How Do Program Trade Halts Affect Large Order Imbalances? *

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June 22, 2010

Abstract

Most trade halts studies focus on volatility, an effect of price movement. In this study, we focus on order imbalance, a driver of price movement. To our knowledge we are the first to study the interaction between trading halts and order imbalance. Another characteristic of the trade halt literature is that it concentrates on individual firm halts and market wide halts. However, program trading has been isolated as a potential cause of market instability, again a cause, not an effect. Laws have been enacted to regulate program trading during volatile markets. This study is the first to conduct a detailed analysis of program trading restrictions during large market moves. To address this issue, we analyze the effect of sidecars (halts that only affect program trades) using intraday data from the Korean securities market. The Korean market and regulatory environment have several properties that lend itself to such a study. The effect of program trading halts in the spot market and in the futures market are explored. Sidecars are found to be ineffective at controlling the order imbalance levels around large market movements. Program trades, at least a subset, provide liquidity when it is at a premium. We conclude that program trading should not be totally eliminated during large market moves.

JEL subject classifications: G12, G13, C14, G22

Key words: Order imbalance, sidecar, trading halts, Korea, program trading, KOSPI 200.

*We would like to thank seminar participants at Cambridge University, EDHEC, Hong Hong Polytechnic University, Hong Kong University of Science and Technology, Korea Advanced Institute of Science and Technology, Korea University, Loughborough University, Peking University, Seoul National University, Sungkyungkwan University, Sun Yat-sen University, University of Hull, and University of Macau. This paper was presented at the 2010 China Economics Conference and at the Third Erasmus Liquidity Conference. We would like to thank Elisabeth Bui and Gishan Dissanaike for comments on an earlier draft of this paper.

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1 Introduction

Circuit breakers such as trading halts and sidecars[1] have their proponents and opponents in both academia and practice. The benefit of these mechanisms is highly debated.[2] Previous empirical studies have focused on individual and market wide halts. There exists no study that specifically addresses the influence of program trading halts during large market moves.[3] To address this issue, we analyze the effect of halts on program trades using the intraday data of the Korean securities market.

There are several advantages to studying the Korean market versus the US market. One important advantage the Korean data has over the US data is that the initiating party for each trade is identified. Thus, in our data we observe exactly if a trade is a buy or sell initiated trade. This eliminates one estimation step in the trade signing methodology, e.g., Lee and Ready (1991). Such trade signing methodologies depend on several assumptions and have been documented to have a large degree of error. The error seems particularly large for non-NYSE and overseas data sets (see Aitken and Frino, 1996; Theissen, 2001). The standard trade signing algorithms have particular difficulty signing trades during unusual market activity, such as during high volume. This is exactly the conditions under which such algorithms are employed, e.g., during large market moves and periods surrounding trade halts (see Ellis, Michaely, and O'Hara, 2000). The sign misclassification can be magnified when the estimates are used in secondary procedures, e.g., to estimate PIN (see Boehmer, Grammig, and Theissen, 2007). By eliminating this estimation step our inferences are potentially more precise. A second advantage is that on the Korea Exchange (KRX) program trading halts (called sidecars) cover all program trading including index arbitrage and non-index arbitrage, while on the NYSE program trading inhibitors (sometimes called the collar rule[4] or Rule 80A) cover only index arbitrage trades. So we are able to explore a new dimension not available with NYSE data. Probably even more important is that the KRX sidecar simultaneously halts program trades on the spot, futures, and options markets. So program trading is eliminated from all markets allowing for a cleaner test of the effects of program trading on market characteristics. Another important advantage of the Korean market is that there is no substitute asset for the KOSPI 200[5] futures index during the trade halt. It is difficult to replicate the index as futures/options trading on

[1]Circuit breakers is a general term used to capture all trade regulating mechanisms. Circuit breakers can be classified in different ways. One useful classification of these regulations is into halts and inhibitors. Halts completely stop targeted trading, while inhibitors allow trade under different rules. One may classify both halts and inhibitors into rules that affect all assets (market wide), a subset of assets (e.g., the S&P 500 constituent stocks), or an individual asset. Circuit breakers can also be classified by the trade type it affects, e.g., all trades, program trades, or index arbitrage trades. A sidecar is a circuit breaker that applies only to program trades. The sidecar scheme that we study refers to a rule that lets the Korea Exchange (KRX), the bourse operator, halt program trading on the KOSPI 200 constituent stocks during periods of extreme market moves. A definition of the KRX sidecar is available in English on the KRX website: http://eng.krx.co.kr/m7/m7_4/m7_4_1/m7_4_1_4/UHPENG07004_01_04_04.html

[2]Please refer to the literature survey section of this paper.

[3]Rule 80a of the NYSE is a trade inhibitor, thus program trading still exists when the rule is implemented, only the rules of trade change.

[4]The NYSE collar rule was eliminated on November 2, 2008.

[5]KOSPI stands for Korean Composite Stock Price Index. The KOSPI 200 consists of the largest 200 stocks in the KRX by market cap.

individual Korean stocks is illiquid or nonexistent. Also, US markets are closed during the Korean market trading hours. In the US market, options and futures markets remain open when Rule 80A is in effect and these markets are deep enough to replicate an index. Thus, the Korean data provides a better experimental setup to test market connectedness. Finally, only the Korean data can be used to answer the question of whether it is optimal to allow program trading during large market moves.[6] This is true as the KRX sidecar is a true halt across all markets, while the US sidecar (Rule 80A) only inhibits index arbitrage trading in the spot market.[7]

Most past studies investigate the effect of trading halts on volatility or price discovery. To date, this literature has not been able to make any decisive conclusions. In this paper, we take a step back. Instead of studying the *effect* of large price movements (volatility), we investigate a *driver* of price movements (order imbalance). That order imbalance is a primary driver of price moves is fundamental to economics and has strong intuition in the basic supply/demand framework. If there are many buy orders and few sell orders to absorb the buy orders, then this large buy order imbalance must push price up to attract more sell orders. Similar intuition exist for a large sell order imbalance. Ultimately, the justification of stepping back to study a driver, rather than an effect, of large price movements is in the results. If we are able to find something interesting that has not been observed in the literature that focuses on volatility, then our approach is justified.

Another contribution of this paper is that we study program trade halts.[8] To date, the literature has exclusively focused on individual stock trade halts and market wide trade halts.[9] However, after large market crashes, two trade types are typically singled out as potential culprits: short sales and program trades. Sidecars, rules regulating program trading, are typically initiated after market crashes. For example, Rule 80A was implemented after the 1987 NYSE crash. Thus, program trading is of primary interest to market regulators, as they have attempted to control market characteristics via regulating program trades. Whether program trades on average consist of thoughtless computers sending sell orders when markets drop to hit prescribed limits or whether program trades represent sophisticated traders that can lend needed liquidity during large market moves is an important open question. Thus, studying program trading and regulation designed to control these trades is of primary interest. Have

[6]We should note here that the true test we can conduct is a conditional test, conditional on the existence of a trade halt rule. This follows as the data exists for actual halts (i.e. markets with no program trading) and we are able to construct proxies for the counterfactual where markets have large price movements and program trading is allowed. Thus, we can make the desired comparison. If a trade rule does not exist, then the counterfactual of large market moves with no program trading cannot be constructed.

[7]An interesting fact about the KOSPI 200 options contract is that it is the most highly ranked among options index in the world in terms of trading volume... greater than the S&P 500 or other US indices. It has been so for the last decade.

[8]It should be noted that the terminology "program trade" has different definitions in different contexts. In the common media, a program trade typically means a trade submitted by a computer. That is there is no thinking process. When a prespecified criteria is met, a computer sends coordinated trade orders. In the finance literature, an additional meaning exists in the context of sophisticated traders, e.g., hedge funds, that may use coordinated strategies to take advantage of temporary market inefficiencies. Finally, in a regulatory perspective, program trading has to be defined according to observable criteria. Definitions usually consist of the number of different assets traded or whether various markets are traded simultaneously.

[9]Harris (1998) is the lone exception.

these rules benefited market participants? Have the current halt rules achieved the intent of the regulation? What is the primary behavior of program trading during large market moves? We provide some empirical evidence that helps to answer these questions.

Our main results can be summarized as follows. First, when we consider actual sidecar events, there is a significant decrease in order imbalance after the sidecar is implemented. This is true for all trade types. The decrease in normal trades is less than that of program trades, as one would expect if the sidecar were targeting the problem trades. One must be careful when interpreting these results as no controls have been used for market conditions or for firm characteristics. We investigate both these possible alternatives. We attempt to control for market conditions, i.e., markets that have experienced a large price move, by constructing a pseudo-sidecar sample. By collecting events where large market moves occurred, but no sidecar was triggered, we can compare the resolution of order imbalance when there is a halt and when there is no halt. The advantage of this technique is that we can use each firm as its own control, implying a high degree of matching over firm risk characteristics. We find that markets function better, i.e., resolve imbalances more fully, when the program trade is allowed. The reduction in order imbalance is larger in all cases when a sidecar is not implemented. We investigate why eliminating program trades decreases market recovery. Using the prior night US market return as a control, we find that program trades tend to provide liquidity in line with taking contrarian positions with respect to the prior night US market return. During large market moves, particularly those associated with large order imbalance, liquidity trading should be encouraged, not discouraged.

To analyze the effect of program trading halts on order imbalance, we partition our sample in different ways. In addition to the usual control for risk characteristics, we also need to control for market dynamics since we are studying markets that have experienced unusually large market moves. First, we compare program trade stocks against non-program trade stocks. Since normal trading (non-program trading) is allowed during a sidecar, we are able to use the same time period that the sidecar occurred to perfectly control for market dynamics. The normal stock group then acts as a control group not subject to the halt regulation for the program trading stocks (see Figure 1, Actual Sidecar). This allows us to test if order imbalance is a market level or a program-trading level problem at sidecar trigger events. This is important for if it is a market-wide property, then program trading is an unlikely candidate as a cause of the order imbalance. Next, we separate and contrast all our results for all-market halts, for up-market halts, and for down-market halts. We conduct this test as previous research has documented that up markets and down markets can possess different pricing dynamics. We also decompose the set of program trades into an index arbitrage trade sample and compare it with the non-index arbitrage trade sample.[10] We also explore the linkage between the futures and spot markets before and after halts.

[10]On the KRX, program trades consist of two kinds: index-arbitrage trades and non-index-arbitrage trades. Index arbitrage trades are defined as any order that contains both an order in the KOSPI 200 stock group and a KOSPI 200 futures or options order. It is not necessary for the stock and futures/options orders to be made at the same time. For example, it is possible to buy a futures or options contract and then sell a stocks from the KOSPI 200 group or vice versa (see the KRX English website for more details: http://eng.krx.co.kr/m7/m7_4/m7_4_1/m7_4_1_4/UHPENG07004_01_04_04.html). A non-index arbitrage trade is a trade with no futures index order and consisting of a simultaneous order of 15 or more KOSPI 200 stocks.

Probably the best way to control for risk characteristics is to use the firm as its own control. To construct this control sample we use the pseudo sample technique.[11] We isolate a sample of large market moves for which the sidecar rule was not triggered (see Table 1 for details). There is a possible criticism of the pseudo sample. A market that experiences trading restrictions may have different characteristics than one that does not. One simple example is that ex-post we know there was a limit to the imbalance in the pseudo-sidecar event sample. As trading was restricted, we can never be sure of the limits of the move if the halt was not implemented. However we document similar dynamics for order imbalance in the pseudo- and actual-sidecar events, that is, similar to the actual events, the program trades experience a larger decrease in order imbalance than normal trades. Also, in both the actual- and pseudo-sidecars, we find that non-index arbitrage trades have a larger drop in order imbalance after the sidecar in comparison to the index arbitrage trades. When we compare the change in market recovery across events, there is always a statistically larger drop when the market remains open than when trading is restricted. Given there is natural mean reversion in markets, one would expect that larger market moves should on average have larger recoveries. We see the opposite result between the actual- and pseudo-sidecar samples. Thus, we can conclude that natural market mechanisms when program trading is allowed are likely aiding the recovery process. These results hold in tests when we control for other variables associated with liquidity. We conclude that the sidecar inhibits the natural mechanisms in markets to regulate imbalances.

A natural experiment can be performed in order to test the effect of program trading on order imbalances during large market moves. If two subsamples can be defined that differ in the amount of asymmetric information in the market, then if trade is important for resolving order imbalances (in this case due to asymmetric information) then the differences in resolution should be magnified in the high asymmetric information environment compared to the low asymmetric information environment. To conduct this test, for each event, we identify if there was a large public news announcement in the time leading up to the sidecar trigger. We classify those events with no public news event as our high asymmetric information subset and those events with public news as our low asymmetric information subset. We observe a larger order imbalance resolution between the actual- and pseudo-sidecar events in the high asymmetric subset. This finding supports the hypothesis that trade is an important mechanism to resolve order imbalance during large market moves.

Overall, we find that trading halts, sidecars specifically, are not effective at controlling order imbalances. Resolution of order imbalances is more effective when trade is unrestricted. This has policy implications. Our results support a policy of eliminating or modifying program trading halts. Program trades, at least in some instances, are market stabilizing, i.e., program trades provide liquidity when it is at a premium. In these instances, restricting program trades during large market moves reduces the market's ability to resolve imbalances. Thus our results suggest that regulators and academics need to carefully study the various situations for which large market moves occur and categorize them into those where program trades add liquidity and those where program trades are destabilizing.

The main contributions of the paper are as follows: (1) this is the first study for the effect

[11] Such pseudo-sample tests are utilized in the following studies: Lee, Ready, and Seguin (1994); Christie, Corwin, and Harris (2000); and Goldstein and Kavajecz (2000); Corwin and Lipson (2002).

of trading halts on a driver of large market moves, (2) we are one of only a few papers that specifically look at sidecars, (3) we use microstructure measures for order imbalance calculated from intra-day data, (4) the KOSPI 200 spot and futures data set has unique features, such as identifying a trade as buy or sell initiated, (5) we use a data set for which program trading is simultaneously halted in all markets (spot, futures, and options) and where there is no good substitute for the index, and (6) we explore policy implications for improvement of circuit breakers system.

2 Literature Survey

2.1 Proponents of Trading Halts System

One argument is that trading halts can reduce short-term volatility and information asymmetry which benefits investors, regulators, and exchange organizers (Stein, 1987; Greenwald and Stein, 1988 and 1991; Kodres and O'Brien, 1994). Circuit breakers can limit credit risk by providing a "time-out" amid hectic trading to collect intraday margin calls. The time-out may facilitate price discovery by providing a cooling-off period to evaluate information and publicize order imbalances. When circuit breakers are triggered, the traditional pricing mechanisms may be constrained, but information could be processed and dispersed in an alternative fashion. In this case, with a noise-generated panic, circuit breakers accompanied by the dissemination of information and order imbalances could be beneficial, decreasing panic-type volatility. An alternative effect is on information asymmetry and noise or uninformed trading (French and Roll, 1986; Harris, 1998). In this case, trading halts can reduce information asymmetry and stabilize the market. Brennan (1986) notes that price limits can reduce the volatility and stabilize the market when traders tend to overreact to new information.

There are empirical results that support the positive effect of market-wide trading halts. Goldstein, Evans, and Mahoney (1998) study the effect of NYSE Rule 80A on market volatility. Comparing periods when the rule is in effect and when it is not, they conclude that volatility is reduced by a small, yet statistically significant, amount. Lauterbach and Ben-Zion (1993) study the effect of circuit breakers on the Tel Aviv Exchange during the crash of October 1987. They find that circuit breakers reduced the next-day opening order imbalance and the initial price loss. In the commodity and treasury bond markets, Ma, Rao, and Sears (1989a, 1989b) find that traders tend to overreact and thus, circuit breakers play a positive role by reducing both overreaction and volatility.

There is also a body of research on individual trading halts. Fabozzi and Ma (1988) examine over-the-counter market trading activity for stocks temporarily suspended by the NYSE. They find increased volatility without a corresponding increase in information. Kryzanowski and Nemiroff (2001) study intraday data for halted stocks and find that adverse selection is highest right before the halt compared to other times in the day. Engelen and Kabir (2006) study Euronext Brussel stock halts and find that trading suspensions are effective mechanisms in order to disseminate new information. They find an increase in trading volume, but not in volatility, when trading is resumed. Corwin and Lipson (2000) find that information transfer increases during the halt period and trading halts have a positive function in gathering and reflecting new information. Christie, Corwin, and Harris (2002) conclude that long-term halts (halts longer than 90 minutes where the market does not open until the next day) benefit from reduced volatility and insignificant bid-ask spread effects.

Another self-fulfilling effect, the magnetic or gravitational effect, may lead to an increase in market instability around times of information asymmetry. The intuition is that when prices approach a break limit, market participants will trade more aggressively in order to not get "locked" into the market during the close. Arak and Cook (1997) study the magnet effect in the Treasury bond futures market. Berkman and Steenbeek (1998) study the magnet effect in the Nikkei futures. Neither study confirms the hypothesis that price limits may become self-fulfilling.

2.2 Opponents of Trading Halts System

Madhavan (1991) and Lee, Ready, and Seguin (1994) argue that even if investor predictions about future prices improve during the halt period, post-halt volatility will be greater. In other words, if traders are unable or reluctant to reveal their demand fully during the halt, or if they are impaired by the reopening mechanism, the reopening price may be noisy, resulting in higher subsequent volume and volatility (Lee et al., p.189). This finding is supported by Goldstein and Kavajecz (2000) who study the first market-wide halt on the NYSE due to the implementation of a circuit breaker. They document that this halt was followed by record breaking volume and a record breaking market move.

There is a body of empirical results suggesting that circuit breakers are ineffective. Overdahl and McMillan (1998) find that NYSE Rule 80A has little effect on trading costs and intermarket linkage. This is true in spite of the fact that it significantly curtails index arbitrage trading. Amihud and Mendelson (1987) demonstrate that, in general, open-to-open returns are more volatile than close-to-close returns. Thus, a continuous trading process is superior for discovering the equilibrium price. Gerety and Mulherin (1992) show that there is an increase in demand at the close of the market. This implies a hidden increase to trading costs for circuit breakers. Comparing actual halts to pseudo halts, Lee et al. (1994) find that halts increase both volume and volatility. There are other potential detrimental effects of halting trading. Trading halts could expand information asymmetry by restricting the participation of informed traders (Harris, 1998; Kim and Rhee, 1997). Grundy and McNichols (1989) develop a model in which information is contained within the trading process itself. Thus, trading halts can have a negative role on the price adjustment process. Ackert, Hao, and Hunter (1997) study the effect of rule changes in circuit breaker implementation and find that the changes had no effect on expected volatility. Finally, Veld-Merkoulova (2003) find that price limits delay price discovery instead of facilitating it.

Individual trading halt research also has its opponents. Contrary to Ma, Rao, and Sears; Chen (1998) finds that day-to-day price returns are unpredictable after big price swings. He also finds that after a halt, the market tends to move in the same direction as the pre-halt move, suggesting that halts only create pent-up demand. Christie, Corwin, and Harris (2002) find the inside quote spreads are more than double normal levels and volatility can increase to more than nine times normal levels for halts that open after only five minutes.

There is theoretical and empirical support that the magnetic or gravitational effect may lead to an increase in market instability around times of information asymmetry. Subrahmanyam (1994) suggests that if the price is close to the breaker limit, the circuit breakers can force traders to suboptimally advance their trades in time, thus, increasing price volatility. Goldstein and Kavajecz (2004) study the behavior of NYSE market participants during the volatile October 1997 period. They document evidence that participants trading activity is consistent with the magnetic effect before market closures.

2.3 Circuit breakers vs. Sidecars

With the exception of the studies on the NYSE Rule 80A (which is not a halt), the previous literature focuses on market wide or individual halts, rather than on sidecars. Halts, whether market wide or on individual securities, are an important mechanism to understand. However, securities commissions have identified program trading as a contributor to market volatility. Thus, it is important to study sidecars as these give us isolated knowledge of the effect of program trading restrictions on market characteristics.

The seminal study in program trading is Harris, Sofianos, and Shapiro (1994). They study S&P 500 index stocks from 1989-1990 and conclude that program trading does not create short-term liquidity problems. Harris (1998) is the seminal study for program trading halts. In this paper, he looks at the relationship between both circuit breakers and program trading halts and their relationship with volatility. He concludes that there is not enough information to conclude that these mechanisms are effective at controlling volatility. Other than Harris (1998), we have not been able to find papers that specifically cover sidecars.[12] Our paper adds to the knowledge of sidecars. We study the affects of program trading halts on the level of order imbalance in the market. We decompose our results to compare program trades with normal trades and to compare index-arbitrage trades with non-index-arbitrage trades. Since program trading has been singled out by regulators, our results are an important addition to the knowledge on exchange controls. Another novelty of our paper is that we investigate the affect sidecars have on order imbalance. Volatility has been the dominant focus of past papers. However, volatility is an effect of large price moves, not a fundamental driver.

[12]There are a few papers that cover Rule 80A on the NYSE. This rule, which is a program trade inhibitor, only covers index arbitrage trades, a subset of program trades. These papers include Overdahl and McMillan (1998) and Goldstein, Evans, and Mahoney (1998).

3 Data and Trade Halt Mechanisms

3.1 Sample Period and Data

The sample period used is from January 4, 1999 to December 31, 2004. This period is chosen for several practical reasons. First, it covers the period after the Asian Financial Crisis of 1997. Second, this period has consistent regulations concerning trading halts on the Korean securities market. Major changes in the sidecar provisions on the KRX occurred on July 17, 1998.

The sample data consists of historical records for sidecars on the KRX.[13] Data was also collected from the Institute of Finance and Banking at Seoul National University and the Korea Stock Exchange (IFB/KSE) order and trade database. The data set is unique in that it is an intraday order/trade data covering all KOSPI 200 stocks and the KOSPI 200 futures on the KRX. This database has the time-stamp when each order arrives and the time-stamp when an order is executed. The number of sidecar events in our sample totals 108 days. We refine this sample to exclude the events occurring from 9:00AM - 9:30AM as we require a pre-event estimation period. The final number of sidecar events used in our analysis is 92 days. We conduct our tests on the full sample. We also break the sample into up-market halts and down-market halts and conduct tests separately for each subgroup. Our sample contains 48 buy-sidecar days (up-market sample) and 44 sell-sidecar days (down-market sample).

For each sidecar event, we break our sample of trades into two subsets using two separate criteria. The first construction of our stock subsamples are based on the trade type in the pre-period (10 minutes before the event). We first classify trades as:

Program trading sample: KOSPI 200 stocks for which program trading occurred in the pre-period.

Normal trading sample: KOSPI 200 stocks for which no program trading occurred in the pre-period.

The union of the program trading sample and the normal trading sample consists of the full sample of KOSPI 200 stocks. This subdivision allows us to explore if sidecars are effective at reducing imbalances or if the reduction is a market wide phenomenon. Next we decompose the program trade group into an index arbitrage and a non-index arbitrage group. Intuitively, one would expect these two trade types to differ in their affect on the market. Index arbitrage trades are designed to capture mispricing between markets, regardless of the direction of the mispricing. On the other hand, non-index arbitrage trades are more likely to be directional in nature and thus may be a natural medium for smart money to transact.

Arbitrage trading sample: KOSPI 200 stocks for which index arbitrage trading occurred in the pre-period.

[13]The KRX was created when the three existing Korean spot and futures exchanges (Korea Stock Exchange, Korea Futures Exchange, and KOSDAQ) were merged by the enactment of the Korea Stock and Futures Exchange Act.

Non-arbitrage trading sample: KOSPI 200 stocks for which program trading, but no index arbitrage trading occurred in the pre-period.

The rules governing program trading on the KOSPI 200 spot, futures, and options markets are a combined trading restriction of price limit and trading halt. When a certain price move from the previous days close in the KOPSPI 200 futures index is maintained for one minute, then a halt period is enforced (see next section for explanation of the halt mechanism). Since the trading on the KOSPI 200 futures are very active, halts have been exerted over one hundred times since its introduction.[14]

Our final sample construction consists of a set of matched pseudo-sidecar events. Pseudo-sidecar events are extreme price movement periods that did not result in an actual sidecar event. We use this sample as an alternative control sample in our tests. Although the pseudo-sidecar sample is not able to perfectly control for market dynamics, we can get near perfect firm risk characteristic control by utilizing each stock as its own control. We define the pseudo sample in various ways in order to ensure our results are robust. We summarize the actual-sidecar and pseudo-sidecar events in Table 1.

[Table 1 about here.]

Another important property of our data is that unlike other futures products, such as S&P 500 futures and Nikkei 225 futures, there is no substitute product for the KOSPI 200 futures. The KOSPI 200 futures contracts are traded only on the KRX. When a sidecar is triggered by the KOSPI 200 futures market, program trading using the KOSPI 200 futures and options is also halted. There are no other index futures products based on the KOSPI 200 trading on the KRX. Although trading on the KOSPI 200 options contract has the highest volume in the world among such contracts, trading in futures and options contracts on individual Korean stocks is very small and inactive. Thus, it is not possible to reconstruct the index futures using individual stock futures and optioins. During the KRX trading hours, the US market is closed. So exchange traded funds on the US market cannot act as a substitute during the trade halts. This means that the information link mechanism such as index arbitrage between futures and spot markets cannot work during the halt periods used in our study. Thus, compared to the US, the Korean data provides a better natural setting, to test for connectedness between the spot and futures markets.

Finally, in the KOSPI 200 futures market, the halt triggering point is symmetric. Changes of 5% from the previous closing price, either up or down, will initiate a trading halt. This provides an opportunity to investigate and compare the role of sidecars in an up-market to that in a down-market.

[14]Sidecar rules were introduced on May 1996 for the KOSPI 200 futures and on January 2003 for the Star futures, a futures index comprised of 30 blue chip Korean Securities Dealers Automated Quotations (KOSDAQ) companies.

4 Methodology

4.1 Order Imbalance Measures

We measure order imbalance for a specific period of time as the number of buy initiated orders during that period less the number of sell orders initiated during that period. We take this difference and scale it by the total number of trades during the period. This measure is our signed order imbalance measure (SIM). We take the absolute value of SIM to get our absolute order imbalance measure (AIM). AIM is defined as:

$$AIM = \frac{|B - S|}{B + S} \tag{1}$$

Typically an order signing algorithm is used to sign trades, e.g., the Lee and Ready (1991) procedure can be used to calculate B, the buy orders over the time interval, and S, the sell orders over the time interval. However, the Korean trade and quote data signs each trade as buy or sell initiated, thus eliminating this estimation step. This should make inferences from this data more precise.

We implement AIM on three underlying variables in order to test the robustness of our results. We calculate AIM utilizing the number of shares traded, the value of shares traded, and the number of trades. That is, we implement the following three measures:

AIMS $= \|(BS - SS)/(BS + SS)\|$, where BS is the buyer-initiated number of shares traded and SS is the seller-initiated number of shares traded. We append AIM with an "S" for shares traded.

AIMV $= \|(BV - SV)/(BV + SV)\|$, where BV is the buyer-initiated value of shares traded and SV is the seller-initiated value of shares traded. We append AIM with an "V" for value traded.

AIMN $= \|(BN - SN)/(BN + SN)\|$, where BN is the number of buyer-initiated trades and SN is the number of seller-initiated trades. We append AIM with an "N" for number of trades.

When trade direction is of concern, we calculate our measure of order imbalance without the absolute value signs. The appropriate definitions are as follows:[15]

[15] An example of the SIMS construction may be useful. Suppose there are only 3 assets: A, B, and C. Assume in a specific period that for asset A: 100 shares were buy initiated normal trades, 200 shares were sell initiated normal trades, 300 shares were buy initiated index-arbitrage trades, 100 shares were sell initiated index-arbitrage trades, 0 shares were buy initiated non-index-arbitrage trades, and 0 shares were sell initiated non-index-arbitrage trades. Assume in the same period that for asset B: 200 shares were buy initiated normal trades, 100 shares were sell initiated normal trades, 0 shares were buy initiated index-arbitrage trades, 0 shares were sell initiated index-arbitrage trades, 200 shares were buy initiated non-index-arbitrage trades, and 100 shares were sell initiated non-index-arbitrage trades. Assume in the same period that for asset C: 300 shares were buy initiated normal trades, 200 shares were sell initiated normal trades, 200 shares were buy initiated index-arbitrage trades, 300 shares were sell initiated index-arbitrage trades, 100 shares were buy initiated non-

SIMS = (BS-SS)/(BS+SS), where BS is the buyer-initiated number of shares traded and SS is the seller-initiated number of shares traded. We append AIM with an "S" for shares traded.

SIMV = (BV-SV)/(BV+SV), where BV is the buyer-initiated value of shares traded and SV is the seller-initiated value of shares traded. We append AIM with an "V" for value traded.

SIMN = (BN-SN)/(BN+SN), where BN is the number of buyer-initiated trades and SN is the number of seller-initiated trades. We append AIM with an "N" for number of trades.

Our results are qualitatively identical across all three measures. So we report only the results for the number of trades. Our main tests utilize AIMN when we are interested in measuring order imbalance using the full sample or directional effects are not of primary concern. We use SIMN when we are interested in trade directional effects. SIMN should only be calculated utilizing the subset of halts in up markets or the subset of halts in down markets. This is because it has different signs in each situation and unwanted cancellation occurs.

4.2 Trade direction is observed

In the prior literature on circuit breakers, most papers use the two methodologies to classify a trade as a buy trade or a sell trade (see Bessembinder, 2003; Ellis, Michaely, and O'Hara, 2000; and Lee and Ready, 1991 for a discussion of the trade classification literature). In our data, we observe what side of the trade is the initiating trade. Thus, we know if a transaction is a buy transaction or a sell transaction. This makes our analysis more accurate as we do not have to make any simplifying assumptions or estimates in order to sign trades.

4.3 Matched control sample

We compare the test sample with a matched control sample in order to conduct our primary tests concerning the effectiveness of sidecars. The matched sample is constructed by looking at each KOSPI 200 stock in the pre-sidecar period. If at least one program trade involved the stock in the pre-event period, then that stock is assigned to the program trade sample (test sample). If no program trade involved the stock in the pre-event period, then the stock is assigned to the normal trade sample (control sample). A similar classification procedure is used for breaking program trades into index arbitrage and non-index arbitrage subsamples.

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index-arbitrage trades, and 100 shares were sell initiated non-index-arbitrage trades. Then we can calculate the SIMS as follows:

Normal SIMS $\frac{(100+200+300)-(200+100+200)}{(100+200+300)+(200+100+200)} = \frac{600-500}{600+500} = \frac{1}{11}$

Index arb SIMS $\frac{(300+0+200)-(100+0+200)}{(300+0+200)+(100+0+200)} = \frac{500-300}{500+300} = \frac{1}{4}$

Non-index arb SIMS $\frac{(0+200+100)-(0+100+100)}{(0+200+100)+(0+100+100)} = \frac{300-200}{300+200} = \frac{1}{5}$

4.4 Construction of the pseudo-sidecar sample

We follow Lee, Ready, and Seguin (1994) in our construction of the pseudo-sidecar event sample, i.e., the actual-sidecar event sample vs. pseudo-sidecar event sample. The pseudo-sidecar event sample consists of a set of events for which the futures price moved up or down within 1% of the trigger level, but a trading halt was not triggered. In our pseudo-sidecar sample, there are no trading halts; thus, normal information transfer works between the futures and spot market. We can analyze the information transfer between spot and futures markets and the changes in order imbalance around the trading halt by comparing the test sample and the pseudo sample (non-halt day sample). See Table 1.

4.5 Research design

We study the order imbalance surrounding the sidecar event utilizing the event study framework. Our "event" consists of a sidecar halt, i.e., a halt on program trading in the spot, futures, and options markets. We measure order imbalance with AIM and SIM at one minute intervals from 9:00AM to 2:50PM. We measure order imbalance both before and after the sidecar event in order to determine its affect on the trading environment. Our pre-halt period consists of the 10-minute period immediately preceding the halt, and our post-halt period consists of the 10-minute period immediately following the halt.

We conduct our comparisons for the full sample, the program-trading sample vs. normal (non-program-trading) sample, and the index-arbitrage trading sample vs. the non-index-arbitrage trading sample. We compare the actual-event sample with both a matched sample and the pseudo-event sample. We also break the full sample up according to the market direction. Thus, in addition to analyzing the full sample of all sidecar halts, we analyze an up-market sample (sidecars implemented for extreme up-market moves) and a down-market sample (sidecars implemented for extreme down-market moves).

Our research design is constructed to answer three main questions. First, we are interested in whether sidecars are an effective mechanism to reduce extreme order imbalances. To answer this, we analyze and compare imbalances surrounding sidecar events. We measure the order imbalance of all KOSPI 200 stocks surrounding the sidecar events. We analyze each subsample, i.e., the total-sidecar sample, the buy-sidecar sample, and the sell-sidecar sample.

The second question of interest is what channel exists for transmitting information between markets. That is, we ask whether program trading is important for maintaining the connection between the spot prices and the futures price. There are two possible hypotheses. According to no arbitrage, information can be transmitted via the action of arbitrageurs engaging in index arbitrage trades. An alternative hypothesis is that there is a smart-money effect. That is, some traders have information and target individually mispriced assets to take advantage of this information and, in the process, push the mispriced market to equilibrium. To discern between these two competing theories, we take all program trades and classify them as index-arbitrage trades and non-index-arbitrage trades. If the no-arbitrage theory holds, then the index arbitrage trades should have a larger affect on the price connectedness across markets.

Finally, we want to find out if sidecars are even necessary. That is, would markets correct themselves in the absence of a sidecar implementation? To answer this question, we use our matched sample of normal trades, i.e., stocks that were not involved in an index-arbitrage trade in the pre-event period. If these stocks behave similar to those that are involved in index arbitrage, then it is difficult to classify index arbitrage as the driving mechanism. In addition, we use our pseudo-sidecar sample to test if extreme market moves are associated with similar imbalance reduction patterns that we document in the actual-sidecar sample. If so, then the sidecar is of questionable utility as markets are adjusting in a similar manner on their own. Table 2 and Figure 1 summarize the comparisons we make across the various subsamples.

[Table 2 and Figure 1 about here.]

4.6 Robustness: Factors that affect changes in order imbalance

As a robustness check on how dependent our results are to the methodology employed, we implement tests in a regression framework utilizing variables that have been documented to influence changes in the order imbalance environment. Our dependent variable is one of the imbalance variables measured during the event period. We use the following as independent control variables: trading volume, spread, volatility,market trend, a time of day dummy that equals 1 if the halt occurs before noon and zero others wise, and a dummy variable equal to 1 if it is a halt period and 0 otherwise. We utilize a difference-of-difference regression framework.

5 Empirical Results

5.1 Do sidecars reduce order imbalances?

Our first analysis uses the SIM measure of imbalance in order to explore market characteristics before and after a sidecar event. SIM allows us to see whether buy or sell pressure is driving the large price movement. We report the mean values for all KOSPI 200 stocks for the total sample, i.e., all actual program trading halts, and for both the up-market and down-market sidecar event subsamples. Our results are reported in Table 3.

[Table 3 about here.]

Panel A reports the full sample results. The first thing we can see is that in the full sample there is excess selling pressure in both the pre- and post-sample periods. However, for all measures employed, the sell pressure is greater in the post-sample period than it is in the pre-sample period. The differences are statistically significant with either parametric t-tests or with non-parametric Wilcoxon rank sum tests. At first blush, it seems the sidecar halts are exacerbating the order imbalance environment, rather than easing it. However, the next two panels show that analyzing the full sample with SIM does not reveal the true nature of the effects of the sidecar. Breaking the sidecar events into those that occurred in a rising market and those that occurred in a falling market reveals a different picture.

Panel B of Table 3 gives the SIM results for the upmarket subset of our sidecar sample. In the pre-event period, there is excess buying pressure, rather than excess selling pressure as suggested in the full sample. In all measures employed, the level of imbalance falls. The excess buy pressure is reduced when the sidecar is implemented. In some cases, excess sell pressure is attained, implying the sidecar was able to impose a mean reverting price process, which would be desirable if the excess buy pressure was due to temporary market malfunction leading to cascading trades based on previous price/trades rather than trades based on individual investor information. Panel C gives a similar picture for down markets. In the pre-event, there is excess selling pressure. For all measures employed the selling pressure is reduced by the implementation of the sidecar. The main difference is that in a down market, the sidecar is not sufficient to completely eliminate the sell order imbalance. Although the excess sell capacity is reduced, the sell pressure remains after the sidecar.

It appears that the sidecar event is useful in reducing (eliminating in the case of an up market) the excess trading pressure due to temporary fluctuations in supply and demand. Figure 2 graphically demonstrates each case. Panel A of Figure 2 shows that in an up market and several minutes before a sidecar event, there is a marked increase in buy pressure. When program trading resumes, after 3 minutes, there is a noticeable reduction in the excess buy pressure, with excess sell pressure realized after 5 minutes. Panel B of Figure 2 shows similar behavior for down markets, with the exception that excess sell pressure, although reduced, remains over the whole post-period.

[Figure 2 about here.]

Next we consider the AIM measure of imbalance. Table 4 gives the results. Panel A gives the results for the full sample, while Panels B and C give the results for the up-market and down-market sidecars, respectively. For both the full sample and for both the up and down markets, all measures employed give consistent results. The sidecar helps to reduce, but does not eliminate the excess buy/sell pressure. The results are statistically significant both with the parametric t-test and the non-parametric Wilcoxon p-values. Figure 3 graphically demonstrates the results. Again, there is a marked increase before the event and a large reduction after trading restrictions are relaxed. In all cases, the excess sell/buy pressure remains, but at reduced levels. Again, the sidecar has an overall affect in the desired direction.

[Table 4 about here.]

[Figure 3 about here.]

Given that all results are qualitatively similar under all measures, from this point forward we only report results for $AIMN$ and $SIMN$ in order to preserve space.

5.2 Information transfer mechanisms

A sidecar halts program trading only. The question is whether this is effective. By "effective" we mean stocks that are involved in program trades have the order imbalance reduced more than stocks that are not involved in program trades. To explore this, the sample of stocks are separated into two subgroups. The first subgroup, called the program trading sample, consists of stocks that are listed in at least one program trade during the pre-event period. If a stock occurs in a non-program trade in the pre-event period, then it is assigned to the normal trading sample. We test the level of order imbalance for each group, both pre- and post-event. We also test the change in order imbalance for each group between the pre-event period and the post-event period. Our results in Table 5 confirm that stocks that are involved with program trading experience a larger level of order imbalance both pre- and post-event. Even more compelling is the fact that there is a larger decrease in the imbalance across the pre-event period and the post-event period for the program trading sample than for the normal trading sample. This evidence suggests that the sidecar may be effective in reducing order imbalance, and it is specifically so for those stocks that are involved in the program trading. It appears to be effective for its target group of stocks. This is true for the full sample and for both the up-market and the down-market samples.

[Table 5 about here.]

Next we explore the affect of the actual-sidecar on different program trade types. We take all program trades and separate them into two subsets. The first is the set of all program trades that consist of index arbitrage. Index arbitrage is defined as trades that include a KOSPI 200 futures and at least one other KOSPI 200 asset. If a trade does not include both of these assets and a trade consists of more than 15 stocks in the KOSPI 200, then the trade is classified as a non-index arbitrage trade. We measure the order imbalance for the actual-sidecar events both in the pre-event period and the post-event period. Table 6 summaries the results. Our results are again consistent across the full sample and both the up-market and down-market samples. We find that for all types of trades (normal, index arbitrage, and non-index arbitrage), the order imbalance is higher in the pre-sidecar period than in the post-sidecar period. These results are statistically significant using both the parametric t-tests and nonparametric Wilcoxon p-values. These results agree with and support the earlier conclusions from Tables 3 and 4. What is new in Table 6 is the comparison of the index arbitrage and non-index arbitrage trades. We see that the arbitrage trades always have a slightly higher, but statistically significant, level of imbalance. However, the reduction in order imbalance after the sidecar for the non-index arbitrage trades is always larger than that for the index arbitrage trades. Thus, we have documented that in the actual-sidecar event that the reduction in order imbalance is greatest for non-index arbitrage trades, next is for the index arbitrage trades, and is smallest for normal trades.

[Table 6 about here.]

5.3 Are sidecars necessary?

We construct a pseudo-sample of sidecar events. This sample consists of large market moves that approached, but did not trigger a sidecar event. We use alternative definitions of the pseudo-sidecar to make sure our results are robust. We can use this sample as a control in order to study the market characteristics of a large stock move under a sidecar event and a large stock move absent a sidecar event. If the market characteristics observed in the actual-sidecar sample are not present in the pseudo-sidecar sample, then we can conclusively conclude that the program trading halts are effective at controlling order imbalance during large market moves. However, if the observed ordering in order imbalances are observed in both samples, it then becomes a matter of magnitude, i.e., which sample has a larger reduction in imbalance. A priori, given that mean reversion exists in markets, we would expect larger market moves and larger order imbalances to have on average larger corrections. Thus, we expect to find a larger correction in order imbalances for the actual-sidecar events. If the pseudo-sidecar events have a larger correction, then this is bad news for the effectiveness of program trading halts and we can safely conclude that actual-sidecars are on average inhibiting the market's self-regulating mechanisms. That is, the sidecar is not necessary to observe the reduction in order imbalance associated with a large market move. The market self-adjusts via its own internal mechanisms and eliminating program trading reduces the market's capacity to adjust for large order imbalances during large market moves.

To investigate this possibility, we repeat our experimental design over our pseudo-sidecar events. Table 7 reports the results for the full sample of events. Table 8 reports the results for the up-market events and for the down-market events separately. We find a similar pattern across all market types. Order imbalance is larger in the pre-event period before a large stock move. Notably, in most cases, the imbalance level is larger in the actual sample compared to that observed in the pseudo sample. Again, in all cases the post-event period, the level of imbalance drops. We find this result holds both for program trades and for normal trades. We also find a similar pattern for index-arbitrage trades and non-index-arbitrage trades. All the level results are significant both with the parametric t-test and the non-parametric Wilcoxon p-values. We also observe a drop in order imbalance from the pre-event period to the post-event period. This holds true for all trade types and in all market types. Finally, we find that the reduction in order imbalance is higher for program trades compared to normal trades, and we find that the change in order imbalance is higher for non-index-arbitrage trades compared to index-arbitrage trades. Again, all results are statistically significant. These are the same patterns documented for our actual-sidecar sample. Figure 4 represents this visually. In each panel, the time series of order imbalance appears very similar.

[Tables 7 and 8 about here.]

[Figure 4 about here.]

To help us discern whether there is a difference between the pseudo-sidecar sample and the actual-sidecar sample, we compare changes across samples. The results are reported in the

"Difference (Pseudo-Actual)" column of Tables 7 and 8. The differences compare changes in order imbalance in Tables 5 and 7, and in Tables 6 and 8. Somewhat surprisingly, the reduction in the order imbalance across the pre-event and post-event period is larger in the pseudo-sidecar sample than in the actual-sidecar sample. This result holds in both up markets and in down markets. The one exception is for the full market results for the non-index arbitrage trades. The results are statistically significant both with the parametric t-test and the non-parametric Wilcoxon p-values. Thus, we conclude that the program trading is not responsible for the observed order imbalance dynamics during large price moves. The sidecar is not necessary for the market to adjust. After a large price move that is associated with a large level of order imbalance, the market will adjust itself and the order environment will normalize more fully when program trading is allowed than when it is restricted. The sidecar is an unnecessary burden on the natural correction mechanisms of the market.

In Table 9, we investigate the pseudo-event sample and actual-event sample for SIMs. This gives us information on the direction of order imbalance resolution. For an up market, we see in Panel A that there is always a reduction in the buy-order imbalance. The normalizing effect is larger in the pseudo-sidecar sample than in the actual-sidecar sample. Panel B gives similar intuition for down markets. In all samples, there is a reduction in the sell order imbalance. Again, the normalizing effect is larger for the pseudo-event sample. Again, the sidecar seems to interfere with the natural self-adjusting process of an open market.

[Table 9 about here.]

6 Robustness Checks

6.1 Do sidecars reduce order imbalances?

We report in Tables 3 and 4 that the sidecar reduces order imbalance from the pre-event period to the post-event period. We also documented that the reduction is larger for the pseudo-sidecar sample for all trade types than it is for the actual-sidecar sample. In order to test the robustness of these results, we employ a regression based framework. We regress the order imbalance on our independent variables. We capture the sidecar effect as a dummy variable (PRE). We estimate the regression of actual AIM or SIM for each subset of trades: normal trading stocks, program trading stocks, arbitrage trading stocks, and non-arbitrage trading stocks. We control for time, a market dummy, and several control variables. Our control variables specifically control for liquidity, as that is a possible alternative cause of order imbalance. We control for liquidity in order to demonstrate that our results are still valid above and beyond any liquidty effect. The regression model is as follows:

$$
\begin{aligned}
OI_j &= \beta_0 + \beta_1 \cdot PRE + \beta_2 \cdot TIME + \beta_3 \cdot MARKET \\
&\quad + \beta_4 \cdot VOLATILITY + \beta_5 \cdot VOLUME + \beta_6 \cdot SPREAD
\end{aligned}
\tag{2}
$$

In Equation 2, the dependent variable OI_j, for order imbalance, is AIM if $j = 1$ and SIM if $j = 2$. In the regression, we use cross-sectional and time-series pooled data constructed during the 10 minutes of the pre-halt period and post-halt period for each sidecar event. PRE takes the value of one in the pre-halt period and zero in the post-halt period. $TIME$ takes the value of one if sidecar is triggered before 12:00 and zero otherwise. $MARKET$ takes the value of one if sidecar is triggered on the sell side (down market), and zero otherwise (up market). A common critique of order imbalance is that it is also related to liquidity. To control for this confounding effect, we use the following control variables for liquidity: $VOLATILITY$, $VOLUME$, and $SPREAD$. $VOLATILITY$ is the standard deviation of the midpoint for log return measured at one-minute intervals in the pre-halt period and post-halt period. $VOLUME$ is the proportion of trading shares in the pre-halt period and post-halt period to total daily trading shares. $SPREAD$ is the mean of the quote spread divided by the midpoint price measured at one-minute intervals in the pre-halt period and post-halt period.

If the coefficient on PRE is positive and significant, then order imbalance, OI_j, is higher in the pre-event period than in the post-event period. If it is negative and significant, then the regression would indicate that the imbalance actually increased from the pre- to the post-event period. Table 10 reports the results for the regression in Equation 2. AIM is used as the dependent variable. In all stock/trade subsets, the sidecar is associated with a reduction in order imbalance from the pre-event period to the post-event period. In all cases, the effect is significant at the 1% level. Thus, our previous finding that a sidecar is associated with a reduction in order imbalance is robust to inclusion of other influential variables.

[Table 10 about here.]

6.2 Information transfer mechanisms

Also in Table 10, the magnitude and significance of the coefficient on PRE gives us the relative importance of a sidecar halt for resolving asymmetric imbalances across the different trade types. Under the hypothesis that the main mechanism for transferring information between the spot and futures market is index arbitrage, we would expect the magnitude of PRE to be largest for the index arbitrage trade sample. We note, however, that this is not the case. The magnitude of the coefficient on PRE is larger for the non-index arbitrage sample than it is for the index arbitrage sample. This violates the thesis that index arbitrage is the main information transfer mechanism, directly supporting our previous findings.

Even the normal trading sample, those stocks not involved in program trades during the pre-halt period, have a positive and significant coefficient on PRE. Thus, information is being transferred between markets outside of the program trading environment. This result directly supports a smart-money effect.

6.3 To restrict program trading or not?

The main result we find is that the pseudo-sidecar sample has identical market characteristics for order imbalance resolution as the actual-sidecar sample. The only difference is that contrary to basic intuition the resolution is greater in the pseudo-sidecar sample. In order to test the robustness of our results in a regression framework, we use a difference-of-differences regression model. We estimate results for the regression of AIM and SIM of Normal trading stocks, Program trading stocks, Arbitrage trading stocks, and Non arbitrage trading stocks. The regression is estimated based on following model:

$$\begin{aligned} OI_j &= \beta_0 + \beta_1 \cdot PRE + \beta_2 \cdot TIME + \beta_3 \cdot MARKET \\ &\quad + \beta_4 \cdot VOLATILITY + \beta_5 \cdot VOLUME + \beta_6 \cdot SPREAD \\ &\quad + \beta_7 \cdot USRET + \beta_8 \cdot ACTUAL + \beta_9 \cdot PRE \cdot ACTUAL \end{aligned} \tag{3}$$

All variables are defined as in Equation 2. We have added three terms to this regression. The first is the variable $ACTUAL$, which is a dummy equal to 1 if the observation is from an actual sidecar and 0 if from a pseudo sidecar. $PRE \cdot ACTUAL$ is the interaction between PRE and $ACTUAL$. This cross term captures the differences-of-differences effect ($\Delta AIM_{actual} - \Delta AIM_{pseudo}$, where the difference is the change in order imbalance between the pre- and post-periods).[16] This differences-of-differences effect is a main focus of this study. Finally, Asian markets are highly correlated with the return in the US market. To control for this effect, we use $USRET$, which is the open-to-close log return of the S&P500 index of the previous day to the sidecar date. We use cross-sectional and time-series pooled data of observations constructed during the 10 minutes of the pre-halt period and post-halt period of the actual and pseudo sidecar event.

[Table 11 about here.]

Table 11, Panel A reports the results for AIM for the total sample. PRE is positive and significant for all trade types. Thus, in all trade subsets, the sidecar is associated with a reduction in order imbalance from the pre-event period to the post-event period. We also find that liquidity is an important explanatory factor. All liquidity variables are significant in the regression for all trade types. The main result we present in these regression results is contained in the sign and significance of the cross term PREx$ACTUAL$. In all trade types the coefficient

[16] This can most easily be seen by looking at the following:

$$\beta_1 \cdot PRE + \beta_9 \cdot PRE \cdot ACTUAL = (\beta_1 + \beta_9 \cdot ACTUAL) \cdot PRE$$

If $ACTUAL = 0$, then β_1 captures the change in order imbalance for the pseudo-sidecar sample. On the other hand, if $ACTUAL = 1$, then $\beta_1 + \beta_9$ captures the change in order imbalance for the actual-sidecar sample. Thus, β_9 is the additional change of the actual over the pseudo samples. Our previous finding that markets with program trading allowed adjust more fully to order imbalances after large market moves than markets with program trade restrictions will be confirmed if $\beta_9 < 0$.

is negative and significant. Thus, after controlling for liquidity the conclusion remains that markets adjust order imbalances more fully when program trades are allowed than when they are not allowed. Table 11, Panel B reports the results for AIM for both the up-market and down-market samples separately. Table 11, Panel C reports the results for SIM for both the up-market and down-market samples separately. In all cases, except the non-arbitrage trade type in up markets, the results are robust to up and down market subsamples.

6.4 Why does eliminating program trading adversely affect order imbalance during large market moves?

So far we have documented that restricting program trades via the sidecar rule inhibits the market's natural ability to eliminate order imbalances during large market moves. It is interesting to ask why. Asian markets over our time period have a tendency to follow the US market. One interesting question is to control for US market returns and investigate the trading behavior of normal trades and the various types of program trades. This result is reported in Table 11.

In Table 11, Panel A we see that in the normal trade group there is an insignificant effect on USRET. However, in the program trade groups, there are significant and opposite signs for the index arbitrage and the non-index arbitrage trade groups. Thus, each group has a different effect on order imbalance in relation to US market moves. If the non-index arbitrage trade group is providing liquidity, that is they are contrarian trading with respect to previous day US market returns, then it is not wise to remove these trades from the market when liquidity is at a premium. To better understand the impact on order imbalance of each trade group with respect to US market returns, we study SIM (as sign is important) and break the analysis into up market and down market subgroups. In Panel C we find that the normal trade group exacerbates the order imbalance in both the up and down markets. On the other hand, both program trade types lean against the previous US market return. Thus, program trades, at least in this instance, provide liquidity to the market. When large market moves occur due to large order imbalances, liquidity is at a premium. Removing liquidity from the market during such times should reduce market efficiency. This is what we observe with the sidecar rule.

7 A Natural Experiment

If two samples could be found, one with a higher asymmetric information environment than the other, then we can make predictions concerning the effect of a sidecar on the order imbalance. If the sidecar inhibits the market's ability to adjust large order imbalances, then when asymmetric information is high, we would expect to see a particularly high realization of order imbalance when trade is allowed compared to when trade is restricted. That is, we would expect to see a larger difference between the actual- and pseudo-sidecar samples.

We attempt to differentiate the information environment by dividing our sample of events into two groups. We divide both the actual and the pseudo samples into two groups. The first group is the set of large market moves that were subject to a public information shock. If a news event occurred during the period from the previous day to the sidecar event time, we classify that sidecar into the Public-News sample. We identify news by searching for each event the representative daily newspapers (Maeil Business News and Dong-A Ilbo) and the KRX website's disclosure and news section. If no public news announcements were found, then the sidecar event is tagged as a No-Public-News event. Our actual and pseudo samples break down as in Table 12.

[Table 12 about here.]

Table 13, Panel A reports the results for the Public-News sample and Panel B reports the results for the No-Public-News sample. We first note that in each subsample, the same ordering of the magnitudes in order imbalance reduction is observed as in the full sample. This is true for both the actual and pseudo subsamples. Again, with the exception of the arbitrage trades in the Public-News sample, the reduction in order imbalance is larger in the pseudo sample than in the actual sample. Thus, markets work better at resolving order imbalance when trade is unrestricted. The final observation concerns the comparison across information environments. The magnitude of the order imbalance difference between the actual- and pseudo- sidecar samples is smaller in the sample of events that experienced public news announcements, compared to the no-public-news sample. Interestingly, the only case where the sidecar seems to have a positive effect is on arbitrage trades during news driven market moves. When private information is more likely to exist, this no-public-news group experiences a sharp drop in ability to adjust to large order imbalances. Overall, the results are in line with the hypothesis that sidecars are inhibiting the markets natural adjustment mechanism.

Table 13, Panels A and B also compare the actual- and pseudo sidecar samples in both the public-news sample and the no-public-news sample. When there is an important public news announcement the difference between the order imbalance resolution in the actual and pseudo samples are not significantly different from zero. The one exception is the for the non-index arbitrage class of trades. In stark contrast, in the no-public-news sample, the sample where private information is more likely to be driving the market imbalance, we find a large and significant difference across all trade types. This is exactly as expected if the trading is important to alleviating large order imbalances during times of high asymmetric information. Without trade, it is difficult for the market to engage in discovery and the uninformed stay away from the market.

8 Futures Markets

Tables 7 and 8 report, for all subsets of stocks and trades and for all market conditions, the pseudo-event sample had similar order imbalance dynamics as the actual-event sample. As a robustness test, we explore the asymmetric dynamics in the KOSPI 200 futures market. Again, we compare order imbalance, measured by AIM, before the event and after the event. We conduct these measurements for both the actual- and the pseudo-event samples. Again, Table 14 finds a similar pattern across all market types. order imbalance is larger in the pre-event period before a large stock move. In the post-event period, the level of order imbalance drops. All the level results are significant both with the parametric t-test and the non-parametric Wilcoxon p-values. We also observe a drop in order imbalance from the pre-event period to the post-event period. This holds true for all market types. Again, all results are statistically significant. These are the same patterns documented in Tables 7 and 8. Figure 5 represents this visually.

[Table 14 about here.]

[Figure 5 about here.]

In Table 9, we found that sidecars are an unnecessary burden on the natural information discovery process of the market based on the fact that markets are self-adjusting with respect to order imbalance after a large price move. As this is the most important result we report, we subject this result to several robustness tests. First, we calculate the basis as the nearest expiry KOSPI 200 futures index less the KOSPI 200 spot price. The basis is a measure of the inter-market linkage between the KOSPI 200 futures and spot markets. We then calculate the change in the basis from the pre-event period to the post-event period for both the actual-event sample and the psuedo-event sample. The results are contained in Table 15. We find that in both samples, the basis does not change. That is, after a large price move, whether a sidecar is implemented or not, the two markets remain linked at a constant level before and after the event. This supports our previous finding that the sidecar is ineffective.

[Table 15 about here.]

We next run a regression-based robustness test for the results reported in Table 9. The hypothesis behind our test is that as the basis increases, i.e., as the markets become less linked, so should the asymmetric information as informed trades will enter the market more aggressively.[17] Thus, we use $Basis$ as our dependent variable. We control for market type by including a dummy variable for the market type ($MARKET$) that takes the value of 1 if the sidecar was triggered in a down market and the value of 0 in an up market. Our main hypothesis concerns the explanatory power of the arbitrage program trading. If index arbitrage is the only mechanism important for information transfer between the spot and futures markets, then index arbitrage program trading ($ABTSIM$) should be positively correlated with the basis, while the other samples should be insignificantly correlated. The regression model is as follows:

$$\begin{aligned} Basis &= \beta_0 + \beta_1 \cdot MARKET + \beta_2 \cdot NTSIM \\ &\quad + \beta_3 \cdot ABTSIM + \beta_4 \cdot NABTSIM \end{aligned} \tag{4}$$

[17]Kaul, Lei, and Stoffman (2008) provide justification for using order imbalance as a proxy for asymmetric information.

Where $NTSIM$ is the SIM of the normal trade sample, and $NABTSIM$ is the SIM of the non-index arbitrage sample. Table 16 reports the results of the above regression. We find that arbitrage trades are significantly and positively correlated with the basis. However, we also find that the non-index arbitrage trades are significantly and positively correlated with the level of market linkage. The normal trading sample are not correlated with the basis.

[Table 16 about here.]

We also investigate the trading activity on the KOSPI 200 spot market surrounding both the actual-sidecar and pseudo-sidecar events. Table 17 reports the difference in trading activity levels before and after a large market move. Results are reported for the normal trading sample, the index arbitrage sample, and the non-index arbitrage sample. We utilize three different measures of trading activity: the actual number of trades executed, the total number of shares traded, and the value of all shares traded. For the actual-sidecar event sample, for all measures of trading activity and for all sample types, we find the trading activity increases or is the same after the sidecar. This indicates that during the sidecar halt, there is a pent-up demand that builds until the market reopens. In stark contrast, in the pseudo-sidecar sample, for all measures of trading activity and for all sample types, we find the trading activity decreases after the pseudo sidecar. All results are statistically significant. This table demonstrates that, in addition to not being effective in controlling order imbalance, the implementation of a sidecar inhibits market participants from trading. The increase in trading activity after the halt in program trading implies that information asymmetry is not fully resolved during the halt period. When markets are allowed to function openly, then trading activity decreases with the drop in order imbalance, as should be expected, if the imbalance is being resolved through trading activities.

[Table 17 about here.]

We consider the trading activity on the KOSPI 200 futures market. The difference in trading activity levels before and after a large market move are calculated. We utilize three different measures of trading activity: the actual number of trades executed, the total number of contracts traded, and the value of all contracts traded. We report the results in Table 18. For the actual-sidecar event sample, for all measures of trading activity, we find the trading activity decreased, but not significantly, after the sidecar. In the pseudo-sidecar sample, we find the trading activity decreases after the pseudo sidecar for all trade types, but it is significant only for the number of trades. For both the contracts traded and the value traded, the difference in trading activity before and after the event are not significantly different from zero. We conclude that the trading activity in the futures market measured by either number of contracts or value of contracts is not affected by implementing a sidecar. On the other hand, the number of trades actually increases after the actual sidecar while it decreases after the pseudo sidecar. Again, this shows that the sidecar works to restrict trading and causes demand to queue.

[Table 18 about here.]

Finally, we divide our sample period into two subperiods. The first period is from January 4, 1999 to May 10, 2001. This corresponds to the period for which the sidecar had a 4% trigger on the market return. The second period is from May 11, 2001 to December 31, 2004. This period corresponds to the period for which the sidecar had a 5% trigger on the market return. The subperiod analysis accomplishes two tasks. First, it tests if the reported results are sensitive to the trigger level. Second, it determines if the results from the whole analysis are robust across subperiods. The results of both periods are consistent with the results from the whole sample. The relationships across levels, differences between trade types, and differences between actual and pseudo sidecars are identical in both subperiods. The results are available on request.

Our robustness tests support our conclusions that the sidecar rule is not effective at reducing order imbalance. order imbalance is reduced similarly or even more when markets are allowed to remain open during a large price move and market forces are allowed to act on price. We also find that implementation of a sidecar is associated with an increase in trading after the halt implying that market participants are inconvenienced.

9 Conclusion

Trading halts have been studied extensively with regards to circuit breakers (all trading is halted) and how circuit breakers affect volatility and price discovery. The results of this research are mixed. Harris (1998) concludes that a main critique of this literature is the small number of observations, which reduces the power of the statistical analysis.

We add to the above literature in several ways. First, we study sidecars (only program trading is halted while the market remains open). Other than the seminal paper by Harris (1998), we are the only study to consider this popular regulatory mechanism. Like the previous studies, Harris investigates how program trading halts affect volatility. We investigate how program trading halts affect the order imbalance environment of the market. To our knowledge, we are the first to study the possible link between order imbalance and trading halts. In addition, we use a unique feature of the Korean market that allows us to observe the sign of the trade, thus eliminating a potential source of error. Using the Korean data rather than US data allows us to explore the relationship between index-arbitrage trades and non-index arbitrage trades. Rule 80A on the NYSE applies only to index-arbitrage trades, while the KRX sidecar applies to both types of trades.

We develop several testable hypothesis. The first hypothesis concerns changes in order imbalance around (before/after) trading halts. If sidecars are an effective mechanism to reduce order imbalance, then we should see a reduction in both the futures market and the cash market. The second hypothesis is that a trade halt induces pent-up demand. We hypothesize that stocks actively traded by program trades should exhibit higher levels of order imbalance. Finally, we hypothesize that the observed order imbalance dynamics around an actual-sidecar event should exhibit a larger reduction in order imbalance than in a control pseudo-sidecar event.

Our results support the first two hypotheses. A very important exception is the violation of the third hypothesis, in that, pseudo-sidecar events exhibit significantly larger drops in order imbalance than the actual-sidecar events. Combined with the fact that demand increases after a sidecar, but not after a pseudo sidecar, implies that sidecars are only not effective at controlling order imbalance, but they interfere with the markets self-adjusting mechanisms and add costs to market participants, manifested as pent-up demand. Our main results are consistent across several robustness tests. Our results suggest that the sidecar is not effective and should be eliminated, at least in its current status as used on the Korean market.

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Table 1: Actual-sidecar sample vs. Pseudo-sidecar sample

A pseudo-sidecar is an event that had a large price fluctuation but did not trigger a program trading halt. The pseudo-sidecar events are used as a control sample in our tests.

The sidecar system on the KRX works as follows. When the benchmark KOSPI futures contract moves more than X % (X depends on the sample period, see table below) from the previous close and does so continuously for at least 1 minute, the KRX halts program trading on the 200 constituent stocks in the KOSPI 200 index for five minutes in order to cool down the buying or selling pressure. That is, program trades cannot be executed on either the futures or the spot markets during the halt period. Unlike Rule 80A on the NYSE, which applies to only index arbitrage trades, the KRX sidecar applies to all program trades, both index arbitrage trades and non-index arbitrage trades.

Robustness tests were performed using two alternative definitions of the pseudo sidecar. The first alternative utilized a difference of 0.5% from the actual sidecar trigger, i.e. first period trigger of 3.5% and second period trigger of 4.5%. The second alternative utilized a difference of 1.5% from the actual sidecar trigger, i.e. first period trigger of 2.5% and second period trigger of 3.5%. Similar results were found for all three definitions, so only the 1% difference results are reported. Results with the other definitions of sidecars are available from the authors.

Sample period	**Actual-sidecar sample**	**Pseudo-sidecar sample**
Jan. 4, 1999–May 10, 2001	Trigger provision: In case the price change of the nearest KOSPI 200 futures contract is greater than 4% compared to the closing price of previous day continuously for 1 minute.	Trigger provision: In case the price change of the nearest KOSPI 200 futures contract is greater than 3% compared to the closing price of previous day continuously for 1 minute (but the sidecar has not been triggered).
May 11, 2001-Dec.31, 2004	Trigger provision: In case the price change of the nearest KOSPI 200 futures contract is greater than 5% compared to the closing price of previous day continuously for 1 minute.	Trigger provision: In case the price change of the nearest KOSPI 200 futures contract is greater than 4% compared to the closing price of previous day continuously for 1 minute (but the sidecar has not been triggered).
Total number of sidecar events	92	147
Number of up-market events	48	75
Number of down-market events	44	72

Table 2: Summary for Analysis of Experimental Design

We utilize two order imbalance measures: Absolute order imbalance (AIM) and signed order imbalance (SIM). We implement two test methods: T-test and Non-parametric Wilcoxon test. Before refers to the 10 minute pre-halt period, while After refers to the 10 minute post-halt period. Normal refers to stocks that were involved in non-program trades in the 10 minute pre-halt period, while Program refers to stocks that were involved in program trades in the 10 minute pre-halt period. The Program sample of stocks is divided into two groups. The first Index arbitrage group consists of program trade stocks for which the program trade included an order for a futures contract, while the Non-index arbitrage group consists of program trade stocks with no index futures contract orders and a minimum of 15 simultaneous orders on KOSPI 200 stocks. The Actual sidecar and Pseudo sidecar events are described in detail in Table 1.

	Normal trading sample	**Program trading sample (Index arbitrage and Non-index arbitrage)**	**Difference test**
Actual sidecar	Before vs. After	Before vs. After	Normal vs. Program Index arb vs. Non-index arb
Pseudo sidecar	Before vs. After	Before vs. After	Normal vs. Program Index arb vs. Non-index arb
Difference test	Actual vs. Pseudo	Actual vs. Pseudo	

Table 3: Analysis Results for SIM Surrounding the Actual Sidecar Events

Total Sample represents the sample of all actual program trading halts (sidecars), Buy Sample represents the program trading halts sample in an up-market and Sell Sample represents the down-market sample. Pre and Post represent the pre-period and the post-period, respectively. Values reported in the table are mean values for the KOSPI 200 stocks for 92 event days (48 events occurred in up markets, while 44 events occurred in down markets). Values in ( ) represent standard deviations. % of signif. dates represents the ratio of sample days to total sample days in which the difference is significant at the 5% level.

SIMS = (BS-SS)/(BS+SS), BS: buyer-initiated trading shares, and SS: seller-initiated trading shares.
SIMV = (BV-SV)/(BV+SV), BV: buyer-initiated trading value, and SV: seller-initiated trading value.
SIMN = (NB-NS)/(NB+NS), NB: number of buyer-initiated trading, and SB: number of seller-initiated trading.

	Pre (B)	Post (A)	difference (B-A)	test for difference			
				t-test		non-parametric test	
				t-stat	% of signif. dates	Wilcoxon p-value	% of signif. dates
Panel A. Total Sample							
SIMS	-0.169	-0.191	0.022	3.91	56.52	0.000	61.96
	(0.629)	(0.588)	(0.752)				
SIMV	-0.168	-0.191	0.023	3.98	56.52	0.000	60.86
	(0.629)	(0.589)	(0.753)				
SIMN	-0.151	-0.166	0.015	2.95	60.87	0.000	66.30
	(0.588)	(0.539)	(0.661)				
Panel B. Buy Sample							
SIMS	0.056	-0.021	0.077	9.24	52.27	0.000	61.36
	(0.624)	(0.583)	(0.784)				
SIMV	0.057	-0.020	0.077	9.26	52.22	0.000	59.09
	(0.624)	(0.584)	(0.784)				
SIMN	0.082	0.012	0.070	9.35	54.54	0.000	61.36
	(0.578)	(0.527)	(0.694)				
Panel C. Sell Sample							
SIMS	-0.407	-0.372	-0.035	-4.54	65.91	0.000	62.50
	(0.541)	(0.538)	(0.713)				
SIMV	-0.406	-0.371	-0.034	-4.44	65.91	0.000	62.50
	(0.541)	(0.538)	(0.714)				
SIMN	-0.394	-0.352	-0.042	-6.20	66.66	0.000	70.83
	(0.492)	(0.486)	(0.619)				

Table 4: Analysis Results for AIM Surrounding the Actual Sidecar Events

Total Sample represents the sample of all actual program trading halts (sidecars), Buy Sample represents the program trading halts sample in an up-market and Sell Sample represents the down-market sample. Pre and Post represent the pre-period and the post-period, respectively. Values reported in the table are mean values for KOSPI 200 stocks for 92 event days (48 events occurred in up markets, while 44 events occurred in down markets). Values in ( ) represent standard deviations. % of signif. dates represents the ratio of sample days to total sample days in which the difference is significant at the 5% level.

AIMS = |(BS-SS)/(BS+SS)|, BS: buyer-initiated trading shares, and SS: seller-initiated trading shares.
AIMV = |(BV-SV)/(BV+SV)|, BV: buyer-initiated trading value, and SV: seller-initiated trading value.
AIMN = |(NB-NS)/(NB+NS)|, NB: number of buyer-initiated trading, and SB: number of seller-initiated trading.

	Pre (B)	Post (A)	difference (B-A)	test for difference			
				t-test		non-parametric test	
				t-stat	% of signif. dates	Wilcoxon p-value	% of signif. dates
Panel A. Total Sample							
AIMS	0.568	0.522	0.047	14.94	45.65	0.000	43.48
	(0.318)	(0.333)	(0.412)				
AIMV	0.568	0.522	0.046	14.61	45.65	0.000	44.56
	(0.319)	(0.333)	(0.412)				
AIMN	0.523	0.465	0.058	19.13	57.61	0.000	54.35
	(0.307)	(0.319)	(0.394)				
Panel B. Buy Sample							
AIMS	0.538	0.483	0.055	12.616	43.18	0.000	38.64
	(0.321)	(0.328)	(0.412)				
AIMV	0.537	0.483	0.055	12.521	43.18	0.000	38.64
	(0.322)	(0.328)	(0.412)				
AIMN	0.493	0.424	0.069	16.212	56.82	0.000	50.00
	(0.312)	(0.312)	(0.394)				
Panel C. Sell Sample							
AIMS	0.601	0.563	0.038	8.453	47.92	0.000	45.83
	(0.312)	(0.332)	(0.411)				
AIMV	0.600	0.563	0.036	8.087	47.92	0.000	50.00
	(0.313)	(0.332)	(0.412)				
AIMN	0.555	0.508	0.047	10.800	58.33	0.000	58.33
	(0.299)	(0.319)	(0.393)				

Table 5: AIMs of Program and Normal Trading Sample Surrounding the Actual Sidecar Events

Total Sample represents the sample of all actual program trading halts (sidecars), Buy Sample represents the program trading halts sample in an up-market and Sell Sample represents the down-market sample. Pre and Post represent the pre-period and the post-period, respectively. Values reported in the table are mean values for KOSPI 200 stocks for 92 event days (48 events occurred in up markets, while 44 events occurred in down markets). Values in ( ) represent standard deviations. % of signif. dates represents the ratio of sample days to total sample days in which the difference is significant at the 5% level.

PTAIM = |(PB-PS)/(PB+PS)|, PB: Number of buyer-initiated program trading, and PS: Number of seller-initiated program trading.
NTAIM =|(NB-NS)/(NB+NS)|, NB: Number of buyer-initiated normal trading, and NS: Number of seller-initiated normal trading shares

				test for difference			
				t-test		non-parametric test	
	Pre (B)	Post (A)	difference (B-A)	t-stat	% of signif. dates	Wilcoxon p-value	% of signif. dates
Panel A. Total Sample							
NTAIM	0.531	0.466	0.064	20.00	53.26	0.000	48.91
	(0.314)	(0.331)	(0.411)				
PTAIM	0.957	0.778	0.179	45.39	71.74	0.000	69.56
	(0.152)	(0.380)	(0.402)				
NTAIM—PTAIM	-0.426	-0.312	-0.114				
	(0.262)	(0.350)	(0.407)				
t-stat	-129.45	-70.94	-22.40				
Wilcoxon p-value	(0.000)	(0.000)	(0.000)				
Panel B. Buy Sample							
NTAIM	0.502	0.427	0.075	16.71	56.25	0.000	47.91
	(0.316)	(0.324)	(0.408)				
PTAIM	0.962	0.766	0.195	32.20	62.50	0.000	60.42
	(0.136)	(0.389)	(0.408)				
NTAIM—PTAIM	-0.460	-0.339	-0.120				
	(0.267)	(0.347)	(0.408)				
t-stat	-93.38	-52.84	-16.04				
Wilcoxon p-value	(0.000)	(0.000)	(0.000)				
Panel C. Sell Sample							
NTAIM	0.561	0.508	0.054	11.55	45.45	0.000	52.27
	(0.308)	(0.333)	(0.414)				
PTAIM	0.953	0.787	0.166	32.13	81.81	0.000	79.54
	(0.163)	(0.372)	(0.398)				
NTAIM—PTAIM	-0.392	-0.279	-0.113				
	(0.256)	(0.350)	(0.407)				
t-stat	-88.93	-46.44	-16.11				
Wilcoxon p-value	(0.000)	(0.000)	(0.000)				

Table 6: AIMs of Normal, Index Arbitrage, and Non-index Arbitrage Trading Sample Surrounding the Actual Sidecar Events

Total Sample represents all of each respective sample, Buy Sample represents the up-market and Sell Sample represents the down-market sample. Pre and Post represent the pre-period and the post-period, respectively. Values in the table are the mean values of the KOSPI 200 stocks for 92 event days (48 events occurred in up markets, while 44 events occurred in down markets). % of signif. dates represents the ratio of sample days to total sample days in which the difference is significant at the 5% level. NTAIM, ABTAIM, and NABTAIM represent the normal trading sample, the arbitrage trading sample, and the non-index arbitrage trading sample, respectively.

NTAIM = |(NB-NS)/(NB+NS)|, NB: Number of buyer-initiated normal trading, and NS: Number of seller-initiated normal trading.
ABTAIM = |(APB-APS)/(APB+APS)|, APB: Number of buyer-initiated index-arbitrage trading and APS: Number of seller-initiated index-arbitrage trading.
NABTAIM =|(NPB-NPS)/(NPB+NPS)|, NPB: Number of buyer-initiated non-index arbitrage program trading, and NPS: Number of seller-initiated non-index arbitrage program trading.

	Pre (B)	Post (A)	difference (B-A)	test for difference			
				t-test		non-parametric test	
				t-stat	% of signif. dates	Wilcoxon p-value	% of signif. dates
Panel A. Total Sample							
NTAIM	0.531	0.466	0.064	20.00	53.26	0.000	48.91
ABTAIM	0.978	0.767	0.211	47.09	48.91	0.000	46.74
NABTAIM	0.965	0.614	0.350	54.53	68.48	0.000	65.22
NTAIM — ABTAIM	-0.448	-0.301	-0.147				
t-stat	-131.55	-63.71	-26.96				
Wilcoxon p-value	(0.000)	(0.000)	(0.000)				
ABTAIM — NABTAIM	0.013	0.152	-0.139				
t-stat	6.58	20.99	-18.23				
Wilcoxon p-value	(0.000)	(0.000)	(0.000)				
Panel B. Buy Sample							
NTAIM	0.502	0.427	0.075	16.71	56.25	0.000	47.91
ABTAIM	0.986	0.769	0.217	31.70	50.00	0.000	47.92
NABTAIM	0.969	0.568	0.401	40.01	47.72	0.000	47.72
NTAIM — ABTAIM	-0.485	-0.342	-0.143				
t-stat	-93.18	-49.54	-17.66				
Wilcoxon p-value	(0.000)	(0.000)	(0.000)				
ABTAIM — NABTAIM	0.017	0.201	-0.184				
t-stat	6.70	17.70	-15.66				
Wilcoxon p-value	(0.000)	(0.000)	(0.000)				
Panel C. Sell Sample							
NTAIM	0.561	0.508	0.054	11.55	45.45	0.000	52.27
ABTAIM	0.973	0.765	0.207	34.91	47.72	0.000	47.72
NABTAIM	0.961	0.650	0.312	37.55	87.50	0.000	81.25
NTAIM — ABTAIM	-0.412	-0.258	-0.154				
t-stat	-91.79	-39.81	-20.60				
Wilcoxon p-value	(0.000)	(0.000)	(0.000)				
ABTAIM — NABTAIM	0.011	0.115	-0.104				
t-stat	3.73	12.26	-10.42				
Wilcoxon p-value	(0.000)	(0.000)	(0.000)				

Table 7: AIMs of Normal, Program, Arbitrage, and Non-arbitrage Trading Stocks Surrounding the Pseudo-sidecar Events

This table shows the AIMs of Normal trading stocks, Program trading stocks, Arbitrage trading stocks, and Non-arbitrage trading stocks surrounding the pseudo-sidecar events. Sample period is from Jan 4, 1999 to Dec. 31, 2004. Pseudo-sidecar sample is the sample which has a large price fluctuation but the sidecar has not been triggered. The number of actual-sidecar events is 92 (48 events occurred in up markets, while 44 events occurred in down markets) and the number of pseudo-sidecar events is 147 (75 events occurred in up markets, while 72 events occurred in down markets). NTAIM represents the normal trading sample, ABTAIM represents the arbitrage program trading sample, NABTAIM represents the non-index arbitrage program trading sample, and PTAIM represents the program trading sample which is the sum of ABTAIM and NABTAIM. Subsample construction is based on the trading types for the period 10 minutes before the sidecar event. Pre and Post represent the 10-minute period before the event and the 10-minute period after the event, respectively. Values reported in the table are mean values of AIM for all KOSPI 200 stocks that are included in each subsample. AIM is defined as follows:

AIMN = |(BN-SN)/(BN+SN)|, BN: number of buyer-initiated trades, and SN: number of seller-initiated trades.

Values in ( ) represent standard deviations.

	Pseudo sidecar					Differences of changes in AIMs of Actual and Pseudo sidecar		
	pre (D)	post (C)	change (D-C)	t-stat	Wilcoxon p-value	Difference (Pseudo - Actual)	t-stat	Wilcoxon p-value
Panel A. AIM								
NTAIM	0.521	0.423	0.098	27.87	0.000	0.033	6.97	0.000
	(0.312)	(0.323)	(0.402)			(0.407)		
PTAIM	0.940	0.700	0.240	48.23	0.000	0.061	9.78	0.000
	(0.181)	(0.423)	(0.456)			(0.431)		
ABTAIM	0.981	0.673	0.307	53.71	0.000	0.096	13.17	0.000
	(0.106)	(0.458)	(0.474)			(0.449)		
NABTAIM	0.935	0.547	0.388	54.53	0.000	0.038	3.98	0.000
	(0.192)	(0.472)	(0.519)			(0.501)		
Panel B. Difference of AIM between trading types								
NTAIM—PTAIM	-0.419	-0.276	-0.142					
	(0.268)	(0.365)	(0.423)					
t-stat	-111.60	-54.14	-24.07					
Wilcoxon p-value	(0.000)	(0.000)	(0.000)					
ABTAIM — NABTAIM	0.045	0.126	-0.081					
	(0.149)	(0.464)	(0.494)					
t-stat	16.57	14.91	-8.99					
Wilcoxon p-value	(0.000)	(0.000)	(0.000)					

Table 8: Market Condition and AIMs of Normal, Program, Arbitrage, and Non-arbitrage Trading Stocks Surrounding the Pseudo-sidecar Events

This table shows the AIMs of Normal trading stocks, Program trading stocks, Arbitrage trading stocks, and Non-arbitrage trading stocks surrounding the pseudo-buy sidecar and the pseudo-sell sidecar events. The sample period is from Jan 4, 1999 to Dec. 31, 2004. Pseudo-sidecar sample is the sample which has a large price fluctuation but the sidecar has not been triggered. The number of actual sidecar events is 92 (48 events occurred in up markets, while 44 events occurred in down markets) and the number of pseudo-sidecar events is 147 (75 events occurred in up markets, while 72 events occurred in down markets). NTAIM represents the normal trading sample, ABTAIM represents the arbitrage program trading sample, NABTAIM represents the non-index arbitrage program trading sample, and PTAIM represents the program trading sample which is the sum of ABTAIM and NABTAIM. Pre and Post represent the 10 minute period before the event and the 10 minute period after the event, respectively. Values reported in the table are mean values of AIM for all KOSPI 200 stocks that are included in each subsample. AIM is defined as follows:

AIMN = |(BN-SN)/(BN+SN)|, BN: number of buyer-initiated trading, and SN: number of seller-initiated trading.

In Panel A and Panel B, values in ( ) represent standard deviations and values in [ ] represent Wilcoxon p-values for the difference tests. In Panel C, values represent t-statistics for the difference between AIM of an up-market sample and a down-market sample with Wilcoxon p-values in [ ].

	Pseudo sidecar					Differences of changes in AIMs of Actual and Pseudo sidecar		
	pre (D)	post (C)	change (D-C)	t-stat	Wilcoxon p-value	Difference (Pseudo - Actual)	t-stat	Wilcoxon p-value
Panel A. Up market (Buy sample)								
NTAIM	0.483	0.407	0.075	15.88	0.000	0.001	0.08	0.933
	(0.309)	(0.311)	(0.390)			(0.400)		
PTAIM	0.934	0.702	0.232	33.53	0.000	0.036	3.99	0.000
	(0.188)	(0.422)	(0.459)			(0.434)		
ABTAIM	0.970	0.680	0.290	40.29	0.000	0.073	6.92	0.000
	(0.131)	(0.456)	(0.483)			(0.452)		
NABTAIM	0.947	0.591	0.356	37.93	0.000	-0.045	-3.29	0.000
	(0.171)	(0.462)	(0.492)			(0.495)		
Panel B. Down market (Sell sample)								
NTAIM	0.562	0.440	0.122	23.57	0.000	0.068	9.78	0.000
	(0.309)	(0.336)	(0.413)			(0.413)		
PTAIM	0.945	0.697	0.249	34.82	0.000	0.082	9.60	0.000
	(0.173)	(0.424)	(0.452)			(0.420)		
ABTAIM	0.992	0.666	0.326	33.53	0.000	0.118	11.99	0.000
	(0.068)	(0.459)	(0.464)			(0.446)		
NABTAIM	0.923	0.499	0.424	39.40	0.000	0.112	8.25	0.000
	(0.211)	(0.479)	(0.544)			(0.505)		
Panel C. Test on differences of Up-market sample and Down-market sample								
NTAIM	-14.74	-5.85	-6.65					
	[0.000]	[0.000]	[0.000]					
PTAIM	-2.75	0.63	1.67					
	[0.061]	[0.812]	[0.648]					
ABTAIM	-8.37	1.30	-3.12					
	[0.000]	[0.367]	[0.000]					
NABTAIM	4.63	7.16	-4.79					
	[0.000]	[0.000]	[0.000]					

Table 9: Market Condition and SIMs of Normal, Program, Arbitrage, and Non-arbitrage Trading Stocks Surrounding the Actual- and Pseudo-sidecar Events

This table shows the SIMs of Normal trading stocks, Program trading stocks, Arbitrage trading stocks, and Non-arbitrage trading stocks surrounding the actual-buy sidecar, the actual-sell sidecar, the pseudo-buy sidecar, and the pseudo-sell sidecar events. The sample period is from Jan 4, 1999 to Dec. 31, 2004. Pseudo-sidecar sample is the sample which has a large price fluctuation but the sidecar has not been triggered. The number of actual-sidecar events is 92 (48 events occurred in up markets, while 44 events occurred in down markets) and the number of pseudo-sidecar events is 147 (75 events occurred in up markets, while 72 events occurred in down markets). NTSIM represents the normal-trading sample, ABTSIM represents the index arbitrage program trading sample, NABTSIM represents the non-index arbitrage-program trading sample, and PTSIM represents the program trading sample which is the sum of ABTSIM and NABTSIM. Pre and Post represent the 10 minute period before the event and the 10 minute period after the event, respectively. Values reported in the table are mean values of SIM for all KOSPI 200 stocks that are included in each subsample. SIM is defined as follows:

SIMN = (BN-SN)/(BN+SN), BN: number of buyer-initiated trading, and SN: number of seller-initiated trading.

In Panel A and Panel B, values in ( ) represent standard deviations and values in [ ] represent Wilcoxon p-values for the difference tests. In Panel C, values represent t-statistics for the difference between AIM of an up-market sample and a down-market sample with Wilcoxon p-values in [ ].

	Actual sidecar				Pseudo sidecar				Differences of changes in SIMs of Actual and Pseudo sidecar	
	pre (B)	post (A)	change (C=B-A)	t-stat [Wilcoxon p-value]	pre (E)	post (D)	change (F=E-D)	t-stat [Wilcoxon p-value]	Difference (C-F)	t-stat [Wilcoxon p-value]
Panel A. Up market (Buy sample)										
NTSIM	0.012	-0.063	0.075	9.22	0.001	-0.095	0.097	10.88	-0.021	-1.79
	(0.593)	(0.532)	(0.744)	[0.000]	(0.573)	(0.504)	(0.736)	[0.000]	(0.740)	[0.000]
PTSIM	0.378	0.300	0.078	7.47	0.513	0.279	0.235	18.36	-0.156	-9.49
	(0.895)	(0.806)	(0.702)	[0.000]	(0.803)	(0.771)	(0.849)	[0.000]	(0.778)	[0.000]
ABTSIM	0.378	0.275	0.103	9.45	0.602	0.359	0.243	17.96	-0.140	-8.15
	(0.914)	(0.827)	(0.670)	[0.000]	(0.772)	(0.736)	(0.810)	[0.000]	(0.741)	[0.000]
NABTSIM	0.417	0.299	0.118	7.01	0.429	0.185	0.243	15.84	-0.124	-5.49
	(0.884)	(0.683)	(0.839)	[0.000]	(0.862)	(0.727)	(0.804)	[0.000]	(0.821)	[0.605]
Panel B. Down market (Sell sample)										
NTSIM	-0.372	-0.332	-0.040	-5.22	-0.343	-0.228	-0.115	-13.02	0.074	6.39
	(0.521)	(0.508)	(0.684)	[0.000]	(0.542)	(0.505)	(0.705)	[0.000]	(0.693)	[0.000]
PTSIM	-0.406	-0.244	-0.162	-17.92	-0.522	-0.252	-0.269	-22.02	0.108	7.24
	(0.878)	(0.836)	(0.696)	[0.000]	(0.807)	(0.775)	(0.772)	[0.000]	(0.727)	[0.000]
ABTSIM	-0.352	-0.246	-0.107	-12.23	-0.582	-0.304	-0.278	-20.76	0.172	11.20
	(0.917)	(0.833)	(0.640)	[0.000]	(0.806)	(0.749)	(0.768)	[0.000]	(0.691)	[0.000]
NABTSIM	-0.673	-0.282	-0.392	-30.12	-0.491	-0.147	-0.344	-22.15	-0.047	-2.38
	(0.701)	(0.7360	(0.740)	[0.000]	(0.809)	(0.6760	(0.785)	[0.000]	(0.760)	[0.000]
Panel C. Test on differences of Up market and Down market										
NTSIM	43.91	32.98	10.30		35.39	15.14	16.83			
	[0.000]	[0.000]	[0.000]		[0.000]	[0.000]	[0.000]			
PTSIM	44.85	33.48	17.39		58.82	31.42	28.36			
	[0.000]	[0.000]	[0.000]		[0.000]	[0.000]	[0.000]			
ABTSIM	37.52	29.53	15.08		62.25	36.99	27.34			
	[0.000]	[0.000]	[0.000]		[0.000]	[0.000]	[0.000]			
NABTSIM	52.01	30.53	24.36		39.99	17.23	26.86			
	[0.000]	[0.000]	[0.000]		[0.000]	[0.000]	[0.000]			

Table 10: Sidecar Effect on Order Imbalance Around the Sidecar Event Including Control Variables

This table shows the estimation results for the regression of actual AIM of Normal-trading stocks, Program-trading stocks, Arbitrage-trading stocks, or Non-arbitrage-trading stocks on sidecar, time, a market dummy variable, and several control variables. The regression model is as follows;

$$AIM = \beta_0 + \beta_1 \cdot PRE + \beta_2 \cdot TIME + \beta_3 \cdot MARKET + \beta_4 \cdot VOLATILITY + \beta_5 \cdot VOLUME + \beta_6 \cdot SPREAD$$

In the equation, the dependent variable is AIM (Panel A) and SIM (Panel B). In the regression, we use cross-sectional and time-series pooled data of observations constructed during the 10 minutes of the pre-halt period and post-halt period of each sidecar event. PRE takes the value of one in the pre-halt period and zero in the post-halt period. TIME takes the value of one if sidecar is triggered before 12:00 and zero otherwise. MARKET takes the value of one if sidecar is triggered on the sell side (down market), and zero otherwise (up market). Control variables are VOLATILITY, VOLUME and SPREAD. VOLATILITY is the standard deviation of the midpoint for the log return measured at one-minute intervals in the pre-halt period and post-halt period. VOLUME is the proportion of trading shares in the pre-halt period and post-halt period to total daily trading shares. SPREAD is the mean of the quote spread divided by the midpoint price measured at one-minute intervals in the pre-halt period and post-halt period. T-values for coefficients are provided in parenthesis. *, **, *** represent the statistical significance at 10%, 5%, and 1% level, respectively.

	normal	program	arbitrage	non-arbitrage
Dependent variable : AIM				
Intercept	0.354 (84.67)***	0.766 (152.07)***	0.787 (139.82)***	0.597 (70.58)***
PRE	0.073 (20.30)***	0.187 (44.19)***	0.222 (47.47)***	0.349 (51.75)***
TIME	-0.042 (-12.07)***	-0.006 (-1.70)*	-0.055 (-12.41)***	0.028 (4.44)***
MARKET	0.059 (16.99)***	0.004 (1.21)	-0.009 (-2.03)**	0.036 (5.60)***
VOLATILITY	-0.154 (-5.22)***	-0.269 (-6.24)**	-0.312 (-6.74)***	-0.031 (-0.45)
VOLUME	5.811 (10.26)***	4.740 (7.08)**	8.251 (11.27)***	0.645 (0.55)
SPREAD	13.737 (37.15)***	-0.537 (-1.23)	-3.122 (-6.56)***	-4.123 (-4.59)***
Adj R^2	0.073	0.089	0.126	0.210

Table 11: Actual Sidecar Effect on Order Imbalance Around the Sidecar Event Including Control Variables

This table shows the estimation results for the regression of AIM and SIM of Normal trading stocks, Program trading stocks, Arbitrage trading stocks, and Non arbitrage trading stocks. The regression is estimated based on following model.

$$AIM\,(SIM) = \beta_0 + \beta_1 PRE + \beta_2 TIME + \beta_3 MARKET + \beta_4 VOLATILE + \beta_5 VOLUME$$
$$+ \beta_6 SPREAD + \beta_7 USRET + \beta_8 ACTUAL + \beta_9 PRE \times ACTUAL$$

In the above equation, the dependent variables is AIM. We use cross-sectional and time-series pooled data of observations constructed during the 10 minutes of the pre-halt period and post-halt period of the actual and pseudo sidecar event. PRE takes the value of one in the pre-halt period and zero in the post-halt period. TIME takes the value of one if sidecar is triggered before 12:00 and zero otherwise. MARKET takes the value of one if sidecar is triggered on the ask side(down market), and is zero on otherwise(up market). A common critique of order imbalance is that it is also related to liquidity. To control for this confounding effect, we use the following control variables for liquidity: VOLATILITY, VOLUME and SPREAD. VOLATILITY is the standard deviation of the midpoint log return measured at one-minute intervals in the pre-halt and post-halt periods. VOLUME is the proportion of trading shares in the pre-halt and post-halt periods to the total daily trading shares. SPREAD is the mean of quote spread divided by the midpoint price measured at one-minute intervals in the pre-halt and post-halt periods. USRET is the open-to-close log return of the S&P500 index of the previous day to the sidecar date. ACTUAL takes the value of one if the sample is an actual sidecar and takes the value of zero if the sample is a pseudo sidecar. PRE×ACTUAL is the interaction between PRE and ACTUAL. This cross term captures the differences-of-differences effect (ΔAIM_actual - ΔAIM_pseudo, where the difference is the change in order imbalance between the pre- and post-periods). T-values for coefficients are provided in parenthesis. *, **, *** represent the statistical significance at 10%, 5%, and 1% level, respectively.

Panel A reports the results for AIM for the total sample. Panel B reports the results for AIM for both the up-market and down-market samples separately. Panel C reports the results for SIM for both the up-market and down-market samples separately.

	normal	program	arbitrage	non-arbitrage
Panel A. Dependent variable : AIM				
Intercept	0.324 (107.80) ***	0.706 (184.64)***	0.671 (152.91) ***	0.586 (104.31) ***
PRE	0.104 (36.91) ***	0.236 (66.37) ***	0.296 (73.43) ***	0.398 (77.57) ***
TIME	-0.052 (-24.37) ***	-0.011 (-4.08) ***	0.007 (2.38) **	-0.053 (-13.30) ***
MARKET	0.051 (19.67) ***	0.000 (0.11)	0.011 (3.09) ***	-0.039 (-8.20) ***
VOLATILITY	-0.236 (-11.41) ***	-0.113 (-3.65) ***	-0.104 (-3.14) ***	-0.078 (-1.48)
VOLUME	4.969 (14.78) ***	4.326 (9.87) ***	6.387 (12.81) ***	3.799 (5.70) ***
SPREAD	15.560 (66.10) ***	-1.615 (-5.39) ***	-3.810 (-11.47) ***	-2.410 (-4.79) ***
USRET	0.023 (0.27)	0.099 (0.93)	0.768 (6.45) ***	-0.785 (-5.05) ***
ACTUAL	0.031 (10.13) ***	0.067 (17.21) ***	0.081 (18.58) ***	0.067 (11.36) ***
PRE×ACTUAL	-0.025 (-5.83) ***	-0.051 (-9.24) ***	-0.077 (-12.58) ***	-0.037 (-4.54) ***
Adj R^2	0.087	0.113	0.156	0.236

	normal		program		arbitrage		non-arbitrage	
Panel B. Dependent variable : AIM								
	up	down	up	down	up	down	up	down
Intercept	0.320	0.369	0.722	0.706	0.700	0.668	0.607	0.542
	(82.44)***	(92.66)***	(142.42)***	(144.12)***	(119.70)***	(119.39)***	(82.45)***	(74.92)***
PRE	0.086	0.121	0.222	0.250	0.272	0.320	0.369	0.430
	(22.41)***	(29.55)***	(44.09)***	(49.10)***	(47.29)***	(55.51)***	(51.90)***	(58.49)***
TIME	-0.046	-0.065	0.001	-0.003	-0.010	0.033	0.019	-0.109
	(-14.92)***	(-20.44)***	(0.42)	(-0.91)	(-2.17)**	(7.91)***	(3.31)***	(-18.75)***
VOLATILITY	-0.309	-0.196	-0.082	-0.098	-0.002	-0.107	-0.100	-0.114
	(-10.05)***	(-7.01)***	(-1.16)	(-2.85)***	(-0.03)	(-2.94)***	(-1.01)	(-1.83)*
VOLUME	0.951	8.749	4.885	3.603	7.129	5.453	2.650	4.018
	(2.05)**	(18.06)***	(7.79)***	(5.90)***	(10.12)***	(7.74)***	(2.77)***	(4.38)***
SPREAD	20.069	12.876	-2.131	-1.489	-4.729	-3.301	-5.016	-1.242
	(53.41)***	(42.52)***	(-4.21)***	(-4.02)***	(-8.47)***	(-8.00)***	(-5.96)***	(-2.00)**
USRET	0.455	-0.699	-1.401	1.860	-0.014	2.192	-2.575	-0.133
	(3.87)***	(-5.09)***	(-9.31)***	(11.46)***	(-0.09)	(11.91)***	(-11.20)***	(-0.59)
ACTUAL	0.011	0.048	0.054	0.090	0.073	0.097	-0.006	0.142
	(2.74)***	(10.65)***	(9.43)***	(16.60)***	(11.41)***	(16.14)***	(-0.72)	(17.57)***
PRE×ACTUAL	0.002	-0.053	-0.026	-0.074	-0.056	-0.101	0.030	-0.101
	(0.46)	(-8.35)***	(-3.30)***	(-9.82)***	(-6.16)***	(-12.06)***	(2.56)**	(-8.87)***
Adj R^2	0.083	0.083	0.111	0.122	0.147	0.171	0.231	0.261

Panel C. Dependent variable : SIM								
	up	down	up	down	up	down	up	down
Intercept	-0.143	-0.209	0.506	0.532	0.557	0.543	0.443	0.434
	(-19.44)***	(-17.65)***	(57.44)***	(37.42)***	(61.08)***	(34.02)***	(41.72)***	(21.36)***
PRE	0.555	0.615	0.473	0.452	0.452	0.557	0.556	0.459
	(75.75)***	(52.28)***	(53.08)***	(29.41)***	(49.83)***	(31.90)***	(52.40)***	(23.32)***
TIME	-0.081	0.045	-0.047	-0.016	-0.024	0.021	-0.008	-0.078
	(-13.76)***	(4.77)***	(-6.43)***	(-1.33)	(-3.23)***	(1.59)	(-1.00)	(-3.99)***
VOLATILITY	-0.283	-0.175	0.007	-0.030	0.086	0.034	-0.073	0.187
	(-4.68)***	(-2.40)**	(0.06)	(-0.33)	(0.69)	(0.38)	(-0.48)	(1.13)
VOLUME	11.904	-13.014	9.026	2.072	8.590	3.284	5.894	-3.344
	(14.67)***	(-9.38)***	(8.02)***	(1.07)	(7.45)***	(1.60)	(4.24)***	(-1.09)
SPREAD	11.034	9.870	1.049	4.824	-2.013	1.034	-3.418	8.969
	(15.09)***	(12.55)***	(1.19)	(4.71)***	(-2.31)**	(0.97)	(-2.79)***	(4.79)***
USRET	1.417	-0.419	-5.251	19.088	-4.466	25.466	-4.502	4.203
	(6.36)***	(-1.11)	(-19.33)***	(26.09)***	(-17.02)***	(30.94)***	(-11.88)***	(4.56)***
ACTUAL	0.062	-0.082	0.177	0.305	0.135	0.411	0.088	0.089
	(7.78)***	(-6.01)***	(16.99)***	(17.80)***	(12.72)***	(23.00)***	(6.94)***	(3.32)***
PRE×ACTUAL	-0.046	0.075	-0.152	-0.121	-0.132	-0.227	-0.069	-0.049
	(-4.09)***	(3.91)***	(-10.33)***	(-5.50)***	(-8.80)***	(-9.72)***	(-3.87)***	(-1.38)
Adj R^2	0.311	0.359	0.196	0.228	0.201	0.291	0.276	0.204

Table 12: Number of sidecar events in Public- and No-Public-news sample.

To construct of Public-News- and the No-Public-News sample we classified the sidecar events with market-wide (macro-economic, political, or social) news events during the period from the previous day to the event time as the Public-News sample. Events with no news are classified as the No-Public-News sample. News was identified in the representative daily Korean newspapers (Maeil Business News Paper and Dong-A Ilbo) and on the KRX website (disclosure and news). This table provides the number of actual- and pseudo-sidecar events in each news sample.

	Actual	Pseudo
Public-News sample	36	43
No-Public-News sample	56	104

Table 13: Comparison of public-news sample and no-public-news sample

This table shows the AIMs of Normal trading stocks, Program trading stocks, Arbitrage trading stocks, and Non-arbitrage trading stocks surrounding the pseudo-buy sidecar and the pseudo-sell sidecar events. Each sample (actual and pseudo) are broken into a Public-News subsample (Panel A) and a No-Public-News subsample (Panel B). Panel C compares the levels of order imbalance of the news and no-news samples, while Panels A and B make the appropriate comparisons of the differences in the change in order imbalance. News is identified from the local Korean business newspapers (Maeil Business News Paper and Dong-A Ilbo) and the KRX website. The sample period is from Jan 4, 1999 to Dec. 31, 2004. Pseudo-sidecar sample is the sample which has a large price fluctuation but the sidecar has not been triggered. The number of actual sidecar events is 92 (36 public news, 56 no-public news) and the number of pseudo-sidecar events is 147 (43 public news, 104 no-public news). NTAIM represents the normal trading sample, ABTAIM represents the arbitrage program trading sample, NABTAIM represents the non-index arbitrage program trading sample, and PTAIM represents the program trading sample which is the sum of ABTAIM and NABTAIM. Pre and Post represent the 10 minute period before the event and the 10 minute period after the event, respectively. Values reported in the table are mean values of AIM for all KOSPI 200 stocks that are included in each subsample. AIM is defined as follows:

AIMN = |(BN-SN)/(BN+SN)|, BN: number of buyer-initiated trading, and SN: number of seller-initiated trading.

Values in ( ) represent standard deviations, values in { } represent t-statistic, and values in [ ] represent Wilcoxon p-value.

	Actual sidecar				Pseudo sidecar					
	pre (D)	post (C)	change (D-C)	t-stat p-value	pre (D)	post (C)	change (D-C)	t-stat p-value	Pseudo-Actual	t-stat p-value
Panel A. Public-news sample										
NTAIM	0.536	0.463	0.074	{13.90}	0.524	0.451	0.073	{15.77}	-0.001	{-0.10}
	(0.316)	(0.335)	(0.415)	[0.000]	(0.313)	(0.327)	(0.406)	[0.000]		[0.917]
PTAIM	0.942	0.718	0.224	{31.88}	0.941	0.706	0.235	{37.67}	0.011	{1.14}
	(0.186)	(0.414)	(0.447)	[0.000]	(0.178)	(0.422)	(0.455)	[0.000]		[0.254]
ABTAIM	0.967	0.664	0.303	{37.21}	0.967	0.678	0.289	{40.21}	-0.014	{-1.32}
	(0.150)	(0.459)	(0.492)	[0.000]	(0.140)	(0.454)	(0.483)	[0.000]		[0.188]
NABTAIM	0.968	0.652	0.316	{31.15}	0.953	0.576	0.377	{43.59}	0.061	{4.59}
	(0.133)	(0.455)	(0.474)	[0.000]	(0.159)	(0.464)	(0.494)	[0.000]		[0.000]
Panel B. No-Public-news sample										
NTAIM	0.527	0.469	0.059	{14.52}	0.527	0.419	0.108	{36.43}	0.049	{9.91}
	(0.312)	(0.329)	(0.408)	[0.000]	(0.315)	(0.325)	(0.404)	[0.000]		[0.000]
PTAIM	0.966	0.816	0.150	{32.57}	0.943	0.693	0.249	{58.21}	0.099	{14.84}
	(0.125)	(0.351)	(0.369)	[0.000]	(0.176)	(0.425)	(0.457)	[0.000]		[0.000]
ABTAIM	0.986	0.835	0.150	{30.18}	0.988	0.670	0.318	{64.76}	0.168	{23.92}
	(0.083)	(0.358)	(0.369)	[0.000]	(0.084)	(0.460)	(0.471)	[0.000]		[0.000]
NABTAIM	0.963	0.591	0.371	{44.91}	0.928	0.524	0.403	{65.12}	0.032	{3.10}
	(0.142)	(0.467)	(0.492)	[0.000]	(0.204)	(0.476)	(0.528)	[0.000]		[0.000]
Panel C. Difference [(PublicPanel A) – (No-PublicPanel B)]										
NTAIM	0.009	-0.006	0.015			-0.004	0.031	-0.035		
	(0.313)	(0.330)	(0.410)			(0.314)	(0.325)	(0.404)		
	{1.77}	{-1.13}	{2.27}			{-0.90}	{7.12}	{-6.42}		

	[0.095]	[0.156]	[0.027]	[0.441]	[0.000]	[0.000]
PTAIM	-0.024	-0.098	0.073	-0.002	0.013	-0.015
	(0.151)	(0.376)	(0.400)	(0.176)	(0.424)	(0.456)
	{-8.03}	{-12.97}	{9.15}	{-0.63}	{1.84}	{-1.96}
	[0.000]	[0.000]	[0.000]	[0.909]	[0.205]	[0.351]
ABTAIM	-0.019	-0.171	0.152	-0.02	0.008	-0.029
	(0.114)	(0.401)	(0.422)	(0.105)	(0.458)	(0.475)
	{-7.59}	{-19.95}	{16.89}	{-10.63}	{1.06}	{-3.39}
	[0.000]	[0.000]	[0.000]	[0.000]	[0.992]	[0.037]
NABTAIM	0.005	0.060	-0.055	0.025	0.052	-0.026
	(0.138)	(0.462)	(0.485)	(0.191)	(0.472)	(0.517)
	{1.36}	{4.80}	{-4.19}	{6.40}	{5.22}	{-2.40}
	[0.189]	[0.000]	[0.000]	[0.000]	[0.000]	[0.005]

Table 14: Market Condition and AIMs of KOSPI 200 Futures Market Surrounding the Actual- and Pseudo-sidecar Events

This table shows the AIM for the KOSPI 200 futures market surrounding the actual- and pseudo-sidecar events. The sample period is from Jan 4, 1999 to Dec. 31, 2004. Pseudo-sidecar sample is the sample which has a large price fluctuation but sidecar has not triggered. The number of actual-sidecar events is 92 (48 events occurred in up markets, while 44 events occurred in down markets) and the number of pseudo-sidecar events is 147 (75 events occurred in up markets, while 72 events occurred in down markets). Pre and Post represent the 10-minute period before the event and the 10-minute period after the event, respectively. Values in table are mean values of AIM for the nearest KOSPI 200 futures contract. Values in ( ) represent standard deviations and Values in [ ] represents Wilcoxon p-value for difference test. AIM is defined as follows:

AIMN = |(BN-SN)/(BN+SN)|, BN: number of buyer-initiated trading, and SN: number of seller-initiated trading.

	Actual sidecar					Pseudo sidecar					Differences of changes in AIMs of Actual and Pseudo sidecar		
	pre (B)	post (A)	change (C=B-A)	t-stat	[Wilcoxon p-value]	pre (E)	post (D)	change (F=E-D)	t-stat	[Wilcoxon p-value]	change (C-F)	t-stat	[Wilcoxon p-value]
All	0.226	0.133	0.092	4.753	[0.000]	0.196	0.123	0.073	6.389	[0.000]	0.019	0.94	[0.345]
	(0.127)	(0.119)	(0.186)			(0.111)	(0.096)	(0.138)			(0.158)		
Up market (Buy sample)	0.225	0.124	0.101	2.703	[0.000]	0.219	0.123	0.096	3.380	[0.000]	0.005	0.16	[0.950]
	(0.118)	(0.099)	(0.155)			(0.113)	(0.103)	(0.142)			(0.147)		
Down market (Sell sample)	0.227	0.143	0.084	4.362	[0.000]	0.175	0.124	0.051	5.712	[0.000]	0.033	1.08	[0.181]
	(0.135)	(0.136)	(0.213)			(0.105)	(0.090)	(0.132)			(0.167)		
difference (up-down)	-0.002	-0.019	0.017			0.044	-0.001	0.045					
	(0.127)	(0.119)	(0.187)			(0.109)	(0.097)	(0.137)					
t-stat	-0.07	-0.75	0.43			2.47	-0.07	2.02					
Wilcoxon p-value	[0.894]	[0.434]	[0.642]			[0.009]	[0.443]	[0.020]					

Table 15: Changes in Basis Surroundings the Actual- and Pseudo-sidecar Events

Basis is the price of the nearest KOSPI 200 futures minus the KOSPI 200 index. It is measured at one-minute intervals in both the pre-halt period and post-halt period. Pseudo-sidecar sample is the sample which has a large price fluctuation but the sidecar has not been triggered. The number of actual sidecar events is 92 (48 events occurred in up markets, while 44 events occurred in down markets) and number of pseudo-sidecar events is 147 (75 events occurred in up markets, while 72 events occurred in down markets). Pre and Post represent the 10 minute period before the event and the 10 minute period after the event, respectively. Figures in [ ] are the ratio of positive basis days to the total number of days in each subsample. Positive basis days are calculated by mean of minute-by-minute basis during the pre (post) period. %(Pre>Post) represents the ratio of days of which of average basis in the pre-period is greater than in the post-period.

	Pre (B)	Post (A)	Diff (B-A)	% (Pre>Post)	t-test	Wilcoxon p-value
Panel A. Actual sidecar						
Up market (Buy sample)	0.396 (1.235) [64.58]	0.428 (1.249) [66.67]	-0.033 (1.242)	45.83	-0.42	(0.763)
Down market (Sell sample)	-0.201 (1.709) [47.72]	-0.375 (1.615) [47.72]	0.173 (1.663)	63.63	1.65	(0.385)
Panel B. Pseudo sidecar						
Up market (Buy sample)	0.363 (1.091) [55.70]	0.389 (1.095) [59.49]	-0.026 (1.093)	41.77	-0.48	(0.503)
Down market (Sell sample)	0.314 (0.924) [60.29]	0.331 (0.965) [57.35]	-0.018 (0.944)	45.59	-0.35	(0.823)

Table 16: Regression Results of Basis on SIM

This table shows the regression results of basis on SIM. Basis is the price of the nearest KOSPI 200 futures minus the KOSPI 200 index. It is measured at one-minute intervals in both the pre-halt period and post-halt period. MARKET takes the value of one if sidecar is triggered on the ask side (down market) and is zero otherwise (up market). NTSIM represents the normal trading sample, ABTSIM represents the arbitrage program trading sample, NABTSIM represents the non-index arbitrage program trading sample. Values in ( ) are t-statistics and *, **, *** represent the statistical significance at 10%, 5%, and 1% level, respectively.

	Pre-period					Post-period				
Panel A. Model Estimation										
Intercept	-0.288	-0.379	-0.322	-0.347	-0.284	-0.068	-0.042	-0.094	0.043	-0.039
	(-4.08)***	(-4.54)***	(-4.57)***	(-4.21)***	(-4.04)***	(-0.97)	(-0.43)	(-1.30)	(0.44)	(-0.54)
MARKET	0.643	0.786	0.696	0.726	0.641	0.357	0.366	0.449	0.190	0.325
	(6.48)***	(6.95)***	(7.07)***	(6.48)***	(6.49)***	(3.54)***	(2.50)**	(4.43)***	(1.30)	(3.16)***
$NTSIM_t$		-0.154		-0.253			0.352		0.359	
		(-0.84)		(-1.39)			(1.58)		(1.64)	
$ABTSIM_t$	0.377			0.386	0.300	0.466			0.464	0.429
	(5.49)***			(5.58)***	(4.18)***	(6.07)***			(6.05)***	(5.45)***
$NABTSIM_t$			0.328		0.237			0.246		0.153
			(4.90)***		(3.40)***			(3.26)***		(2.01)**
Adj R^2	0.091	0.060	0.085	0.093	0.106	0.070	0.033	0.042	0.072	0.073

Panel B. F Test for equality of coefficient

	Pre-period	Post-period
$NTSIM_t = ABTSIM_t$	10.05 (0.001)***	0.20 (0.651)
$ABTSIM_t = NABTSIM_t$	0.30 (0.585)	5.20 (0.023)**

Table 17: Trading Activity of KOSPI 200 Spot Markets Surrounding the Actual- and Pseudo-sidecar Events

This table shows trading activities of KOSPI 200 spot markets for the 10 minutes before and the 10 minutes after the actual- and pseudo-sidecar events. The sample period is from Jan 4, 1999 to Dec. 31, 2004. Pseudo-sidecar sample is the sample which has a large price fluctuation but sidecar has not triggered. The number of actual-sidecar events is 92 and number of pseudo-sidecar events is 147. NORM represents the normal trade, ARBT represents the index arbitrage program trade, and NARBT represents the non-index arbitrage program trade. Pre and Post represent the 10-minute period before the event and the 10-minute period after the event, respectively. Values reported in the table are mean values of KOSPI 200 stocks that are included in each trading type. Values in ( ) represent standard deviations.

	Actual sidecar				Pseudo sidecar				Difference between Actual and Pseudo sidecar			
	pre (B)	post (A)	diff. (B-A)	t-stat [Wilcoxon p-value]	pre (D)	post (C)	diff. (D-C)	t-stat [Wilcoxon p-value]	pre (B-D)	t-stat [Wilcoxon p-value]	post (A-C)	t-stat [Wilcoxon p-value]
Panel A. Number of trades												
NORM	62.0	61.9	0.1	0.10	66.6	61.4	5.2	4.31	-4.59	-2.23	0.49	0.29
	(169.7)	(157.1)	(142.0)	[0.002]	(191.3)	(141.2)	(141.0)	[0.000]	(179.6)	[0.000]	(150.2)	[0.458]
ARBT	6.7	6.9	-0.3	-2.20	7.1	4.9	2.2	18.39	-0.46	-2.51	2.01	10.45
	(11.6)	(13.6)	(12.0)	[0.000]	(11.6)	(9.7)	(9.9)	[0.000]	(11.59)	[0.005]	(12.09)	[0.000]
NARBT	4.3	4.7	-0.4	-3.54	5.0	3.9	1.1	10.26	-0.70	-5.50	0.81	4.86
	(6.5)	(9.5)	(8.8)	[0.000]	(7.2)	(8.2)	(8.0)	[0.000]	(6.81)	[0.000]	(8.91)	[0.000]
Panel B. Share volume												
NORM	29,418	31,522	-2,105	-1.72	48,056	38,583	9,473	1.39	-18,638	-2.71	-7,060	-2.07
	(185,135)	(213,276)	(159,065)	[0.000]	(871,034)	(376,270)	(799,052)	[0.000]	(598,094)	[0.000]	(297,305)	[0.000]
ARBT	1,517	1,602	- 85	-2.17	1,899	1,316	583	11.97	-382	-4.82	285	4.06
	(3,836)	(4,436)	(3,734)	[0.000]	(6,186)	(4,385)	(4,051)	[0.000]	(4,981)	[0.000]	(4,414)	[0.000]
NARBT	1,011	1,245	- 234	-6.30	1,300	1,034	265	6.56	-288	-5.97	210	3.70
	(2,086)	(3,244)	(2,821)	[0.022]	(2,975)	(2,751)	(2,976)	[0.000]	(2,554)	[0.000]	(3,016)	[0.000]
Panel C. Trading value (10,000 Won)												
NORM	32,841	34,869	-2,027	-2.83	36,727	33,987	2,739	3.22	-3,885	-2.40	881	0.63
	(132,909)	(127,686)	(93,281)	[0.000]	(149,752)	(114,346)	(99,493)	[0.000]	(140,678)	[0.012]	(93,281)	[0.059]
ARBT	3,167	3,326	-159	-1.24	3,503	2,466	1037	7.45	-336	-1.47	860	3.87
	(14,385)	(16,686)	(12,385)	[0.000]	(14,465)	(11,502)	(11,582)	[0.000]	(14,419)	[0.000]	(14,689)	[0.000]
NARBT	2,321	3,009	-688	-5.61	3,001	2,739	263	2.31	-680	-3.48	270	1.13
	(7,963)	(11,877)	(9,334)	[0.224]	(12,382)	(13,370)	(8,345)	[0.000]	(10,336)	[0.000]	(12,620)	[0.000]

Table 18: Trading Activities of KOSPI 200 Futures Market Surrounding the Actual- and Pseudo-sidecar Events.

The sample period is from Jan 4, 1999 to Dec. 31, 2004. Pseudo-side car sample is the sample that has a large price fluctuation but the sidecar has not been triggered. The number of actual-sidecar events is 92 and number of pseudo-sidecar events is 147. Pre and Post represent the 10 minute period before the event and the 10 minute period after the event, respectively. Values reported in table are the mean values for the nearest KOSPI 200 futures contract. Values in ( ) represent standard errors of means. *, **, *** represent the statistical significance of non-parametric Wilcoxon test at 10%, 5%, and 1% level, respectively.

Actual sidecar			Pseudo sidecar			Difference	
pre (B)	post (A)	diff. (B-A)	pre (D)	post (C)	diff (D-C)	pre (B-D)	post (A-C)
Panel A. Number of trade							
825	841	-16	1,035	899	136	-210	-57
(450)	(624)	(543)	(715)	(568)	(645)*	(626)**	(590)
Panel B. Number of contract							
3,140	3,371	-231	3,716	3,257	459	-576	114
(2,291)	(3,325)	(2,855)	(2,869)	(2,335)	(2,615)	(2,660)	(2,759)
Panel C. Value of contract (10,000 Won)							
13,699	14,466	-767	16,097	14,171	1,926	-2,398	294
(11,148)	(14,536)	(12,953)	(12,416)	(10,189)	(11,358)	(11,943)	(12,054)

Figure 1: Experimental Design

The actual sidecar event consists of a10-minute pre-period (PRE), the actual 5-minute halt of program trading on the KOSPI 200 constituent stocks, and a 10-minute post-period (POST). To have excellent control for market dynamics, we utilize the experience for different portfolios of stocks, all in the actual sidecar event. The downside to this approach is that firm risk characteristics are difficult to control. For example, the set of firms involved in index arbitrage trade may systematically differ from those involved in normal trades. In order to construct a sample of events that have excellent risk characteristic controls, i.e., we can use each firm as its own control, we construct a pseudo-sidecar sample. The pseudo sidecar sample is selected according to several criteria, but the focus is to pick these events in order to control for the large price movement dynamics experienced in the actual sidecar sample. We match on time of day and calendar proximity large market moves that did not trigger the sidecar rule. The pseudo-sidecar allows program trading during the 5-minute-pseudo-halt period, which allows us to compare market characteristics with that observed under the 5-minute actual-halt period. Tables 1 and 2 define the criteria used to select the pseudo sidecars and the comparisons made between actual and pseudo events.

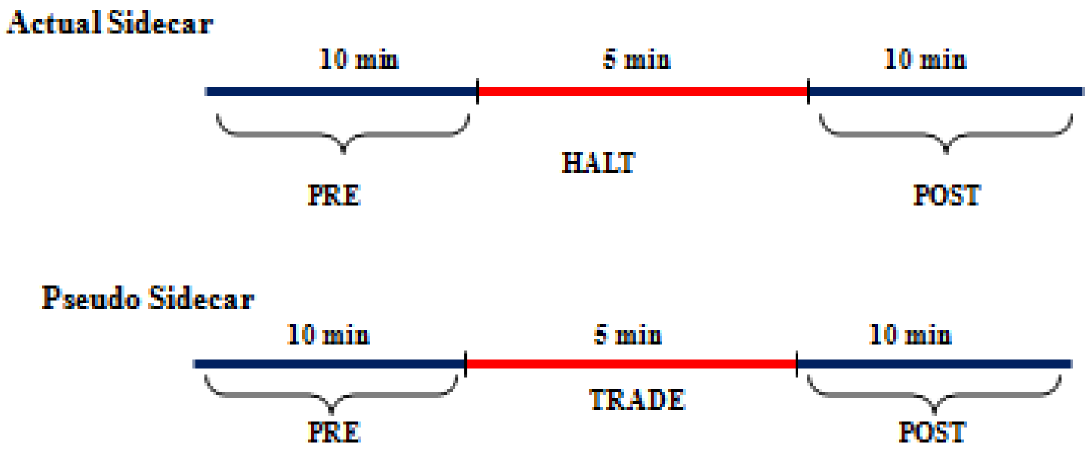
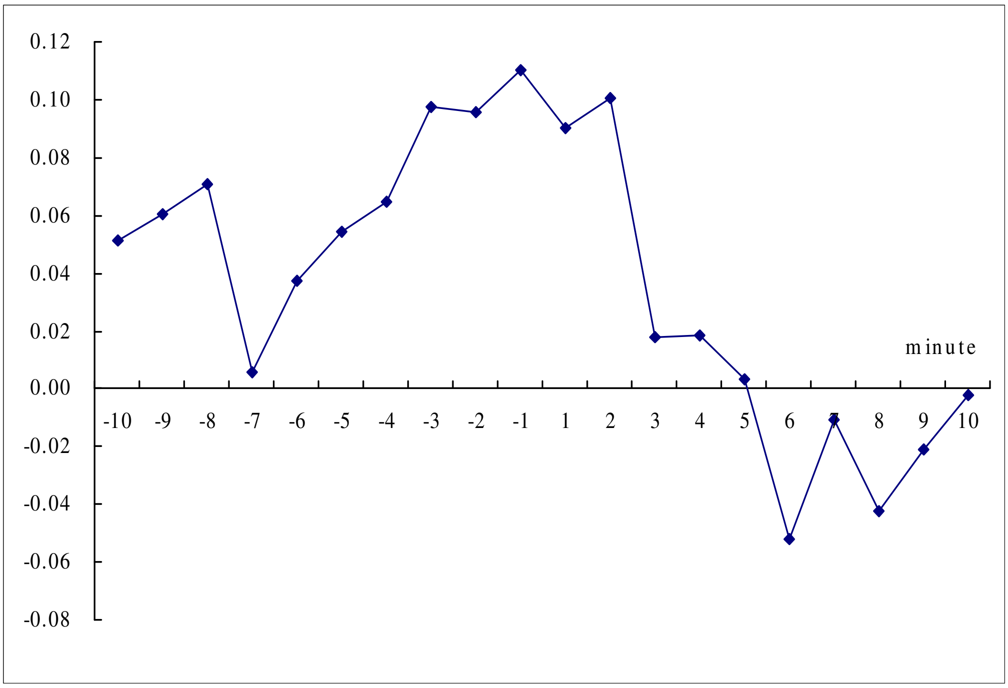


Figure 2: SIMN Surrounding the Actual-sidecar Events

Panel A: Buy sample



Panel B : Sell sample

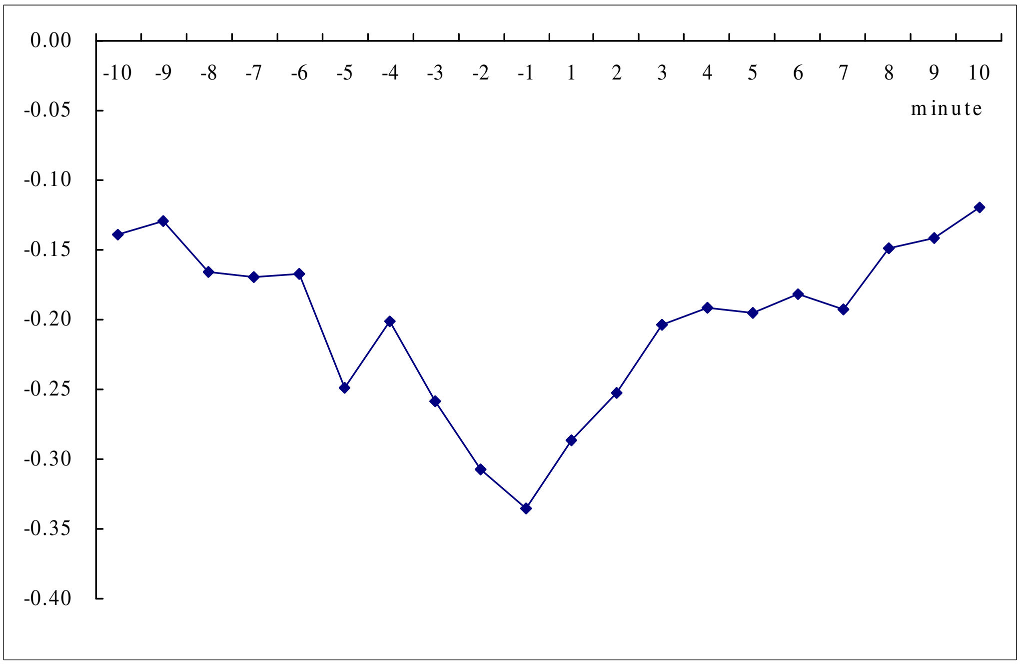
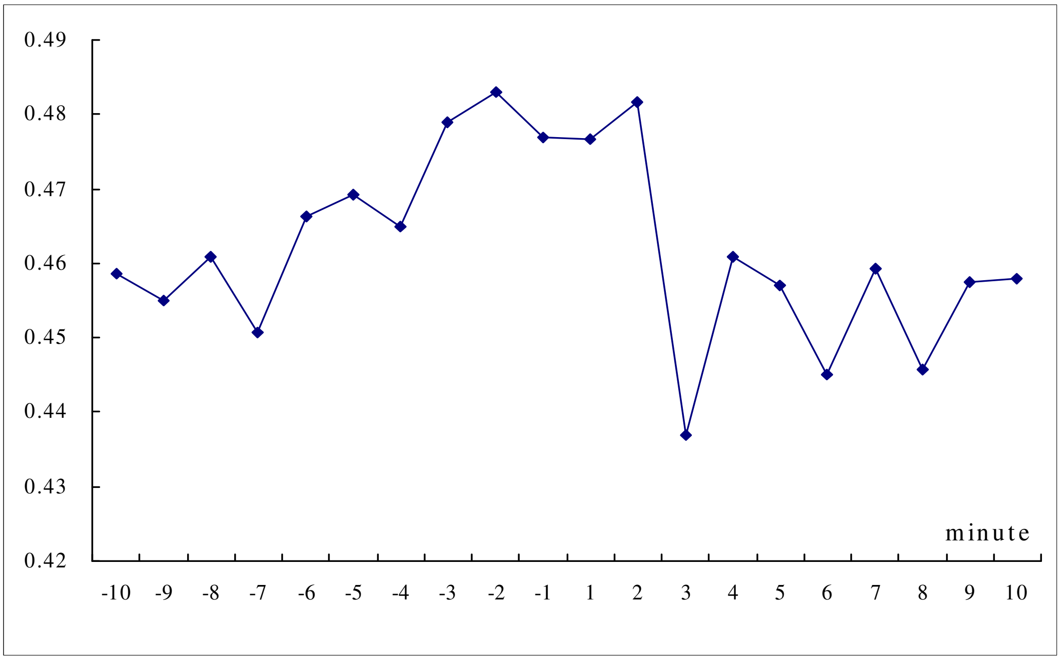


Figure 3: AIMN Surrounding the Actual-sidecar Events

Panel A: Buy sample



Panel B : Sell sample

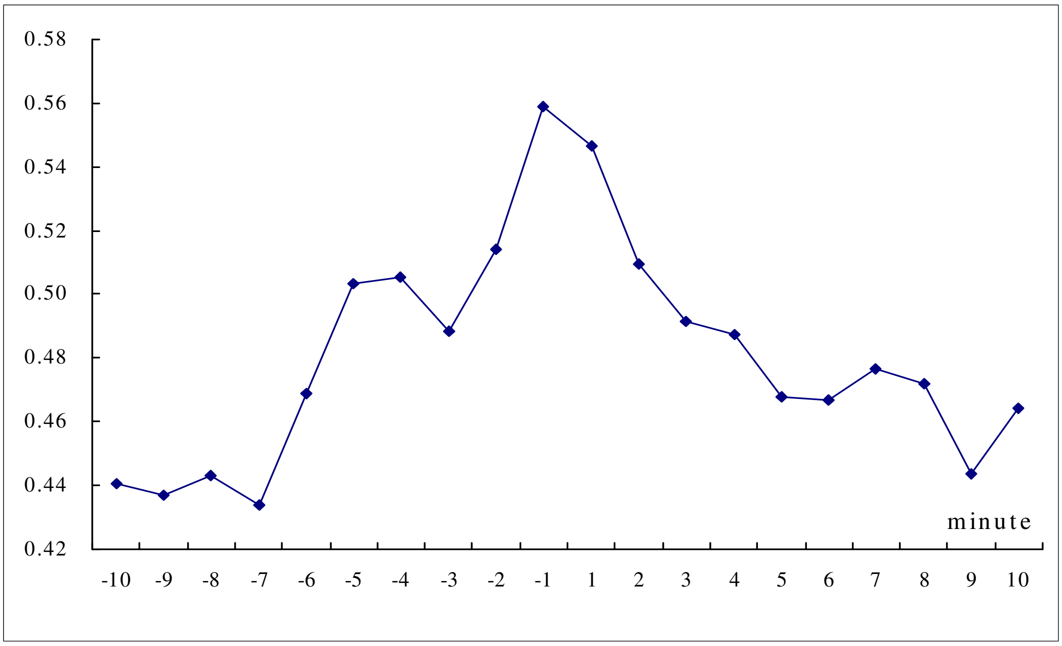
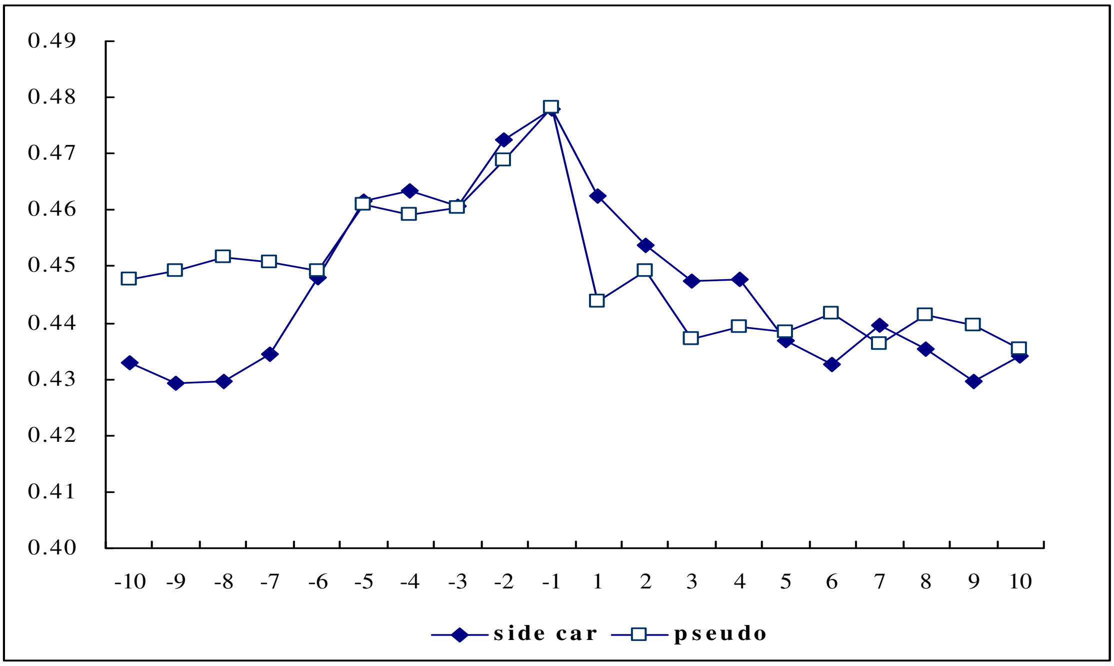
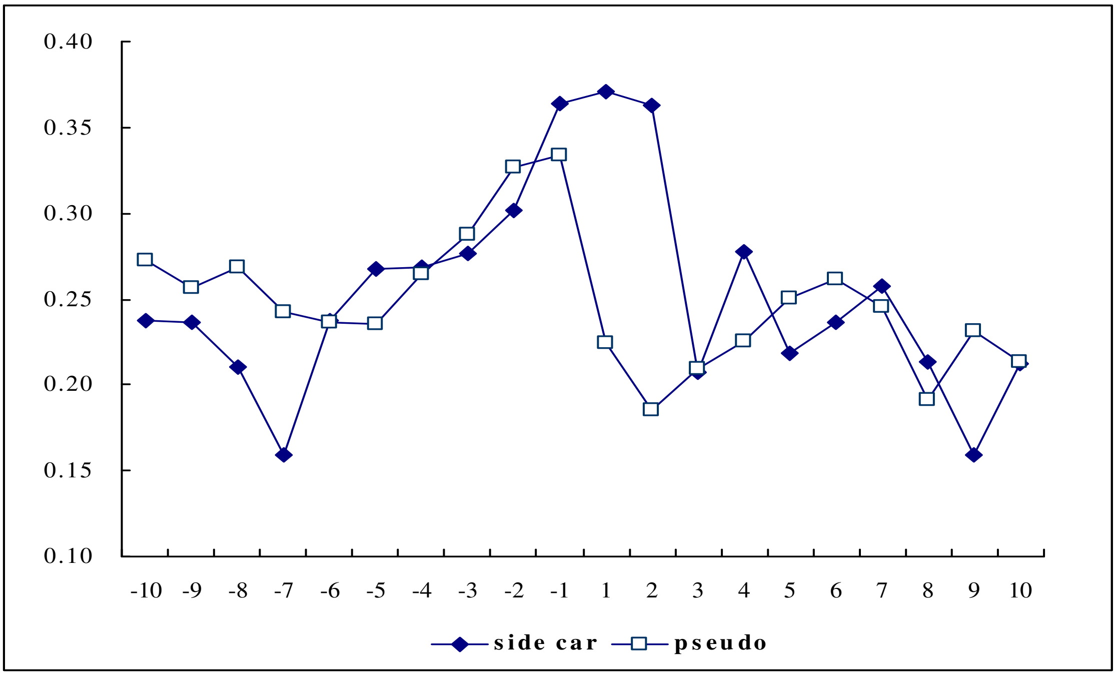


Figure 4: Patterns of AIM of Normal-trading Stocks, Program-trading Stocks, Arbitrage-trading Stocks, and Non-arbitrage-trading Stocks Surrounding the Actual- and Pseudo-sidecar Events

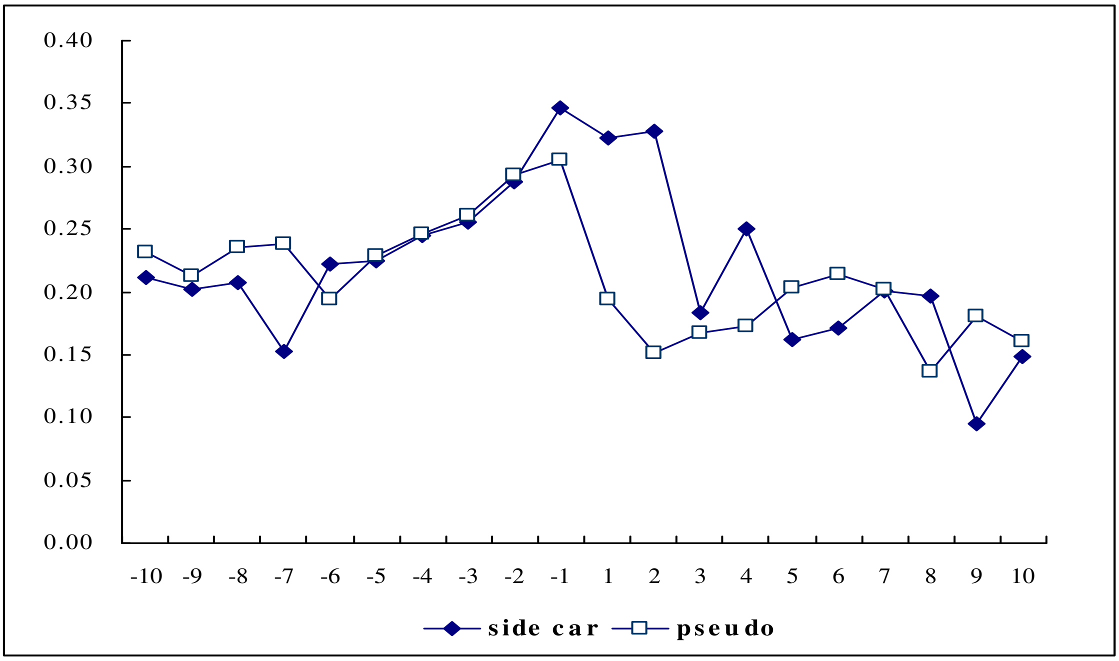
Panel A. Normal trading



Panel B. Program trading



Panel C. Arbitrage program trading



Panel D. Non-arbitrage program trading

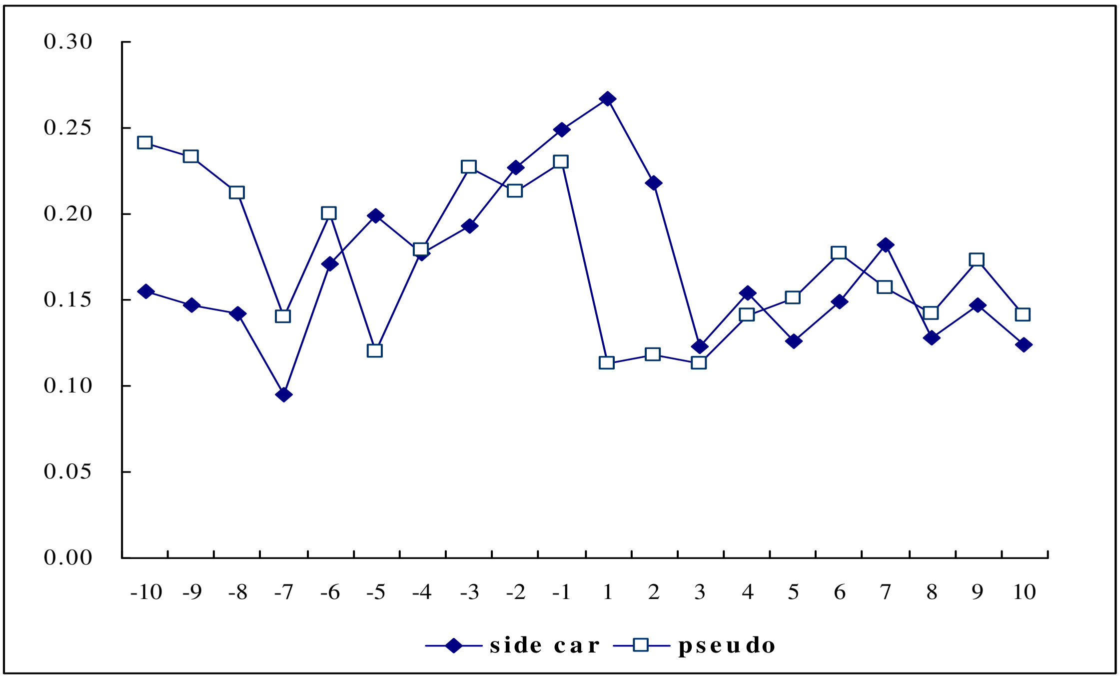


Figure 5: Patterns of AIM of KOSPI 200 Futures Market Surrounding the Actual- and Pseudo-sidecar Events