Program Trading and Market Linkage *

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Abstract

Program trading, e.g., index arbitrage, has been identified as a mechanism that links the futures and spot markets. It has also been identified as a potential cause of market instability leading to laws that regulate program trading during volatile markets. These program trade halts provide a natural experiment to test the hypothesis that program trading is an important mechanism that maintains relative market pricing. This study is the first to conduct an analysis of the effect of removing all program trades on the connectedness of the spot and futures markets during large market moves. We analyze the effect of sidecars (regulation that only halts 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 market linkage is unaffected when program trading is eliminated during large market moves.

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Abstract
Program trading, e.g., index arbitrage, has been identified as a mechanism that links the futures and spot markets. It has also been identified as a potential cause of market instability leading to laws that regulate program trading during volatile markets. These program trade halts provide a natural experiment to test the hypothesis that program trading is an important mechanism that maintains relative market pricing. This study is the first to conduct an analysis of the effect of removing all program trades on the connectedness of the spot and futures markets during large market moves. We analyze the effect of sidecars (regulation that only halts 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 market linkage is unaffected when program trading is eliminated during large market moves.

1 Introduction

Our main research question is whether eliminating program trading during volatile markets breaks the link between the futures and spot markets? To answer this question, we utilize a natural experiment where program trade, and only program trade, is halted simultaneously in the spot, futures, and options markets. There currently exists no study that specifically addresses the influence of program trading halts (sidecars) during large market moves.[1] We concentrate on large market moves as these are the market conditions regulators specifically single out program trading. To address this issue, we analyze the effect of program trade halts on market connectedness using Korean intraday data.

Using Korean versus US data has several advantages. One advantage is that in the Korean data the initiating party for each trade is identified. That is, we know if a trade is initiated by a buy or sell trade. Therefore, one estimation step is eliminated in the trade signing methodology, potentially making our inferences more precise.[2] A second advantage is that on the Korea Exchange (KRX) sidecars cover all program trade types, while on the NYSE program trade inhibitors (sometimes called the collar rule[3] or Rule 80A) cover only index arbitrage trades. We are able to explore differences across program trade types, which is not available with NYSE data. More importantly, the KRX sidecar simultaneously halts program

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

[2] Such trade signing methodologies depend on several assumptions and have been documented to have a large degree of error. The error seems particularly large for non-NYSE and overseas data sets, see Aitken and Frino (1996) and Theissen (2001) who explore sign trade algorithm performance, e.g., Lee and Ready (1991), for international data. 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).

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

trades on the spot, futures, and options markets.[4] This allows for a cleaner test of the effects of program trading on market characteristics. A third advantage is there is no substitute asset for the KOSPI 200 futures during the trade halt.[5] In the US market, options and futures markets are deep and remain open when Rule 80A is in effect. However, futures/options trading on individual Korean stocks is illiquid or nonexistent (see Section 3.2), making it difficult to replicate the KOSPI 200 futures. Also, US markets are closed during the Korean market trading hours, so US ETFs are not available. A fourth advantage 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 eliminating program trading during large market moves affects the link between the futures and spot markets. This answer is possible because the KRX sidecar is a true program trade halt across all markets; there is no good substitute for the index futures/options, and individual firm futures/options are illiquid or nonexistent.

Our main results are summarized as follows. First, we find that the basis (the link between the spot and futures market price) is not affected by a program trade halt. Thus, program trade (including index arbitrage trade) is not required for markets to be linked. This result is important as (1) our data allows for a clean test of this hypothesis and (2) index arbitrage is often identified as an important mechanism for information transfer between the spot and futures markets. It appears that either a smart-money effect exists or another undocumented mechanism exists to keep markets linked during large market moves.

A second result is that when we consider actual sidecar events, there is a significant decrease in order imbalance (OIB) in the spot market after the sidecar is implemented. This is true for all trade types. The decrease in non-program trades is less than that of program trades. We attempt to control for market conditions, i.e., markets that have experienced a large price move, by constructing a pseudo-sidecar sample. By collecting events where large market moves occurred, but no sidecar was triggered, we can compare the resolution of order imbalance when there is a halt and when there is no halt. The advantage of this technique is that we can use each firm as its own control, implying a high degree of matching over firm risk characteristics. We find that markets function better, i.e., resolve imbalances more fully, when the program trade is allowed. In contrast to the spot market, the sidecar event has no discernible effect on OIB correction in the futures market. That is halting program trade does not appear to affect the futures market quality.

Third, when trading activity is examined, the spot market is adversely affected. During a program trade halt, trade is backlogged leading to an increase in trading activity after the

[4] 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.

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

halt. This result holds whether trading activity is measured as the number of trades, as the number of shares traded, or as the value traded. This does not happen in the pseudo-sidecar sample. Again, in contrast to the spot market, there is no trade backlog in the futures market. Thus, the adverse effects of a program trade halt on market quality are limited to the spot market.

Finally, we consider if market characteristics are related to the effectiveness of a sidecar rule. We consider the sign of the basis (a measure of market mispricing) and the direction of the market move. We find that in all instances, there are substantial costs, measured by increases in market mispricing. However, sidecars were designed to control large down market moves. In the case of a large market move and when this move is likely due to non-information reasons, we find that index arbitrage contributes to market mispricing pre-halt, but not post-halt. Thus, in one of four instances the sidecar achieves its objective. There are important policy implications for regulators. Given that we document costs to a program trade halt, it seems that the sidecar as currently designed is too broad. Market specific conditions, particularly the level and sign of basis mispricing, should be included in the sidecar trigger criteria.

The remainder of the paper is as follows: Section 2 reviews the relevant literature. Section 3 describes our data and the sidecar regulations. Section 4 details the methodology used in the empirical tests. Section 5 examines the basis during the pre-halt, halt, and post-halt periods. Section 6 looks at whether order imbalance by trade type can explain the basis, while Section 7 examines trading activity across the three periods. Section 8 investigates if systematic differences exist in up vs. down markets or in negative vs. positive basis events. Section 9 concludes.

2 Literature Review

Our main goal is to investigate whether program trade halts are effective at controlling market quality, specifically market connectedness. In this section, we summarize the literature that utilizes alternative market quality measures and relate how our study adds to current knowledge.

2.1 Debate on trade halts

We summarize the economic intuition for each side of the debate on the effectiveness of program trade halts. One argument is that trading halts can reduce short-term information asymmetry which benefits investors, regulators, and exchange organizers (Stein, 1987; Greenwald and Stein, 1988 and 1991; Kodres and O'Brien, 1994). Circuit breakers[6] provide a "time-out" amid

[6]Circuit breakers is a general term used to capture all trade regulating mechanisms. Circuit breakers can be classified in different ways. One useful classification of these regulations is into halts and inhibitors. Halts completely stop targeted trading, while inhibitors allow trade under different rules. One may classify both halts and inhibitors into rules that affect all assets (market wide), a subset of assets (e.g., the S&P 500 constituent stocks), or an individual asset. Circuit breakers can also be classified by the trade type it affects, e.g., all trades, program trades, or index arbitrage trades. A sidecar is a circuit breaker that ap-

hectic trading to collect intraday margin calls. The time-out may facilitate price discovery by providing a cooling-off period to evaluate information and publicize order imbalances. When circuit breakers are triggered, the traditional pricing mechanisms may be constrained, but information could be processed and dispersed in an alternative fashion. In this case, with a noise-generated panic, circuit breakers accompanied by the dissemination of information and order imbalances could be beneficial, allowing markets to remain connected.

There is an opposing view. Due to a lower cost structure and no short constraints, information traders prefer the futures market. Program trade, e.g., index arbitrage, is an important information transfer mechanism and keeps the spot and futures markets fairly priced relative to each other. Madhavan (1991) and Lee, Ready, and Seguin (1994) argue that even if investor predictions about future prices improve during the halt period and 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. The induced noise may decouple the spot and futures markets. 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.

2.2 Order imbalance as a proxy for 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 that is consistent with our OIB measure.

Our study is related to the earlier literature on the relation between the futures-spot basis and liquidity. Kumar and Seppi (1994) note that both basis and arbitrage activities may be affected by liquidity. In the reverse direction, market-wide order imbalances resulting from arbitrage trades in response to a wide basis may have a contemporaneous as well as a persistent impact on liquidity, e.g., see Stoll (1978), O'Hara and Oldfield (1986), Chordia, Roll, and Subrahmanyam (2002). Roll, Schwartz, and Subrahmanyam (2007) find that the absolute level of the basis is positively related to market illiquidity.

OIB is an important determinant of price movement for all markets. Inasmuch, Chordia and Subrahmanyam (2004) and Chordia, Roll, and Subrahmanyam (2008) find a stock's OIB is positively correlated with its future return. In addition, Chan and Fong (2000) find that a substantial portion of the daily price movement is well explained by OIB. 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, while Su, Chen, and Chen (2009) show that contemporaneous OIB on the NYSE is significant to the stock returns on the Toronto Stock Exchange. Finally, Madhavan and Smidt (1993) find that the daily price

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plies 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 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 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.

We contribute to the literature by studying how program-trade halts affect the basis, for which there is little prior research. We explore the behavior of OIBbefore 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).

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.[7] This period is chosen for several practical reasons. First, it covers the period after the Asian Financial Crisis of 1997. Second, major changes in the sidecar provisions on the KRX occurred in July 1998 and 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 the Korean data is that each trade is marked as one of two program trade types (index and non-index arbitrage) or as a non-program trade. An index arbitrage trade is defined as a trade that includes a KOSPI

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

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. 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 duration. 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.[8] 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.[9] 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.

[8]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.

[9]Sidecar rules were introduced in May 1996 for the KOSPI 200 futures and in 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 Section 2.2).

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 2) 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. [10]

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 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.

[10] 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.

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.[11] 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.[12]

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 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,

[11] 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.

[12] 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.

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.[13] 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 provide robustness checks 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 pseudo- 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 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

The main motive is to study the effect of program trade halts on market connectedness. We select basis as the proxy for the market linkage. We select OIB as our measure of market

[13] 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.

quality. Our tests concentrate on periods experiencing large market moves. Program trading is a major mechanism for information transfer between the spot and futures markets. Thus, we define our "event" as 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, does the existence of program trading alter the level of market connectedness before and after a large market move? To accomplish this we utilize the basis as our primary measure of market linkage. The basis is the difference between the price of the nearest expiry KOSPI 200 futures contract and the KOSPI 200 spot price.

Our second question concerns 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.

Our third question explores the effect of OIB on the market linkage. For details, we explore the effects of negative vs. positive basis events and up vs. down market events. We explore the effects and cross effects within a regression framework. In all cases, we pay special attention to the potential effects of OIB broken down by the various trade types.

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.]

5 Basis Analysis

In this section, we explore the behavior of the basis prior to, during, and subsequent to a program trade halt. The basis is defined as the price of the nearest expiry KOSPI 200 futures contract minus the KOSPI 200 spot price. It is calculated each minute in the pre-halt, halt, and post-halt periods. The basis is a measure of the inter-market linkage between the KOSPI 200 futures and spot markets. It captures the relative pricing of the KOSPI 200 index between the futures and spot markets. Table 3 provides the results.

[Table 3 about here.]

Panel A gives the basis for the actual-sidecar events. The analysis is done for all markets, and for both up and down markets separately. We explore the value of the basis separately for the pre-halt period, the halt period, and the post-halt period. Finally, we compare the basis for each period in order to determine the effect of the program trade halt on market connectedness when only program trading is halted. What we see in Panel A is that during actual program trade halts, the basis is unaffected. When the pre-halt basis is compared with the halt basis the difference (A-B) is 0.048 and statistically insignificant from zero (t-value = 0.60). The difference between the halt and post-halt basis (0.022) is also statistically insignificant from zero (t-value = 0.28). Likewise, the pre-halt and post-halt basis are statistically indistinguishable. When the actual sidecar events are separated into up-market events and down-market events, the results do not change. For example, the difference between the pre-halt basis and the halt basis is -0.013 (0.122) for the up-market (down-market) events and this difference is statistically insignificant with a t-value of -0.15 (0.97).

Panel B gives the basis results for our control sample, i.e., for the pseudo-sidecar events. Again, the analysis is done for all markets, and for both up and down markets separately. The value of the basis is explored separately for the pre-halt period, the halt period, and the post-halt period. Again, we compare the basis for each period to determine the effect of the program trade halt on market connectedness when only program trading is halted. The results contained in Panel B mirror the results of Panel A. During pseudo program trade halts, the basis is unaffected. When the pre-halt basis is compared with the halt basis the difference (A-B) is -0.010 and statistically insignificant from zero (t-value = -0.22). The difference between the halt and post-halt basis (-0.013) is also statistically insignificant from zero (t-value = -0.29). Likewise, the pre-halt and post-halt basis are statistically indistinguishable. When the pseudo sidecar events are separated into up-market events and down-market events, the results are unchanged. For example, the difference between the pre-halt basis and the halt basis is -0.038 (0.023) for the up-market (down-market) events and this difference is statistically insignificant with a t-value of -0.58 (0.39).

We find that in both the actual and pseudo samples, the basis does not change. That is, after a large price move, whether a sidecar is implemented or not, the two markets remain linked at a constant level before, during, and after the event. This suggests that the program trading is not necessary to maintain the linkage across the spot and futures markets.

Next we compare the difference between the actual and pseudo events. What is of interest here is the analysis for the up and down markets separately. The results are reported in Panel C. For the up-market events, the difference between actual sidecars (no program trade) and pseudo sidecars (program trade exists) is statistically insignificant from zero. This is true for the pre-halt period (0.033, t-stat = 0.49), the halt period (0.009, t-stat = 0.09), and the post-halt period (0.039, t-stat = 0.58). In contrast, for the down-market events, the difference between the actual and pseudo events is always negative. In the actual events the spot price is higher than the futures price. In the pseudo events, the basis is always positive. Given the different signs of the basis between up and down markets, we later analyze the results for negative basis days and positive basis days.

6 Can trade-type order imbalance explain the basis?

In this section we explore whether order imbalance (OIB) has explanatory power for the basis. We investigate whether $|OIB|$ differs by trade type. First, we summarize some properties of $|OIB|$ in both the spot and futures markets. Then we compare the market characteristics between actual and pseudo events.

6.1 $|OIB|$ characteristics for the spot and futures markets

We report the mean values of $|OIB|$ for all KOSPI 200 stocks for the total sample, i.e., all actual program trading halts, and for both the up-market and down-market sidecar event subsamples. Our results are reported in Table 4. Panel A gives the results for the full sample, while Panels B and C provide results for the up-market and down-market sidecars, respectively. For both up and down markets, the sidecar helps to reduce (columns C and F are all positive), but does not eliminate the excess buy/sell pressure. This is true for both the actual and pseudo samples. The results are statistically significant both with the parametric t-test and the non-parametric Wilcoxon p-values.

[Table 4 about here.]

We separate all trades into non-program (NPT), index arbitrage (IA), and non-index arbitrage (NIA). We calculate the change in $|OIB|$ between the pre-event and post-event period. We find that the reduction in $|OIB|$ is largest for the NIA trades, followed by that for IA trades, and is smallest for the NPT trades. This is true for the total sample and for both the up-market and the down-market samples. It also holds for both the actual and pseudo samples.[14] The results suggest that information is transferred via all trade types, but the fact that the drop is most prominent for NIA trades implies a strong smart-money effect.

[14]There are two possible mechanisms for information to flow between these markets. The first is via index arbitrage. In this case, the KOSPI 200 index and the KOSPI 200 futures are traded against each other. This has the advantage of low cost and ease of implementation. In this instance, the market as a whole is traded. This is in effect a macro-adjustment. The second mechanism involves non-index arbitrage trades. These can include (1) non-index arbitrage trades, i.e., trades between specific firm stocks and specific firm futures or a

To help us discern whether there is a difference between the pseudo-sidecar sample and the actual-sidecar sample, we compare changes across the actual and pseudo samples. The results are reported in the "Difference-in-Differences" (Pseudo-Actual) column of Table 4. The reduction in the order imbalance across the pre-event and post-event period is larger in the pseudo-sidecar sample than in the actual-sidecar sample.[15] This result holds in both up markets and in down markets. The one exception is the up market results for the non-index arbitrage trades. The results are statistically significant both with the parametric t-test and the non-parametric Wilcoxon p-values. Thus, we conclude that the program trading is not responsible for the observed order imbalance dynamics during large price moves. The sidecar is not necessary for the market to adjust. After a large price move that is associated with a large level of order imbalance, the market will adjust itself and the order environment will normalize more fully when program trading is allowed than when it is restricted. Therefore, the sidecar is an unnecessary burden on the natural correction mechanisms of the market.

Next, we explore the asymmetric dynamics in the KOSPI 200 futures market. Again, we compare order imbalance, measured by $|OIB|$, before the event and after the event. We conduct these measurements for both the actual- and the pseudo-event samples. The results are reported in Table 5. We find a similar pattern across all market types. Order imbalance is larger in the pre-event period before a large stock move. In the post-event period, the level of order imbalance drops. All the level results are significant both with the parametric t-test and the non-parametric Wilcoxon p-values. We also observe a drop in order imbalance from the pre-event period to the post-event period, e.g., in up markets the drop in $|OIB|$ for the actual sidecar events is 0.101 and is statistically significant (t-stat = 2.703). This holds true for both the up-market and down-market events in both the actual and pseudo samples. Again, all results are statistically significant. These level and pre-minus-post results are the same patterns documented in Tables 4. The main difference between the futures and spot markets is in the difference-in-differences results. In the spot market, the changes were larger for the pseudo sidecar sample. In the futures market, the actual event pre-minus-post drop is statistically insignificant from the pseudo event pre-minus-post drop. For example, the up (down) market difference-in-differences result is 0.005 (0.033) with a t-stat of 0.16 (1.08). This is graphically depicted in Figure 2. Thus, the adverse effect of the sidecar appears to be confined to the spot market.

[Table 5 about here.]

smart trader may only trade in one market to take advantage of the mispricing and (2) non-program trades, i.e., trades on stocks that are not part of a program trade in the pre-event period. This is more akin to a micro-adjustment process. The alternative information transfer hypothesis is that smart traders can identify mispriced assets. If index arbitrage is the main mechanism to transfer information between markets, then the asymmetric information should be higher for index-arbitrage program trades than for non-index-arbitrage program trades.

[15] A priori, given that mean reversion exists in markets, we would expect larger market moves and larger order imbalances to have on average larger corrections. Thus, we expect to find a larger correction in order imbalances for the actual-sidecar events. If the pseudo-sidecar events have a larger correction, then this is bad news for the effectiveness of program trading halts and we can safely conclude that actual-sidecars are on average inhibiting the market's self-regulating mechanisms. That is, the sidecar is not necessary to observe the reduction in order imbalance associated with a large market move. The market self-adjusts via its own internal mechanisms and eliminating program trading reduces the market's capacity to adjust for large order imbalances during large market moves.

[Figure 2 about here.]

6.2 Basis regression on signed OIB by trade type

In Table 4 we document systematic differences across trade types around periods of large market moves. Our next question is whether OIB affects the basis? We explore this for the various trade types and for the pre-halt, halt, and post-halt periods. We calculate the change in the basis from the pre-event period to the post-event period for both the actual-event sample and the psuedo-event sample. We next run a regression-based test. We use $Basis$ as our dependent variable. Our main hypothesis concerns the explanatory power of the index-arbitrage program trading. If index arbitrage is the only mechanism important for information transfer between the spot and futures markets, then index arbitrage program trading (IA) should be positively correlated with the basis, while the other trade type OIB should be insignificantly correlated. The regression model is as follows:

$$\begin{aligned} Basis \quad = \quad \beta_0 \quad & + \beta_1 \cdot MKT + \beta_2 \cdot NPT + \beta_3 \cdot IA + \beta_4 \cdot NIA + \beta_5 \cdot PSU \\ & + \beta_6 \cdot MKT \times PSU + \beta_7 \cdot NPT \times PSU \\ & + \beta_8 \cdot IA \times PSU + \beta_9 \cdot NIA \times PSU \end{aligned} \tag{1}$$

Where MKT refers a market dummy variable that takes the value of one if the sidecar is triggered on an up market move (Up Market sample). NPT is the OIB of the non-program trades. IA and NIA are the OIB of the index arbitrage and non-index arbitrage trades, respectively. We can pool the actual- and psudo-sidecar events by including a pseudo dummy variable (PSU that equals 1 if the event is a pseudo event and 0 otherwise) and appropriate cross terms. Newey-West (1994) corrected t-statistics are reported. Table 6 reports the results.

[Table 6 about here.]

In the pre-period, the coefficients of MKT have large positive values and are statistically significant. This means that on average the basis is greater when the market has a large up move, compared to that when the market has a large down move. This is true in both the pre-halt and post-halt periods, however, the magnitude and significance is smaller in the post-period. Thus, the futures market leads the spot market in up moves, possibly implying an information event. However, the markets move more in tandem in a down market spike implying potential panic trading.

We first discuss the actual sidecar sample. We compare the effect of OIB on the level of basis for the various trade types. NPT has an insignificant relation with the basis. It appears that uninformed trading is not a driver of cross-market mispricing. On the other hand, both IA and NIA have positive and significant relations with the basis in both the pre- and post-periods. In the pre-period, the sign of the effect of NPT on the basis is opposite those of program trading and the differences of effects are significant, e.g., in Panel B the F-test for equality between the NPT and IA coefficients is 15.00 and significant at the 1% level. However, in the post-period, all trade types have a positive relation with basis and the differences of effects are not significant, e.g., the F-test for equality between the NPT and IA coefficients is 0.17 and insignificant. When we compare IA vs. NIA we find that the difference of the effects is not significant in the pre-period. However, in the post-period, the different program trade types have a significantly different magnitude effect on the basis. One interpretation is that in the pre-period both arbitrage and smart money mechanisms drive market connectedness, but in the post-halt period, the index arbitrage mechanism is stronger. This result could indicate that informed traders are taking advantage of the higher volatility of a large market move during periods of asymmetric information. The sidecar halt seems to have some affect in alleviating the advantage for informed traders.

We next discuss the pseudo sidecar sample (PSU and cross terms in Panel A). In the pre-halt period, the coefficient of PSU is positive, significant, and larger than that in the actual sidecar sample. Thus, unlike the actual sample, the futures market leads the spot market in the pre-halt period indicating that information is likely leading the relative mispricing. The cross terms including NPT, IA, and NIA are all insignificant. Thus, the effect of OIB on the basis for all trade types is statistically indistinguishable in the actual- and pseudo-sidecar events. This is true in both the pre- and post-halt periods.

7 Trade activity around sidecar events

We investigate the trading activity on the KOSPI 200 spot market surrounding both the actual-sidecar and pseudo-sidecar events. Table 7 reports the difference in trading activity levels before and after a large market move. Results are reported for the non-program trading sample, the index arbitrage sample, and the non-index arbitrage sample. We utilize three different measures of trading activity: the number of trades executed (Panel A), the number of shares traded (Panel B), and the value of all shares traded (Panel C). For the actual-sidecar event sample, for all measures of trading activity and for all sample types, we find the trading activity increases or is the same after the sidecar. This indicates that during the sidecar halt, there is a pent-up demand that builds until the market reopens. In stark contrast, in the pseudo-sidecar sample, for all measures of trading activity and for all sample types, we find the trading activity decreases after the pseudo sidecar. All results are statistically significant. This table demonstrates that, in addition to being ineffective in controlling order imbalance, the implementation of a sidecar inhibits market participants from trading. The increase in trading activity after the halt in program trading implies that information asymmetry is not fully resolved during the halt period. When markets are allowed to function openly, then trading activity decreases with the drop in order imbalance, as should be expected, if the imbalance is being resolved through trading activities.

[Table 7 about here.]

We also consider the trading activity on the KOSPI 200 futures market. The difference in trading activity levels before and after a large market move is calculated. We utilize three different measures of trading activity: the number of trades executed (Panel A), the number of contracts traded (Panel B), and the value of all contracts traded (Panel C). We report the results in Table 8. For the actual-sidecar event sample, for all measures of trading activity, we find the trading activity increased, but not significantly, after the sidecar. In the pseudo-sidecar sample, we find the trading activity decreases after the pseudo sidecar for all trade types, but it is significant only for the number of trades. For both the contracts traded and the value traded, the difference in trading activity before and after the event are not significantly different from zero. We conclude that the trading activity in the futures market measured by either number of contracts or value of contracts is not affected by implementing a sidecar. Again, this shows that the sidecar appears to impede the efficiency of the market in the spot market, but it has little effect in the futures market.

[Table 8 about here.]

8 Negative vs. positive basis days

Given the different signs of the basis between up and down markets documented in Table 3, we break down and analyze the results for negative basis days and positive basis days. We first look at the minute-by-minute behavior of the basis surrounding the sidecar events. We then analyze the relation of OIB to the basis for both negative and positive basis days.

8.1 Negative and positive basis patterns

We consider the minute-by-minute (MIN) KOSPI 200 basis for: (1) the 10-minute pre-event period, (2) the 5 minutes during the actual or pseudo-sidecar event, and (3) the 10-minute post-event period. The sample is divided into the negative basis subsample and the positive basis subsample. Negative and positive basis samples are classified based on the average basis of pre-period. The values are reported each minute. The results are provided in Table 9.

[Table 9 about here.]

For the negative basis subsample of events, we see that the basis is more negative for actual-sidecar events than for pseudo-sidecar events. This is true for events whether the market has recently gained or lost value. In contrast, in the positive basis subsample of events the value of the basis is similar for actual and pseudo events. Figure 3 depicts the four possible combinations between Negative/Positive basis days and Up/Down markets. The graphs tend to show similar time series patterns for the basis in both the actual and pseudo samples.

[Fig 3 about here.]

8.2 Negative and positive basis regressions

In this section, we run regressions of the basis on signed OIB for both the negative and positive basis samples. Given that we documented systematic differences between negative and positive basis days, we are interested in whether OIB for various trade types differs by basis type. Negative and positive basis samples are classified based on the average basis of pre-period. For each of the four possible Up/Down market and Negative/Positive basis combinations, we run the following regression:

$$\begin{aligned} Basis \;=\; \beta_0 \; & + \beta_1 \cdot NPT + \beta_2 \cdot IA + \beta_3 \cdot NIA + \beta_4 \cdot PSU \\ & + \beta_5 \cdot NPT \times PSU + \beta_6 \cdot IA \times PSU + \beta_7 \cdot NIA \times PSU \end{aligned} \tag{2}$$

NPT represents the OIB of non-program trades, IA represents the OIB of index-arbitrage program trades, and NIA represents the OIB of non-index arbitrage program trades. PSU is a dummy variable that equals 1 for a pseudo sample and 0 otherwise. Newey-West (1994) corrected t-statistics are reported.

In this section, we look at the basis/market combinations. Thus, it is useful to delineate the possible states and note the characteristics of each state. Each state is labeled by the panel that it corresponds to in Table 10.

	POSITIVE BASIS	NEGATIVE BASIS
UP MARKET	**PANEL A** Futures > Spot Futures leading $\Rightarrow$ Informed move	**PANEL C** Spot > Futures Spot leading $\Rightarrow$ Uninformed move $\Rightarrow$ Herding, greed
DOWN MARKET	**PANEL B** Futures > Spot Spot leading $\Rightarrow$ Uninformed move $\Rightarrow$ Herding, panic, fear	**PANEL D** Spot > Futures Futures leading $\Rightarrow$ Informed move

It is well documented that information is first incorporated in the futures markets where transaction costs are lower and short positions can be taken. Thus, we see that Panels A and D are likely information driven market moves, while Panels B and C are driven by investor sentiment. When the deviations are irrational or driven by sentiment, arbitrageurs should engage. This should be true in both an actual or pseudo sidecar event. We see exactly this scenario. Index arbitrage (IA) is statistically significant only in Panels B and C, i.e., in the uninformed events. IA is statistically insignificant in the information states, i.e., in Panels A and D. Thus, our data suggests that arbitrage exist and appears to be able to identify sentiment motivated moves.

[Table 10 about here.]

If we now look only at up markets, we see that the basis is not materially changed in an actual sidecar between the pre- and post-periods. PSU is insignificant in the pre- and post-periods implying that the basis has similar behavior in actual and pseudo samples. Thus, in an up market move, the sidecar is ineffective at controlling or affecting the level of mispricing between the spot and futures markets. The down market states are completely different. When sentiment is the driver (Panel B), the mispricing between markets increases after an actual sidecar halt. In a pseudo event, this mispricing effect is reduced, i.e., PSU is negative and significant in the POST period. Thus, halting program trades has an adverse effect on market linkage indicating that sentiment-driven mispricing is exacerbated. This contradicts the argument given for halts that other information transfer mechanisms are more effective than trade during large market moves. It also contradicts the argument that a timeout allows for fear or greed to abate. In a down market when information is the driver (Panel D), the actual sidecar reduces the level of mispricing (the basis becomes less negative). However, again we see that if trade were allowed (PSU = 1), then the level of mispricing would have been significantly less. So in all scenarios, halting trade either is ineffective or mispricing is exacerbated.

Next consider the difference between the different trade types. In information-driven markets, trade type does not matter, i.e., the coefficients on both the trade type variable and their cross products are insignificant. In the sentiment-driven markets, there is variation by trade type. In both up and down markets with an actual sidecar (at the 5% significance level), we see that non-program trades change from insignificant in the pre-period to significantly adding to the mispricing in the post-period. Given the evidence presented in Tables 7 and 8, this is likely due to pent-up demand caused by the trade halt. When trade is allowed, i.e., in the pseudo event, we see the opposite effect in down markets, i.e., mispricing is reduced. As for non-program trades, we see that after an actual sidecar that mispricing increases, i.e., in POST the coefficient on NPT is significant and the same sign as the basis (see Panels B and C). Thus, program trade halts inhibit the markets natural adjustment mechanism. There is one bright spot for the sidecar rule. For the actual sidecar, IA appears to exacerbate the mispricing in a large down market (Panel B) during the pre-event. However, after the sidecar IA is insignificant. Since sidecars were designed to protect against adverse down market moves driven by program trading, this result indicates that the law may have achieved one of its objectives. We document that this objective has considerable costs to market participants. Unfortunately, we don't have the data to do a cost-benefit analysis. It is also not clear what the proper weighting functions are in such an analysis (e.g., should non-program trade benefits be weighted greater than program trade costs?). Given the costs, it seems that the sidecar as currently designed is too broad. Market specific conditions, particularly the level and sign of basis mispricing, should be included in the sidecar trigger criteria.

9 Conclusion

Trading halts have been studied extensively with regards to circuit breakers (all trading is halted) and how circuit breakers affect volatility and price discovery. The results of this research are mixed.

We add to the above literature in several ways. First, we study sidecars (only program trading is halted while the market remains open). Other than the seminal paper by Harris (1998), we are the only study to consider this popular regulatory mechanism. Previous studies investigate how program trading halts affect volatility. We extend this research by investigating how program trading halts affect the market connectedness, the order imbalance environment of the market, and trading activity pre and post halt. To our knowledge, we are the first to study the possible link between order imbalance and trading halts. In addition, we use a unique feature of the Korean market that allows us to observe the sign of the trade, thus eliminating a potential source of error. Using the Korean data rather than US data allows us to explore the relationship between index arbitrage trades and non-index arbitrage trades. Rule 80A on the NYSE is a trade modifier (not a true halt) and only applies to index-arbitrage trades, while the KRX sidecar applies to both program trade types.

We develop several testable hypothesis. The first hypothesis concerns changes in order imbalance around (before/after) trading halts. If sidecars are an effective mechanism to reduce order imbalance, then we should see a reduction in both the futures and spot markets. This reduction should be larger for the actual sidecar events compared to large market moves for which program trade is allowed. The second hypothesis is that a trade halt induces pent-up demand. That is, we hypothesize that stocks actively traded by program trades should exhibit higher levels of order imbalance. Finally, we hypothesize that program trade is an important information transfer mechanism between the spot and futures markets during large market moves. That is, we expect the basis to be adversely affected (increase in magnitude) when program trade is halted.

Our results do not support the first hypotheses. Pseudo-sidecar events exhibit significantly larger drops in order imbalance than the actual-sidecar events. We find support for the second hypothesis that demand increases after a sidecar, but not after a pseudo sidecar. Combining these first two results implies that sidecars are not only ineffective at controlling order imbalance, but they also interfere with the markets self-adjusting mechanisms and add costs to market participants, manifested as pent-up demand. Interestingly, the adverse effect to market quality we document is restricted to the spot market. The sidecar does not affect the quality of the futures market. Our final hypothesis is rejected. The basis is not affected by eliminating program trading. This is important as our data provides a clean test for this hypothesis and program trade is often cited as an important mechanism to keep the spot and futures markets linked. Overall, our results suggest that the sidecar is ineffective and should, at the least, be altered from its current implementation in the Korean market.

Finally, we consider if market characteristics are related to the effectiveness of a sidecar rule. We consider the sign of the basis (a measure of market mispricing) and the direction of the market move. We find that in all instances, there are substantial costs, measured by increases in market mispricing. However, sidecars were designed to control large down market moves. In the case of a large market move and when this move is likely due to non-information reasons, we find that index arbitrage contributes to market mispricing pre-halt, but not post-halt. Thus, in one of four instances the sidecar achieves its objective. There are important policy implications for regulators. Given that we document costs to a program trade halt, it seems that the sidecar as currently designed is too broad. Market specific conditions, particularly the level and sign of basis mispricing, should be included in the sidecar trigger criteria.

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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 200 constituent stocks in the KOSPI 200 index for five minutes in order to cool down the buying or selling pressure. That is, program trades cannot be executed on either the futures, options, or the spot markets during the halt period. 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: Change in Basis Surrounding the Actual- and Pseudo-sidecar Events

This table gives results for the basis. Basis is the price of the nearest KOSPI 200 futures minus the KOSPI 200 index. It is measured each minute in the halt, pre-halt, and post-halt periods. Pseudo sidecars are the sample of events that have a large price fluctuation but the sidecar has not been triggered. The number of actual sidecar events is 92 (48 events occurred in up markets, while 44 events occurred in down markets) and number of pseudo-sidecar events is 147 (75 events occurred in up markets, while 72 events occurred in down markets). PRE and POST represent the 10 minute period before the event and the 10 minute period after the event, respectively. HALT represents the 5 minute halt period. UP stands for the subset of events that occurred during positive market moves, while DOWN stands for the subset of events that occurred in negative market moves. ALL represents the total sample of events. Panels A, B, and C provide results for the actual-, pseudo-, and difference-between-actual-and-pseudo sidecar events, respectively. Numbers in [ ] are the ratio of positive basis days to the total number of days in each subsample. Positive basis days are events where the mean of minute-by-minute basis during the pre (post) period is positive. %(X>Y) represents the ratio of days of which the average basis in period X is greater than that in period Y. Numbers in () are standard deviations. p-val represents the nonparametric Wilcoxon p-values.

Panel A: Actual Sidecar Event Basis

	PRE (A)	HALT (B)	POST (C)	(A-B) %(A>B)	t-stat p-val	(B-C) %(B>C)	t-stat p-val	(A-C) %(A>C)	t-stat p-val
ALL	0.101	0.053	0.031	0.048	0.60	0.022	0.28	0.070	1.03
	(1.517)	(1.435)	(1.497)	(1.490)	0.77	(1.476)	0.99	(1.507)	0.64
	[56.67]	[56.67]	[58.89]	48.9%		47.8%		63.6%	
UP	0.396	0.410	0.428	-0.013	-0.15	-0.019	-0.21	-0.033	-0.42
	(1.235)	(1.182)	(1.249)	(1.217)	0.75	(1.227)	0.96	(1.242)	0.76
	[65.22]	[71.74]	[69.57]	30.4%		54.4%		45.7%	
DOWN	-0.201	-0.323	-0.375	0.122	0.97	0.052	0.43	0.173	1.65
	(1.709)	(1.579)	(1.615)	(1.666)	0.50	(1.603)	0.95	(1.663)	0.39
	[47.73]	[40.91]	[47.73]	68.2%		40.9%		63.6%	

Panel B: Pseudo Sidecar Event Basis

	PRE (A)	HALT (B)	POST (C)	(A-B) %(A>B)	t-stat p-val	(B-C) %(B>C)	t-stat p-val	(A-C) %(A>C)	t-stat p-val
ALL	0.340	0.350	0.363	-0.010	-0.22	-0.013	-0.29	-0.023	-0.62
	(1.015)	(1.047)	(1.038)	(1.027)	0.65	(1.040)	0.92	(1.027)	0.51
	[59.03]	[59.03]	[59.72]	44.4%		52.1%		41.7%	
UP	0.363	0.401	0.389	-0.038	-0.58	0.012	0.18	-0.026	-0.48
	(1.091)	(1.123)	(1.095)	(1.103)	0.40	(1.105)	0.79	(1.093)	0.50
	[57.89]	[59.21]	[61.84]	34.2%		60.5%		42.1%	
DOWN	0.314	0.292	0.331	0.023	0.39	-0.040	-0.67	-0.018	-0.35
	(0.924)	(0.950)	(0.965)	(0.933)	0.83	(0.960)	0.67	(0.944)	0.82
	[60.29]	[58.82]	[57.35]	55.9%		42.7%		41.2%	

Panel C: Difference of Actual and Pseudo Sample Basis

	PRE (A)	HALT (B)	POST (C)
ALL	-0.239	-0.297	-0.331
	(1.235)	(1.209)	(1.238)
t-stat	-4.40	-4.12	-6.12
p-val	0.003	0.004	0.000
UP	0.033	0.009	0.039
	(1.148)	(1.146)	(1.156)
t-stat	0.49	0.09	0.58
p-val	0.043	0.227	0.075
DOWN	-0.515	-0.614	-0.706
	(1.295)	(1.233)	(1.272)
t-stat	-6.13	-5.61	-8.71
p-val	0.000	0.000	0.000

Table 4: $|OIB|$ of KOSPI 200 Spot Market Surrounding the Actual- and Pseudo-sidecar Events

This table shows the $|OIB|$ for the KOSPI 200 stocks surrounding the actual- and pseudo-sidecar events. Pseudo-sidecar sample is the set of events that have a large price fluctuation for which a sidecar has not been triggered, whereas in the actual-sidecar sample, the sidecar has been triggered. The number of actual-sidecar events is 92 (48 events occurred in up markets, while 44 events occurred in down markets) and the number of pseudo-sidecar events is 147 (75 events occurred in up markets, while 72 events occurred in down markets). Panels A, B, and C contain results for all, up-market, and down-market events, respectively. PRE and POST represent the 10-minute period before the event and the 10-minute period after the event, respectively. Difference-in-Differences is the difference between the change in actual events and the change in pseudo events. Values in table are mean values of $|OIB|$ for each trade type for the KOSPI 200 index constituent stocks. ALL stands for the all trades. NPT and PT stand for the subset of non-program and program trades, respectively. IA and NIA stand for the subset of index-arbitrage and non-index-arbitrage trades, respectively. Values in [ ] are labeled "p-value" and represent nonparametric Wilcoxon p-values.

	Actual sidecar					Pseudo sidecar					Difference-in-Differences		
	PRE (B)	POST (A)	(C=B−A)	t-stat	p-value	PRE (E)	POST (D)	(F=E−D)	t-stat	p-value	(C−F)	t-stat	p-value
Panel A: All Sample													
NPT	0.531	0.466	0.064	20.00	[0.000]	0.521	0.423	0.098	27.87	[0.000]	-0.033	-6.97	[0.000]
IA	0.978	0.767	0.211	47.09	[0.000]	0.981	0.673	0.307	53.71	[0.000]	-0.096	-13.17	[0.000]
NIA	0.965	0.614	0.350	54.53	[0.000]	0.935	0.547	0.388	54.53	[0.000]	-0.038	-3.98	[0.000]
Panel B: Up-Market Sample													
NPT	0.502	0.427	0.075	16.71	[0.000]	0.483	0.407	0.075	15.88	[0.000]	-0.001	-0.08	[0.933]
IA	0.986	0.769	0.217	31.70	[0.000]	0.970	0.680	0.290	40.29	[0.000]	-0.073	-6.92	[0.000]
NIA	0.969	0.568	0.401	40.01	[0.000]	0.947	0.591	0.356	37.93	[0.000]	0.045	3.29	[0.000]
Panel C: Down-Market Sample													
NPT	0.561	0.508	0.054	11.55	[0.000]	0.562	0.440	0.122	23.57	[0.000]	-0.068	-9.78	[0.000]
IA	0.973	0.765	0.207	34.91	[0.000]	0.992	0.666	0.326	33.53	[0.000]	-0.118	-11.99	[0.000]
NIA	0.961	0.650	0.312	37.55	[0.000]	0.923	0.499	0.424	39.50	[0.000]	-0.112	-8.25	[0.000]

Table 5: $|OIB|$ of KOSPI 200 Futures Market Surrounding the Actual- and Pseudo-sidecar Events

This table shows the $|OIB|$ for the KOSPI 200 futures market surrounding the actual- and pseudo-sidecar events. Pseudo-sidecar sample is the set of events that have a large price fluctuation for which a sidecar has not been triggered, whereas in the actual-sidecar sample, the sidecar has been triggered. The number of actual-sidecar events is 92 (48 events occurred in up markets, while 44 events occurred in down markets) and the number of pseudo-sidecar events is 147 (75 events occurred in up markets, while 72 events occurred in down markets). PRE and POST represent the 10-minute period before the event and the 10-minute period after the event, respectively. Difference-in-Differences is the difference between the change in actual events and the change in pseudo events. Values in table are mean values of $|OIB|$ for the nearest KOSPI 200 futures contract. ALL stands for the full set of events. UP stands for the subset of events that occurred during positive market moves, while DOWN stands for the subset of events that occurred in negative market moves. UP – DOWN is the difference in the Up and Down market events. Values in () represent standard deviations, values in {} represent t-stats and values in [ ] are labeled "p-value" and represent nonparametric Wilcoxon p-values.

	Actual sidecar				Pseudo sidecar				Difference-in-Differences	
	PRE	POST		t-stat	PRE	POST		t-stat		t-stat
	(B)	(A)	(C=B−A)	p-value	(E)	(D)	(F=E−D)	p-value	(C−F)	p-value
ALL	0.226	0.133	0.092	{4.753}	0.196	0.123	0.073	{6.389}	0.019	{0.94}
	(0.127)	(0.119)	(0.186)	[0.000]	(0.111)	(0.096)	(0.138)	[0.000]	(0.158)	[0.345]
UP	0.225	0.124	0.101	{2.703}	0.219	0.123	0.096	{3.380}	0.005	{0.16}
	(0.118)	(0.099)	(0.155)	[0.000]	(0.113)	(0.103)	(0.142)	[0.000]	(0.147)	[0.950]
DOWN	0.227	0.143	0.084	{4.362}	0.175	0.124	0.051	{5.712}	0.033	{1.08}
	(0.135)	(0.136)	(0.213)	[0.000]	(0.105)	(0.090)	(0.132)	[0.000]	(0.167)	[0.181]
(UP – DOWN)	-0.002	-0.019	0.017		0.044	-0.001	0.045			
	(0.127)	(0.119)	(0.187)		(0.109)	(0.097)	(0.137)			
t-stat	{-0.07}	{-0.75}	{0.43}		{2.47}	{-0.07}	{2.02}			
p-value	[0.894]	[0.434]	[0.642]		[0.009]	[0.443]	[0.020]			

Table 6: Regression Results of Basis on OIB with Pseudo dummy and Cross terms

This table shows the regression results of basis on OIB for the different trade types. Basis is the price of the nearest KOSPI 200 futures minus the KOSPI 200 index. It is measured each minute in both the pre-halt period and post-halt period. Panel A provides the regression results, while Panel B provides F-tests for equality for various trade types. "b"is the intercept. MKT takes the value of one if sidecar is triggered on a positive market move (UP market sample) and is zero on a negative market move (DOWN market sample). NPT represents the OIB of non-program trades, IA represents the OIB of index-arbitrage program trades, NIA represents the OIB of non-index arbitrage program trades. PSU is a dummy variable that equals 1 for a pseudo sample and 0 otherwise. PRE and POST represent the 10 minute period before the event and the 10 minute period after the event, respectively. R2 is the adjusted r-square of the regression. The superscript PSU (ACT) is the pseudo (actual) event sample that has a large market move for which a sidecar event was not (was) triggered. Newey-West (1994) corrected t-stats are given by *, **, *** and represent the statistical significance at 10%, 5%, and 1% level, respectively.

Panel A. Model Estimation

	PRE						POST					
b	-0.375*	-0.288**	-0.322**	-0.347*	-0.373*	-0.284**	-0.027	-0.069	-0.095	0.052	0.017	-0.038
MKT	0.792***	0.653***	0.707***	0.725***	0.770***	0.641***	0.349	0.362**	0.459**	0.171	0.281	0.320*
NPT	-0.141			-0.259	-0.219		0.406			0.393	0.370	
IA		0.377***		0.388***		0.299***		0.472***		0.470***		0.436***
NIA			0.335***		0.342***	0.245**			0.248***		0.241***	0.158*
PSU	0.770***	0.754***	0.764***	0.765***	0.763***	0.749***	0.335	0.517***	0.486***	0.335*	0.307	0.493***
MKT×PSU	-0.697***	-0.686***	-0.659***	-0.719***	-0.679***	-0.673***	-0.163	-0.397*	-0.400*	-0.124	-0.132	-0.371*
NPT×PSU	-0.147			-0.033	-0.096		-0.619			-0.600	-0.601	
IA×PSU		0.012		0.002		0.069		-0.154		-0.154		-0.155
NIA×PSU			-0.160		-0.154	-0.172			-0.039		-0.026	-0.007
R2	0.060	0.098	0.074	0.103	0.079	0.105	0.034	0.066	0.043	0.069	0.047	0.071

Panel B. F Test for equality of coefficient

	PRE			POST		
$NPT^{ACT} = IA^{ACT}$	15.00***			0.17		
$NPT^{PSU} = IA^{PSU}$	52.60***			31.99***		
$NPT^{ACT} = NIA^{ACT}$		11.33***			0.44	
$NPT^{PSU} = NIA^{PSU}$		26.29***			22.41***	
$IA^{ACT} = NIA^{ACT}$			0.33			7.83***
$IA^{PSU} = NIA^{PSU}$			16.20***			3.05*

Table 7: 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. Panel A, B, and C represent the actual number of trades executed, the total number of shares traded, and the value of shares traded in terms of 10,000 Korean Won, respectively. Pseudo-sidecar sample is the sample which has a large price fluctuation but tthe sidecar has not been triggered, whereas in the actual-sidecar sample, the sidecar has been 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. Statistical significance is given by *, **, and *** at the 10%, 5%, and 1% level, respectively.

	Actual sidecar			Pseudo sidecar			Actual - Pseudo	
	PRE (B)	POST (A)	DIFF (B-A)	PRE (D)	POST (C)	DIFF (D-C)	PRE (B-D)	POST (A-C)
Panel A: Number of Trades								
NPT	62.0	61.9	0.1	66.6	61.4	5.2***	-4.6***	0.5
	(169.7)	(157.1)	(142.0)	(191.3)	(141.2)	(141.0)	(179.6)	(150.2)
IA	6.7	6.9	-0.3***	7.1	4.9	2.2***	-0.5***	2.0***
	(11.6)	(13.6)	(12.0)	(11.6)	(9.7)	(9.9)	(11.59)	(12.09)
NIA	4.3	4.7	-0.4***	5.0	3.9	1.1***	-0.7***	0.8***
	(6.5)	(9.5)	(8.8)	(7.2)	(8.2)	(8.0)	(6.81)	(8.91)
Panel B: Share Volume								
NPT	29,418	31,522	-2105**	48,056	38,583	9473	-18638***	-7060***
	(185,135)	(213,276)	(159,065)	(871,034)	(376,270)	(799,052)	(598,094)	(297,305)
IA	1,517	1,602	-85***	1,899	1,316	583***	-382***	285***
	(3,836)	(4,436)	(3,734)	(6,186)	(4,385)	(4,051)	(4,981)	(4,414)
NIA	1,011	1,245	-234***	1,300	1,034	265***	-288***	210***
	(2,086)	(3,244)	(2,821)	(2,975)	(2,751)	(2,976)	(2,554)	(3,016)
Panel C: Trading Value (10,000 KRW)								
NPT	32,841	34,869	-2027***	36,727	33,987	2739***	-3885***	881
	(132,909)	(127,686)	(93,281)	(149,752)	(114,346)	(99,493)	(140,678)	(93,281)
IA	3,167	3,326	-159	3,503	2,466	1037***	-336	860***
	(14,385)	(16,686)	(12,385)	(14,465)	(11,502)	(11,582)	(14,419)	(14,689)
NIA	2,321	3,009	-688***	3,001	2,739	263***	-680***	270
	(7,963)	(11,877)	(9,334)	(12,382)	(13,370)	(8,345)	(10,336)	(12,620)

Table 8: Actual- & Pseudo-Sidecar Trading Activity - KOSPI 200 Futures Market
Values reported in table are the mean trading values for the nearest KOSPI 200 futures contract. Panel A gives the raw number of trades; Panel B gives the number of contracts traded; and Panel C gives the value of trades in terms of 10,000 Korean Won. Pseudo-sidecar is the set of events that has a large price fluctuation but the sidecar has not been triggered, whereas in the actual-sidecar sample, the sidecar has been triggered. The number of actual-sidecar events is 92 and number of pseudo-sidecar events is 147. PRE and POST represent the 10 minute period before the event and the 10 minute period after the event, respectively. Difference represents the difference between the Actual and Pseudo events. Values in () represent standard errors of means. *, **, *** represent the statistical significance of non-parametric Wilcoxon test at 10%, 5%, and 1% level, respectively.

Panel A: Number of Trades

Actual sidecar			Pseudo sidecar			Actual - Pseudo	
PRE (B)	POST (A)	DIFF (B-A)	PRE (D)	POST (C)	DIFF (D-C)	PRE (B-D)	POST (A-C)
825	841	-16	1,035	899	136*	-210**	-57
(450)	(624)	(543)	(715)	(568)	(645)	(626)	(590)

Panel B: Number of Contracts Traded

Actual sidecar			Pseudo sidecar			Actual - Pseudo	
pre (B)	post (A)	diff. (B-A)	pre (D)	post (C)	diff (D-C)	pre (B-D)	post (A-C)
3,140	3,371	-231	3,716	3,257	459	-576	114
(2,291)	(3,325)	(2,855)	(2,869)	(2,335)	(2,615)	(2,660)	(2,759)

Panel C: Value of Contracts Traded (10,000 KRW)

Actual sidecar			Pseudo sidecar			Actual - Pseudo	
pre (B)	post (A)	diff. (B-A)	pre (D)	post (C)	diff (D-C)	pre (B-D)	post (A-C)
13,699	14,466	-767	16,097	14,171	1,926	-2,398	294
(11,148)	(14,536)	(12,953)	(12,416)	(10,189)	(11,358)	(11,943)	(12,054)

Table 9: Minute-by-Minute Basis Surrounding the Sidecar Events

This table shows for each minute (MIN) the KOSPI 200 basis 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 S0 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, which has a large market move and the sidecar was triggered. 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. Values reported in the table are the beginning of the minute value of KOSPI 200 basis. The sample is divided into the negative basis subsample and the positive basis subsample. Negative and positive basis samples are classified based on the average basis of pre-period. The values are reported each minute. "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). The number of days reported in parentheses ( ) are the number of days experience with specific combination of negative/positive, down/up, and actual/pseudo. All numbers are significant at 1% level.

	Negative Basis Sample				Positive Basis Sample			
	Down Market		Up Market		Down Market		Up Market	
	actual	pseudo	actual	pseudo	actual	pseudo	actual	pseudo
TIME	(23 days)	(30 days)	(18 days)	(31 days)	(21 days)	(42 days)	(30 days)	(42 days)
-10	-1.198	-0.55	-0.748	-0.647	0.981	0.957	0.976	1.022
-9	-1.209	-0.554	-0.774	-0.622	0.972	0.944	0.991	1.008
-8	-1.181	-0.555	-0.801	-0.619	0.961	0.939	0.997	1.039
-7	-1.176	-0.574	-0.766	-0.592	0.991	0.925	0.975	1.027
-6	-1.193	-0.54	-0.763	-0.583	0.988	0.913	0.996	1.025
-5	-1.191	-0.546	-0.761	-0.57	0.955	0.911	1.033	1.046
-4	-1.24	-0.549	-0.773	-0.544	0.943	0.847	1.054	1.065
-3	-1.234	-0.58	-0.791	-0.544	0.922	0.848	1.062	1.07
-2	-1.223	-0.61	-0.781	-0.553	0.923	0.808	1.04	1.113
-1	-1.273	-0.619	-0.711	-0.563	0.869	0.79	1.059	1.124
S0	-1.382	-0.702	-0.594	-0.456	0.757	0.697	1.133	1.183
S1	-1.393	-0.611	-0.643	-0.56	0.735	0.803	1.111	1.134
S2	-1.379	-0.573	-0.682	-0.574	0.724	0.865	1.047	1.104
S3	-1.195	-0.532	-0.724	-0.595	0.736	0.946	0.909	1.081
S4	-1.218	-0.525	-0.754	-0.605	0.702	0.963	0.931	1.075
S5	-1.119	-0.52	-0.738	-0.618	0.75	1.042	0.946	1.061
1	-1.34	-0.531	-0.739	-0.594	0.725	0.987	1.043	1.08
2	-1.34	-0.528	-0.763	-0.613	0.736	1.028	1.004	1.033
3	-1.345	-0.559	-0.751	-0.592	0.754	1.017	0.998	1.018
4	-1.333	-0.551	-0.719	-0.597	0.715	0.984	1.013	1.025
5	-1.358	-0.586	-0.775	-0.59	0.695	0.951	0.993	1.07
6	-1.368	-0.571	-0.745	-0.54	0.731	0.934	1.028	1.082
7	-1.351	-0.545	-0.693	-0.518	0.768	0.956	1.02	1.079
8	-1.356	-0.57	-0.711	-0.482	0.768	0.946	1.077	1.069
9	-1.34	-0.576	-0.707	-0.477	0.755	0.933	1.089	1.05
10	-1.338	-0.569	-0.637	-0.448	0.73	0.948	1.089	1.077

Table 10: Regression Results of Basis on OIB for Positive and Negative Basis Subsamples with Pseudo dummy and Cross terms

This table shows the regression results of basis on OIB for the different trade types. Basis is the price of the nearest KOSPI 200 futures minus the KOSPI 200 index. It is measured each minute in both the pre-halt period and post-halt period. Negative and Positive basis samples are classified based on the average basis of pre-period. "b"is the intercept, NT represents the OIB of non-program trades, IA represents the OIB of index-arbitrage program trades, NIA represents the OIB of non-index arbitrage program trades. PSU is a dummy variable that equals 1 for a pseudo sample and 0 otherwise. PRE and POST represent the 10 minute period before the event and the 10 minute period after the event, respectively. R2 is the adjusted r-square of the regression. Superscripts PSU and ACT are defined as in Table 6. Newey-West (1994) corrected t-statistics are given by *, **, *** and represent the statistical significance at 10%, 5%, and 1% level, respectively.

Panel A. Positive Basis and Up Market Sample

	PRE						POST					
b	1.033***	1.053***	1.046***	1.039***	1.030***	1.051***	1.092***	1.038***	1.034***	1.108***	1.104***	1.047***
NPT	0.400			0.421	0.395		-0.477			-0.466	-0.462	
IA		-0.019		-0.046		-0.035		-0.071		-0.06		-0.051
NIA			0.048		0.042	0.058			-0.096		-0.085	-0.084
PSU	0.113	0.055	0.096	0.062	0.106	0.058	0.053	0.066	0.103	0.006	0.042	0.061
NPT×PSU	-0.574			-0.608*	-0.586*		0.362			0.337	0.348	
IA×PSU		0.189*		0.220*		0.181		0.204		0.198		0.196
NIA×PSU			0.067		0.080	0.015			0.079		0.074	0.036
R2	0.008	0.010	0.005	0.017	0.012	0.010	0.009	0.009	0.003	0.014	0.008	0.008
$NPT^{ACT} = IA^{ACT}$				4.35**						2.99*		
$NPT^{PSU} = IA^{PSU}$				9.56***						5.92**		
$IA^{ACT} = NIA^{ACT}$						0.59						0.07
$IA^{PSU} = NIA^{PSU}$						0.58						4.81**
$NPT^{ACT} = NIA^{ACT}$					2.76*						2.56	
$NPT^{PSU} = NIA^{PSU}$					7.23***						0.88	

Panel B. Positive Basis and Down Market Sample

	PRE						POST					
b	0.660***	0.672***	0.700***	0.609***	0.652***	0.680***	1.447***	0.959***	0.975***	1.460***	1.447***	0.959***
NPT	-0.237			-0.292	-0.230		1.715***			1.803***	1.713***	
IA		0.280***		0.288***		0.311***		0.318***		0.369***		0.319***
NIA			0.064		0.059	-0.078			0.058		0.013	-0.008
PSU	0.291***	0.342***	0.325***	0.329***	0.292***	0.332***	-0.603***	-0.017	-0.054	-0.578***	-0.598***	-0.015
NPT×PSU	-0.204			-0.132	-0.217		-1.954***			-1.999***	-1.954***	
IA×PSU		-0.007		-0.023		-0.051		-0.125		-0.196		-0.161
NIA×PSU			0.065		0.077	0.141*			0.155		0.202**	0.197**
R2	0.075	0.106	0.045	0.142	0.083	0.106	0.080	0.030	0.014	0.116	0.095	0.041
$NPT^{ACT} = IA^{ACT}$				10.81***						38.63***		
$NPT^{PSU} = IA^{PSU}$				56.71***						12.47***		
$IA^{ACT} = NIA^{ACT}$						10.81***						6.15***
$IA^{PSU} = NIA^{PSU}$						6.03**						0.10
$NPT^{ACT} = NIA^{ACT}$					2.67						47.31***	
$NPT^{PSU} = NIA^{PSU}$					34.84***						16.85***	

Panel C. Negative Basis and Up market sample

	PRE						POST					
b	-0.676***	-0.729***	-0.726***	0.670***	-0.666***	-0.735***	-0.602**	-0.765***	-0.767***	-0.598***	-0.601***	-0.766***
NPT	-0.477			-0.849*	-0.844*		-0.761**			-0.767**	-0.767***	
IA		0.301***		0.425***		0.237***		-0.015		-0.038		-0.020
NIA			0.232*		0.337***	0.171			0.020		0.034	0.023
PSU	0.165	0.217	0.215	0.157	0.155	0.223*	-0.029	0.183	0.018	-0.036	-0.030	0.183
NPT×PSU	0.462			0.827	0.821*		1.162***			1.160***	1.152***	
IA×PSU		-0.249**		-0.372**		-0.190		0.087		0.082		0.066
NIA×PSU			-0.205		-0.308**	-0.157			0.091		0.057	0.079
R2	0.013	0.023	0.020	0.036	0.033	0.025	0.044	0.009	0.012	0.041	0.044	0.009
$NPT^{ACT} = IA^{ACT}$				13.97***						6.71***		
$NPT^{PSU} = IA^{PSU}$				0.23						5.57		
$IA^{ACT} = NIA^{ACT}$						0.15						0.08
$IA^{PSU} = NIA^{PSU}$						0.08						0.25
$NPT^{ACT} = NIA^{ACT}$					12.67***						7.98***	
$NPT^{PSU} = NIA^{PSU}$					0.11						4.27**	

Panel D. Negative Basis and Down market Sample

	PRE						POST					
b	-1.528***	-1.480***	-1.301***	-1.683***	-1.477***	-1.426***	-0.907***	-1.179***	-1.165***	-0.910***	-0.888***	-1.163***
NPT	-0.672			-0.740	-0.702		0.818			0.820	0.819	
IA		-0.300		-0.331		-0.307		0.013		-0.009		0.007
NIA			0.200		0.214	0.207			0.052		0.053	0.052
PSU	0.974***	0.917***	0.747**	1.123***	0.925***	0.864***	0.252	0.629***	0.598***	0.263	0.225	0.605***
NPT×PSU	0.693			0.761	0.712		-1.172			-1.174	-1.169	
IA×PSU		0.277		0.308		0.274		0.003		0.028		0.018
NIA×PSU			-0.162		-0.177	-0.163			-0.093		-0.085	-0.096
R2	0.121	0.121	0.117	0.131	0.126	0.125	0.103	0.085	0.086	0.100	0.100	0.083
$NPT^{ACT} = IA^{ACT}$				2.10						5.41**		
$NPT^{PSU} = IA^{PSU}$				0.03						3.28*		
$IA^{ACT} = NIA^{ACT}$						10.32***						0.07
$IA^{PSU} = NIA^{PSU}$						0.25						0.25
$NPT^{ACT} = NIA^{ACT}$					9.92***						5.02**	
$NPT^{PSU} = NIA^{PSU}$					0.01						2.39	

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.

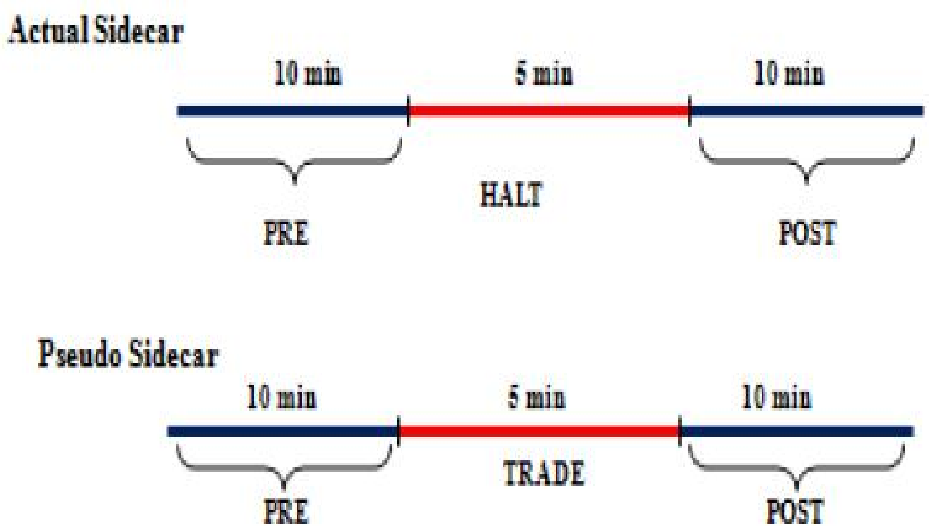


Figure 2: Patterns of $|OIB|$ for KOSPI 200 Futures Market Surrounding the Actual- and Pseudo-Sidecar Events

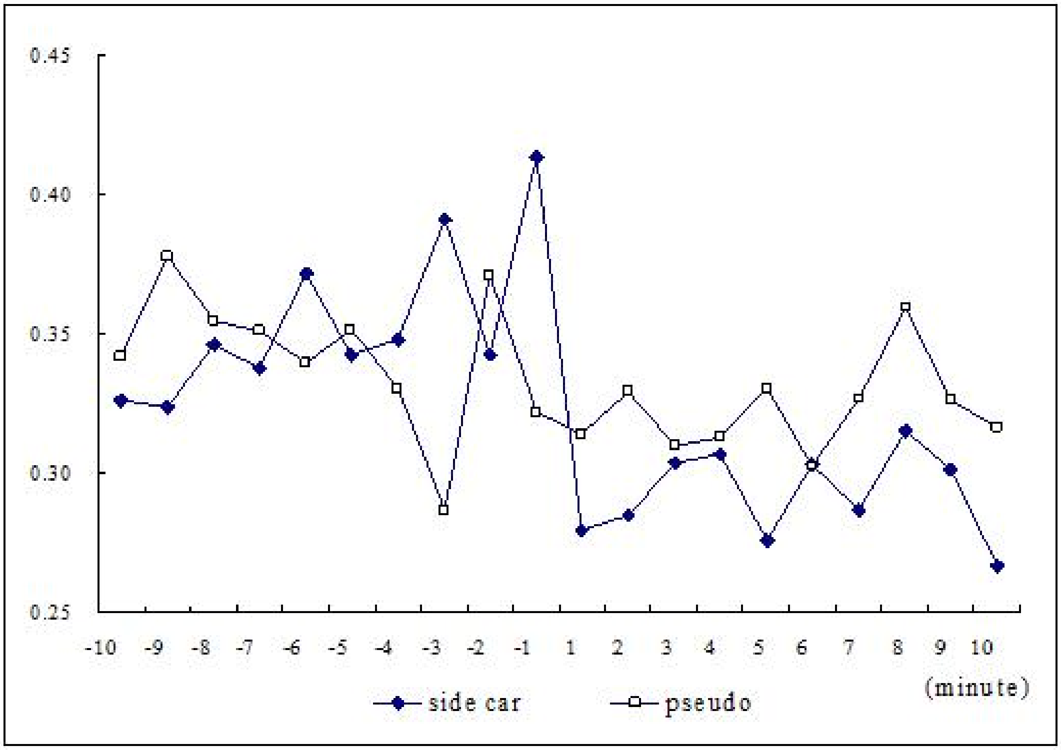
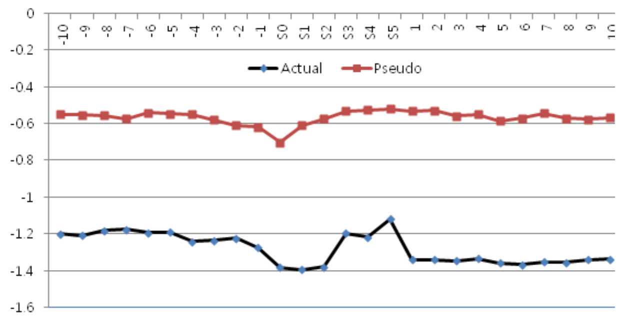
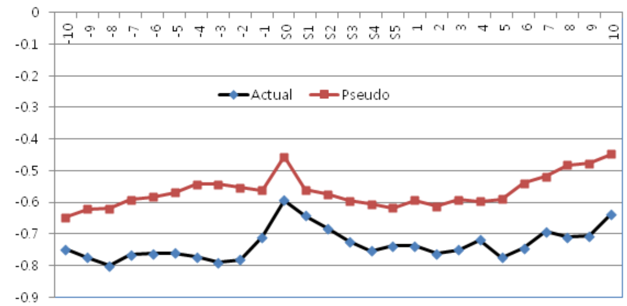


Figure 3: Basis Patterns Surrounding the Sidecar Events & Classification of Positive and Negative Basis Samples

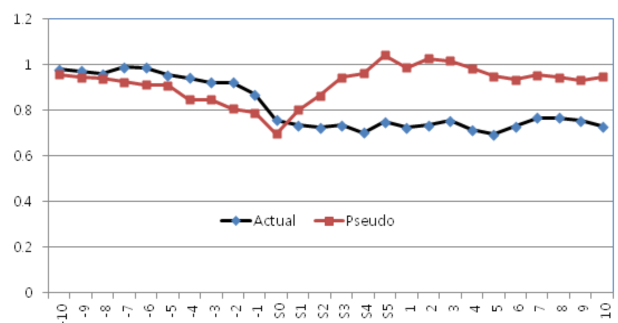
This figure compares the basis for the actual- and pseudo-sidecar samples. The analysis is broken down over two dimensions: (1) whether the event is a negative or a positive basis day and (2) whether the sidecar was triggered by an up market move or a down market move. Negative and positive basis samples are classified based on the average basis of the pre-period.



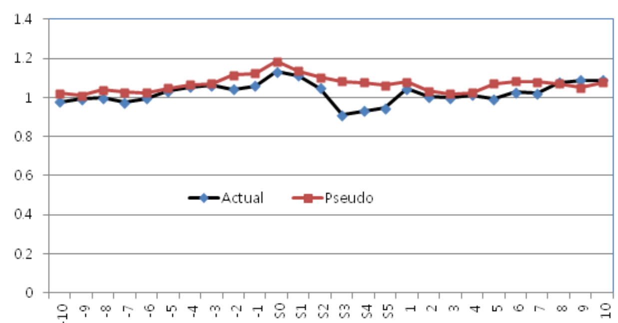
(a) Negative Basis and Down Market Sample



(b) Negative Basis and Up Market Sample



(c) Positive Basis and Down Market Sample



(d) Positive Basis and Up Market Sample