Do Day-traders Destabilize the Market?

The Case of the KOSPI200 Futures Market

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We analyze the trading records of 25 day-traders from a brokerage firm to explore how day-traders trade and how their trades affect futures prices. We find evidence that day-traders herd and follow positive feedback trading strategies. Day-traders trade with positive feedback within 3 minutes before they place a buy or a sell order. Even though day-traders are often blamed to destabilize the financial market, neither herding nor positive feedback trading necessarily destabilize prices. When we investigate the impact of heavy volume of orders by day-traders on futures prices during the day, no convincing evidence is found that day-traders destabilize prices in the financial markets. On the contrary, they quickly catch up the signal of price changes and spread the information by placing sell or buy orders.

1. Introduction

Since the late 1990s, online trading has become popular throughout the world thanks to the rapid spread of Internet and as a consequence, a new group of investors called day-traders appeared. Day-traders are those who buy and sell some securities repeatedly on the same day. They are distinguished from the other investors in that they are short-term speculators who pursue profits arising from small changes in the price of securities. Most day-traders hold securities only for hours or even for seconds, closing out positions for small profits. They hardly hold positions overnight, because they don't want to take the risk arising from price changes during the night time in which they cannot trade. Due to these speculative trading behaviors, day-traders are often blamed to increase the volatility of securities and to make the market price deviate from the fundamental value. On the other hand, some people say that day-traders make markets more efficient by narrowing the bid-ask spread and providing a better deal to all investors (Malkiel, 1999).

However, relatively little is known about day-traders' trading strategies. Trading strategies of other investor groups such as institutional investors and foreign investors are widely studied; Lakonishok, Shleifer, and Vishny (1992, henceforth LSV) and Wermers (1999) examine the trading behavior of institutional investors of the U.S., and Choe, Kho, and Stulz (1999, henceforth CKS) examine the trading behavior of foreign investors who traded in Korea during the financial crisis in 1997. On the other hand, it is hard to find a study examining trading records of day-traders, since brokerage firms that carter to day-traders have been reluctant to provide the trading information of their clients (Barber and Odean, 2001). There are some papers on the relationship between day-trading and market volatility applying Granger-causality test or VAR method on day-trading and volatility fluctuation. However, they analyze the aggregate market data of day-trading, not the individual trading records of day-traders. Another related study is the paper on SOES trading and market volatility (Battalio, Hatch, and Jennings, 1997) since SOES bandits' trading behavior is similar to day-trading, but the data is not the direct records of day-traders.

Fortunately, we obtained a proprietary data set of 25 day-traders' trading records of KOSPI200 index futures for 62 trading days from a brokerage firm (henceforth, brokerage firm A) that is one of the largest brokerage firms in Korea. This paper will be especially meaningful in which we research on the trading strategies of day-traders with day-traders' detailed trading records. This set of trading records contains the information about whether the order is a buy order or a sell order, the date, the exact ordering time in milliseconds, the code of traded security, the trading volume, and the price that day-traders ordered as well as the information about those after the order is completed in securities market. Day-traders analyzed in this paper are the biggest 25 traders whose trading volume is the largest in the brokerage firm A. The 25 sample day-traders constitute about 25% of the 1209 individual traders who trade futures in the brokerage firm A. The number of KOSPI200 futures contracts they traded during the sample period are 72,705 contracts, about 33.7% of the total contracts traded through the brokerage firm A.

The KOSPI200 futures market is ideal for studying day-trading. First, the KOSPI200 index futures market is one of the largest index futures market: it ranked as 4th in 2003 among the largest index futures market as we can see in Table 1. The KOSPI200 futures contracts are more actively traded than the S&P500 futures contracts. In 2002, the trading volume of the KOSPI200 futures contracts is around 42.8 million, while that of the S&P500 futures contracts is around 2.4 million. Second, the proportion of individual investors trading futures is much higher in Korea than in U.S. The individual traders are given much weight in the total KOSPI200 futures market.[1] The increasing trend of day-trading in Korea coincided with the increasing trend of individual investors' trading (Byun, 2002). Individual investors account for more than 90% of stocks, about 60% of the options, and about 55% of the KOSPI200 futures which overwhelmed the foreign investors and institutional investors. Third, online trading in Korea is more popular than other countries and the highly developed information technology system in Korea enables traders to check the market movement in real time and to place orders very quickly. Thus, KOSPI200 futures market has equipped with good conditions for speculation and day-traders who pursue speculative profit in that market are likely to destabilize the price.

Our paper examines whether day-traders destabilize the financial market using the data set of the 25 day-traders in the KOSPI200 futures market. Two conditions are required to prove that day-traders destabilize the price. First, day-traders should herd. Day-traders' demand

[1] See APEC Working Group paper.

should not offset each other's demand to have an effect on trade price. Second, day-traders should be positive feedback traders who destabilize the price. Positive feedback traders are said to increase the volatility of the price by increasing their buy (sell) order when the price goes up (down) (DeLong, Shleifer, Summers and Waldman, 1990).

We find evidence that day-traders herd and follow positive feedback trading strategies. Day-traders trade with positive feedback within short time interval such as 3 minutes before they give a buy or a sell order. However, neither herding nor positive feedback trading necessarily destabilize prices. When we investigate the impact of large volume of orders by day-traders on futures prices during the day, no convincing evidence is found that day-traders destabilize prices in the financial markets. On the contrary, they quickly catch up the signal implying price movement and spread the information to the market by giving sell orders or buy orders.

Section 2 of this paper reviews the literature on the impact of the trading of a group of investors on prices and develops hypotheses. Section 3 describes the data and KOSPI200 futures market and defines terminologies used in this paper. Section 4 presents empirical evidence on day-traders' behavior based on our proprietary data set: the detailed trading records of 25 representative day-traders. Section 5 concludes our analysis.

2. The impact of the trading of a group of investors on prices

There are many papers examining whether a specific group of investors destabilize the price of securities. Notable examples are those by Lakonishok, Shleifer, and Vishny (1992, henceforth LSV), Wermers (1999), Choe, Kho, and Stulz (1999, henceforth CKS). LSV (1992) tested whether institutional investors, especially pension funds, destabilize prices through herding and following positive feedback strategies, but they found no convincing evidence that institutional investors destabilize individual stocks. Instead, they found that institutional investors' strategies are various and offset each other without having a strong impact on prices. Wermers (1999) investigated the herding behavior of mutual funds. CKS tested whether foreign investors contributed on the destabilization of Korean stock market during the Asian financial crisis from 1996 and 1997. The empirical results didn't show any evidence of destabilization effect arising from foreign investors' trades. On the contrary, they found herding behavior and positive feedback trading of foreign investors mostly disappeared during the crisis period.

This paper is distinguished from above papers as follows. First, we analyze day-traders' trading behavior whereas LSV (1992) and Wermers (1999) analyzed institutional investors' strategies and CKS (1999) analyzed foreign investors' trading strategies. Second, LSV (1992) and Wermers (1999) used quarterly data in testing herding behavior, which fails to separate out window dressing effect (Lakonishok, Shleifer, Thaler, and Vishny, 1991) from herding effects resulted from investment strategies. However, this paper has advantage in which we can use intraday transaction data to test herding behavior more precisely. CKS (1999) also uses intraday data, but they assumed all investors of a specific country as the same investor because their dataset does not contain information to identify individual investors. Our proprietary dataset enables us to identify who trades a specific trade exactly, and so our paper has successfully analyzed day-traders' behavior in more detail. On the other, since our data set contains only a part of day-traders, not the whole set of day-traders, our empirical analysis should be interpreted more carefully. However, we believe that day-traders in our sample can represent day-traders in general.

There are also papers which investigated day-traders' trading behavior. Notably, Silber (1984) analyzed trading records of a representative scalper in New York Futures Exchange and found that the scalper makes earnings by providing liquidity services to incoming market orders. Our study is similar to Silber (1984)'s in that our study analyzed the data of a futures exchange and trading records of day-traders. However, our study is different from Silber's in that our study examines mainly whether day-traders' trading affects destabilization of prices, whereas Silber focused on the role of scalpers as marketmakers. Choe, Chung, and Kho (2004, working paper, henceforth CCK) examined the impact of day-trading activity on the return volatility by using trade records of 540 stocks on the Korea Stock Exchange during 1999 and 2000. They defined day-trading activity with their own standards because they couldn't identify individual day-trading activity. They found weak evidence that day-traders use short-term contrarian trading strategies and their order imbalance has impact on intraday stock returns. Our paper is different from theirs in that our paper uses exactly identified day-traders' detailed trading records.

3. DATA

3.1 Day-traders

This paper defines the day-trader as individual investors who buy and sell at least one contract of the same futures on the same day. As we can see in Table 2, day-traders in our data traded on average about 7.7 trades in a day. Day-traders are also those who attempt to clear their position, by the end of day to avoid the risk arising from holding overnight positions. This definition is in line with principles that most day-traders try to follow. It, however, does not restrict day-traders as those who buy and sell strictly the same number of shares for a future. Some day-traders may hold the position for next days, for example, when unprofitable.

We use two distinct data sets in this paper. One consists of complete day-trading records of a given sample period from brokerage firm A, which specializes in providing execution and clearing services to day-traders. The other consists of complete trading records of the given sample period of the first one from KSE (Korea Securities Exchange).

The first data set consists of 25 day-traders' trading records from brokerage firm 'A' for the 62 consecutive trading days from July 2, 2002 to September 30, 2002. During the sample period, total individual investors who traded through the brokerage firm A accounts for about 1.85% of the whole KOSPI200 futures volume. The dataset of 25 day-traders from brokerage firm A consist of confirmation records from 72,705 trades, which is about 33.7% of the total individual trading volume in firm A and about 0.33% of the whole KOSPI200 futures volume traded during the sample period. The data contains (among other items) the information regarding whether the order is a buy or sell, the ordered price and volume, the executed price and volume, the ordered date and time, the execution date and time, the maturity of the traded KOSPI200 futures, and an indication of order-type, i.e., whether the trades were made using a market order, a limit order, or a working order. This proprietary dataset is valuable for our research, because it provides complete information on the trading patterns of day-traders.

Table 2 shows summary statistics on trading records of day-traders in our dataset. The holding time represents the time difference between ordered time and executed time. Day-traders hold a position about 3 minutes on average. The day-trader's average size of an order in our dataset is about 11.3 contracts per order.

The data set from KSE consists of all trades of the KOSPI200 futures for the 3 months from July 1, 2002 to September 30, 2002. For each trade, the data indicates if the order is a buy or sell, the maturity of the future, the date and time of the trade (order), the trade price, the identity of the trader, and the method of the order (firm A terminal, wireless terminal, fixed line terminal, and HTC).

3.2. The description of the KOSPI200 futures market during the sample period

Our dataset from the Korea Stock Exchange allows us to classify buying and selling investors into four categories: institutional investors, individual investors, foreign investors, and other investors. The amount of traded contracts of each investor to the total amount of traded contracts from July to September, 2002 were 30.87%, 53.35%, 12.30%, and 3.49%, respectively. The amount of money they traded were 30.91%, 53.51%, 12.28%, and 3.50%, respectively.

During the sample period, KOSPI200 futures index was 94.93 at the beginning of July 2nd, 2002 and 81.80 at the end of the September 30th, 2002. The price was fallen about 13.83% during the sample period. As Figure 1 shows, KOSPI200 futures market was going up for a while at the beginning of the sample period but has shown down trend in general during the sample period.

3.3. Transaction

When a trader ordered a buy or a sell order through the electronic order system and the order is executed, it is called transaction for purchase or sale respectively. When more than one contract are ordered and hit by split orders, we do not consider each split transaction as an individual transaction but the sum of split orders as one transaction. In the similar way, when a trader gives several split orders and those split orders are executed at the same time, we consider them as one transaction.

3.4. Trade

A trade is defined as the transaction clearing the outstanding position. That is the case when a buy order is hit by a sell order or when a sell order is hit by a buy order. Thus, the case that a buy or a sell order is hit when there is no outstanding position is considered not as a trade but as a transaction.

4. Empirical Analysis

4.1. Herding

Froot, Scharfstein, and Stein (1992) insist that if speculators have short horizons, they may show herding behavior as demands for the information become strategic complement. Day-traders have reasons to herd in investments because they are intrinsically speculators who have short horizon. To investigate whether day-traders herd, we modified the approach of LSV (1992) and Wermers (1999) to estimate the degree of herding. I compute their herding measure using a daily horizon to inspect herding behavior. Later, we will do intraday experiment considering that most day-traders clear their position by the end of the day.

Specifically, the herding measure is computed as HMt=|Nt-E(Nt)|-AF(i), where Nt is the proportion of buy orders on day t among all orders day-traders ordered on day t relative to the whole orders including buy and sell orders. Pt is defined as the expected proportion of buy orders on day t relative to all buy and sell orders on day t. AF(i) is an adjustment factor computed under the null hypothesis is calculated through Monte Carlo simulation methods as in Wermers (1999). We assume that in the absence of herding behavior, the number of purchases of futures (buy orders) follows a binomial distribution.

$$HM_t = | N_t - P_t | - AF(i)$$

$$N_t = \frac{NL_t}{NL_t + NS_t} \text{(upwarding market)} \qquad \text{……………………………….(*)}$$

$$N_t = \frac{NS_t}{NL_t + NS_t} \text{(downwarding market)}$$

We computed herding measures on upward and downward days which are defined by checking the return of one day before the trading day. The herding measures of upward or downward day are computed as above, which is (*). If the return of one day before day t is positive (negative), day t is considered as upward (downward) day. These measures are useful in the sense that they show us whether day-traders are positive feedback traders as well as whether day-traders are herding. Positive feedback traders are momentum traders who buy when the price is rising and sell when the price is falling. This positive feedback trading may make the pride deviate from the true value and may destabilize price. If day-traders are positive feedback traders, they may buy more futures when the price is rising and sell more futures when the price is falling. So, we defined the herding measure separately with respect to upward or downward market on day t. If the return of day t-1 is positive (negative), we put the number of buy (sell) orders of futures on the numerator of Nt.

If we treat each purchase as a purchase by a distinct day-trader, it may overstate the degree of herding as happened in the CKS (1999). CKS (1999) divided foreign investors based on both 47 countries and 14 investor types to avoid the overstate problem of the degree of herding. Classes that CKS developed still don't have obvious common trading characteristics, since each class of 14 investor type including institutional investors consists of many investors such as fund managers of various funds. Our data, however, has particular advantage in which each day-trader's order or trade can be exactly identified and analyzed accordingly.

Table 3 shows the estimates of herding measures on upward days and on downward days. The first column reports the mean and median herding measures of upward day t when the return of day t-1 was positive. The second column reports those for downward day t when the return of day t-1 was negative. The mean herding measure, 0.085 and 0.0688, each on upward or downward day is higher than 0.027 reported by LSV (1992).

The mean herding measure on an upward day, 0.085 implies that if p, the probability of buy or sell order is ordered under the null hypothesis of no herding, was 0.5, then 58.58% of the orders were buy orders on an upward day. Similarly, the mean herding measure on a downward day, 0.0688 implies that 55.22% of orders were sell orders on a downward day. The difference of herding measures between on an upward day and on a downward day implies that day-traders in our sample buy more KOSPI200 futures when the price is rising probably with the expectation of further increase, whereas they do not sell actively when the KOSPI200 futures price is falling as much as they buy on an upward day. Even though day-traders expect further decrease of the KOSPI200 futures price when falling, they might not give sell orders to take profits from selling high first and buying low later because this strategy is too risky. If the price is rising right after day-traders sell and do not fall until the end of trading time on that day, their loss will be bigger than the loss from the fallen price itself because of margin call system. Their account should be refilled with money as much as the loss at the end of the day, if not, their remaining position will be cancelled forcibly. If day-traders buy more when the price is rising, net gain at the end of the day is likely to be increased. In opposite way, if day-traders sell more when the price falling, net loss at the end of the day is likely to be increased and the amount of money they should refill into account will be bigger. Thus, day-traders tend to buy more when the price is rising rather than sell more when the price is falling.

This result might not be strong enough to support that day-traders of our sample follow positive feedback strategies as a herd. We, however, should note that day-traders trade actively within a day rather than overnight and the result is computed based on daily horizon may not show day-traders' herding behavior properly. At the end of the day, aggregating across all orders, there can be no herding, since every share bought at the end of the day is a share sold during the day because day-traders typically do not hold any position overnight.

LSV (1992) insist that herding within subsets of investors such as pension fund managers can certainly exist, although they did not find any evidence. Since we are analyzing one such subset (day-traders of A security company), herding within this subset can certainly exist as LSV (1992) insisted. So, we changed our approach from daily horizon to intraday horizon. Taking account of day-traders' general trading characteristics, having short term horizon and making profits through changing orders minute by minute, this approach fits better to inspect whether day-traders are herding or investing with positive feedback strategies.

4.2. Positive feedback

Day-traders take an extremely active trading strategy. They move quickly in and out of futures positions to catch small profits on each trade. Most day-traders clear their remaining positions by the end of each trading day to avoid the risk related to overnight price changes. Day-traders are often blamed for increasing the volatility of the market with their extremely active trading strategy or making price diverge from the fundamentals by adopting positive feedback strategy. One particular common example of a potentially destabilizing short-term strategy is trend chasing, or positive-feedback trading. If day-traders trade randomly or trade in a way similar to other traders, there is little reason to believe that day-trading activity destabilizes the price. If day-traders do herd and follow positive feedback strategy as is widely believed, they may destabilize the price of futures market. However, we can not rule our other possible effects they will bring about by herding and following positive feedback strategies. We saw weak evidence supporting that they herd with respect to different price movement signals in the previous section. From now on, we test whether they follow positive feedback strategy and so they buy in upward moving markets and sell in downward moving markets.

First, we test whether daily return of KOSPI200 futures affects the order imbalance of day-traders. We calculated the return at one day before and after as well as the day of trading; each is R_{mt-1}, R_{mt+1}, and R_{mt}, respectively. Order imbalance is computed as the proportion of the difference between the number of daily buy orders and the number of daily sell orders of day-traders relative to the number of the average daily orders of the whole market. We used the data provided by KSE for the average daily orders during the period from July 3 to September 30, 2002.

Table 4 shows the result. The first column of Table 4 indicates whether each return of day t-1, t, and t+1 are positive or negative with the total days counted in parenthesis. Second column indicate the order imbalance of day t with standard deviation in parenthesis. The positive sign of order imbalance means that the buy orders of day-traders are larger or more frequent than sell orders and the negative sign of order imbalance means that the sell orders of day-traders are larger or more frequent than buy orders on day t. Table 4 implies that the return of the day before and after of the trading day has negative relation to the order imbalance whereas the return of trading day has positive relation to the order imbalance. We may interpret these results as evidence showing that day-traders follow contrarian strategies with daily horizon and positive feedback strategies on intraday horizon. However, these results should be interpreted with care since day-traders usually close out their positions by the end of the trading day. Nest, we examine the intraday order imbalance in more detail.

We examine whether day-traders place buy orders when the price movement right before they quote was upward (downward). In addition, we examine day-traders' behavior 3 minutes before and 5 minutes before they quote, respectively. To examine how day-traders react to the market trend, we matched the day-traders' quote time to the traded time of the whole KOSPI200 futures market and then computed the price change of the market right before, 3 minutes before, and 5 minutes before the quote of day-traders. Panel A of Table 5 shows the price change right before the quote of the day-traders and percentage of each case. For example, the first row of Panel A implies that the ratio of day-traders placing a buy order right after the price goes up to the whole quotes of day-traders (23092 trades) is about 31.51%. Similarly, the percentage of the case that the day-traders place a sell order right after the price goes down is about 31.28%.

If we look at Panel B and Panel C of Table 5, we can see that the percentage of buy or sell orders is almost the same regardless of the previous price change. It implies that day-traders respond to the price change within short time. Thus, there is evidence that day-traders follows positive feedback trading strategies at least within 3 minutes before they place buy or sell orders. If we recall that day-traders quickly move in and out of positions to catch small profits on each trade, 3 minutes is reasonable to do positive feedback trading. In addition, we saw that average holding time of day-traders is less than one minute.

4.3. Event study for large volume orders

In the last section, we have seen that day-traders follow positive feedback strategies in a short time interval. However, this result does not necessarily imply that day-traders destabilize KOSPI200 futures prices. We examine this question further in this section through studying the changes of returns of KOSPI200 futures before and after the large volume orders are ordered by day-traders. We consider the event that day-traders order more than 200 volume of buy or sell orders. This analysis provides us deeper understanding of the impact of day-traders' trading on the KOSPI200 futures prices.

The event is defined as the one that that a day-trader orders extraordinarily large volume more than 200. We examine the price behavior of the KOSPI200 futures market from 30 minutes before the event to 45 minutes after the event. We measure 5-minute returns for this event study, but we also look at 1-minute returns for the period from 5 minutes before the event to 5 minutes after the event. Each return calculated as the price change divided by the beginning price as follows; $Ar_{i,t}=(P_{i,t}-P_{i,t-1}-1)/P_{i,t-1}$. That is, we assume that the expected return for a 5-minute interval is negligible. This analysis provides us deeper understanding of the impact of day-traders' trading on the KOSPI200 futures prices. We rule out the cases that day-traders ordered before 9:30 AM or after 14:30 PM to make sure that the pre-event or the post-event period doesn't change days

Figure 2 presents the results of the return of KOSPI200 futures 5 minutes before and after the large buy orders are placed by day-traders. The returns increase step by step before day-traders order large volume of buy orders. The return jumps dramatically after day-traders order large volume of buy and then remains steadily. The effect is obvious when we see the 5-minute interval. This result implies that day-traders follow positive feedback trading strategies, but do not destabilize prices. Instead, they seem to quickly catch the instantaneous up signal and spread the information to the market by ordering large volume of buy orders.

Figure 3 presents the result of the event study for large volume of sell orders. Day-traders give large volume of sell orders when the market prices are falling. The return decreases after the large volume of sell orders, but there is no permanent significant negative effect following large sales by day-traders. Day-traders seem to follow positive feedback trading strategies by giving sell orders when prices are falling. However, this does not necessarily imply that day-traders destabilize prices, even though Figure 3 shows a little fluctuation of prices after they give large volume of sell orders. The t-statistics do not reject the null hypothesis that cumulated abnormal returns after the event are zero. Overall, there is no evidence that large purchases or sales by day-traders directly destabilize prices.

5. Conclusion

In our paper, we use the trading records of 25 day-traders from brokerage firm A to explore how day-traders trade and how their trades affect futures prices. Day-traders are often blamed because they are believed to make noise in the market by frequently moving in and out positions to capture small profits arising from instantaneous price change. We examined whether day-traders destabilized prices by engaging in positive feedback trading and herd. We find evidence that day-traders herd and follow positive feedback trading strategies. Day-traders trade with positive feedback within short time interval within 3 minutes before they give a buy or a sell order. However, neither herding nor positive feedback trading necessarily destabilize prices. When we investigate the impact of heavy volume of orders by day-traders on futures prices during the day, no convincing evidence is found that day-traders destabilize prices in the financial markets. On the contrary, they quickly catch up the signal of price change and spread the information by giving sell orders or buy orders.

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Table 1. Global index futures volume

This table shows the ranking of global index futures volume of U.S., German, Korea, and France.

(unit: million contracts)

Ranks	Country	Index	Number of contracts
1	U.S.	E-Mini S&P 500	161
2	German	DJ EURO STOXX 50	116
3	U.S.	E-Mini NASDAQ 100	68
4	Korea	KOSPI 200	62
5	France	CAC 40	29

From FIA statistics, 2003

Table 2. Summary statistics on day-trading

This table shows summary statistics on day-trading. The holding time represents the time difference between ordered time and executed time. Contracts per trade represent how many contracts day-traders ordered in one time.

	Mean	Std	Max	min
Holding time	0:03:03	0:11:13	3:04:19	0:00:00
Contracts per trade	11.3	25.5	344	1

Table 3. Herding statistics

The herding measure is computed as HMt=|Nt- Pt|-AF(i), where Nt is the proportion of buy or sell orders on day t among all orders day-traders ordered on day t relative to the whole orders including total buy and sell orders. If the return of day t-1 is positive (negative), we put the number of buy (sell) orders of futures on the numerator of Nt. The Pt defined as the expected proportion of buy orders on day t relative to all buy and sell orders on day t. AF(i) is an adjustment factor computed under the null hypothesis is calculated through a Monte Carlo simulation methods as in Wermers (1999). Standard deviations are in parenthesis.

	Herding Statistics	
	Up signaling	Down signaling
Mean	0.0858	0.0688
	(0.0375)	(0.0594)
Median	0.0974	0.0522

Table 4. Daily Order Imbalance

For KOSPI200 futures from Jul. 2, 2002 to Sep. 30, 2002, the daily order imbalance (buy volume less sell volume) is computed according to the sign of the return of previous day and today and expected return of tomorrow.

		Order Imbalance** (mean*100)
Rmt-1>0	(29 days)	-0.85179
		(0.0693)
<0	(29 days)	2.3464
		(0.0786)
Rmt>0	(29 days)	1.121
		(0.0640)
<0	(29 days)	0.36277
		(0.0855)
Rmt+1>0	(29 days)	-0.55366
		(0.0719)
<0	(29 days)	1.7743
		(0.0783)

**order imbalance = (daily buy vol-daily sell vol)/average daily vol

Table 5. Intraday order imbalances.

The intraday order imbalances of day-traders from Jul. 2, 2002 to Sep. 30, 2002 are computed in three ways. Panel A shows order imbalances right before the order is given. Panel B shows order imbalances 3 minutes before the order is given. Panel C shows order imbalances 5 minutes before the order is given. Each panel shows the volume and the percentage of volume when buy orders or sell orders are given after the price change is positive or negative, respectively.

Panel A. Order imbalances right before the order

△P	order type	volume	%
+	Buy	7276	31.51
	Sell	4308	18.66
-	Buy	4261	18.45
	Sell	7223	31.28
0	Buy	16	0.07
	Sell	8	0.03
	Total	23092	

Panel B. Order imbalances 3 minutes before the order

△P	order type	volume	%
+	Buy	5841	25.76
	Sell	5520	24.34
-	Buy	5506	24.28
	Sell	5809	25.62
0	Buy	0	
	Sell	0	
	Total	22676	

Panel C. Order imbalances 5 minutes before the order

△P	order type	volume	%
+	Buy	5878	26.03
	sell	5560	24.62
-	buy	5434	24.06
	sell	5712	25.29
0	buy	0	
	sell	1	
	total	22585	

Table 5. Abnormal returns for an event study of the impact of large volume orders by day-traders

This table shows returns and cumulated abnormal returns before and after the event that day-traders give large volume of buy or sell orders. The sample consists of a total 27 events for buy orders and 24 events for sell orders. Abnormal returns are computed in 1 minute interval from –5 minute to 5 minute of the event in Panel A and in 5-minute interval from -30 minute to 45 minute of the event in Panel B. Panel C shows statistics for the results of Panel B.

Panel A. 1 minute interval from -5 minute to 5 minute

Event	Buy orders > 200		Sell orders > 200	
Time	Mean AR	Mean CAR	Mean AR	Mean CAR
-5	0.000176172	0.000176172	-0.000173923	-0.000173923
-4	-1.7931E-05	0.000158241	-0.000106269	-0.000280192
-3	0.000287	0.000445241	0.000150692	-0.0001295
-2	0.000113517	0.000558759	-0.000133	-0.0002625
-1	0.00025169	0.000810448	-0.000166615	-0.000429115
0	0.000611966	0.001422414	-0.000452692	-0.000881808
1	5.82414E-05	0.001480655	-0.000151731	-0.001033538
2	-2.15517E-05	0.001459103	0.000176308	-0.000857231
3	0.000154138	0.001613241	-0.0001225	-0.000979731
4	-1.54138E-05	0.001597828	-7.01154E-05	-0.001049846
5	-1.65862E-05	0.001581241	-6.78462E-05	-0.001117692

Panel B. 5-minute interval from -30 minute to 45 minute

Event	Buy orders > 200		Sell orders >200	
Time	Mean AR	Mean CAR	Mean AR	Mean CAR
-30	0.000100667	0.000100667	0.000317792	0.000317792
-25	-1.96296E-06	9.87037E-05	0.000482875	0.000800667
-20	-4.85926E-05	5.01111E-05	0.000236917	0.001037583
-15	0.000167074	0.000217185	0.000145292	0.001182875
-10	0.000760259	0.000977444	-1.76667E-05	0.001165208
-5	0.00010163	0.001079074	-0.000560125	0.000605083
0	0.001194852	0.002273926	-0.000696583	-9.15E-05
5	0.000149407	0.002423333	-0.000353542	-0.000445042
10	2.3037E-05	0.00244637	-0.000062	-0.000507042
15	8.22222E-05	0.002528593	-0.00009525	-0.000602292
20	4.62963E-06	0.002533222	-0.000343125	-0.000945417
25	0.000102037	0.002635259	0.000210792	-0.000734625
30	-0.000271	0.002364259	0.000530708	-0.000203917
35	-0.000125407	0.002238852	-9.51667E-05	-0.000299083
40	-0.000120185	0.002118667	0.000327625	2.85417E-05
45	0.000550074	0.002668741	0.000140792	0.000169333

Panel C. Statistics of an event study of large volume orders (5-minute interval)

	CAR[5,45]	
	Buy orders > 200	Sell orders > 200
Mean	0.000395	0.000261
Std	0.003306	0.004643
T statistics	0.620477	0.275227

Figure 1. KOSPI200 futures price and CD rate during sample period

The figure shows the trend of KOSPI200 futures prices and CD rate during the sample period. We showed only for the KOSPI200 futures which expired on September 13.

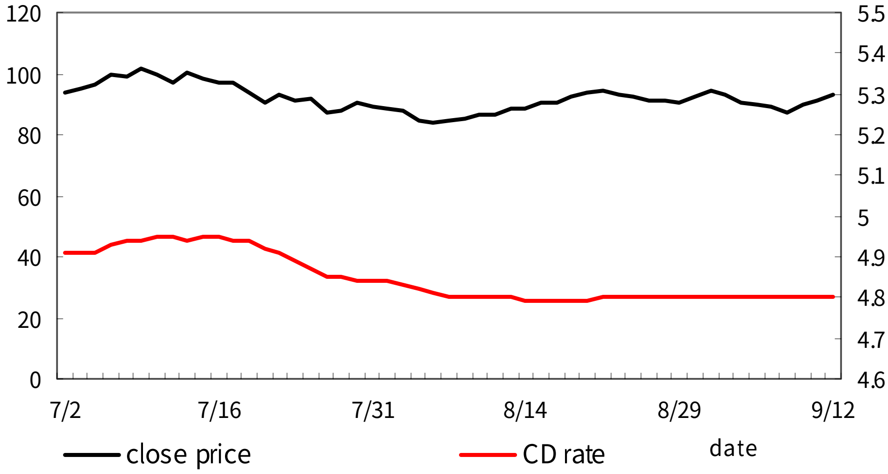
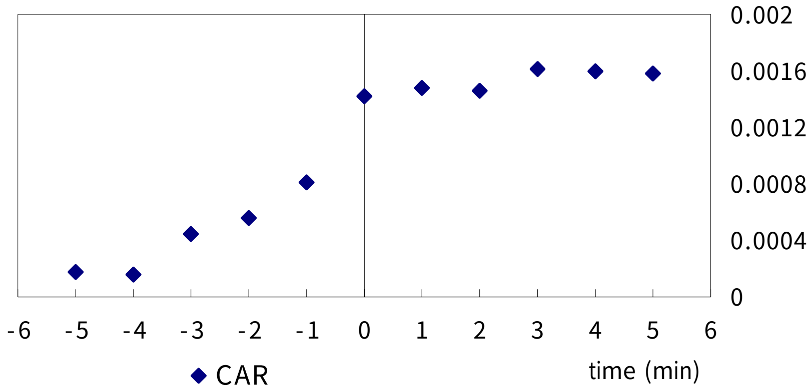


Figure 2. Event study for the large buy volume ordered by day-traders

The figure shows the result of event study that examines return before and after day-traders give large volume of buy orders. Penal A shows the results for 5 minutes before and after the event. Panel B shows the results of 30 minutes before the event and 45 minutes after the event.

Panel A. The number of ordered buy volume > 200



Panel B. The number of ordered buy volume >200

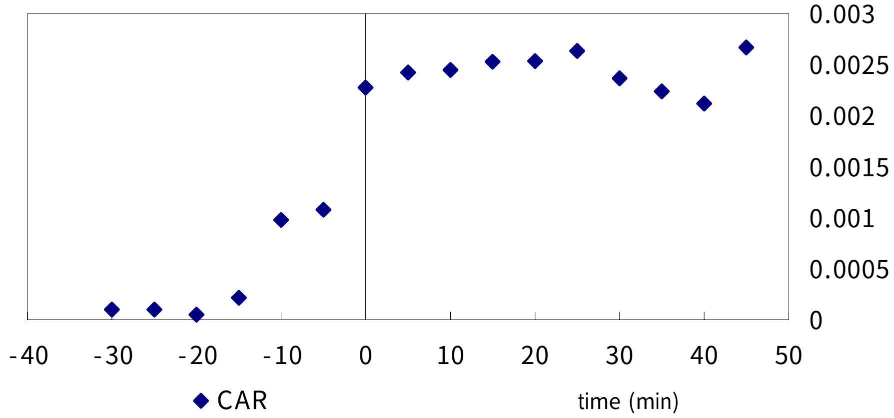
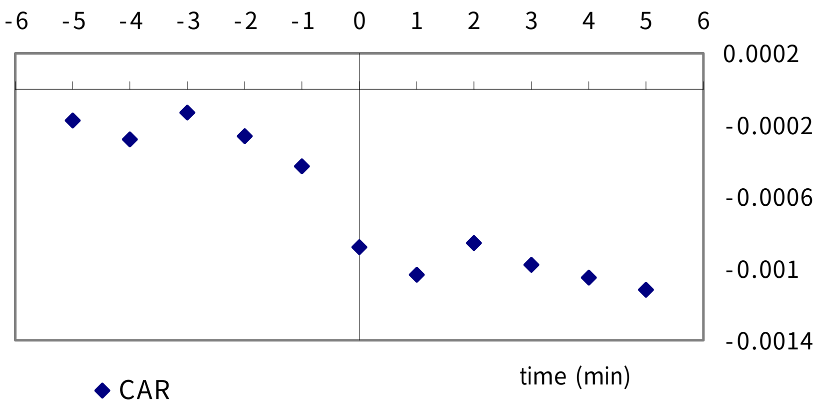


Figure 3. Event study for the large sell volume ordered by day-traders

The figure shows the result of event study that examines return before and after day-traders give large volume of sell orders. Penal A shows the results for 5 minutes before and after the event. Panel B shows the results of 30 minutes before the event and 45 minutes after the event.

Panel A. The number of ordered sell volume > 200



Panel B. The number of ordered sell volume > 200