y', p = q(y')] = \varphi(y',y')$. *Q.E.D.*

Appendix 5 (Naive traders' bidding strategy after circuit breakers have been triggered): By the same reasoning used in a proof of Theorem 2, the optimal bidding price of naive trader i as a solution to (3.15) is given as $\bar{b}_N = \varphi(x',x')$. As far as $\varphi(x',x')$ is an admissible bidding price, trader i will submit it as his own bid. On the other hand, when $\varphi(x',x')$ is greater (smaller) than the limit price, his optimal bid becomes the maximum (minimum) bid allowed by the exchange. Hence, (3.16) is optimal for trader i. Since the market clearing price $\bar{p}$ is the M^{th} highest bid, $\bar{p} = \varphi(y',y')$ where $y' = \gamma \cdot y + (1-\gamma) \cdot E[Y|X_i = y, Y \geq c]$. Notice that $\varphi(y',y') > \varphi(y,y)$ since $y'>y$. Hence, the market clearing price determined in a market with circuit breakers is greater than the one determined in a market without circuit breakers. *Q.E.D.*

Appendix 6 (A proof of lemma 2): Sophisticated trader i's maximization problem is given in (3.20). Suppose that the price functional $\pi(Y)$ is equal to $\varphi(Y,Y)$. Then, the problem for trader i degenerates into the one shown in the benchmark model without corcuit breakers. The optimal strategy $\bar{b}_s$ is equal to $\varphi(x,x)$. Next, suppose that $\pi(Y) > \varphi(Y,Y)$. Then, the optimal bid is a solution to the following:

$$\underset{\underline{\delta} \leq b \leq \bar{\delta}}{Max} \int_c^{\pi^{-1}(b)} \{\varphi(x,\omega) - \pi(\omega)\}\ h(\omega / x, \omega \geq c)\ d\omega$$

Notice that $\varphi(x,Y) - \pi(Y)$ is positive at a sufficiently small value of Y and negative at any value of Y greater than x. Since $\varphi(x,Y) - \pi(Y)$ is a monotonically decreasing function in Y, there exists a unique value of Y denoted by y' such that $\varphi(x,y') = \pi(y')$. Since $\varphi(x,Y) - \pi(Y)$ is negative when $Y=x$, y' is smaller than x. Regardless of the conditional density of Y, the maximum is achieved by integrating over Y such that $\{Y|\varphi(x,Y) - \pi(Y) \geq 0\}$. Hence, $\pi^{-1}(b) = y'$ *i.e.*, $\bar{b}_S = \pi(y')$. Since $\bar{b}_S = \pi(y')$ and $\pi(y') = \varphi(x,y') < \varphi(x,x)$, the optimal bid $\bar{b}_S$ is smaller than $\varphi(x,x)$. In other case when $\pi(Y) < \varphi(Y,Y)$, we can be prove using similar arguments. *Q.E.D.*

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