Scalpel or Hatchet?
Program Trade Regulation *

Woo-Baik Lee
Korea National Open University †

Jong Won Park
University of Seoul ‡

Steven J. Jordan
Econometric Solutions §

April 21, 2012

Abstract
Most trade halt studies concentrate on individual-firm and market-wide halts. However, program trading has been isolated as a potential cause of market instability. As a result, laws have been enacted to regulate program trading during volatile markets. This study addresses the effectiveness of program trade regulation by conducting an 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 unique properties not available in US data that lend itself to such a study. We find that sidecars are not as effective at controlling the order imbalance levels around large market movements as when program trade is allowed. Program trades, at least a subset, provide liquidity when it is at a premium. We conclude that program trade restrictions should be more carefully crafted as some program trades are market stabilizing.

JEL subject classifications: G12, G13, C14, G22
Keywords: Order imbalance, sidecar, trading halts, Korea, program trading, KOSPI 200.

---

*We would like to thank seminar participants at Cambridge University, EDHEC Business School (Nice, France), Hong Hong Polytechnic University, Hong Kong University of Science and Technology, Korea University, Loughborough University, Peking University, Seoul National University, Singapore Management University, Sungkyungkwan University, Sun Yat-sen University, Universidad Adolfo Ibanez, 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, Gishan Dissanaike, and Erik Theissen for comments on an earlier draft of this paper.

†Department of Business Administration, Korea National Open University, 169 Dongsung-dong, Jongno-gu, Seoul, Korea 110-791; email:`datalover@knou.ac.kr`.

‡College of Business Administration, University of Seoul, 90 Jennong-dong, Dondaemun-gu, Seoul, Korea 130-743; email:`parkjw@uos.ac.kr`.

§Corresponding author. Econometric Solutions; email: `econometric.solutions@yahoo.com`.

Scalpel or Hatchet?
Program Trade Regulation

Abstract
Most trade halt studies concentrate on individual-firm and market-wide halts. However, program trading has been isolated as a potential cause of market instability. As a result, laws have been enacted to regulate program trading during volatile markets. This study addresses the effectiveness of program trade regulation by conducting an 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 unique properties not available in US data that lend itself to such a study. We find that sidecars are not as effective at controlling the order imbalance levels around large market movements as when program trade is allowed. Program trades, at least a subset, provide liquidity when it is at a premium. We conclude that program trade restrictions should be more carefully crafted as some program trades are market stabilizing.

1 Introduction

Circuit breakers such as sidecars[1] have their proponents and opponents in both academia and practice. Proponents believe that markets enter periods of extreme uncertainty, even panic, and halting trade gives market participants a chance to reevaluate and cool off. Opponents, on the other hand, believe the primary mechanism of accurate pricing is trade. Halting trade only delays price discovery, possibly even causing further unwanted volatility. Thus, the benefit of these mechanisms is highly debated.[2] Previous empirical studies have focused on individual-firm and market-wide halts. However, program trading has been identified as a potential cause of market instability. There exists no study that specifically addresses the influence of program trade[3] halts during large market moves.[4] To address this issue, we analyze the effect of program trade halts on market quality using Korean intraday data. Our measure of market quality ($|OIB|$) is the absolute value of the order imbalance (OIB) defined in Chordia, Roll, and Subrahmanyam (2002,2008) as "...the number of buyer- less the number of seller-initiated trades divided by the total number of trades." Our main research question is whether program trade halts (sidecars) affect the market's ability to absorb order imbalance, i.e., is order imbalance resolved more quickly when program trading is allowed or restricted? If so, why?

There are several advantages to studying the Korean market versus the US market. One 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 according to the initiating trade. This eliminates one estimation step in the trade signing methodology. Such trade signing methodologies depend on several assumptions

[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 (e.g., price limits, tick rules, position limits, collars, etc…). 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] 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.

[4] The few papers we found that addressed program trading rules for large market moves all examined the NYSE Rule 80A. However, Rule 80A is a trade inhibitor, thus program trading still exists under most implementations, only the rules of trade change.

and have been documented to have a large degree of error. The error seems particularly large for non-NYSE and overseas data sets[5] 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). By eliminating this estimation step our inferences are potentially more precise. A second advantage is that on the Korea Exchange (KRX) sidecars cover all program trading including index arbitrage and non-index arbitrage, while on the NYSE program trading inhibitors (sometimes called the collar rule[6] or Rule 80A) cover only index arbitrage trades. We are able to explore a new dimension not available with NYSE data. Even more important is that the KRX sidecar simultaneously halts program trades on the spot, futures, and options markets. Thus, program trading is eliminated from all markets allowing for a cleaner test of the effects of program trading on market characteristics. A third advantage of the Korean market is that there is no substitute asset for the KOSPI 200 futures during the trade halt.[7] It is difficult to replicate the KOSPI 200 futures because futures/options trading on individual Korean stocks is illiquid or nonexistent (see Section 3.2). 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. A fourth advantage for using Korean data is that there is a potential concern with off-NYSE trading activity. US off-NYSE trade is a significant portion of total US trade. Its existence may allow program trading to affect the market even when a US sidecar is in effect (see Chakrabarty, Corwin, and Panayides, 2009). This off-NYSE trade offers an alternative explanation for the insignificant results of every US sidecar study. Thus, the Korean data provides a better experimental setup to test the effect of a sidecar rule. Finally, the Korean data can be used to answer the question of whether it is optimal to allow program trading during large market moves. This answer is possible because the KRX sidecar is a true halt across all markets; there is no good substitute for the index futures/options, and individual firm futures/options are illiquid or nonexistent. [8]

We study how trade imbalance varies across trade type during large market moves. The main reason to specifically study OIB is that it is a critical element in trade halt rule design, e.g., on the NYSE,

[5]See Aitken and Frino (1996) and Theissen (2001) who explore sign trade algorithm performance, e.g., Lee and Ready (1991), for international data.

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

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

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

"non-regulatory" halts are triggered when prespecified levels of OIB are met. According to the Brady Commission, a study of the 1987 crash, "...circuit breakers can have a calming effect on the markets because they provide a 'time-out' to pause, evaluate, inhibit panic, and *publicize order imbalances*" (see Ackert, Hao, and Hunter, 1997). Thus, it is important to document and understand how OIB is affected during large market moves to understand how such regulations should be designed. In addition, regulators are interested in controlling pure speculation, severe liquidity deficiencies, or, in the case of program trading, trigger-induced trading. That is, regulators are concerned with transitory volatility, not information driven volatility. Pascual and Veredas (2010) find that "Transitory volatility is triggered by noise or liquidity trading." Thus, large OIB can result in a market subject to panic or herding, making OIB an important market characteristics to understand in markets with large price moves. Unfortunately, the typical measures of market quality (i.e., price discovery and volatility) are unobservable. However, OIB is directly observable making it of primary interest.[9] Observability allows regulators to design halt triggers keyed off of OIB in real time. In addition, OIB affects market characteristics such as liquidity, volatility, and price convergence. Chordia et al. (2002) study the relationships among OIB, spreads, and market returns for the S&P 500 stock index and find that OIB affects liquidity and returns at the aggregate market level. Huang and Chou (2007) demonstrate that (1) the spread depends on OIB and market microstructure and (2) OIB has an impact on market liquidity and volatility. Fung (2007) shows that the time it takes for an error to converge to zero is significantly and positively related to the magnitude of OIB. The importance of OIB to markets is nicely summarized by Chordia, Roll, and Subrahmanyam (2002): "Our analysis also indicates that order imbalances are significantly associated with daily changes in liquidity and with contemporaneous market returns, after controlling for the level of unsigned trading activity. The latter result underscores the role of excess buying and selling activity, as opposed to just trading volume, as a determinant of fluctuations in market returns."

Our research contributes insight on three important questions. First, what are the characteristics of OIB for different trade types (i.e., non-program, program, index-arbitrage, and non-index-arbitrage trades) around program trade halts? To answer this, we analyze and compare imbalances surrounding sidecar events. We measure the OIB of all KOSPI 200 stocks by trade type. We analyze all sidecar events, the up-market-sidecar subsample, and the down-market-sidecar subsample. We control for market dynamics and firm characteristics. Our initial result is that the resolution of OIB is greater for program trades than for non-program trades. We also document that non-index arbitrage trades experience higher OIB resolution

[9] See Section 2.4 in the literature review.

than index arbitrage trades. In addition, we find that there is an increase in trade volume after a sidecar, indicating pent up trade demand.

Second, a fundamental question in finance is how information is embedded into price. We explore two possible hypotheses. According to no arbitrage, information can be transmitted via the action of arbitrageurs engaging in index arbitrage trades. In this scenario, mispricing is corrected by simultaneously taking a long position in the undervalued market, while shorting the overvalued market. An alternative hypothesis is that there is a smart-money effect. In this scenario, some traders have better private information and target individually mispriced assets to take advantage of this information advantage. These "smart trades" push the mispriced asset to equilibrium. To discern between these two competing theories, we take all program trades and classify them as either index-arbitrage or non-index-arbitrage trades. The information transfer mechanism that is more important should have a larger OIB resolution across the sidecar event. We find that the smart-money effect is stronger than the index arbitrage effect.

Third, we explore how markets correct themselves in the absence of a sidecar implementation, i.e., are program trade halts necessary? To answer this question, we use our pseudo-sidecar sample to test if extreme market moves are associated with similar imbalance reduction patterns in the actual-sidecar sample. If so, then the sidecar is of questionable utility as markets are adjusting on their own. In the pseudo-sidecar control, we use the same trade types during a different time period with similar market dynamics. A priori given that mean reversion exists in markets, we would expect larger market moves and larger OIB to have on average larger corrections. Thus, we expect to find a larger correction in OIB for the actual-sidecar events. However, we find the opposite. The pseudo-sidecar events have a larger correction compared to when program trading is halted. We 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 OIB associated with a large market move. The market self-adjusts via its own internal mechanisms. Therefore, program trade halts reduce the market's capacity to adjust for large OIB during large market moves.

We perform a natural experiment to test the effect of program trading on OIB during large market moves. If two subsamples can be defined that differ in the amount of asymmetric information in the market and trade is important for resolving OIB (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 announcement as our high asymmetric information subset and those events with public news as our low asymmetric information subset. We observe a larger OIB resolution between the actual- and pseudo-sidecar events in the high asymmetric subset. This finding demonstrates that trade is an important mechanism to resolve OIB during large market moves.

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 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. Overall, we find that program trade halts, i.e., sidecars, are not effective at controlling OIB. Resolution of OIB is more effective when trade is unrestricted. This has policy implications. Our results support a policy of modifying program trading halts. Our robustness tests indicate that program trades, at least in some instances, are market stabilizing, i.e., program trades provide liquidity when it is at a premium, while at other times they are market destabilizing. On average, restricting all program trades during large market moves reduces the market's ability to resolve imbalances. Thus our results suggest that regulators and academics should 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 paper is one of the first studies on the effect of program trading halts on a driver of large market moves, (2) this paper is one of a few papers that specifically look at sidecars, (3) this paper uses microstructure measures for OIB 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, or identifying a trade as normal or belonging to a program trade, (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 futures or options, and (6) we explore policy implications for improving program trade regulation. Our work suggests that a scalpel, not a hatchet, is the more appropriate approach to program trade rule design.

2 Trade Halt Literature Review - Are Halts Effective?

In this section, we summarize the literature and relate how our study adds to current knowledge. First, we describe the economic intuition both for and against trade halts. We then summarize the nascent sidecar literature. This is followed by a review of the market-wide and firm-level halt literature. Finally, we consider the literature on OIB as a measure of market quality.

2.1 Trade halt debate

Here we summarize the economic intuition for each side of the debate.

Proponents' intuition: 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 to publicize OIB. 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 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). That is, 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.

Opponents' intuition: 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 (2004) 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.

Contribution: Halts stop all trade and studies of halts are silent on the differences across trade types. Sidecars restrict program trade, but allow non-program trade. Thus studies using sidecars can address the affect of a specific trade type on market quality. Our data is unique in that it identifies each trade by trade type. Thus, we can explore the importance of the various program trade types on market quality. For example, information transfer can occur via an intermediary market (index arbitrage) or via informed/positional trading (non-index arbitrage). We also can explore whether there is a buildup of demand and if this systematically differs by trade type. This trade-type dimension has not been explored in the prior empirical literature.

2.2 Sidecars - Empirical evidence

In this subsection, we review the small literature that exists on sidecars.

Sidecar evidence: There are only a few studies of NYSE Rule 80A. Every Rule 80A paper except one focuses on the sell-plus/buy-minus rule, which is not a trade halt rule. The one exception is Santoni and Liu (1993) who examine all the implementations of Rule 80A, including simultaneous halts across the spot and futures markets. They use a dummy variable approach to capture rule regimes, but this does not control for confounding effects due to the existence of multiple rules (see their Table I, pages 263-264) . Recognizing this limitation, Santoni and Liu study each possible rule implementation separately. However, there were only 7 observations of simultaneous program trade halts in the spot and futures markets (see their Table AI in the appendix). In addition, their data only includes index arbitrage trade.

NYSE Rule 80A attempts to inhibit or slow index-arbitrage program trading. Empirical research suggests that NYSE index arbitrage is severely reduced during the NYSE sidecar implementation. However, the empirical evidence also suggests that this has little impact on market dynamics. An important open question is: Are index-arbitrage traders able to trade in spite of Rule 80A or do index-arbitrage trades have little impact on market quality or information transfer? One obvious concern is that there are ready substitutes for the S&P 500 index. Another relevant concern is that US options and futures markets are deep, thus replication of strategies may be possible. An alternative and very interesting concern is off-NYSE trading activity, discussed by Chakrabarty, Corwin, and Panayides (2009). They document that not only is trade allowed during NYSE sidecar implementation, but this trade is informative and affects price. Off-NYSE trade is growing rapidly making this concern more and more relevant.

Contribution: Our study adds to the program trading literature in several ways. First, we study a true program trade halt. An important quality of the Korean sidecar is that it precludes the possibility of program trade being implemented via other mechanisms as program trade is halted simultaneously on all markets.

Second, our data records two types of program trades (index and non-index arbitrage) allowing us to address information transfer. Finally, we implement our control sample in a way that is consistent with more recent halt studies. Specifically, we construct various control samples from data after the regulatory change. We also use control time periods close to the actual event period. This approach mitigates possible concerns that the underlying market dynamics has changed in a substantial way between actual and control events. Besides market dynamics, we control for trade-type and firm-specific characteristics. Unlike the prior literature, we find that program trade halts have an adverse effect on important market characteristics.

2.3 Non-program trading halts - Empirical evidence

We review the empirical evidence here. First, we discuss the market-wide halt literature. We then summarize the firm-level halt literature.

Proponents' market-wide evidence: There are empirical results that support the positive effect of market-wide trading halts. Kim, Yague, and Yang (2008) find that both volume and bid-ask spreads are unaffected after a halt, yet both increase under a price limit rule. Two papers find that trade halts are necessary to control for severe asymmetric information imbalances (see Bhattacharya and Spiegel, 1991; Edelen and Gervais, 2003). 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, Gerety and Mulherin (1992) conclude that there is a cost to mandating market-wide trade halts.

Opponents' market-wide evidence: There is a body of empirical results suggesting that circuit breakers are ineffective. 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 trade. 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.

Proponents' firm-level evidence: There is also a body of research on individual trading halts. 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 for disseminating 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.

Opponents' firm-level evidence: Individual trading halt research also has its opponents. 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. 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. In markets that operate open electronic limit order books, Frino, Lecce, and Segarawe (2011) find trading halts increase volume, volatility, bid-ask spreads, while reducing market depth at the best-quotes in the immediate post-halt period.[10]

Contribution: We specifically study whether program trade halts affect market quality. Program trading is targeted as causing market imperfections, particularly during market crashes, and program trade regulations exist in many countries. Few papers study program trade halt rules and their effect on market quality. The prior literature mostly studies either firm-specific halts or market-wide halts, whereas this paper targets program trade halts. Unlike a halt that stops all trade, a sidecar only stops a specific type of trade, allowing all other type of trades to be executed. A fundamental question is: During large market moves, are there specific trade types providing or demanding liquidity? Eliminating liquidity providers will reduce market quality. A targeted halt rule, like a sidecar, can be used to answer this question.

[10]There is an earlier literature that investigates program trading under usual market conditions and its relation to market characteristics. The findings are almost uniformly that during normal trading periods program trade does not adversely affect market quality. This literature is not closely related to our paper as it does not specifically consider extreme market conditions.

2.4 Order imbalance as a measure of market quality

We review the extensive literature connecting OIB to various market characteristics. The papers in this section consider net-trade measures of order imbalance in agreement with our OIB measure.

Previous OIB literature: OIB is an important determinant of price movement for all markets. Chordia and Subrahmanyam (2004) and Chordia, Roll, and Subrahmanyam (2008) find a stock's OIB is positively correlated with its future return. Chan and Fong (2000) find that a substantial portion of the daily price movement is well explained by OIB. Andrade, Chang, and Seasholes (2008) argue that a significant amount of OIB is uninformed trading, but the OIB still affects stock returns. Bollen and Whaley (2004) show option values are affected by buying or selling pressure. Brandt and Kavajecz (2004) find OIB is a major source of bond yield fluctuations. Su, Chen, and Chen (2009) find that contemporaneous OIB on the NYSE is significant to the stock returns on the Toronto Stock Exchange. Madhavan and Smidt (1993) find that the daily price change is strongly related to the information contained in the OIB.

Other market characteristics are related to OIB. Chordia, Roll, and Subrahmanyam (2002) find that order imbalances in either direction, either excess buy or sell orders, reduce liquidity. Foucault (1999) provides a game theory model of price formation and order placement decisions where the trading costs for buy and sell market orders are related to the ratio of buy to sell orders. Menkhoff and Schmeling (2010) find that traders treat their own and others market orders as more informative than limit orders. Chan and Fong (2000) analyze how OIB changes the contemporaneous relation between stock volatility and volume. Huang and Chou (2007) show, for both order-driven markets and quote-driven markets, OIB has an impact on market liquidity and volatility. Chakravarty and Ray (2010) find that trading volume is driven by private information, while OIB are driven by heterogeneous beliefs. Chordia, Roll, and Subrahmanyam (2002) underscore the role of OIB as an important determinant of market return fluctuations.

Contribution: A potential contribution of our paper is that we study OIB and how it relates to program trade halts for which there is little prior research. We explore the behavior of OIB both before and after a large market move. This behavior is contrasted between large market moves with and without program trading. We specifically study how OIB is affected by various trade types (non-program, program, index arbitrage, and non-index arbitrage).

Another contribution is that we expand the set of market quality measures used.[11] Utilizing a new

[11] Most previous studies concern volatility, liquidity, and price discovery. The majority focus on volatility. The empirical evidence based on volatility is mixed.

dimension of market quality has the potential to find new and interesting insights that may be difficult to detect with the standard market quality measures. OIB is an important concern to regulators who have used it as a trigger mechanism for program trade rules. Even more basic, OIB is a fundamental characteristic of how well a market is functioning. When orders are highly imbalanced, the market has failed to assimilate information in order to attract adequate supply and demand. This paper helps to fill this gap in the literature by specifically addressing the effects sidecars have on OIB.

3 Data and Trade Halt Mechanisms

This section describes the unique features of the Korean trade-and-quote data set. Since the trades are categorized by trade type, we define the various trade types in our sample. This is followed by a description of the program trade halt mechanism.

3.1 Sample period and data

The sample period used is from January 4, 1999 to July 31, 2006.[12] This period is chosen for several practical reasons. First, it covers the period after the Asian Financial Crisis of 1997. Second, a major changes in the sidecar provisions on the KRX occurred in July 1998. Third, a major change in the program trading rules occurred in August 2006. Thus, our sample period has consistent regulations concerning trading halts on the Korean securities market.

The sample data consists of historical records for sidecars on the KRX. 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 intraday trade data covering all KOSPI 200 stocks and the KOSPI 200 futures on the KRX. This database has the time-stamp when an order is executed. A unique feature of our data is that each trade is marked as one of two program trade types (index and non-index arbitrage) or as a normal (non-program) trade. An index arbitrage trade is defined as a trade that includes a KOSPI 200 futures and at least one other KOSPI 200 asset. If a trade does not include both of these assets and it consists of more than 15 stocks in the KOSPI 200, then the trade is classified as a non-index arbitrage trade. We have 108 sidecar events in total. 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

[12] We have data to December 31, 2006, however there was a major change in the program trading rule in August 2006 creating a different regulatory regime. Thus, we use data only to July 2006.

days. Our sample contains 48 sidecar events when the market increased (up-market sample) and 44 sidecar events when the market decreased (down-market sample).

3.2 Trade halt mechanism

The rules governing program trading halts on the KOSPI 200 spot, futures, and options markets are a combined trading restriction of price limit and trading halt. When the nearest KOSPI 200 futures price increases or decreases more than X% (in our sample either 4% or 5%) from the previous day's close and this price change is maintained for one minute, then a halt period is triggered where program trading is suspended for five minutes. That is, program trades cannot be executed on either the futures, options, or the spot markets during the five-minute halt period.[13] Note, non-program trades are still valid during a sidecar event. Since the trading on the KOSPI 200 futures are very active, halts have been exerted over 100 times since its introduction.[14] In the KOSPI 200 futures market, the halt triggering point is symmetric. Changes of X% 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.

An important property of the Korean sidecar 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 options. 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.

[13] Unlike Rule 80A on the NYSE, which applies only to index arbitrage trades, the KRX sidecar applies to all program trades, both index and non-index arbitrage trades.

[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

We use OIB as the key empirical measure of market quality. There is an extensive literature supporting the claim that OIB is a good indicator for price discovery (see subsection 2.4).

4.1 Trade direction is observed

In the prior literature on circuit breakers, most papers use 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-initiated transaction or a sell-initiated transaction. This makes our analysis more accurate as we do not have to make any simplifying assumptions or estimates in order to sign trades.

4.2 Order imbalance measures

Following Chordia et al (2002, 2008), we implement OIB on three underlying variables in order to test the robustness of our results. We calculate $|OIB|$ utilizing the number of shares traded (OIBSH), the value of shares traded (OIBDOL, OIB$), and the number of trades (OIBNUM, OIB#).For each event j, we calculate the one-minute OIB for the 10-minute period both pre- and post-event. Our measure is the absolute order imbalance, $|OIB|$, calculated for each 1 minute period, as:

$$|OIB|_{j,i}^{Pre} = \frac{|B_{j,i}^{Pre} - S_{j,i}^{Pre}|}{B_{j,i}^{Pre} + S_{j,i}^{Pre}} \quad \text{and} \quad |OIB|_{j,i}^{Post} = \frac{|B_{j,i}^{Post} - S_{j,i}^{Post}|}{B_{j,i}^{Post} + S_{j,i}^{Post}}$$

where $B_{j,i}^{p}$ ($S_{j,i}^{p}$) in the pre-event period ($p = Pre$) or the post-event period ($p = Post$) is the buy-initiated (sell-initiated) number of trades, shares, or value for subperiod i, for each event j. As we observe the initiating party of the trade, we do not have to use an order signing algorithm. We calculate our final OIB measure as:

$$\Delta|OIB|_j = |OIB|_j^{Pre} - |OIB|_j^{Post}$$

where

$$|OIB|_j^{Pre} = \frac{1}{10}\sum_{i=1}^{10} |OIB|_{j,i}^{Pre} \quad \text{and} \quad |OIB|_j^{Post} = \frac{1}{10}\sum_{i=1}^{10} |OIB|_{j,i}^{Post}$$

Note that we do not pool across minutes, we average to form one estimate pre-halt and one estimate post-halt. As the halts are **independent events** that occur over 7.5 years, we have 92 independent paired observations. In our data, the sidecar is a local event. The Korean sidecar is imposed for only 5 minutes. Our analysis (see Figure 1) demonstrates that 10 minutes pre- and post-sidecar captures the interesting market dynamics. When trade direction is of concern, we calculate our measure of OIB without the absolute value signs, i.e., with OIBNUM, OIBSH, and OIBDOL. [15]

4.3 Expected OIB recovery

Each trade in our data is classified as a non-program trade (NPT) or a program trade (PT). If a trade is a PT, then it is further classified as an index-arbitrage trade (IA) or a non-index-arbitrage trade (NIA). Only PT is halted during the sidecar. NPT are still allowed.

We estimate the expected OIB recovery for PT over the sidecar event if program trade had not been halted. There are two natural candidates. First, since NPT is allowed, it is interesting to compare $\Delta|OIB|_j^{PT}$ with $\Delta|OIB|_j^{NPT}$. This comparison has the advantage that market dynamics is controlled for perfectly as both values are calculated using the same time period j. Its disadvantage is that the risk characteristics of an average PT trader likely differs systematically from that of an average NPT trader. Thus, controlling for trade type is important. A second and more appealing estimate for expected OIB recovery is to compare PT OIB recovery during event j (the treatment effect) with PT OIB recovery during a different time period, k, where PT trade was not halted with comparable market dynamics (the control effect). That is we compare $\Delta|OIB|_j^{PT}$ with $\Delta|OIB|_k^{PT}$. This second comparison has the advantage that trade type is perfectly

[15] An example of the $|OIBSH|$ construction will help clarify the calculation. Suppose there are only 3 assets: A, B, and C. Let NPT = Non-Program Trade, IA = Index-Arbitrage Trade, NIA = Non-Index Arbitrage Trade. Assume in a specific period the following trades took place for each type of trade, where the trade is classified according to the initiating trade type:

Stock	NPT-buy	NPT-sell	IA-buy	IA-sell	NIA-buy	NIA-sell
A	100	200	300	100	0	0
B	200	100	0	0	200	100
C	300	200	200	200	100	100

Then we can calculate the $|OIBSH|$ for each trade type as follows:

$$NPT\ |OIBSH| = \left|\frac{(100+200+300)-(200+100+200)}{(100+200+300)+(200+100+200)}\right| = \left|\frac{600-500}{600+500}\right| = \frac{1}{11}$$

$$IA\ |OIBSH| = \left|\frac{(300+0+200)-(100+0+200)}{(300+0+200)+(100+0+200)}\right| = \left|\frac{500-300}{500+300}\right| = \frac{1}{4}$$

$$NIA\ |OIBSH| = \left|\frac{(0+200+100)-(0+100+100)}{(0+200+100)+(0+100+100)}\right| = \left|\frac{300-200}{300+200}\right| = \frac{1}{5}$$

Each $|OIBSH|$ calculation only includes trades initiated by a specific trade type. Thus, each $|OIBSH|$ number represents the net trade imbalance of that specific trade type during the period under consideration. These calculations are done for each minute in the 10-minute pre- and post-halt periods. The value used in our tests is the average over the ten one-minute values for each period.

matched. Market dynamics will not be perfectly matched, but should be representative. We perform both comparisons. We address the construction and properties of the control- or pseudo-sample next.

4.4 Construction of the pseudo-sidecar sample

Markets anticipate events. Prices reflect market expectations of future events. One manifestation of this "expectational nature" of markets is the magnetic or gravitational effect. The intuition for the magnetic effect is that when price approaches a break limit, market participants will trade more aggressively in order to not get "locked" into the market during the close. 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 existance of circuit breaker rules 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.

The impact of the gravitational effect provides solid theoretical validation for our pseudo-event methodology as our tests concern spot markets. With any control group it is always a major concern that the control does not capture important characteristics of the actual event.[16] In our case, we want to identify control events in which program trade is allowed that have similar characteristics to an actual-sidecar events where program trade is not allowed. If market participants anticipate the halt, i.e., the market is aware of the sidecar rules when the trigger mechanism is approached, the market will behave identically in both the true event and the pseudo event as long as the trigger is "close enough." In such situations, a pseudo-event control should be valid as similar market behavior will exist. We find that the 4% trigger is close enough.[17]

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 is within 1% of the trigger level, but a trading halt was not triggered. Note the second dimension of a sidecar trigger, maintaining the price level

[16] Unfortunately, program trades do not exist during a program trade halt, so making comparisons of the effects of program trades directly is impossible. As we define $|OIB|$ over different trade types, this is again impossible to do when certain trade types do not exist. This is a limitation of the data that every program trade halt study will face when trying to determine the effects of program trading on market quality.

[17] Our pseudo trigger differs from the actual trigger by 1%. To determine if a 1% trigger difference is confounding our results, we construct two alternative pseudo triggers that differ by 1%. We find that the market dynamics are the same for these alternative trigger-events demonstrating that a 1% difference in trigger level is not driving our results. These tests are available upon request.

for a minimum of 1 minute, must be met as well. In our pseudo-sidecar sample, there are no trading halts; thus, normal information transfer via program trading works between the futures and spot markets. We can analyze the information transfer between spot and futures markets and the changes in OIB around the trading halt by comparing the actual-sidecar sample (treatment) and the pseudo-sidecar sample (control). See Table 1 for details of the pseudo-sidecar construction.

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. Although the pseudo-sidecar sample is not able to perfectly control for market dynamics, we can get near perfect trade-type characteristic control by utilizing each trade type 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.]

Although not directly obvious, our pseudo sidecar design also controls for the size of the market move. We used three alternative pseudo-sidecar designs.[18] All designs meet the 1-minute duration requirement. The three rules correspond to price move differences of 0.5%, 1.0%, and 1.5%, respectively, of the actual sidecar trigger price move. In all cases we get qualitatively similar results, which provides a robustness check on our results. More importantly, this does control for the size of the price change. We get the same result regardless of the price change difference, which should not be true if the price change is fundamental to the results. For example, the 0.5% and the 1.5% pseudo-sidecar definitions lead to qualitatively the same results. This price change is of the same order or more than the price change differential between the actual and pseudo sample periods. Tables for these results are available upon request.

To verify that our pseudo events have similar characteristics as actual events, we classify stocks into eight categories depending on whether the stock experiences one of three types of trading activity (non-program, index arbitrage, and non-index arbitrage) in the pre-event period. We then calculate the distribution of these categories for both the psuedo- and actual-event pre-periods. The distributions are very similar. For example, stocks that only experience non-program trades account for 37.3% of the stocks in the actual events, while

[18]There are two dimensions necessary for a sidecar trigger: magnitude and duration. We can use both dimensions to form the pseudo-sidecar sample. Currently we only use the price change dimension, but it is plausible to do a direct control using the time dimension, i.e., we can define the pseudo sidecar as the same price change but with smaller duration. Unfortunately, under this alternative definition we could not get an adequate number of pseudo sidecars.

the corresponding number is 37.7% for our pseudo sample. Stocks that experience all three types of trading activity account for 23.6% of stocks in the actual sample and for 25.7% of stocks in the pseudo sample. Finally, stocks that experience no trading activity represent 5.4% of stocks in the actual events, while the corresponding percent for the pseudo events is 4.0%. The remaining 5 categories are also similar. Thus, trading behavior is similar during large events whether or not the sidecar is triggered. Besides being a standard methodology used in halt studies, the pseudo-sample control method used here has two desirable characteristics: (1) there is theoretical and empirical support for the similarities between the control sample and the actual sample, and (2) important characteristics of the data are similar in both the control and actual samples.

4.5 Research design

We study the OIB 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 $|OIB|$ at one minute intervals from 9:30AM to 2:50PM. We calculate one pre-event and one post-event OIB number for each event in our sample. We conduct our comparisons of OIB for the full sample, for program trades vs. non-program trades, and for index-arbitrage trades vs. non-index-arbitrage trades.

Our research design is constructed to answer three main questions. First, what are the OIB characteristics before and after a sidecar? To answer this, we analyze and compare imbalances before and after sidecar events. For all KOSPI 200 stocks, we analyze the total sample (all sidecar events), the up-market sample (sidecar events occurring in up markets), and the down-market sample (sidecar events occurring in down markets). To control for expected OIB reduction, we use our matched sample of non-program trades for which trade occurs during the sidecar. If the non-program trades behave similar to program trades, then it is unlikely that the underlying mechanism of OIB correction is the trade halt.

The second question of interest is what channel exists for transmitting information between markets. There are two possible hypotheses. According to no arbitrage, information can be transmitted via the action of arbitrageurs engaging in index arbitrage trades across markets. As futures markets tend to lead spot markets, information is incorporated into spot prices faster when index arbitrage is allowed. 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- 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 construct pseudo-sidecar events to test if extreme market moves are associated with similar imbalance reduction patterns that we document in the actual-sidecar events. 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. In the first case, we use allowed trades (non-program trades) during the same time period as the halt to control for market dynamics. This is a perfect control for market dynamics, but an imperfect control for trade characteristics. In the second case, in the pseudo-sidecar control, we use the same trade types (program trades) during a different time period that experienced similar market dynamics. This is an imperfect control for market dynamics, but a good control for trade type characteristics. It is not possible to construct a perfect control sample that simultaneously controls both market dynamics and risk characteristics. However, by conducting tests with two different controls, each emphasizing a different dimension of risk, if similar results are found in both then the results are more credible.

[Table 2 about here.]

[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 OIB 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 otherwise, 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

In this section we present empirical results that address the relationship between program trade halts and OIB, the information transfer mechanism, and whether sidecars achieve the goal they were designed for.

5.1 Order imbalance characteristics around sidecar events

Sidecars target program trades. If sidecars are affective, we would like to see a larger change in OIB for program trades than that for non-program trades. Our first analysis is graphical and uses the signed OIB measure in order to explore market characteristics before and after a sidecar event. Signed OIB allows us to see whether buy or sell pressure is driving the large price movement. As it is signed, signed OIB has to be analyzed for up markets and down markets separately. Figure 2 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. It is interesting to note that in Figure 2, OIB barely declines after a five-minute halt (compare minute -1 OIB of 0.110 and minute 1 OIB of 0.0900 in Panel A), but after only three-minutes trading OIB is almost completely resolved (compare minute 1 OIB of 0.900 and minute 3 OIB of 0.018).

[Figure 2 about here.]

Next we consider the $|OIB|$ measure of imbalance. Table 3 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 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.

[Table 3 about here.]

Given that all results are qualitatively similar under all measures, from this point forward we only report results for $|OIB\#|$ and will refer to it as $|OIB|$ in order to preserve space.

A sidecar halts program trading only. The main question is how are OIB characteristics across program and non-program trades affected by the sidecar. We test the level of OIB for each trade type, both pre- and post-event.[19] We also test the change in OIB for each trade type between the pre- and the post-event period. Our results in Table 4 for NPT, PT, and $NPT - PT$ confirm that program trades experience a larger level of OIB both pre- and post-event. There is also a larger decrease in the imbalance across the pre- and the post-event period for program trades than for non-program trades. This is true for the full sample and for both the up-market and the down-market samples.[20]

[Table 4 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: index and non-index arbitrage. We measure the OIB for the actual-sidecar events both in the pre- and post-event periods. Table 4 summaries the results for IA, NIA, and $IA - NIA$. Our results are again consistent across the full sample and both the up-market and down-market samples. We find that for both types of program trades (index and non-index arbitrage), the OIB 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. We see that the index-arbitrage trades always have a slightly higher, but statistically significant, level of imbalance. However, the reduction in OIB after the sidecar for the non-index arbitrage trades is always larger than that for the index-arbitrage trades. Thus, we document that in the actual-sidecar event the reduction in OIB is greatest for non-index arbitrage trades; this is followed by the reduction for the index-arbitrage trades; and it is smallest for non-program trades.

5.2 Information transfer mechanisms

Information can affect markets via different mechanisms. One possibility is that arbitrageurs see mispricing and then trade across markets to bring prices in line with private information. Another is that smart money may take positions (long in undervalued assets and short in overvalued assets). This smart-money mechanism does not require simultaneously establishing trades in various markets. Table 4 shows that the non-index arbitrage sample has stronger OIB reduction than the arbitrage sample. The private information revealed by smart-money has a substantially stronger OIB resolution after the sidecar when compared to that

[19] We control for firm risk characteristics by using trades for the same portfolio of stocks in the pre- and post-periods.

[20] Since the program trade OIB is larger in the pre-sidecar period, one may be concerned about mean reversion, i.e., that the larger OIB should have a larger change if data is noisy or markets are mean reverting for any other reason. We note that the same ordering holds for percentage reductions.

from index arbitrage. One interpretation of this result is that the sidecar allows the market time to learn about new information and this learning process is more important for private information than from information transfer between markets.

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 can use this sample as a control in order to compare 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 conclude that the program trading halts are effective at controlling OIB during large market moves. However, if the observed ordering in OIB is 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 OIB to have on average larger corrections.[21] Thus, we expect to find a larger correction in OIB 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 OIB 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 OIB during large market moves.

To investigate this possibility, we repeat our experimental design over our pseudo-sidecar events. Table 5, Panel A reports the results for the full sample of events. Table 5, Panels B and C report the results for the up-market events and for the down-market events separately. We find a similar pattern across all market types. OIB is larger in the pre-event period before a large stock move. Notably, in most cases when comparing Table 4 and Table 5, the imbalance level is larger in the actual sample compared to that observed in the pseudo sample. We find this result holds both for program and for non-program trades. We also find a similar pattern for index- 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 OIB from the pre-event period to the post-event period. This holds true for all trade types and in all market types. Finally,

[21] This intuition is supported by Bhattacharya and Spiegel (1998) who find significant reversals for OIB-triggered halts in the NYSE. A similar finding is reported in Chordia, Roll, and Subrahmanyam (2001) who find that market-wide returns reverse themselves after high negative OIB where the reversal is partially predictable from both the level of the imbalance and return.

we find that the reduction in OIB is higher for program trades compared to non-program trades, and we find that the change in OIB 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.

[Table 5 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 event samples. The results are reported in the $\Delta|OIB|^{psu} - \Delta|OIB|^{act}$ column of Table 5. The differences compare changes in OIB in Table 4 and Table 5.The reduction in the OIB across the pre-event and post-event periods is larger in the pseudo-sidecar sample than in the actual-sidecar sample. This result holds in all markets and in both up markets and down markets with the one exception of non-index arbitrage trades in the up-market sample. The results are statistically significant both with the parametric t-test and the non-parametric Wilcoxon p-values. Thus, we conclude that program trading is not responsible for the observed OIB 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 OIB, the market will adjust itself and the order environment will normalize more fully when program trading is allowed than when it is restricted. Thus, the sidecar is an unnecessary burden on the natural correction mechanisms of the market.

6 Robustness Checks

In this section we explore the same questions as in the previous section, except we utilize a regression framework that allows us to add better controls for previously documented and potentially confounding relationships. This section also considers a natural experiment that controls for asymmetric information. Finally, robustness to subperiod analysis is explored.

6.1 Order imbalance characteristics around sidecar events

We report in Table 4, Panel A that the sidecar is associated with a reduction in OIB from the pre-event period to the post-event period. We also documented that the reduction is larger for the pseudo-sidecar events for all trade types than it is for the actual-sidecar events. In order to test the robustness of these results, we employ a regression based framework. We regress the $|OIB|$ on our independent variables.[22] We capture

[22]Recall that we average over the 10 one-minute OIB values calculated for each period. Thus for each event, we have one observation pre-halt and one observation post-halt. As the halts are independent events that occur over 7.5 years, we then have 92

the sidecar effect as a dummy variable (PRE). We estimate the regression of actual $|OIB|$ for each subset of trades: non-program, program, index arbitrage, and non-index arbitrage. We control for time, a market dummy, and several control variables. A common critique of OIB is that it is also related to liquidity, so our control variables specifically control for liquidity, which demonstrates that our results are still valid above and beyond any liquidity effect. The regression model is as follows:

$$\begin{aligned} |OIB|_j &= \beta_0 + \beta_1 \cdot PRE_j + \beta_2 \cdot TIME_j + \beta_3 \cdot MARKET_j \\ &\quad + \beta_4 \cdot VOLATILITY_j + \beta_5 \cdot VOLUME_j + \beta_6 \cdot SPREAD_j \end{aligned} \tag{1}$$

In Equation 1, the dependent variable $|OIB|$ is the absolute order imbalance for event j. In the regression, we use cross-sectional and time-series pooled data constructed during the 10 minutes of the pre-event and post-event periods for each sidecar event. PRE takes the value of one in the pre-event period and zero in the post-event 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 during a down market and zero for an up market. 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-event and post-event periods. $VOLUME$ is the proportion of trading shares in the pre-event and post-event periods 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-event and post-event periods.

If the coefficient on PRE is positive and significant, then OIB 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-event to the post-event period. Table 6 reports the results for the regression in Equation 1. We find that for all trade types, the sidecar is associated with a reduction in OIB 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 OIB is robust to inclusion of other influential variables. The regression demonstrates that the OIB resolution is greater for program trades than for non-program trades, and it is greater for non-index arbitrage trades than for index-arbitrage trades. Thus, the regression results confirm our previous findings.

[Table 6 about here.]

independent observation pairs, one for each actual halt.

6.2 Information transfer mechanisms

Also in Table 6, the magnitude and significance of the coefficient on PRE gives us the relative importance of a sidecar for resolving asymmetric imbalances across the different trade types. Under the hypothesis that the main mechanism for transferring information between the spot and futures markets 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 for the index arbitrage sample. This violates the thesis that index arbitrage is the main information transfer mechanism, directly supporting our previous findings on smart-money.

Even the non-program trades have a positive and significant coefficient on PRE. Thus, information is being transferred between markets outside of the program trading environment. This result suggests smart-money exists in non-program trading, but at a vastly smaller scale.

6.3 Are sidecars necessary?

The main result we find is that the pseudo-sidecar sample has identical market characteristics for OIB 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-difference regression model. We estimate results for the regression of $|OIB|$ of non-program, program, index-arbitrage, and non-index arbitrage trades. The regression is estimated based on the following model:

$$
\begin{aligned}
|OIB_j| \quad = \quad & \beta_0 + \beta_1 \cdot PRE + \beta_2 \cdot TIME + \beta_3 \cdot MARKET \\
& + \beta_4 \cdot VOLATILITY + \beta_5 \cdot VOLUME + \beta_6 \cdot SPREAD \\
& + \beta_7 \cdot USRET + \beta_8 \cdot PSEUDO + \beta_9 \cdot PRE \cdot PSEUDO
\end{aligned} \tag{2}
$$

All variables are defined as in Equation 1. However, we have added three terms.The first is the variable $PSEUDO$, which is a dummy equal to 1 if the observation is from a pseudo sidecar and 0 if from an actual sidecar. $PRE \cdot PSEUDO$ is the interaction between PRE and $PSEUDO$. This cross term captures the difference-of-difference effect ($\Delta|OIB|^{psu} - \Delta|OIB|^{act}$, where the difference is the change in OIB between the pre- and post-periods).[23] This difference-of-difference effect is the 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&P 500 index of the previous day to the sidecar date.

Table 7, Panel A reports the results for $|OIB|$ for the total sample. We find that PRE is positive and significant for all trade types. Thus, in all trade subsets, the sidecar is associated with a reduction in OIB from the pre-event period to the post-event period. We also find that all liquidity variables are significant in the regression for all trade types. The main result is contained in the sign and significance of the cross term $PRE \cdot PSEUDO$. In all trade types the coefficient is positive and significant. Thus, after controlling for liquidity the conclusion remains that markets adjust OIB more fully when program trading is allowed than when it is halted. Table 7, Panel B reports the results for $|OIB|$ for both the up-market and down-market samples separately. In all cases, except the non-index-arbitrage trade type in up markets, the coefficients on $PRE \cdot PSEUDO$ are positive in the up- and down-market subsamples.

6.4 The affect of program trade halts 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 OIB 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 test is to control for US market returns and investigate the behavior of non-program trades and the various types of program trades. This result is reported in Table 7.

[Table 7 about here.]

In Table 7, Panel A there is an insignificant effect on USRET for non-program trades. However, for program trades, there are significant and opposite signs for the index arbitrage (0.768) and the non-index arbitrage (-0.785) trade types. Thus, each sample has a different effect on OIB in relation to US market moves. If the non-index arbitrage trade group is providing liquidity, that is, they are contrarian trading with

[23] This can be seen by looking at the following:

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

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

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. In Panel B, we find that the non-program trade sample exacerbates the OIB in both 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 OIB, 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.

6.5 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 OIB. If the sidecar inhibits the market's ability to adjust large OIB, then when asymmetric information is high, we would expect to see a particularly high realization of OIB resolution 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 the actual and pseudo events 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 (pseudo) samples are separated into 36 news events and 56 no-public news events (43 news events and 104 no-public news events).

Table 8, 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 OIB reduction is observed as in the full sample. This is true for both the actual and pseudo events. Again, with the exception of the arbitrage trades in the Public-News sample, the reduction in OIB is larger in the pseudo sample than in the actual sample. Thus, markets work better at resolving OIB when program trade is unrestricted. The new result contained in Table 8 concerns the comparison across information environments. The magnitude of the OIB 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, the no-public-news group experiences a sharp drop in ability to adjust to large OIB. Overall, the results are in line with the hypothesis that sidecars are inhibiting the markets natural adjustment mechanism.

[Table 8 about here.]

Table 8, 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 OIB resolution in the actual and pseudo samples are not significantly different from zero. The one exception is for the non-index arbitrage class of trades. In 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 as expected if the trading is important to alleviating large OIB during times of high asymmetric information. Without program trade, it is difficult for the market to engage in discovery, i.e., private information is impeded from entering market price.

6.6 Trade activity around sidecar events

We also investigate the trading activity on the KOSPI 200 spot market surrounding both the actual-sidecar and pseudo-sidecar events. Table 9 reports the difference in trading activity levels before and after a large market move. Results are reported for non-program trades, index-arbitrage trades, and non-index-arbitrage trades. 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 events, for all measures of trading activity and for all trade 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 contrast, in the pseudo-sidecar events, for all measures of trading activity and for all trade types, we find the trading activity decreases after the pseudo sidecar. All results are statistically significant. This table demonstrates that, in addition to being ineffective in controlling OIB, 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 OIB, as should be expected if the imbalance is being resolved through trading activities.

[Table 9 about here.]

6.7 Subperiod analysis

Next, 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 July 31, 2006. 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 OIB. OIB 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.

6.8 Minute-by-minute order imbalance

Table 10 shows the minute-by-minute order imbalance ($|OIB|$) for KOSPI 200 stocks in the spot market. The OIB activity is calculated for the 10-minute pre-halt period (denoted as minute -10 to minute -1), the 5 minutes during the actual or pseudo-sidecar event (denoted as minute S1 to minute S5), and the 10-minute post-halt period (denoted as minute 1 to minute 10). OIB is shown for both the actual- and pseudo-sidecar event samples. OIB is broken down for each trade type, i.e. non-program trades, index arbitrage program trades, and non-index arbitrage program trades. Values reported in the table are mean values of KOSPI 200 stocks' OIB for each trade type, calculated using only trades from that specific trade type. The values are reported for each one-minute period. Again, both the up-market and the down-market sample results are reported individually.

The most interesting result in Table 10 is that in all eight instances where trade is allowed (both for non-program trades and all types of program trades) the OIB is reduced, and in most instances substantially, over the 5-minute trade interval. For instance, for the non-program trades during the actual up-market events, the trade imbalance dropped from 0.454 to 0.436. For the non-index arbitrage trades during the pseudo down-market events, the trade imbalance dropped from 0.261 to 0.134. The second important point in this table is that in three of the four cases where trading is not allowed OIB increased over the 5-minute halt period. Although this evidence is not statistically based, these results are consistent with all the results conducted in this study.

[Table 10 about here.]

7 Conclusion

Circuit breakers have been studied extensively with regards to both market-wide and firm-specific implementation. Most of these studies investigate how circuit breakers affect volatility and price discovery. The results of this research are mixed.

We add to the above literature in several ways. First, we study sidecars (only program trading is halted while the market remains open). Only a handful of sidecar papers exist and these papers exclusively study the NYSE Rule 80A. Rule 80A is an inhibitor, designed to slow, not necessarily eliminate program trade. However, program trade halt rules exist. We are presently the first study to consider a regulatory mechanism where the spot, futures, and options markets are halted simultaneously. Second, we investigate how program trading halts affect the OIB environment of the market. Third, 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. Finally, using Korean data rather than US data allows us to explore the relationship between index- 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 two testable hypotheses. The first hypothesis is that a trade halt induces pent-up demand. We hypothesize that program trades should exhibit higher levels of OIB when halted than when trade is allowed. The second hypothesis is that the observed OIB dynamics around an actual-sidecar event should exhibit a larger reduction in OIB than in a pseudo-sidecar event.

Our results support the first hypothesis. There is a cost to market participants in that their demand for liquidity is restricted and such demand builds over the sidecar. Importantly the second hypothesis is violated, in that, pseudo-sidecar events exhibit significantly larger drops in OIB than the actual-sidecar events. Combined with the fact that demand increases after a sidecar, but not after a pseudo sidecar, we conclude that sidecars (1) are ineffective at controlling OIB and interfere with the market's self-adjusting mechanisms and (2) add costs to market participants, manifested as pent-up demand. Our main results are consistent across several robustness tests. We demonstrate that program trades are not equal. In our robustness tests, some program trades provide liquidity, while others demand liquidity. Eliminating a group that is providing liquidity during a market experiencing extreme net liquidity demand is not good policy. Our results suggest that the Korean sidecar designed to eliminate all program trades (a hatchet approach) is not an effective regulatory mechanism and should be more carefully designed. A sidecar designed to allow program trades that provide liquidity, while eliminating liquidity demanding trades (a scalpel approach) may be more effective. Thus, a scalpel, not the hatchet, may be a more productive objective to program trade rule design.

8 References

Ackert, Lucy F.; Hao, Jonathan; Hunter, William C., 1997, “The Effect of Circuit Breakers on Expected Volatility: Tests Using Implied Volatilities,” Atlantic Economic Journal 25, pp. 117-27.

Aitken, Michael, and Alex Frino, 1996, “The Accuracy of the Tick Test: Evidence from the Australian Stock Exchange.” Journal of Banking & Finance, 20, pp. 1715-1729.

Amihud, Yakov and Haim Mendelson, 1987, “Trading Mechanisms and Stock Returns: An Empirical Investigation,” Journal of Finance 42, pp. 533-553.

Andrade, Sandro, Charles Chang, and Mark S. Seasholes, 2008, “Trading imbalances, predictable reversals, and cross-stock effects,” Journal of Financial Economics 88, pp. 406-423.

Bessembinder, Hendrik, 2003, “Issues in Assessing Trade Execution Costs,” Journal of Financial Markets 6, pp. 233-258.

Bhattacharya, Utpal and Matthew Spiegel, 1991, “Insiders, outsiders, and market breakdowns,” Review of Financial Studies, 4, pp. 255-283.

Bhattacharya, Utpal and Matthew Spiegel, 1998, “Anatomy of a Market Failure: NYSE Trading Suspensions (1974-1988),” Journal of Business & Economic Statistics 16, pp. 216-226.

Bollen, Nocholas P. and Robert E. Whaley, 2004, “Does net buying pressure affect the shape of implied volatility functions?,” Journal of Finance 59, pp. 711-753.

Brandt, Michael W. and Kenneth A. Kavajecz, 2004, “Price discovery in the U.S. treasury market: The impact of orderflow and liquidity on the yield curve,” Journal of Finance 59, pp. 2623-2654.

Brennan, Michael, 1986, “A Theory of Price Limits in Futures Markets,” Journal of Financial Economics, 16, pp. 213-233.

Chakrabarty, Bidisha, Shane A. Corwin, and Marios A. Panayides, 2009, When a Halt is Not a Halt: An Analysis of Off-NYSE Trading during NYSE Market Closures, Working paper.

Chakravarty, Sugato, and Rina Ray, 2010, “Is it Heterogeneous Investor Beliefs or Private Information that Affects Prices and Trading Volume? Evidence from Indian IPOs,” Working Paper.

Chan, K., and Fong, W.M., 2000, “ Trade Size, Order Imbalance, and the Volatility–Volume Relation,” Journal of Financial Economics, 57, pp. 247-273.

Chen, H., 1998, “Price Limits, Overreaction, and Price Resolution in Futures Markets,” Journal of Futures Markets 18, pp. 243-263.

Chordia, T., Roll, R., and Subrahmanyam, A., 2002, “Order Imbalance, Liquidity, and Market Returns,” Journal of Financial Economics, 65, pp. 111-130.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2008, “Liquidity and Market Efficiency,” Journal of Financial Economics 87, pp. 249-268.

Chordia, Tarun and Avanidhar Subrahmanyam, 2004, “Order Imbalance and Individual Stock Returns: Theory and Evidence,” Journal of Financial Economics 72, pp. 485-518.

Chordia, T., Subrahmanyam, A., Anshuman, V. R., 2001, “Trading Activity and Expected Stock Returns.” Journal of Financial Economics 59, pp. 3-32.

Corwin, Shane A., and Marc L. Lipson, 2000, “Order Flow and Liquidity Around NYSE Trading Halts,” Journal of Finance 55, pp. 1771-1801.

Christie, William G., and Shane A. Corwin, Jeffrey H. Harris, 2002, “Nasdaq Trading Halts : The Impact of Market Mechanisms on Prices, Trading Activity, and Execution Costs,” Journal of Finance 57, pp. 1443-1478.

Edelen, R., and S. Gervais, 2003, “The Role of Trading Halts in Monitoring a Specialist Market,” Review of Financial Studies, 16, pp. 263-300.

Ellis, Katrina, Roni Michaely, Maureen O’Hara, 2000, “The Accuracy of Trade Classification Rules: Evidence from Nasdaq,” Journal of Financial & Quantitative Analysis 35, pp. 529-551.

Engelen, Peter-Jan, and Rezaul Kabir, 2006, “Empirical Evidence on the Role of Trading Suspensions in Disseminating New Information to the Capital markets,” Journal of Business Finance & Accounting 33, pp. 1142-1167.

Fabozzi, Frank J. and Christopher K. Ma, 1988, “The Over-the-Counter Market and New York Stock Exchange Trading Halts,” Financial Review 23, pp. 427-437.

Foucault, T., 1999, “Order Flow Composition and Trading Costs in a Dynamic Limit Order Market,” Journal of Financial Markets, Vol. 2, pp. 99-134.

French, Kenneth and Richard Roll, 1986, “Stock Return Variances: The Arrival of Information and the Reaction of Traders,” Journal of Financial Economics 7, pp. 5-26.

Frino, A., Lecce, S., Segara, R., 2011, “The Impact of Trading Halts on Liquidity and Price Volatility: Evidence from the Australian Stock Exchange Pacific Basin Finance Journal, 19, pp. 298-307.

Fung, J. K. W., 2007, “Order Imbalance and the Pricing of Index,” Journal of Futures Markets, 27, pp. 697-717.

Gerety, M. S. and Mulherin, J. H., 1992, “Trading Halts and Market Activity: An Analysis of Volume at Open and Close,” Journal of Finance 47, pp. 1765-1784.

Goldstein, Michael A., Joan E. Evans, and James M. Mahoney, 1998, “Circuit Breakers, Volatility, and the U.S. Equity Markets: Evidence from NYSE Rule 80A,” Presented Paper in 1998 FMA Meetings.

Goldstein, M.A. and K.A. Kavajecz, 2004, “Trading strategies during circuit breakers and extreme market movements,” Journal of Financial Markets, 7, pp. 301-333.

Greenwald, Bruce C. and Jeremy C. Stein, 1988, “The Task Force Report: The Reasoning Behind the Recommendation,” Journal of Economic Perspectives 3, pp. 3-24.

Greenwald, Bruce C. and Jeremy C. Stein, 1991, “Transactional Risk, Market Crashes, and the Role of Circuit Breakers,” Journal of Business 64, pp. 443-462.

Grundy, B. D., and M. McNichols, 1989, “Trade and Revelation of Information through Prices and direct Disclosure,” Review of Financial Studies 2, pp. 485-526.

Harris, Lawrence, 1998, “Circuit Breakers and Program Trading Limits: What have We Learned?,” in: R.E. Litan and A.M. Santomero, eds., Brookings-Wharton Papers on Financial Services, (Brookings Institutions Press, Washington DC), pp. 17-63.

Huang, Y. C. and Chou, J. H., 2007, “Order Imbalance and Its Impact on Market Performance: Order-driven vs. Quote-driven Markets,” Journal of Business Finance & Accounting, 34, pp. 1596-1614.

Huang, R., and H. Stoll, 1994, “Market Microstructure and Stock Return Predictions,” Review of Financial Studies, 7, pp. 179-213.

Kim, Kenneth A., and S. Ghon Rhee, 1997, “Price Limit Performance: Evidence from the Tokyo Stock Exchange,” Journal of Finance 52, pp. 885-901.

Kim, Y. H.,J. Yague, and J. J. Yang, 2008, “Relative Performance of Trading Halts and Price Limits: Evidence from the Spanish Stock Exchange,” International Review of Economics & Finance, 17, pp. 197-215.

Kodres, Laura E. and Daniel P. OBrien, 1994, “The Existence of Pareto-superior Price Limits,” American Economic Review 84, pp. 919-932.

Kryzanowski, L. and H. Nemiroff, 2001, “Market Quote and Spread Component Cost Behaviour Around Trading Halts for Stocks Interlisted on the Montreal and Toronto Stock Exchanges,” Financial Review 36, pp. 115-138.

Kuserk, Gregory J., Peter R. Locke, and Chera L. Sayers, 1992, “The Effects of Amendments to Rule 80A on Liquidity, Volatility, and Price Efficiency in the S&P 500 Futures,” Journal of Futures Markets 12, pp. 383-410.

Lee, Charles M. C. and Mark J. Ready, 1991, “Inferring Trade Direction from Intraday Data,” Journal of Finance, 46, pp. 733-746.

Lee, Charles M. C., Mark J. Ready, and Paul J. Seguin, 1994, “Volume, Volatility, and New York. Stock Exchange Trading Halts,” Journal of Finance 49, pp. 183-214.

Madhavan, A., 1991, “Security Prices and Market Transparency,” Unpublished manuscript, University of Pennsylvania. McInish,T., and Wood. R., 1992. An analysis of intraday patterns in bid/ask spreads for NYSE stocks, Journal of Finance 47, pp. 753-764.

Madhavan, A. and S. Smidt, 1993, “An Analysis of Changes in Specialist Inventories and Quotations,” Journal of Finance, Vol. 48, pp. 1595-1628.

Menkhoff, L., Schmeling, Maik, 2010, “Trader See, Trader Do: How Do (Small) FX Traders React to Large Counterparties’ Trades?,” Journal of International Money and Finance, 29, pp. 1283-1302.

New York Stock Exchange, 1991, The Rule 80A Index Arbitrage Tick Test: Report to the U.S. Securities and Exchange Commission (NYSE Report). New York: New York Stock Exchange.

Overdahl, James, and Henry McMillan, 1998, “Another Day, Another Collar: An Evaluation of the Effects of NYSE Rule 80A on Trading Costs and Intermarket Arbitrage,” Journal of Business 71, pp. 27-53.

Pascual, R., and D. Veredas, 2010, “Does the Limit Order Book Matter in Explaining Long Run Volatility?,” Journal of Financial Econometrics, 8, pp. 57-87.

Santoni, G. J., and T. Liu, 1993, “Circuit Breakers and Stock Market Volatility,” Journal of Futures Markets 13, pp. 261-277.

Stein, Jeremy, 1987, “Information Externalities and Welfare-reducing Speculation,” Journal of Political Economy 95, pp. 1123-1145.

Su, Y. C., Chen, P. S., Chen, P. W., 2009, "Cross Return, Volatility and Order Imbalance in International Cross-listings," Working Paper.

Subrahmanyam, Avanidhar, 1994, "Circuit Breakers and Market Volatility: A Theoretical Perspective," Journal of Finance 49, pp. 237-254.

Supervision of Markets Division of the Securities and Futures Commission, 2001, "Circuit Breakers: International Practices and Effectiveness," SFC Quarterly Bulletin, Autumn.

Theissen, Erik, 2001, "A Test of the Accuracy of the Lee/Ready Trade Classification Algorithm." Journal of International Financial Markets, Institutions and Money 11, pp. 147-165.

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

This table describes the sidecar rule and pseudo-sidecar construction. A pseudo-sidecar is an event that had a large price fluctuation but did not trigger a program trading halt. The pseudo-sidecar event is used as a control sample in our tests and is referred to as a counterfactual or treatment effect in other lines of literature. The sidecar system on the KRX halts program trading on the futures, options, and spot markets for the 200 constituent stocks in the KOSPI 200 index for five minutes. The KRX sidecar applies to all program trades, both index and non-index arbitrage trades. Non-program trades are allowed during the sidecar.

Period	**Actual-sidecar sample**	**Pseudo-sidecar sample**
Jan. 4, 1999 - May 10, 2001	Trigger provision: When 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: When 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, with the 25 minute event window not intersecting with an actual sidecar event.
May 11, 2001 - July 31, 2006	Trigger provision: When 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: When 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, with the 25 minute event window not intersecting with an actual sidecar event.
Sidecar Up-mkt Down-mkt	92 48 44	147 75 72

Table 2: Summary for Analysis of Experimental Design

This table gives the experimental design. We utilize the absolute order imbalance ($|OIB|$). "Pre" refers to the 10 minute pre-halt period, while "Post" refers to the 10 minute post-halt period. "act" refers to the actual-sidecar events, while "psu" refers to the pseudo-sidecar events. NPT refers to non-program trades on KOSPI 200 stocks, while PT refers to program trades on KOSPI 200 stocks. Then program trades are divided into two groups. The first, IA consists of program trades for which the program trade included an order for a futures contract, while NIA consists of program trades with no index futures contract orders and a minimum of 15 simultaneous orders on KOSPI 200 stocks. Δ represents the difference between the Post and Pre value of $|OIB|$. "market dynamics" indicates in that specific comparison the same market period is used. "trade type" indicates in that specific comparison the same trade type (NPT, PT, IA, or NIA) is used.

	NPT	**PT (IA and NIA)**	**Difference test**
Actual sidecar (control)	Pre vs. Post (market dynamics) (trade type)	Pre vs. Post (market dynamics) (trade type)	ΔNPT^{act} vs. ΔPT^{act} ΔIA^{act} vs. ΔNIA^{act} (market dynamics)
Pseudo sidecar (control)	Pre vs. Post (market dynamics) (trade type)	Pre vs. Post (market dynamics) (trade type)	ΔNPT^{psu} vs. ΔPT^{psu} ΔIA^{psu} vs. ΔNIA^{psu} (market dynamics)
Difference test (control)	ΔNPT^{act} vs. ΔNPT^{psu} (trade type)	ΔPT^{act} vs. ΔPT^{psu} ΔIA^{act} vs. ΔIA^{psu} ΔNIA^{act} vs. ΔNIA^{psu} (trade type)	

Note: Firm-risk characteristics are controlled by setting portfolio for each trade type in the Pre-period and then holding the portfolio for each trade type constant in the Post-period.

Table 3: Actual Sidecar Events - All KOSPI 200 Stocks

Total Sample represents the sample of all actual program trading halts (sidecars), Up-Market Sample represents the subset of events during positive market moves and Down-Market Sample represents the subset of events during negative market moves. 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. % sig events represents the ratio of event days to total event days in which the difference is significant at the 5% level.

$$OIBSH = |(BS - SS)/(BS + SS)|$$

$$OIB\$ = |(BV - SV)/(BV + SV)|$$

$$OIB\# = |(BN - SN)/(BN + SN)|$$

Where BS (SS) is the buyer (seller) initiated trading shares, BV (SV) is the buyer (seller) initiated trading value, and BN (SN) is the number of buyer (seller) initiated trading.

				Test for Difference			
				t-test		non-parametric test	
	Pre (B)	Post (A)	Difference (B-A)	t-stat	% sig events	Wilcoxon p-value	% sig events
Panel A: Total Sample							
OIBSH	0.568	0.522	0.047	14.94	45.65	0.000	43.48
	(0.318)	(0.333)	(0.412)				
OIB$	0.568	0.522	0.046	14.61	45.65	0.000	44.56
	(0.319)	(0.333)	(0.412)				
OIB#	0.523	0.465	0.058	19.13	57.61	0.000	54.35
	(0.307)	(0.319)	(0.394)				
Panel B: Up-Market Sample							
OIBSH	0.538	0.483	0.055	12.616	43.18	0.000	38.64
	(0.321)	(0.328)	(0.412)				
OIB$	0.537	0.483	0.055	12.521	43.18	0.000	38.64
	(0.322)	(0.328)	(0.412)				
OIB#	0.493	0.424	0.069	16.212	56.82	0.000	50.00
	(0.312)	(0.312)	(0.394)				
Panel C: Down-Market Sample							
OIBSH	0.601	0.563	0.038	8.453	47.92	0.000	45.83
	(0.312)	(0.332)	(0.411)				
OIB$	0.600	0.563	0.036	8.087	47.92	0.000	50.00
	(0.313)	(0.332)	(0.412)				
OIB#	0.555	0.508	0.047	10.800	58.33	0.000	58.33
	(0.299)	(0.319)	(0.393)				

Table 4: Actual Sidecar Events - Non-Program, Program, Index-Arbitrage, and Non-Index-Arbitrage Trades

Panel A represents all events; Panel B represents the subset of events during positive market moves; and Panel C represents the subset of events during negative market moves. Pre and Post represent the pre-event and the post-event period, respectively. $|OIB|^{act}$ is the absolute trade imbalance for the actual events. $\Delta|OIB|^{act}$ is the difference in $|OIB|$ between the Pre and Post periods. Values in the table are the mean $|OIB|$ values of the KOSPI 200 stocks for 92 event days (48 events occurred in up markets and 44 in down markets). t-stat tests if the difference is different than 0, while Wilcoxon is the non-parametric Wilcoxon p-value. % of sig events represents the ratio of event days to total event days in which the difference is significant at the 5% level. NPT, PT, IA, and NIA represent non-program, program, index-arbitrage, and non-index-arbitrage trades, respectively.

	Pre	Post		$\Delta|OIB|^{act}$ Tests			
	$|OIB|^{act}$	$|OIB|^{act}$	$\Delta|OIB|^{act}$	t-stat	% sig events	Wilcoxon	% sig events
Panel A: Total Sample							
NPT	0.531	0.466	0.064	20.00	53.26	0.000	48.91
PT	0.957	0.778	0.179	45.39	71.74	0.000	69.56
IA	0.978	0.767	0.211	47.09	48.91	0.000	46.74
NIA	0.965	0.614	0.350	54.53	68.48	0.000	65.22
NPT - PT	-0.426	-0.312	-0.114				
t-stat	-129.45	-70.94	-22.40				
Wilcoxon	(0.000)	(0.000)	(0.000)				
IA - NIA	0.013	0.152	-0.139				
t-stat	6.58	20.99	-18.23				
Wilcoxon	(0.000)	(0.000)	(0.000)				
Panel B: Up-Market Sample							
NPT	0.502	0.427	0.075	16.71	56.25	0.000	47.91
PT	0.962	0.766	0.195	32.20	62.50	0.000	60.42
IA	0.986	0.769	0.217	31.70	50.00	0.000	47.92
NIA	0.969	0.568	0.401	40.01	47.72	0.000	47.72
NPT - PT	-0.460	-0.339	-0.120				
t-stat	-93.38	-52.84	-16.04				
Wilcoxon	(0.000)	(0.000)	(0.000)				
IA - NIA	0.017	0.201	-0.184				
t-stat	6.70	17.70	-15.66				
Wilcoxon	(0.000)	(0.000)	(0.000)				
Panel C: Down-Market Sample							
NPT	0.561	0.508	0.054	11.55	45.45	0.000	52.27
PT	0.953	0.787	0.166	32.13	81.81	0.000	79.54
IA	0.973	0.765	0.207	34.91	47.72	0.000	47.72
NIA	0.961	0.650	0.312	37.55	87.50	0.000	81.25
NPT - PT	-0.392	-0.279	-0.113				
t-stat	-88.93	-46.44	-16.11				
Wilcoxon	(0.000)	(0.000)	(0.000)				
IA - NIA	0.011	0.115	-0.104				
t-stat	3.73	12.26	-10.42				
Wilcoxon	(0.000)	(0.000)	(0.000)				

Table 5: Pseudo Sidecar Events - Non-Program, Program, Index-Arbitrage, and Non-Index-Arbitrage Trading Samples

This table shows $|OIB|$ for the non-program trades (NPT), program trades (PT), index-arbitrage trades (IA), and non-index-arbitrage trades (NIA) surrounding the pseudo-sidecar events. This table also compares the results of the pseudo events with that from Table 4 for the actual events. A pseudo-sidecar event is the event which has a large price fluctuation but the sidecar has not been triggered. The number of pseudo-sidecar events is 147 (75 events occurred in up markets, while 72 events occurred in down markets). Panel A represents all events; Panel B represents the subset of events during positive market moves; and Panel C represents the subset of events during negative market moves. $|OIB|^{psu}$ is the absolute trade imbalance for the pseudo events. $\Delta|OIB|^{psu}$ is the difference in $|OIB|$ between the Pre and Post periods. Values in the table are the mean $|OIB|$ values of the KOSPI 200 stocks. t-stat tests if the difference is different than 0, while Wilcoxon is the non-parametric Wilcoxon p-value.

	Pre $\|OIB\|^{psu}$	Post $\|OIB\|^{psu}$	$\Delta\|OIB\|^{psu}$	$\Delta\|OIB\|^{psu}$ Tests t-stat	Wilcoxon	$\Delta\|OIB\|^{psu}$ $-\Delta\|OIB\|^{act}$	t-stat	Wilcoxon
Panel A: Total Sample								
NPT	0.521	0.423	0.098	27.87	0.000	0.033	6.97	0.000
PT	0.940	0.700	0.240	48.23	0.000	0.061	9.78	0.000
IA	0.981	0.673	0.307	53.71	0.000	0.096	13.17	0.000
NIA	0.935	0.547	0.388	54.53	0.000	0.038	3.98	0.000
NPT - PT	-0.419	-0.276	-0.142					
t-stat	-111.6	-54.14	-24.07					
Wilcoxon	0.000	0.000	0.000					
IA - NIA	0.045	0.126	-0.081					
t-stat	16.57	14.91	-8.99					
Wilcoxon	0.000	0.000	0.000					
Panel B: Up-Market Sample								
NPT	0.483	0.407	0.075	15.88	0.000	0.001	0.08	0.933
PT	0.934	0.702	0.232	33.53	0.000	0.036	3.99	0.000
IA	0.970	0.680	0.290	40.29	0.000	0.073	6.92	0.000
NIA	0.947	0.591	0.356	37.93	0.000	-0.045	-3.29	0.000
NPT - PT	-0.451	-0.295	-0.157					
t-stat	-121.1	-58.24	-27.30					
Wilcoxon	0.000	0.000	0.000					
IA - NIA	0.023	0.089	-0.066					
t-stat	8.53	12.18	-8.89					
Wilcoxon	0.000	0.000	0.000					
Panel C: Down-Market Sample								
NPT	0.562	0.440	0.122	23.57	0.000	0.068	9.78	0.000
PT	0.945	0.697	0.249	34.82	0.000	0.082	9.60	0.000
IA	0.992	0.666	0.326	33.53	0.000	0.118	11.99	0.000
NIA	0.923	0.499	0.424	39.40	0.000	0.112	8.25	0.000
NPT - PT	-0.383	-0.257	-0.127					
t-stat	-100.9	-46.48	-21.98					
Wilcoxon	0.000	0.000	0.000					
IA - NIA	0.069	0.167	-0.098					
t-stat	24.97	19.05	-10.39					
Wilcoxon	0.000	0.000	0.000					

Table 6: Actual Sidecar Event - Regression Including Control Variables

This table shows the estimation results for the regression of actual $|OIB|$ for Non-program (NPT), Program (PT), Index-arbitrage (IA), and Non-index-arbitrage (NIA) trades on a pre-event, a time, and a market dummy variable, and several control variables. The regression model is as follows:

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

In the regression, we use cross-sectional and time-series pooled data of observations constructed during the 10 minutes of the pre-event period and post-event period of each sidecar event. PRE takes the value of one in the pre-event period and zero in the post-event 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-event and post-event period. $VOLUME$ is the proportion of trading shares in the pre-event and post-event 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-event and post-event period. *, **, *** represent the statistical significance at 10%, 5%, and 1% level, respectively.

	NPT	PT	IA	NIA
Dependent variable : $|OIB|$				
Intercept	0.354***	0.766***	0.787***	0.597***
PRE	0.073***	0.187***	0.222***	0.349***
TIME	-0.042***	-0.006*	-0.055***	0.028***
MARKET	0.059***	0.004	-0.009**	0.036***
VOLATILITY	-0.154***	-0.269**	-0.312***	-0.031
VOLUME	5.811***	4.74**	8.251***	0.645
SPREAD	13.74***	-0.537	-3.12***	-4.12***
Adj R^2	0.073	0.089	0.126	0.21

Table 7: Actual & Pseudo Sidecar Events - Difference-in-Difference Regression

This table shows Regression results for Non-program (NPT), Program (PT), Index-arbitrage (IA), and Non-index-arbitrage (NIA) trades. The model is:

$$|OIB|_j = \beta_0 + \beta_1 \cdot PRE + \beta_2 \cdot TIME + \beta_3 \cdot MARKET + \beta_4 \cdot VOLATILITY + \beta_5 \cdot VOLUME + \beta_6 \cdot SPREAD + \beta_7 \cdot USRET + \beta_8 \cdot PSEUDO + \beta_9 \cdot PRE \cdot PSEUDO$$

We use cross-sectional and time-series pooled data of observations constructed during the 10 minutes of the pre-event and post-event period of the actual- and pseudo-sidecar event. PRE, $TIME$, $MARKET$, $VOLATILITY$, $VOLUME$, and $SPREAD$ are defined as in Table 6. $USRET$ is the open-to-close log return of the S&P 500 index of the previous day to the sidecar date. $PSEUDO$ takes the value of one if the sample is a pseudo sidecar and takes the value of zero if the sample is an actual sidecar. $PRE \cdot PSEUDO$ is the interaction between PRE and $PSEUDO$. This cross term captures the difference-of-difference effect ($\Delta|OIB|^{psu} - \Delta|OIB|^{act}$), where the difference is the change in absolute trade imbalance between the pre- and post-periods and "act" ("psu") are for the actual (pseudo) events. *, **, *** represent the statistical significance at 10%, 5%, and 1% level, respectively. Panel A reports the results for $|OIB|$ for the total sample. Panel B reports the results for $|OIB|$ for both the up-market and down-market samples separately.

Panel A: Dependent variable : $|OIB|$ Total Markets

	NPT	PT	IA	NIA
Intercept	0.355***	0.773***	0.752***	0.653***
PRE	0.079***	0.185***	0.219***	0.361***
TIME	-0.052***	-0.011***	0.007**	-0.053***
MARKET	0.051***	0.000	0.011***	-0.039***
VOLATILITY	-0.236***	-0.113***	-0.104***	-0.078
VOLUME	4.97***	4.33***	6.39***	3.799***
SPREAD	15.56***	-1.62***	-3.81***	-2.41***
USRET	0.023	0.099	0.768***	-0.785***
PSEUDO	-0.031***	-0.067***	-0.081***	-0.067***
PRE·PSEUDO	0.025***	0.051***	0.077***	0.037***
Adj R2	0.087	0.113	0.156	0.236

Panel B: Dependent variable : $|OIB|$ Up & Down Markets

	NPT		PT		IA		NIA	
	up	down	up	down	up	down	up	down
Intercept	0.331***	0.417***	0.776***	0.797***	0.773***	0.765***	0.601***	0.684***
PRE	0.088***	0.068***	0.196***	0.176***	0.216***	0.220***	0.399***	0.329***
TIME	-0.046***	-0.065***	0.001	-0.003	-0.010**	0.033***	0.019***	-0.109***
VOLATILITY	-0.309***	-0.196***	-0.082	-0.098***	-0.002	-0.107***	-0.100	-0.114*
VOLUME	0.951**	8.75***	4.89***	3.61***	7.13***	5.45***	2.65***	4.02***
SPREAD	20.07***	12.88***	-2.13***	-1.48***	-4.73***	-3.30***	-5.02***	-1.24***
USRET	0.455***	-0.699***	'-1.40***	1.86***	-0.014***	2.19***	-2.58***	-0.133
PSEUDO	-0.011***	-0.048***	-0.054***	-0.091***	-0.073***	-0.097***	0.006	-0.142***
PRE·PSEUDO	-0.002	0.053***	0.026***	0.074***	0.056***	0.101***	-0.030**	0.101***
Adj R^2	0.083	0.083	0.111	0.122	0.147	0.171	0.231	0.261

Table 8: Actual & Pseudo Sidecars - Public-News vs. No-Public-News

This table shows $|OIB|$ for non-program trades (NPT), program trades (PT), index-arbitrage trades (IA), and non-index-arbitrage trades (NIA) surrounding the actual- and pseudo-sidecar events. Both the actual and pseudo events 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 Public-News and No-Public-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. 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). 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 $|OIB|$ values for KOSPI 200 stocks that are included in each subsample. Values in ( ) are standard deviations, values in { } are t-statistics, and values in [ ] are Wilcoxon p-values.

	Actual sidecar				Pseudo sidecar				Difference	
	Pre $\|OIB\|^{act}$	Post $\|OIB\|^{act}$	$\Delta\|OIB\|^{act}$	t-stat Wilcoxon	Pre $\|OIB\|^{psu}$	Post $\|OIB\|^{psu}$	$\Delta\|OIB\|^{psu}$	t-stat Wilcoxon	$\Delta\|OIB\|^{psu}$ $-\Delta\|OIB\|^{act}$	t-stat Wilcoxon
Panel A: Public-News sample										
NPT	0.536	0.463	0.074	{13.90}	0.524	0.451	0.073	{15.77}	-0.001	{-0.100}
	(0.316)	(0.335)	(0.415)	[0.000]	(0.313)	(0.327)	(0.406)	[0.000]		[0.917]
PT	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]
IA	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]
NIA	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: N0-Public-News sample										
NPT	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]
PT	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]
IA	0.986	0.835	0.150	{30.18}	0.988	0.671	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]
NIA	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: (Public-News) - (No-Public-News)										
NPT	0.009	-0.006	0.015	{2.27}	-0.004	0.031	-0.035	{-6.42}		
	(0.313)	(0.330)	(0.410)	[0.027]	(0.314)	(0.325)	(0.404)	[0.000]		
PT	-0.024	-0.098	0.073	{9.15}	-0.002	0.013	-0.015	{-1.96}		
	(0.151)	(0.376)	(0.400)	[0.000]	(0.176)	(0.424)	(0.456)	[0.351]		
IA	-0.019	-0.171	0.152	{16.89}	-0.021	0.008	-0.029	{-3.39}		
	(0.114)	(0.401)	(0.422)	[0.000]	(0.105)	(0.458)	(0.475)	[0.037]		
NIA	0.005	0.060	-0.055	{-4.19}	0.025	0.052	-0.026	{-2.40}		
	(0.138)	(0.462)	(0.485)	[0.000]	(0.191)	(0.472)	(0.517)	[0.005]		

Table 9: Actual- & Pseudo-Sidecar Trading Activity - KOSPI 200 Spot Market

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. 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. NPT represents non-program trade, IA represents the index-arbitrage program trade, and NIA 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. Values in { } represent t-statistics and values in [ ] represent Wilcoxon p-values.

	Actual sidecar				Pseudo sidecar				Actual - Pseudo			
	Pre (B)	Post (A)	Change (B-A)	t-stat p-value	Pre (D)	Post (C)	Change (D-C)	t-stat p-value	Pre (B-D)	t-stat p-value	Post (A-C)	t-stat p-value
Panel A: Number of Trades												
NPT	62.0	61.9	0.1	{0.100}	66.6	61.4	5.2	{4.31}	-4.59	-2.23	0.49	{0.290}
	(169.7)	(157.1)	(142.0)	[0.002]	(191.3)	(141.2)	(141.0)	[0.000]	(179.6)	[0.000]	(150.2)	[0.458]
IA	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]
NIA	4.3	4.7	-0.4	{-3.54}	5.0	3.9	1.1	{10.26}	-0.7	-5.5	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												
NPT	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]
IA	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]
NIA	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 KRW)												
NPT	32,841	34,869	-2,027	{-2.83}	36,727	33,987	2,739	{3.22}	-3,885	-2.4	881	{0.630}
	(132,909)	(127,686)	(93,281)	[0.000]	(149,752)	(114,346)	(99,493)	[0.000]	(140,678)	[0.012]	(93,281)	[0.059]
IA	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]
NIA	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 10: Actual & Pseudo Sidecars - Minute-by-minute Actual Order Imbalance of KOSPI 200 Spot Market

This table shows minute-by-minute (MIN) of KOSPI 200 spot markets order imbalance ($|OIB|$) for: (1) the 10-minute pre-event period denoted as minute -10 to minute -1, (2) the 5 minutes during the actual or pseudo-sidecar event denoted as minute S1 to minute S5, and (3) the 10-minute post-event period denoted as minute 1 to minute 10. The actual-sidecar event sample is reported in the "actual" columns. The pseudo-sidecar event sample, which has a large price fluctuation but the sidecar was not triggered, is reported in the "pseudo" columns. The number of actual-sidecar events is 92 and number of pseudo-sidecar events is 147. "NPT" represents the non-program trades, "IA" represents the index-arbitrage program trades, and "NIA" represents the non-index-arbitrage program trades. Values reported in the table are mean values of KOSPI 200 stocks order imbalance for each trade type, calculated using only trades from that type. The values are reported for each 1 minute period. "Up Market" represents the mean values for the up-market sample (the events occurring in an up market), while "Down Market" gives the values for the down-market sample (the events occurring in a down market).

	NPT				IA				NIA			
	Down Market		Up Market		Down Market		Up Market		Down Market		Up Market	
MIN	actual	pseudo	actual	pseudo	actual	pseudo	actual	pseudo	actual	pseudo	actual	pseudo
-10	0.422	0.451	0.444	0.445	0.201	0.202	0.224	0.258	0.124	0.204	0.194	0.278
-9	0.411	0.444	0.446	0.454	0.234	0.248	0.156	0.180	0.161	0.251	0.129	0.216
-8	0.420	0.452	0.438	0.451	0.210	0.267	0.203	0.206	0.145	0.201	0.137	0.222
-7	0.422	0.453	0.446	0.448	0.176	0.280	0.117	0.200	0.114	0.142	0.071	0.138
-6	0.443	0.459	0.452	0.440	0.221	0.239	0.224	0.151	0.173	0.203	0.167	0.198
-5	0.469	0.455	0.455	0.466	0.227	0.253	0.221	0.207	0.224	0.142	0.166	0.099
-4	0.469	0.458	0.458	0.461	0.308	0.252	0.155	0.242	0.140	0.171	0.226	0.187
-3	0.469	0.459	0.453	0.461	0.197	0.225	0.339	0.293	0.192	0.220	0.194	0.234
-2	0.484	0.469	0.462	0.469	0.251	0.307	0.339	0.281	0.276	0.200	0.163	0.225
-1	0.503	0.484	0.454	0.473	0.388	0.298	**0.289**	0.310	**0.280**	0.261	**0.208**	0.201
S1	0.487	0.480	0.440	0.444		0.425		0.337		0.316		0.300
S2	0.493	0.470	0.442	0.433		0.235		0.300		0.202		0.251
S3	0.490	0.461	0.435	0.433		0.190		0.273		0.102		0.254
S4	0.485	0.451	0.428	0.429		0.211		0.228		0.116		0.227
S5	0.479	0.448	0.428	0.438		0.231		0.216		0.135		0.146
1	0.490	0.445	0.436	0.443	0.326	0.207	**0.318**	0.183	**0.289**	0.134	**0.239**	0.092
2	0.476	0.448	0.433	0.450	0.306	0.121	0.360	0.179	0.204	0.122	0.236	0.113
3	0.470	0.427	0.426	0.447	0.193	0.181	0.167	0.155	0.158	0.095	0.078	0.130
4	0.464	0.431	0.433	0.447	0.272	0.220	0.218	0.129	0.184	0.146	0.116	0.135
5	0.442	0.424	0.432	0.452	0.165	0.222	0.157	0.188	0.147	0.166	0.099	0.137
6	0.441	0.427	0.425	0.456	0.209	0.205	0.118	0.223	0.208	0.156	0.072	0.196
7	0.441	0.422	0.438	0.449	0.221	0.170	0.170	0.232	0.258	0.151	0.084	0.163
8	0.441	0.419	0.430	0.463	0.229	0.092	0.149	0.178	0.175	0.115	0.067	0.167
9	0.431	0.419	0.429	0.459	0.073	0.131	0.126	0.227	0.107	0.140	0.198	0.205
10	0.434	0.422	0.435	0.448	0.154	0.181	0.141	0.141	0.111	0.149	0.139	0.134

Figure 1: Experimental Design

The actual-sidecar event consists of a 10-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 perfect control for market dynamics, we utilize the experience for non-program trades in the actual-sidecar event. This is possible, as a sidecar only halts program trades, i.e., non-program trades are still executed. The downside to this approach is that different trade types might be subject to systematic risk differences. In order to construct a sample of events that have perfect trade-type risk characteristic controls, i.e., we can use each trade type 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 subject to program trading with that observed under the 5-minute actual-halt period, which is not subject to program trading. Tables 1 and 2 define the criteria used to select the pseudo sidecars and the comparisons made between actual and pseudo events.

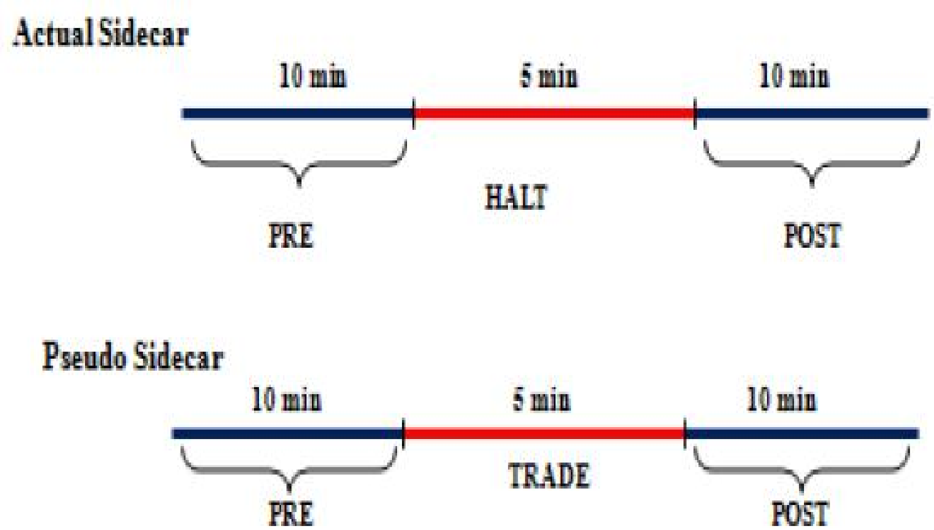
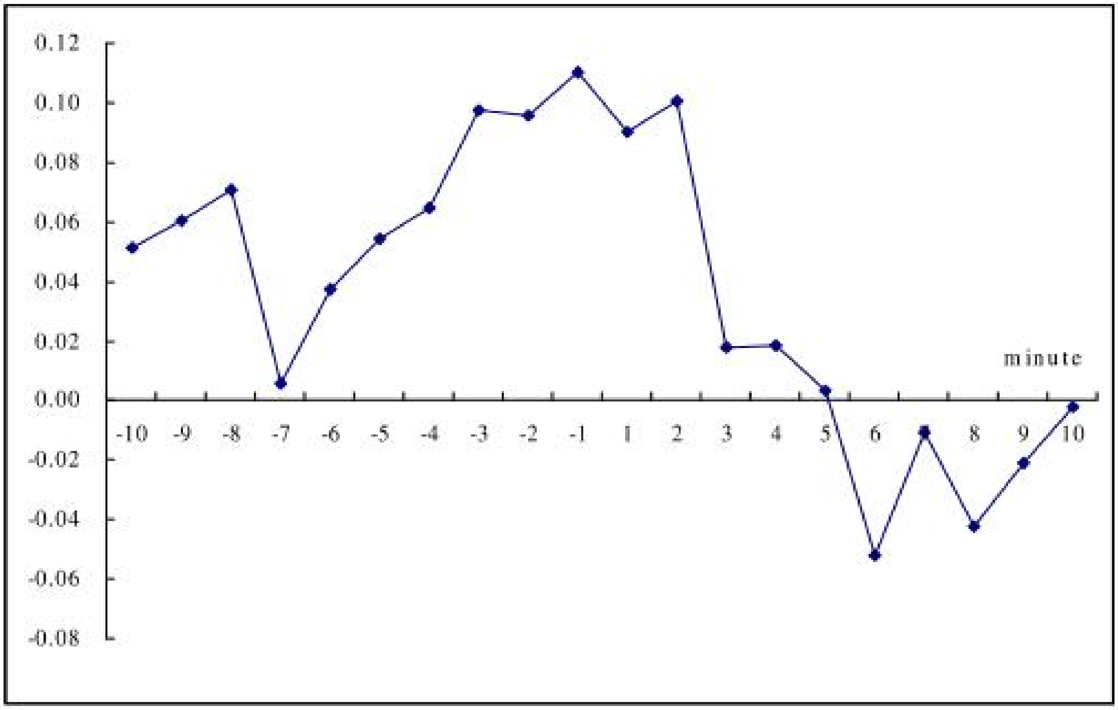


Figure 2: OIBN Surrounding the Actual-sidecar Events

Panel A: Buy sample



Panel B : Sell sample