Intra-Day Revelation of Counterparty Identity in the World's Best-Lit Market*

Thu Phuong Pham†

Peter L. Swan‡

and

P. Joakim Westerholm §

Abstract

We study the impact of post-trade disclosure of broker IDs on market efficiency, trading volume and bid-ask spreads in a unique South Korean experiment. We find that simply revealing the ex-post order flow of the major brokers to the entire market improves market efficiency to the level of a random walk and increases trade volume by facilitating the rapid removal of asymmetric information. The least volatile and largest stocks experience a remarkable 59% rise in volume during the afternoon session. Realized spreads fall, indicating greater competition between liquidity suppliers, whereas market impact increases because of more rapid price discovery.

Keywords: transparency, anonymity, market efficiency, market quality, random walk

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† Adelaide Business School, University of Adelaide, Adelaide, South Australia 5005, Australia. Email: thuphuong.pham@adelaide.edu.au;Tel: 61 (0)8 8313 4510.

‡ School of Banking & Finance, UNSW Business School, The University of New South Wales, NSW 2052, Australia. Email: peter.swan@unsw.edu.au; Telephone +61 (2) 9385 5871. Peter Swan wishes to thank the Australian Research Council (ARC) for financial support.

§ H69 University of Sydney Business School, University of Sydney, NSW 2006, Australia. Email: joakim.westerholm@sydney.edu.au; Tel: 61 (0)29351 6454; Fax: 61(0)2 9351 6461.

Lack of transparency in financial markets has been highlighted as a root cause of the recent global financial crisis; worldwide authorities have therefore reopened the transparency debate and called for more transparency in the secondary markets[1]. Anonymity, one aspect of transparency, refers to the degree to which traders' and/or their brokers' identities (broker IDs) are disclosed either pre- or post-trade. SEC Chair Mary Jo White[2] recently stated: "Transparency is one of the primary tools used by investors to protect their own interests, yet investors know very little about many trading venues that handle their orders." She also raised concerns that dark trading – even if reported in real time – with no disclosure of market participants' identities – can "*detract from market quality, including the informational efficiency*" of the market. Our findings in this paper strongly support the SEC's beliefs and, although we do not address dark trading *per se*, dark trading can be understood as an adverse move taking markets further from full transparency and thus efficiency in trading and price discovery.

Why might we believe that broker IDs impact market quality? The literature shows that traders' and brokers' identities confer information regarding trading motivation (see Linnainmaa and Saar (2012), Benveniste, Marcus, and Wilhelm (1992) and Chakravarty (2001)), which suggests that these identities are informative, i.e., market participants can utilize broker IDs to make inferences about price-relevant private information in the order flow. Hence, different degrees of anonymity may affect market quality.

Most anonymity studies focus on pre-trade transparency, referring to the extent to which traders' identities are attached to limit orders that have been placed. However, little attention is paid to post-trade anonymity, which involves the timeliness of the disclosure of

[1] For example, The Committee of European Securities Regulators introduced formal measures to improve the quality and timeliness of post-trade transparency in European equity markets (see http://www.esma.europa.eu/system/files/10_394.pdf). The International Organisation of Securities Commissions (IOSCO) Technical Committee also suggested that more post-trade transparency may improve price discovery and reduce information asymmetries that "could enable investors to have a better informed view of the market" (see http://www.iosco.org/library/pubdocs/pdf/IOSCOPD306.pdf)

[2] Source: http://www.sec.gov/News/Speech/Detail/Speech/1370542004312

brokers' identities associated with executed orders. Foucault, Pagano, and Röell (2010) argue that anonymity is likely to benefit an informed trader at the expense of an uninformed trader. Several post-trade anonymity studies have resulted in mixed conclusions about its effects on market quality. Naik, Neuberger, and Viswanathan (1999) propose a theoretical model of a negotiated dealer market with a risk-averse market maker and conclude that if the dealer is unable to learn about the motivation for the trade and only learns the trade size, the public investor is better off with trade disclosure. However, in situations in which the dealer learns more, e.g., the information content, the welfare implications become ambiguous because under anonymity, the broker is incentivized to pass on some of his informational benefits to the informed trader and might thus discount his quotes.

Additionally, empirical evidence is inconclusive regarding this issue. One view finds that post-trade anonymity reduces liquidity because it enables informed traders to exploit their private information more effectively (see Waisburd (2003)). However, another view concludes that full anonymity dramatically improves liquidity and reduces trader execution costs due to elimination of what some authors have termed "order anticipation" (see Friederich and Payne (2014)). Order anticipation arises when the counterparty to a large trader learns that a sequence of trades will occur and then switches directions to exploit that information by taking a position ahead of the trader. Kervel and Menkveld (2015) indicate that large institutional investors are concerned about a possible consequence of order anticipation which is referred to as an 'implementation shortfall'. Implementation shortfall is the cumulative price impact of a large trade that has been sequentially executed in smaller quantities. Focusing on the Swedish market, these authors find that high-frequency traders who act as liquidity suppliers reduce these costs when they lean against these orders but increase costs when they trade in the same direction. A higher implementation shortfall cost is a possible consequence of both pre- and post-trade broker ID transparency as the identity of the trader might be revealed early (when the first order is placed in the limit order book with a broker identifier) or when the first portion of a large order is traded and the bulk of the order is still to come (post-trade revelation).

Our study is situated in a different market setting than these empirical papers. We investigate a unique event, i.e., whether introducing the disclosure of broker IDs at the end of the morning and afternoon trading sessions, affects market quality. For this purpose, we utilize a data set from the South Korea Exchange [KRX][3] because, since November 25, 1996[4], the trades of the top five brokers (measured by the cumulative buy and sell volume in each stock) have been revealed to the entire investing public – and not simply to the brokers themselves – at the end of the morning and the afternoon trading sessions[5]; prior to this date, brokers' IDs were unknown to market participants. This event offers a unique opportunity to investigate the effects that post-trade transparency of counterparty identity has on market quality when such identities are revealed during two periods within the same trading date and stock[6]. Our study

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[3] The KRX in Seoul, South Korea resulted from the 2005 merger of the Korean Stock Exchange (the subject of this investigation) and the derivatives exchange.

[4] An official document from KRX confirms this date as the introduction of post-trade broker ID information. Following the Asian financial crisis and in light of the political history of South Korea with its difficult geographical location, the Korean authorities decided that it was necessary to promote a transparent capital market to attract foreign capital, despite the inherent risks involved in a radical departure from stock exchange norms.

[5] From the middle of August 1997, this information was provided to the public in real time. However, our experiment is confined to the initial end-of-session disclosure, as our methodology enables us to exploit this structure in particular. Appendix 1 shows a screenshot of the broker IDs information presented to the public.

[6] KRX increased transparency, whereas other exchanges have typically changed their partially transparent markets in the opposite direction. For instance, the NYSE's Open Book service shows the aggregate limit-order volume available in the NYSE Display Book system at each price point but provides no identities for the participants behind these orders. The single platform for NASDAQ-listed securities (NASDAQ's Integrated Single Book), into which the NASDAQ Market Center, Inet and Brut recently merged, is anonymous; all European trading platforms are anonymous, as well as all electronic communication networks and foreign exchange electronic markets (e.g., Electronic Broking System). On March 13, 2006, the NASDAQ OMX Nordic abolished pre-trade transparency while preserving post-trade transparency on the Helsinki market. On June 2nd, 2008, post-trade anonymity was introduced on the Helsinki market and for the five most heavily traded shares in Stockholm, but on April 14, 2009, the decision regarding Stockholm was reversed, and ex-post transparency was restored to all but the five largest Helsinki stocks that remain anonymous in real time. Anonymity was instituted in the Italian secondary market for treasury bonds (MTS) in 1997, in Euronext Paris in 2001, in Tokyo in 2003, in the Italian Stock Exchange (Borsa Italiana) in 2004 and in the Australian Stock Exchange (ASX) in November 2005. However, the prior transparent regime that had been in effect since the market was automated was restricted such that only fellow brokers could view broker IDs in the limit order book, and the provision of such information to clients was prohibited.

focuses on automated order-driven markets, unlike Friederich and Payne (2014), who examine post-trade anonymity in a dealer market. In our market setting, broker IDs for all stocks are disclosed at the end of each morning and afternoon trading session, which also differs from Waisburd (2003), who considers the real-time identity disclosure for selected stocks only as they are reassigned from one index to another. In addition to the bid-ask spreads that were the focus of earlier studies, we provide a more comprehensive picture of the effect on market efficiency, trading volume, liquidity providers' revenue and the price impact of trades. Market efficiency is not only exceedingly important for investment decisions (see, e.g., Dow and Gorton (1997)) but also important for ensuring that managerial incentives actually motivate managers (see, e.g., Holmström and Tirole (1993)). Ultimately, our objective is to answer the following question: Does post-trade transparency speed up information dissemination to improve trading efficiency and liquidity as predicted by Pagano and Roell (1996) or does it deter market participants from information acquisition, as in the less favorable of the two scenarios in Rindi (2008), such that information dissemination declines and liquidity falls?

Our study contributes to the literature with several novel findings. First, this is the first empirical paper to examine the impact of post-trade broker ID disclosure on market efficiency. Employing the variance ratio test (Lo and MacKinlay (1988))[7] on two-day, ten-day, fifteen-day and twenty-day horizon returns over one-day returns, we document that formerly negatively serially correlated returns[8] at the daily level follow a random walk after post-trade transparent broker IDs. This improvement is strong for stocks characterized by medium and high volatility, whereas the prices of the largest and least volatile stocks seem to follow a random walk in both the post-trade anonymous and transparent periods. Our findings are supported by theoretical predictions developed by Campbell, Grossman, and Wang (1993), who predict that informed trades will not result in serial correlation. Avramov, Chordia, and

[7] Lim and Brooks (2011). These authors report that this test has emerged as the primary tool for testing for serially uncorrelated stock returns.

[8] Serial correlation for returns was not uncommon on stock exchanges in the past. For example, Lo and MacKinlay (1988) reject market efficiency in their tests of the U.S. market. Fama and French (1988) also show that the market could be inefficient for long-term returns horizons due to the mean reversion of the stationary component in stock prices.

Goyal (2006) also provide empirical support for these predictions. Thus, simply revealing the ex-post order flow of the major brokers to the entire market, as in the Korean experiment, eliminates the mean reversion in daily price changes arising from noise trading. This result has important implications for exchanges because it indicates that any return predictability of the future stock price based on today's prices might simply be due to an anonymous trading protocol. The transparency level is particularly important in a market dominated by uninformed noise traders because these traders rely on information from the order flow.

Second, we find that trading volume increases more when the public has access to the broker IDs from the day's morning session during the afternoon session rather than simply the identities from the previous day's afternoon trading session that was followed by overnight market closure. This relative improvement is to be expected, as the identity information obtained from the previous afternoon's trading is relatively stale due to the greater time delay and the new overnight information that has come into the market at the open. The economically and statistically significant improvement in trading volume is 23% in the morning and 36% in the afternoon trading session when all stocks are included and we control for the determinants of trading volume and trend factors. The volume of the largest and least volatile stocks increases the most, by 50% in the morning and 59% in the afternoon, whereas trading volume decreases in the morning session and recovers in the afternoon session for the smallest and most volatile stocks. Hollifield, Miller, Sandås, and Slive (2006) establish that traded volume is a natural indicator of gains from trade. The greater traded volume is generally likely to be associated with greater liquidity and faster price discovery. Although readily measurable and widely followed by market participants, most current studies include volume only as a control variable in their analysis without considering the endogenous nature of trading volume when exchange protocols alter or affect its importance in considering the welfare consequences of these design changes.

Third, we examine liquidity providers' profit using different intervals of trades – trade-time, as opposed to the calendar-time used in conventional studies – to mitigate potential biases due to vast differences in stock liquidity levels and trade rapidity because our data includes nearly all active stocks on the KRX. We find that effective spreads are higher in the transparent period for both the morning and afternoon sessions due to the more rapid dissemination of information with public broker IDs. However, when the relevant broker IDs from the morning session are available during the afternoon session, effective spreads are relatively lower in comparison with the morning session. Realized spreads are significantly lower when the broker IDs are public in both sessions because they net out the higher market impact component of the effective spread. By definition, the effective spread differs from the realized spread by the market impact cost; see Boehmer (2005), Boehmer, Saar, and Yu (2005) and Hendershott and Jones (2005). These findings strongly indicate that providing broker IDs induces more competition among liquidity providers that lowers the realized spread and, as indicated by higher market impact costs, provides for more rapid dissemination of information, which in turn improves market efficiency. These findings are also consistent with the morning session suffering from relatively stale and obsolete broker ID information. Moreover, the effect is stronger in the large, low-volatility stocks that dominate the KRX's trading value. It is not a coincidence that these large stocks also benefit the most from volume increases.

Theoretical models of transparency can help explain our results. As continuous limit order markets are becoming more dominant, an understanding of the effects of transparency in this setting is important. Moreover, some theoretical models of transparency are equally relevant for limit order (order-driven) markets. Pagano and Roell (1996) show that price setters (who can be market makers or limit order providers) widen the bid-ask spread to protect themselves against an adverse selection problem that may potentially be generated by insiders instead of covering their inventory holding costs, as in Biais (1993). They prove that the implicit bid-ask spread of noise traders will be tighter in an auction market with more order flow transparency because the more that uninformed traders learn about the order flow, the more able they are to protect themselves against losses to insiders. In essence, both the informed and uninformed pay uniformly high spreads in opaque markets, but these adverse selection costs are shifted towards informed traders in transparent markets. Hence, these models predict that more transparency is associated with higher liquidity as a consequence of the uninformed paying lower transaction costs. Consistent with the predictions of Pagano and Roell (1996), Fong, Gallagher, Gardner, and Swan (2011) find that when broker IDs were displayed to other brokers but not to the public in the ASX market, informed orders were split across multiple brokers to disguise their information content with relatively uninformed orders executed by a single broker. Complementing Pagano and Roell (1996), Yin (2005) introduces search costs into the Biais (1993) model to show that investors will prefer transparent centralized markets with lower search costs, as transparency promotes competition and thus results in lower spreads.

Foucault, Moinas, and Theissen (2007) and Rindi (2008) develop models that include informational differences between agents and in which transparency allows uninformed agents to observe the order placement of the informed. Rindi's (2008) model can also be applied to generate predictions about the effects of post-trade transparency. Under full transparency, uninformed traders can identify liquidity traders and, hence, are willing to offer liquidity themselves, resulting in increased liquidity. However, when information acquisition is endogenous and costly, broker ID transparency reduces the incentive to acquire information and reduces the number of informed traders as a result. If information acquisition is sufficiently expensive, it follows that broker ID transparency might lower the number of aggressive informed agents who enter the market, thus reducing competition and liquidity (see Rindi (2008)). In a market in which broker IDs are pre-trade anonymous such that limit orders do not reveal the identity of the liquidity provider and are post-trade transparent, any adverse impact on information acquisition should be lower compared with markets that are pre-trade transparent, as information is private until it is traded upon. Only when the anonymous limit order is hit by a market order is the identity of either party revealed. In this paper, we show empirically that post-trade transparent broker IDs have a positive effect on liquidity.

The specific effects of a significant increase in post-trade transparency in a pure automated limit order market have not been previously investigated.[9] We argue that the

[9] Comerton-Forde, Frino, and Mollica (2005) find that the KRX introduced broker identifiers on October 25, 1999 and that "the reduction in anonymity on the KRX is associated with a decline in liquidity" and with an increase in relative and effective bid ask spreads." However, the records from the Exchange that were provided to us by Kyong Shik Eom show that this transformation actually occurred about three years earlier on the KRX and the trading protocol change in 1999 was actually for the uninvestigated KOSDAQ market, not for the larger KRX.

distinction between intermediated and order-driven markets is important. Public broker IDs in an order-driven market allows a categorization of all market participants that is conditioned on how informed they are about a particular security at a particular time, such that less-informed participants can discover price information from the transactions of more-informed participants. By contrast, the argument regarding an intermediated market involves how much information dealers and market makers can extract from the order flow and other market makers' quotes. In both types of market, we are ultimately interested in how changes in transparency affect market liquidity and price efficiency, but the mechanism that provides liquidity and discovers prices is distinctly different in these markets.[10] Based on the current literature, we expect that liquidity and price discovery will improve once broker IDs are reported post-trade because the order flow will contain more information. Making broker IDs transparent only on a post-trade basis will be particularly beneficial for liquidity and price discovery if there are any negative effects of revealing trader identities pre-trade in the limit order book and thus adversely affecting liquidity as in Foucault, Moinas and Theissen (2007).

We also find that market efficiency improves, the volume of trade increases, effective spreads rise but purely as a consequence of higher market impact due to the more rapid release of private information and realized spreads fall (indicating higher competition between market makers). As a robustness check on the role of broker ID transparency on the major measures of market quality, we examine the impact of the subsequent reform in the policy of broker IDs disclosure at the KRX – see Appendix 2. We find that greater transparency on broker IDs, either at the end of each trading session or in real-time, improves market efficiency and induces

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Pham (2015) examines the later introduction of post-trade broker ID information on the far smaller KOSDAQ market to show that it leads to a higher permanent price impact (information effect) of both buyer- and seller-initiated trades in the major Korean Stock Exchange, which indicates that information is disseminated quicker after the change in trade protocol. Toronto Stock Exchange makes display of broker IDs purely voluntary. One might expect from the findings in the literature adverse to broker ID transparency that if participants are given a choice, they would not display identities with their trades. However, Comerton-Forde and Tang (2007) report that most market participants choose to make their orders public when given a choice, as on the Toronto Stock Exchange.

[10] The ultimate outcome may be very similar in a well-designed and fairly regulated market of either type.

higher trading volume. Hence, our policy recommendation is for exchanges to consider the market design of the KRX, which provides pre-trade anonymity for large traders, while it reports the identity of executed orders to ensure that all information contained in the trade is quickly disseminated to the market and its participants.

1. Previous literature

1.1 Anonymity and transparency

A large segment of the theoretical work on transparency addresses pre-trade identification of liquidity demanders either in intermediated market structures with dealers or specialists or in "upstairs" markets (Seppi (1990), Benveniste, Marcus, and Wilhelm (1992), Madhavan and Cheng (1997), Frutos and Manzano (2002), Desgranges and Foucault (2005), Rhodes-Kropf (2005), Bernhardt, Dvoracek, Hughson, and Werner (2005), Green, Hollifield, and Schürhoff (2007)), and Foucault, Pagano, and Roell (2013)). This literature documents that knowing the identity of the counterparty to a trade is important to market quality. On one hand, the effect depends on the number of dealers such that bid-ask spreads may increase when dealers' incentives to compete for order flow are reduced in a more transparent market. On the other hand, it is also found that dealers' exercise substantial market power in an opaque system and, hence, anonymity may thus increase transaction costs for their customers. Because we focus on a limit order book market in our research, we use the predictions from those models that also apply to limit order markets, such as Pagano and Roell (1996) and Rindi (2008). We set out to investigate the market quality impacts of the Korean experiment in three dimensions: market efficiency, trading activity and liquidity.

1.2 Post-trade transparency and market efficiency

The impact of increased post-trade transparency on market efficiency and price discovery relates to the theoretical literature as follows. Samuelson (1965) proposed that competitively determined prices will follow a random walk, and Grossman and Stiglitz (1980) note that markets cannot reflect all available information because then there would be no reward for expensive information gatherers. We expect to observe an improvement in market efficiency as the result of increased transparency when private information in the Korean market is close to costless as would be expected in a liquid, widely traded equities market with the possibility of information leakage from within firms. Without within-firm sources of information, private information can be expected to be very costly to acquire. Thus, Huddart, Hughes, and Levine (2001) extend Kyle (1985) to predict that price discovery should be improved and spreads narrowed with ex-post transparency, while the insider's trading profits are reduced.

In an early model of utility-maximizing agents, Spiegel and Subrahmanyam (1992) replace exogenous noise traders with strategic hedgers (risk sharers) and provide contrasting findings to the extant models with exogenous noise trading. Spiegel and Subrahmanyam (1992) show that more competition between informed traders always makes hedgers worse off and can lead to market breakdown. An implication of their finding is that because transparency ameliorates the effects of information asymmetry[11], hedgers are able to trade more effectively and thus experience welfare gains. With all hedgers able to infer the direction of informed trades in a transparent system, prices rapidly incorporate new information. Arbitrageurs' ability to observe the direction of informed trades and broker trade imbalances induce the stock price to follow a random walk. Bloomfield and O'Hara (1999) show experimentally that transparency improves market efficiency. Linnainmaa and Saar (2012) demonstrate from activity on the Helsinki Exchange that traders can identify the class of trader: household, domestic or foreign institutional trader, from displayed broker IDs. We expect that the informational efficiency of stock prices will improve with the introduction of post-trade transparent broker IDs.

1.3 Post-trade transparency and trading activity

[11] Foucault, Moinas, and Theissen (2007) model uninformed liquidity suppliers – observing the brokerage identification codes – who do not learn whether insiders buy or sell but only the probability that insiders have obtained a signal on the future value of an asset. Thus, it models partial information acquisition and finds empirical support for the greater role of information in transparent regimes. In the case of Korea's natural experiment, uninformed traders do not observe broker IDs on both sides of the limit order book but instead the broker ID of the new component of a typically much larger signed split order and only for the most active brokers. Hence, it would seem better to model transparency as a regime in which the uninformed can infer the future direction of informed trades, as in Rindi (2008). Our paper empirically addresses this important extension of Foucault, Moinas, and Theissen (2007).

Hollifield, Miller, Sandås, and Slive (2006) develop a method for identifying and estimating gains from trade using empirical data from a limit order book market. Their model allows traders to decide to use market or limit orders (or not to submit any orders at all), and the traders' gains from trades are dependent upon the valuations for the securities they trade. Using observable order flow and payoffs from alternative order submission strategies that the traders might have otherwise undertaken, Hollifield, Miller, Sandås, and Slive (2006) work out the gains from trade, which might be interpreted as empirical evidence that traders indeed benefit from trade. Trading volume is often decomposed into informed and uninformed trading. Wang (1994) and Karpoff (1987) show that volume is positively correlated with absolute returns and that informational and non-informational trading lead to different dynamic relations between trading volume and stock returns. An increase in informed volume may signal more rapid price discovery because informed volume is expected to move prices, whereas an increase in uninformed volume would lead to improved liquidity because uninformed volume cushions the effects of informed trades on stock pricing. Johnson (2008) notes that in the classic Kyle (1985) model of asymmetric information, informed demand moves proportionally to exogenously determined uninformed demand and liquidity (inverse of Kyle's lambda) is proportional to the scale of uninformed demand. Thus, there is an association between higher volume and higher liquidity. This logic is supported in the dynamic extensions of Kyle (1985) by Admati and Pfleiderer (1988) and Foster and Viswanathan (1990). Hence, the Kyle (1985) model reconciles a contradiction: Large stocks simultaneously have absolutely more informed trade volume and greater liquidity. Ex-post transparency means that uninformed traders are more likely to know their counterparty and face less informational asymmetry as a result of more immediate price discovery. We expect that post-trade transparency will promote higher uninformed demand, which in turn enables more informed trading and gives rise to both higher trade volume and liquidity.

1.4 Post-trade transparency and liquidity

Flood, Huisman, Koedijk, Mahieu, and Roell (1997) examine the effects of different levels of post-trade transparency on an experimental financial market with market makers, informed traders and uninformed traders. Their results reconcile possibly conflicting theoretical predictions about what occurs when transparency increases: a) Because uninformed traders can discover price information from the trades executed by informed traders, an overall decrease in average transaction costs occurs because every transaction contains more information; b) The increase in transaction information significantly enhances the price discovery process; and c) Spreads are significantly wider at the beginning of trading as market makers are less willing to compete for order flow. These differences decrease over time as transaction information becomes available. We expect that post-trade transparency will improve liquidity because of increased competition between liquidity providers as more information will be disseminated with each transaction when the counterparties are publicly identified.

2. Institutional details, data and descriptive statistics

The KRX is a typical order-driven market in which the trading procedure – from order placement to trade confirmation – is conducted via an electronic order-driven system. Orders are matched during trading hours based on price and time priority. Opening and closing prices are determined by call auctions. On the KRX, every stock has a daily price variation limit set at ±15% of the previous day's closing price.

The KRX is open weekdays from 9:00 a.m. to 3:00 p.m. Investors can submit their orders from 8:00 a.m.[12], one hour prior to opening. Orders delivered to the market during the period from 8:00 a.m. to 9:00 a.m. are queued in the order book and matched in a call auction at 9:00 a.m. to determine opening prices. After opening prices are determined, the trades are executed by continuous auction until 2:50 p.m., which is 10 minutes before close. During the last 10 minutes, orders are pooled again and executed by call auction to determine the day's closing prices. During the 50 minutes from 3:10 p.m. to 4:00 p.m. the exchange operates an after-hours session. During after-hours sessions, orders are matched at the closing prices of the day. The tick sizes vary with the price levels.

[12] Since December 2003, the pre-hours session has lasted from 7:30–8:30 am, and the closing prices of the previous day are applied for orders. Orders delivered to the market from 8:30–9:00 are queued in the order book and matched by the call auction method to determine opening prices.

Notably, prior to May 2000, the KRX had lunchtime breaks that divided the continuous trading period into two separate continuous trading sessions, a morning session and an afternoon session. Since November 25, 1996 the top five brokers in terms of cumulative buy and sell volume in each stock have been revealed to all the public investors at the end of each trading session during the day; prior to that date, this information was unknown to market participants. Our paper exploits this distinct post-trade non-anonymity market setting to investigate how different levels of post-trade non-anonymity on the same trading day affect informed and uninformed traders' strategies and whether various aspects of market quality are changed as a result.

The initial dataset consists of 1,281 companies, which includes all the available common stocks in the Korea Stock Exchange (KSE), as it was then designated, for the period from March 1, 1996 to July 31, 1997, as provided by Thomson Reuters Tick History (TRTH) through the Securities Industry Research Centre of Asia-Pacific (SIRCA). The dataset includes the stocks with intraday trade and quote data including prices, volumes and the bid and ask prices. A filtering process is applied [13].

Consistent with Boehmer and Kelley (2009), we require all common stocks to have at least five hundred transactions per month during the investigated period from March 1, 1996 to July 31, 1997[14]. Our final sample includes 248 actively traded stocks.

In line with Madhavan, Porter, and Weaver (2005), we allow a time delay around the event date, November 25, 1996, to avoid possible bias from proximity to the event. Thus, we exclude the 20 trading days immediately prior to and following the event and further split the event window into two 174-trading-day periods: the pre- and post- periods. The pre-period is

[13] Quotes that have any of the following conditions are removed: (1) non-positive bid prices, (2) non-positive ask prices, and (3) bid price is higher than asking price. Trades with non-positive prices and/or non-positive volumes are excluded. Stocks with a total of more than 22 trading days (a calendar month) missing are eliminated from the final sample.

[14] The choice of this investigated period is based on the longest time window available around the policy change date that is not contaminated by other policy changes. As another transparency reform took effect in mid-August 1997, we exclude August 1997 onward from our sample.

March 19, 1996–October 29, 1996, and the post-period is December 19, 1996–July 31, 1997; these dates are chosen so as not to overlap with any other significant design changes. Moreover, there is negligible overlap with the 1997-1998 Asian financial crisis in which stock prices fell substantially; hence, our documented results are not driven by the price reduction effect in the crisis.

We construct an intraday dataset that includes only transactions occurring at each time-stamp (detailed to milliseconds). We aggregate multiple trades occurring at the same time (stamped to the millisecond) into a single trade, for which the trade size becomes the aggregated total of the value of the individual aggregated trades and price becomes the volume-weighted average price, following Gouriéroux, Jasiak, and Le Fol (1999).

The sample is stratified by daily range-based volatility[15] to control for different effects of the market design change on stocks with different volatilities since Foucault, Moinas, and Theissen (2007) show that volatility is an important determinant of how changes in transparency affect market quality. Quintile 1 includes 50 stocks with the lowest daily range-based volatility, and Quintile 5 includes the 49 most volatile stocks. The reason we use volatility quintiles that are specified prior to the transparency event (rather than the conventional approach of using size quintiles and including volatility as a control) is that volatility alters as a consequence of changes to transparency and is thus endogenous (see Foucault, Moinas, and Theissen (2007)). To avoid this potential endogeneity problem, we classify stocks into range-based volatility quintiles prior to the transparency change so that our classification is unaffected by the alteration to transparency.

3. The effects of post-trade transparency on market efficiency

We examine how transparency affects the informational efficiency of trading prices – an important aspect of market quality – using the variance ratio test, following Lo and MacKinlay (1988). This test exploits the underlying property of the random walk process, in which the

[15] Consistent with Hendershott and Jones (2005), range-based volatility for each stock-day observation is estimated by taking the daily difference between the logarithm of the highest and the lowest transaction prices.

variance of its increments is linear in the observation interval, to estimate how closely stock prices follow a random walk. Using a simple specification test based on variance estimators, we calculate variance ratios for each stock at different daily frequencies[16]. If stock prices are generated by a random walk (possibly with a drift), the variance of $l-day$ returns must be l times as large as the variance of $one-day$ returns. Comparing the (per unit time) variance estimates for $l-day$ and $one-day$ returns (including only the periods when the limit order book is functioning) provides a test for the random walk hypothesis. The variance ratio measures inefficiency as the divergence of a price series from the characteristics that would be expected under a random walk (Lo and MacKinlay (1988)). Thus, we examine whether the variance ratio for $l-day$ returns over $one-day$ returns is significantly different from unity pre-period compared with post-period.

Table 1 reports the number of observations, the variance ratios, and test z^* statistics for the full sample for the combinations of (1, 2)-, (1, 10)-, (1, 15)- and (1, 20)-day return variance ratios. These measures are robust to heteroskedasticity and consistent with Lo and MacKinlay (1988).

Examining the size of the z^* statistic in the pre-period in Table 1, we can reject the random walk null hypothesis at the 1% significance level for the full sample in all the different time horizons when broker IDs are anonymous. All estimates of variance ratios in this period are statistically significant, are less than unity and drop slightly in the longer time horizons, implying a negative serial correlation for the daily returns with no broker IDs that are disclosed to the public. Negative serial correlation is consistent with the prices set by noise traders reverting to the mean.

[16] We estimate how closely stock prices follow a random walk by using a simple specification test based on variance estimators stretching from two-day, ten-day, fifteen-day and twenty-day horizons. Because the transparency change affects only the market when the limit-order book is open, we derive each $one-day$ return for each stock as the difference between daily close-to-open prices to exclude overnight trades. $l-day$ returns is the sum of l- consecutive continuously compounded one-day returns.

The post-period with public broker ID shows the opposite results for all time horizons. The absolute level of the z^* statistic ranges from 0.22 to 1.69, decreasing drastically from the anonymity to the transparency period, which suggests that we cannot reject the null hypothesis of a random walk at the usual significance levels for the full sample. This finding is consistent with our argument that formerly uninformed noise traders in the anonymous regime will now be able to either copycat informed traders or to learn in the informationally rich regime. These results suggest a remarkable improvement in market efficiency following the revelation of broker IDs in the market.

<Insert Table 1 about here>

In Table 2, we report variance ratio test results for sub-samples based on volatility using the various intervals, i.e., (1, 2), (1, 10), (1, 15) and (1, 20) days. The results of the impact of broker ID disclosure on market efficiency are consistent in most of the time horizons. The test results in Panels A and B show no statistical evidence that the variance ratios in all four interval combinations are significantly different from unity for the two least volatility-sorted quintiles in both periods. These findings suggest that prices of these low volatility stocks follow a random walk regardless of the degree of market transparency.

However, the test statistics in Panels C, D and E in the pre-period columns show that the variance ratios of 1-day to 2-day, 1-day to 10-day, 1-day to 15-day and 1-day to 20-day returns are significantly different from one. The evidence indicates a strong rejection of the null hypothesis of a random walk in the three most volatile stock quintiles when traders are unable to identify their counterparties. The variance ratios for these high volatility stock quintiles are less than one, implying negative serial correlation for daily holding-period returns during the pre-period. In the post-period, the test statistics of these three quintiles fall outside the ±1.96 interval, indicating that we cannot reject the random walk for all these volatility quintiles at the usual significance levels with transparent broker IDs. These quintile results are also consistent with the full sample, showing negative serial correlations for the three most volatile quintiles in the anonymous market.

<Insert Table 2 about here>

Overall, the variance ratio results offer evidence that the market is inefficient during the period in which broker IDs are hidden and becomes efficient during the post-period when the public can access broker IDs. This effect is strongest for the low market capitalization and high volatility stocks and insignificant for the high capitalization shares with the least volatile prices. Moreover, these results are to be expected as large capitalization firms are more widely followed and expected to have higher price efficiency from the outset.

4. **The effect of post-trade transparency on volume**

4.1 Univariate tests

Traded volume is computed as the sum of the number of shares traded during the day excluding opening trade volume. We split the sample in two: a morning sample and an afternoon sample. Because the first reporting of broker ID does not occur until after the first session on a given day and because information from the previous afternoon's session is relatively stale by that time, the two sessions are expected to perform differently. We examine whether there is a statistically significant difference in the means and medians of trading volume for the same trading sessions between the pre- and post-event periods using Student *t* and non-parametric Wilcoxon signed-rank tests, respectively.

Table 3 reports the difference between the mean and the median of traded volume in logarithmic form for the full 248 stocks and the volatility-stratified quintiles surrounding the event of November 25, 1996.

<Insert Table 3 about here>

All tables document a highly significant increase in trading activity – with the exception of the most volatile stocks in the morning session – after displaying the broker IDs to the public. For example, morning session trading increases in all samples by a very economically significant 23%, with an even higher afternoon session rise of 36%. As predicted, the afternoon gains are both statistically and economically higher in every volatility quintile as well. Thus, these volume increases indicate that relatively uninformed participants enjoy substantial welfare gains. For example, the lowest volatility quintile enjoys a 40% volume improvement in the morning session during the post-period and an even greater 49% gain in the afternoon session. We document that the greater the volatility, the lower the trading volume rise in the more transparent market (with the exception of quintile 3). Examining the Wilcoxon test results, we also find the same patterns in all the quintiles and the full sample.

4.2 Multivariate tests

As the changes in trading volume found in the univariate results may be attributed to factors other than post-trade broker ID transparency, we use multivariate models to control for these potential determinants. We include a time trend variable in all our regressions to eliminate the possibility that our findings on design changes are simply due to trends and seasonal effects. The time trend variable begins with a value of 1 and increases by 1 unit for each investigated day. We also include daily relative tick size[17] for each stock as a proxy for the price level. In a given day, the relative tick size per stock – the minimum absolute tick size scaled by the session value-weighted average price – is estimated for each trading session. Because the transparency information at the beginning of the afternoon session should be more informative than the relatively stale information from the previous day, the market responses should be different between the two trading sessions. An interaction variable for the trading session and transparency dummy is included to capture this phenomenon.

We estimate the following regression model:

$$\begin{aligned} Ln(Volume_{ijt}) = \alpha + \beta_1 Trend_{ijt} + \beta_2 VWAP\_Rel\_TkSize_{ijt} + \beta_3 Session_{ijt} + \\ + \beta_4 Brok_{ijt} + \beta Brok_{ijt} * Session_{ijt} + \sum_{i=2}^{i=n} \gamma_i D_i + \sum_{k=1}^{i=5} \theta_k Weekday_k + \varepsilon_{ijt}, \end{aligned} \tag{1}$$

where $Ln(Volume_{ijt})$ is the natural logarithm of the volume in shares for stock *i*, trading session j of trading day *t*; $Trend_{ijt}$ is the time trend variable on trading day *t*; $VWAP\_Rel\_TkSize_{ijt}$ is the relative tick size to value-weighted average price in session j of trading day t; $Session_{ijt}$ is equal to 0 for the morning trades and equal to 1 for the afternoon trades on trading day t for

[17] Appendix 3 provides the distribution of minimum tick size as a function of the stock price in the KRX during the investigated period.

stock i; $Brok_{ijt}$ is a dummy identifying the transparency event taking the value of 0 if there is anonymity and 1 otherwise; $\sum_{i=2}^{n}\gamma_i D_i$ represents the $n-1$ estimates for the stock-specific dummies allowing for the stock fixed effect; and $\sum_{k=1}^{i=5}\theta_k Weekday_k$ represents the day-of-week specific dummy variables allowing for the time-fixed effect. If we find that the interaction coefficient β differs significantly from zero, it provides evidence that the change in the policy of disclosure of broker IDs affects trading volume in the afternoon session after we control for other potential determinants. Following Foucault, Moinas, and Theissen (2007), we apply stock fixed effects to control for heterogeneity across stocks. In addition, we also use day-of-week fixed effects to control for the potential effect of the day-of-week on trading volume[18].

Table 4 reports the regressions on the full sample and on the lowest, medium and highest volatility-stratified quintiles[19]. Model 1 presents the results, taking into account both stock fixed and day-of-week fixed effects. Model 2 shows the outputs of the regressions including stock fixed effects only. The reported standard errors are Rogers (1993) clustered by stock, and hence are robust to both heteroskedasticity and correlation within stocks. We do not report the coefficients of the stock dummy and day-of-week dummy variables to save space. The adjusted R-squares are in the range of 21% to 40%, depending on the volatility-stratified quintiles examined. The coefficients of the broker ID dummy are 0.22 and highly statistically significant for the full sample (see Panel A), indicating that the average shares traded in the post-event morning increase 22% compared with the pre-event morning. The coefficient of the interaction variable of approximately 0.14 (*t*-value of 14.07 and 14.09 in Models 1 and 2, respectively) indicates that the broker ID revelation has stronger positive effects on the

[18] Many studies show the day-of-week effects on various aspects of trading. For example: Lakonishok and Maberly (1990) find that trading activity tends to increase on Monday in comparison with other days of the week.

[19] Only selected quintiles, not all, are reported due to space limitations. The remaining results will be provided upon request.

afternoon session, which further increases the average trading volume of the entire market by 14%.

<Insert Table 4 about here>

We document a similar tendency for the changes in trading volume in both trading sessions for all the stock quintiles except for the most volatile. Less volatile stocks experience higher increases in trading volume in the morning session and lesser increases in the afternoon session. Specifically, there is a remarkable increase in trading volume of 50% for the least volatile stocks traded in the post-event morning and a further (marginal) rise of 9% in the post-event afternoon (see Panel B). For the mid-quintile stocks (see Panel C), we also find increases, although of lesser magnitude in the morning (32%) and greater following the broker ID revelation in the afternoon session (14.5%). However, Panel D presents the opposite change for the most volatile stocks, with a decline of 18% in volume traded in the post-event morning and a surge of 23% on average shares traded in the post-event afternoon.

These findings are consistent with our univariate results. Overall, the introduction of the post-trade transparency regime results in remarkable increases in the trading volume in the morning sessions for most stock quintiles compounded by further increases in the afternoon sessions. The policy has a stronger effect on large and less volatile stocks in the morning and less of an effect in the afternoon sessions. This effect is to be expected because, given that broker ID information from the previous day is less relevant for trading in the morning session due to the new overnight news, informed traders at opening have the entire morning session in which to conduct their trades prior to their identities being (potentially) fully revealed. Such strategically informed trading results in a huge rise in trading volume as new information is released. Consistent with Kyle (1985), in which most informed traders hide in the crowd, there is more aggregate information in the large, low-volatility stocks that have a larger liquidity-trader crowd. These large stocks that dominate the dollar trading volume seem to be most affected by the rush to trade prior to revelation. Small, high-volatility stocks experience the reverse. The majority of investors in these stocks is uninformed and can thus afford to delay their trades until broker IDs are displayed in the afternoon session.

5. The effect of post-trade transparency on spreads

We measure execution quality using effective spreads for buyer- and seller-initiated trades in relative percentage form. We use the quote-based rule to classify a trade as a buy if the associated trade price is above the midpoint between the best bid and the best ask quote when the trade occurs and as a sell if the trade price is below the midpoint. The tick rule categorizes trades at the mid-point as a buy (sell) if the trade occurs above (below) the previous price. If there is no price change but the previous tick change was up (down), the trade is classified as a buy (sell). The trade classification is accurate, as the KRX electronic limit order book system records and timestamps orders and trades exactly in the order that they occur in the market.

The effective spread for buys (sells) is the difference between the execution price of buyer- (seller-) initiated trades and the prevailing mid-point price, where the mid-point price is the average of the best bid and best ask price. The percentage effective spread for buys (sells) is the effective spread for buys (sells) scaled by the mid-point price. We further decompose the effective spread into temporary and permanent components. The temporary component measured by realized spreads captures how much profit the liquidity suppliers would make on the trade. The latter (market impact) is the simple estimation of the amount of information released by the trade. The more information that trades contain, the more prices will move in the direction of the trade (up following purchases and down following sales). Traders incorporate the information in the order flow imbalance by permanently adjusting their quotes upward (downward) after a series of buy (sell) orders (Glosten and Milgrom (1985)).

We estimate the realized spreads for buys (sells) as the execution price of buyer- (seller-) initiated trades minus the midpoint prices after 1, 2, 4, 6, 8 and 10 trades on the same side[20]. The relative realized spread for buys (sells) computes as the realized spread scaled by the initial mid-point price. Our measure is consistent with Boehmer (2005), who defines realized spreads using the mid-point price after a specified calendar-time lag and the trade price. However, we explore liquidity suppliers' gains after the lapse of a specified number of trades – the trade-

[20] As the trades used to estimate these measures should be on the same day, the realized spreads of the last 1, 2, 4, 6, 8 and 10 trades prior to the closing time are missing values and hence discarded.

time, not the calendar-time, as in much of the literature – to mitigate possible biases caused by the differences in stock liquidity and trade speed.[21] We compute market impact for buys (sells) as the change in the midpoint prices of 1, 2, 4, 6, 8 and 10 trades later, signed by the trade direction to the initial midpoint price. Relative market impact equals the absolute measure scaled by the initial midpoint price. The effective spread, realized spreads, and market impact calculations for individual buyer- and seller-initiated trades rely on intraday data because the liquidity measures involve trade-time horizons.

5.1 Univariate analysis – transaction costs and liquidity providers' compensation

Tables 5 and 6[22] report the statistical change in the mean and the median of relative effective spread – a measure of transaction costs – relative realized spreads and relative market impact. Market impact is the price effect of the trade at a specific trade-time horizon, and the realized spread is the compensation earned by the counterparty to the trade at a specific trade-time horizon. We apply parametric *t*-tests and non-parametric Wilcoxon signed-rank tests to examine whether these liquidity measures are significantly different prior to and after the event. The liquidity measures are estimated separately for the morning and afternoon trading sessions. As the results for all three of these proxies are identical for all of the examined trade horizons, we report those for the 10-post-trade horizon only.

<Insert Tables 5 about here>

Panel A of Table 5 consistently shows higher average and median effective spreads in both trading sessions in the post-period for buyer-initiated trades. The post-period morning trading session has a larger increase in the average effective spreads than the post-period afternoon session across the full sample and across the individual quintiles. Panel B reports higher revenues for liquidity provision in the post-period morning and then lower figures in the

[21] Our data include most of the active stocks in the KRX, so the different shares have significant differences in the liquidity levels. Thus, using an identical calendar time as a benchmark to measure liquidity suppliers' gains for stocks with vastly varying liquidity/turnover rates may not capture their profits correctly, and it is more appropriate to use trade time.

[22] The results for seller-initiated trades are shown in absolute values for ease of interpretation.

post-period afternoon session across the full sample and the four quintiles. An exception is quintile 1, which has lower liquidity providers' earnings in both trading sessions after the broker ID policy took effect. The results indicate that for the higher-volatility stocks, there is less competition between liquidity providers on the buy side in the post-period prior to the release of broker IDs (see Hendershott and Jones (2005)). It seems that in the post-period, more buyers are not willing to provide liquidity until more information is revealed at the end of the morning session. These traders might become more active in the afternoon session given the information they learn following the disclosure of broker IDs, which might lead to fiercer competition among those providing liquidity. As a result, the average earnings for liquidity provision decline in the afternoon trading sessions. By contrast, buyer-initiated trades on large and less volatile stocks face stronger competition in both post-period trading sessions, evidenced by declines of 0.81 and 2.83 basis points in realized spreads in the morning and afternoon, respectively (see Panel B). This finding is consistent with our argument that more informed traders are hiding in these larger stocks. There would be more aggressive trading in the post-period morning than in the pre-period morning before the information is disclosed at the end of the session. The competition is even tougher in the afternoon as uninformed traders might become quasi-informed and are willing to provide liquidity. Given higher transaction costs, the lower realized spreads in the post-period suggest that buyer-initiated trades have a higher price impact due to a significantly higher amount of information in trades during the afternoon sessions.

<Insert Tables 6 about here>

As with buyer-initiated trades, seller-initiated trades suffer higher transaction costs in the post-period, which is documented by an increase in average effective spreads of 4.9 basis points in the morning and a smaller increase of 4.6 basis points in the afternoon for the full sample (see Panel A). The same tendency for the increased effective spreads in the two trading sessions is documented for the volatility stock quintiles except for quintile 1. Panel B of Table 6 shows that seller-initiated trades earn more for liquidity provision in both post-period trading sessions, with higher benefits in the post-period afternoon session. Because the price impact of a trade is the difference between the effective and the realized spread, a higher increase in the effective spread than in the realized spread in the morning session suggests that there is a larger price impact of trades in the post-period morning. The reverse occurs in the post-period afternoon session. However, unlike buyer-initiated trades, one should be cautious in interpreting the changes in the price impact of seller-initiated trades as representing either more or less information in trades because the market perceived motives for sales might be liquidity rather than information (see Malherbe (2014) and Saar (2001)).

Our findings imply that in a more transparent market, buyer-initiated trades garner higher compensation for liquidity provision in the time leading to the broker ID disclosure and earn less revenue in the following trading sessions, as the competition between liquidity providers is fiercer. The increased competition is likely to arise from the ability of liquidity suppliers to acquire information by observing informed trader direction. We observe that transaction costs, as measured by the effective spread, are higher in both trading sessions but relatively lower in the afternoon after the change to public broker IDs.

5.2 Model of the effect of post-trade transparency on spreads

The literature documents various factors that might affect spreads. Thus, the documented changes in effective spreads and realized spreads using univariate analysis may not be attributable to the broker ID disclosure. Hence, we conduct multivariate regressions to examine whether the findings in the previous sections are driven by factors other than the broker ID policy.

Easley, Kiefer, and O'Hara (1997) find that trade size introduces an adverse selection problem into securities trading. Given that they wish to trade, informed traders prefer substantial trades prior to information-induced price changes. Easley, Kiefer, and O'Hara (1997) show that large trades have approximately twice the informational content as small trades, and Lin, Sanger, and Booth (1995) find that price impacts increase with trade size. These studies all suggest that large trades convey more information to the market and move quoted spreads more quickly than small trades (Lin, Sanger, and Booth (1995)). Thus, we include trade size as a control variable in the model examining the effect of post-trade transparency on spreads.

Several studies document the importance of tick size on spreads, e.g., Foucault, Moinas, and Theissen (2007), and on volatility, e.g., Ronen and Weaver (2001). Ronen and Weaver (2001) find significant decreases in both daily and transitory volatility after minimum tick reduction, reinforcing the hypothesis of a direct association between volatility and tick size. We derive intraday relative tick size for individual trades using the deflator of associated trade price. Regressions utilizing liquidity proxies take into account the trade direction for buys and sells. We estimate the following models to measure the effect of publicly displayed broker IDs on the components of transaction cost:

$$\begin{aligned} S\_M_{it} = \alpha + \beta_1 Trend_{it} + \beta_2 Rel\_TkSize_{it} + \beta_3 Ln(Trade\_Size_{it}) + \\ \beta_4 Brok_{it} \times Ln(Trade\_Size_{it}) + + \beta_5 Session_{it} + \beta_6 Brok_{it} \\ + \beta Brok_{it} * Session_{it} + \sum_{i=2}^{i=n} \gamma_i D_i + \sum_{k=1}^{i=5} \theta_k Weekday_k + \varepsilon_{it,} \end{aligned} \tag{2}$$

where for stock i at trading time t, S_M_{it} is in turn the relative effective spread, realized spread and market impact; $Trend_{it}$ is the time variable to correct for trends in dependent variables; $Brok_{it}$ is the dummy variable taking the value of 0 if broker ID is opaque and 1 if post-trade transparent; Rel_TkSize_{it} is the minimum tick size relative to price; $Ln(Trade\_Size_{it})$ is the logarithm of trade size; $Session_{it}$ is a dummy variable taking a value of 0 if time t is in the morning and 1 if time t is in the afternoon; D_i is the stock-specific dummy variables allowing for stock fixed effects; and $Weekday_k$ represents the day-of-week specific dummy variables. Evaluation of the effect of the broker dummy on S_M_{it} occurs at the average of logarithm of trade size as follows:

$$\frac{\Delta S\_M_{it}}{\Delta Brok_{it}} = \beta_4 Ln(Trade\_Size_{it}) + \beta_6 + \beta * Session_{it}, \tag{3}$$

Since we are interested in the effect of the transparency policy on different trading sessions in the post-period, we re-parameterize equation (2) using mean centering for the logarithm of trade size. As a result, the mean-centered equation (2) becomes:

$$S\_M_{it} = \alpha + \beta_1 Trend_{it} + \beta_2 Rel\_TkSize_{it} + \beta_3 Ln(Trade\_Size_{it}) + \\ \beta_4 Brok_{it} \times \left[Ln(Trade\_Size_{it}) - \mu_{tradesize} \right] + + \beta_5 Session_{it} + \beta_6 Brok_{it} + \\ \beta Brok_{it} * Session_{it} + \sum_{i=2}^{i=n} \gamma_i D_i + \sum_{k=1}^{i=5} \theta_k Weekday_k + \varepsilon_{it}, \tag{4}$$

in which $\mu_{tradesize}$ is the mean of the logarithm of trade size for the full sample and individual quintiles in corresponding regressions of S_M_{it}**.** Hence, the coefficient of broker dummy β_6 reflects the effect of the transparency reform on S_M_{it} in the morning session. The coefficient of the interaction variable for trading session β reflects the impact of the transparency policy on S_M_{it} in the afternoon session. This method of centering the regressors reduces latent multi-collinearity and improves the reliability of the resulting regression equations.

5.2.1 The impact of buyer-initiated trades

Table 7 estimates regression equation (4) using buyer-initiated trades for the full sample and the individual quintiles. The results are presented in the “Model 1” column. The estimates of the equation omitting the day-of-week fixed effect component are shown in the “Model 2” column. Standard errors are clustered by stocks and, as a result, are robust to both heteroskedasticity and correlation within stocks. The estimates of Model 1 and Model 2 are consistent.

<Insert Table 7 about here>

Based on the results for the full sample in Panel A of Table 7, the effective spread increases by 6.9 basis points in the post-period morning session and then declines by approximately 0.5 basis points in the afternoon following the broker ID revelation at mid-day. The regression results on realized spread – a proxy of liquidity providers’ revenues – are different from the univariate analysis, which implies that our univariate findings are driven by other factors, such as relative tick size or trade size. Specifically, the regression results show that the realized spread is lower on average in the morning session – exhibiting a decline of 4.23 basis points – and is narrower in the afternoon session by 4.1 basis points. Because effective spreads can be decomposed into two components, the realized spread and the market impact, higher effective spreads associated with much lower realized spreads reflect a higher market impact (see columns 3 and 4), implying a more informative order flow in the post-period afternoon session (see Boehmer (2005)) when trader identities have been effectively revealed (following the close of the morning session). We find that the transparency policy results in higher market impacts for buyer-initiated trades, resulting in an increase of approximately 11.2 basis points in the morning and a further increase of 3.6 basis points in the afternoon session. The higher market impact of trades is due to the ability to identify informed traders once the ex-post identity is revealed and the threat of the informed trader identity being revealed at the end of the morning session forces informed traders to trade more aggressively in the morning session before their identities are revealed.

Panels B, C, and D of Table 7 show that effective spreads are wider by 6 to 7 basis points in the morning sessions in the post-period for all volatility-stratified quintiles. This measure narrows down in the afternoon session for the least volatile stocks only (approximately 0.6 basis points) following the broker ID disclosure in the post-period. The average effective spreads of the other stock quintiles are not significantly affected following the revelation of the broker ID at the end of the morning session.

The higher effective spreads for all stock quintiles in the post-period morning session are explained by the significantly greater amount of information contained in buyer-initiated trades in this trading session, documented by an increase of approximately 10 basis points in the market impact of trades (see the coefficients of $Brok_{it}$ in columns 3 and 4). This result is consistent with stronger competition among liquidity providers for these quintiles in the morning, documented by falls in the range of 3.8 basis points to 4.2 basis points in realized spreads.

The impact of the broker ID disclosure policy on spreads is diverse in the post-period afternoon session for stocks in the different volatility quintiles. For the large, least volatile stocks, the competition has become fiercer in the afternoon, with a further reduction of 1.9 basis points in realized spreads; however, there is no impact on the permanent price impact component, leading to a reduction in transaction costs of this quintile after the broker IDs are displayed. Moreover, the more volatile stock quintiles experience sizeable drops of approximately five basis points in realized spreads, which is offset by increases in the price impact of buyer-initiated trades and results in no change in the effective spread for these stocks in the afternoon session. A possible explanation for this phenomenon is that the increased liquidity provider competition in the afternoon session does no more than offset the greater release of information due to copycatting of first-session traders now revealed to be informed.

5.2.2 The impact of seller-initiated trades

The effect of the broker ID policy on effective spreads in the morning session for the seller-initiated trades in Table 8 are generally consistent with the results for the buyer-initiated trades presented in Table 7. Estimating the model specified by equation (4) on seller-initiated trades, the coefficients of the transparency broker ID dummy are significantly positive (approximately seven basis points), and the coefficients of the interaction with the session dummy variable are significantly negative (-0.4 basis points) in the effective spread regression for the full sample, Panel A. The results imply that post-trade transparency is associated with a wider effective spread for seller-initiated trades in the relatively opaque morning session, as aggressive informed sellers exploit this opacity prior to their identities being revealed at the close of the morning session. This impact is narrower on transaction costs in the afternoon session.

<Insert Table 8 about here>

We observe that less volatile stocks experience a smaller increase in this coefficient in the post-period morning session. Specifically, the magnitudes of the transparency dummy coefficients indicate that the switch to public broker IDs has increased the average effective spread by 4.4 basis points for the least volatile stocks, 5.9 basis points for medium quintile stocks, and 7.8 basis points for the most volatile stocks in the post-period morning session. There are no further statistically significant changes in transaction costs for seller-initiated trades in the afternoon session after the policy took effect based on the volatility quintiles. There is a discrepancy between buyer-initiated and seller-initiated trades in that the higher effective spreads seem to be a consequence of higher realized spreads for shares traded in the morning in the post-trade transparency period rather than due to an increase in the market impact. In the morning session, post-trade transparency is associated with realized spread increases of seven basis points for the full sample and with increases of five basis points, 7.1 basis points and 8.6 basis points for the least, mid and most volatile quintiles, respectively. These measures are even higher for trades in the post-period afternoon session for the full sample and all volatility stock quintiles when the most active broker IDs traded in the morning session are released. The results suggest that there is less competition among liquidity providers to seller-initiators in both trading sessions during the post-trade transparency period.

Furthermore, Table 8 shows that post-trade transparency lowers the price impact in the afternoon session – although it does not affect the market impact in the morning session – and that this result holds for the full sample and for the individual quintiles. This decrease amounts to approximately 4.7 basis points for the full sample and two basis points for the low volatility sample. Hence, what these results indicate is that informed seller-initiated trades tend to be less aggressive than buyer-initiated trades – most likely because of the high cost and difficulty of short-selling – and are thus less responsive to the conduct trades during the relatively opaque post-period morning session. These informed sellers are, however, less active in the more informed and transparent afternoon period.

6. Conclusions

This paper investigates the impact of changes in post-trade transparency on market quality at the time when the KRX began displaying complete ex-post trade and trade imbalance information to all market participants for the top five most active brokers on both the buy- and sell-side of every stock. This information is first retrieved at the end of the morning trading session and, hence, is not made available to market participants until the afternoon session. Although the morning session is partially informed by the release of the top five active broker IDs from the previous day's afternoon trading session, following the overnight closure, this information is relatively stale by the next morning. This natural division in the post-event degree of transparency enables us to contrast the differences between the partially informed morning session and the fully informed afternoon session.

Ours is the first analysis of this experiment, the first and only case in which a major exchange has adopted post-trade transparency, other than in the Helsinki market. We partition the data into morning and afternoon sessions pre- and post-event (i.e., pre-and post-transparency event) using both an event dummy and a session dummy – as well as interacting the event dummy with the session dummy – in addition to trade size. We use the variance ratio, traded volume, effective spread, realized spread and market impact to measure market quality, whereas market capitalization and volatility are accounted for using firm fixed effects and by stratifying the sample into quintiles by range-based volatility, which is specified prior to the event.

Our variance ratio test shows that the prices of Korean shares for the full sample and for all but the least volatile quintile do not follow a random walk during the period of anonymous broker IDs and begin following a random walk when the investors can observe signed trades and trade imbalances ex-post for the top five brokers whose identities are revealed. Our findings indicate that access to information in Korea must be nearly costless; otherwise, prices in the transparent period would not appear to reflect all available information. Ex-post revelation of broker IDs attached to order flow has eliminated mean reversion in daily price changes due to uninformed noise trading in the opaque period. Applying a panel data approach, accounting for stock-specific characteristics, and testing for market efficiency, our results lead to a reinterpretation of the conclusions from previous research, which are typically adverse to transparent regimes when examined solely from the perspective of trading costs with no attention paid to the critical areas of price discovery and efficiency.

Our study finds that when broker IDs from the morning are publicly displayed at the end of the morning session and when broker IDs from the afternoon session are displayed at the end of the afternoon session on the same trading day, volume for the full sample increases significantly by 22% in the morning session – when only a stale broker ID signal is available – and by a further 14% in the afternoon session following the revelation of ex-post broker IDs from the morning session. For the least volatile quintile consisting of the largest and most valuable stocks, the findings are even more striking, with a 50% rise in the morning and an additional 9% rise in the afternoon session.

The dramatic events taking place here can be better understood as a result of our analysis of transparency-induced changes to the effective spread, market impact, and realized spread. For buyer-initiated trades not subject to the difficulties associated with short-selling, the effective spread widens following a weak broker ID revelation in the morning session only to largely fall back in the more transparent afternoon session, with the realized spread falling significantly in the morning and by even more in the afternoon session. The differences are accounted for by significant rises in the market impacts in both sessions as informed traders are forced to trade aggressively prior to their identities being revealed at the end of the morning session and as their informed trades are copycatted in the afternoon session. The most significant improvements in information dissemination occur for buyer- instead of seller-initiated trades because the difficulty and expense of borrowing stock for the purposes of short sales limits the degree of information contained in seller-initiated trades.

This forced rapid dissemination of information levels – and especially of buyer-initiated trades – levels the playing field by rapidly removing asymmetric information and thus giving liquidity traders much greater confidence in their prospective counterparties. The partial if not complete removal of this asymmetric information risk can help to account for the huge upward shifts in trading volume that we observe in both the morning and afternoon sessions, which is particularly the case in the afternoon session, as it is far more transparent than the morning session.

This study supports the current policy of the KRX in displaying the size and price of orders pre-trade and the identity of the five largest brokers on each side in each stock post-trade to all participants. This policy cleverly provides protection against front-running orders pre-trade while providing transparency as to broker ID post-trade. Because informed traders typically split large orders, ex-post transparency – including order imbalance – enables otherwise uninformed traders to infer both the trade direction and urgency of the underlying order. As a result, it promotes substantially higher traded volume and a variety of other indicators of improved market quality. The KRX appears to have benefited from transparency; the turnover rate in stocks is significantly higher than in Tokyo, for example, and its share index future (the KOSPI 200) is one of the most actively traded stock index futures in the world.

Our results indicate that exchanges should consider providing more limit-order book and, in particular, ex-post trade transparency to the entire investing public, particularly for larger, more liquid and less volatile securities. Obviously, there are considerable benefits received by informed traders of large liquid stocks in the form of cross subsidies paid for by uninformed traders in anonymous markets. As we have shown, this policy comes at the expense of a less efficient and far less liquid market. Fully transparent post-trade broker IDs in real time may also bring positive externalities for large broker-dealers and their clients. A broker-dealer that is frequently visible as one of the top brokers in a stock will attract additional order flow. Traders will see them as important liquidity providers in the securities in which they are active.

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Table 1: Results for variance ratio tests on the KRX – Full sample

This table reports the number of observations and variance ratios for the combination of 1-day to 2-day, 1-day to 10-day, 1-day to 15-day, and 1-day to 20-day returns, in addition to heteroskedasticity robustness test statistics for the pre- and post-November 25, 1996 periods for the full sample. The pre-period and post-period are defined as March 19th 1996–October 29th 1996 and December 19th 1996–July 31st 1997, respectively. The variance ratios are reported, with the test statistic, z*, given in the third row in each panel. Under the random walk null hypothesis, the value of the variance ratio for 1-day to 2-day, 10-day, 15-day and 20-day returns is 1, and the test statistics follow a standard normal distribution (asymptotically). * denotes statistical significance at the 5% level. ** denotes statistical significance at the 1% level.

	pre-period	**post-period**
Panel A: 1-day to 2-day return ratio		
Number of observations	42,850	42,884
Variance Ratio for 1- to 2-day returns	0.97	1.00
Heteroskedastic Robust Test Statistic	-4.76**	0.56
Panel B: 1-day to 10-day return ratio		
Number of observations	42,850	42,884
Variance Ratio for 1 to 10 day returns	0.88	1.00
Heteroskedastic Robust Test Statistic	-6.85**	-0.22
Panel C: 1-day to 15-day return ratio		
Number of observations	42,850	42,884
Variance Ratio for 1 to 15-day returns	0.86	1.02
Heteroskedastic Robust Test Statistic	-6.13**	0.88
Panel D: 1-day to 20-day return ratio		
Number of observations	42,850	42,884
Variance Ratio for 1 to 20-day returns	0.83	1.05
Heteroskedastic Robust Test Statistic	-6.46**	1.69

Table 2: Results for variance ratio tests for 1- to 20-day returns combinations on the KRX – Volatility Quintiles

The table reports the number of observations, variance ratios for the combination of 1-day to 2-day, 1-day to 10-day, 1-day to 15-day and 1-day to 20-day returns and the heteroskedasticity-robust z* statistics for the pre- and post-November 25, 1996 period for five volatility quintiles. The pre-period and post-period is defined as March 19th 1996–October 29th 1996 and December 19th 1996–July 31st 1997, respectively. The variance ratios are reported with the test statistic, z*, given in the third row in each panel. Under the random walk null hypothesis, the value of the variance ratio for 1-day to 2-day, 10-day, 15-day and 20-day return is 1, and the test statistics follow a standard normal distribution (asymptotically). * denotes statistical significance at the 5% and ** at the 1% levels.

	1-day to 2-day returns		**1-day to 10-day returns**		**1-day to 15-day returns**		**1-day to 20-day returns**	
	pre-period	**post-period**	**pre-period**	**post-period**	**pre-period**	**post-period**	**pre-period**	**post-period**
Panel A: Quintile 1 (Least Volatile)								
No of observations	8,693	8,687	8,693	8,687	8,693	8,687	8,693	8,687
Variance Ratio	1.01	1.00	1.00	1.02	1.01	1.02	0.96	1.03
Heteroskedastic Robust Test Statistic	0.49	-0.05	0.03	0.56	0.14	0.39	-0.61	0.46
Panel B: Quintile 2								
No of observations	8,686	8,645	8,686	8,645	8,686	8,645	8,686	8,645
Variance Ratio	0.99	0.98	0.97	1.03	0.94	1.05	0.88	1.08
Heteroskedastic Robust Test Statistic	-1.20	-1.49	-0.85	0.64	-1.26	0.89	-2.23*	1.31
Panel C: Quintile 3								
No of observations	8,637	8,634	8,637	8,634	8,637	8,634	8,637	8,634
Variance Ratio	0.97	1.01	0.88	0.99	0.85	1.04	0.80	1.08
Heteroskedastic Robust Test Statistic	-2.71**	0.52	-3.17**	-0.33	-3.21**	0.76	-3.66**	1.45
Panel D: Quintile 4								
No of observations	8,467	8,466	8,467	8,466	8,467	8,466	8,467	8,466
Variance Ratio	0.96	1.02	0.75	1.03	0.72	1.06	0.68	1.09
Heteroskedastic Robust Test Statistic	-3.92**	1.63	-6.59**	0.71	-6.00**	1.12	-5.72**	1.51
Panel E: Quintile 5 (Most Volatile)								
No of observations	8,367	8,452	8,367	8,452	8,367	8,452	8,367	8,452
Variance Ratio	0.97	1.00	0.87	0.93	0.87	0.95	0.87	0.95
Heteroskedastic Robust Test Statistic	-2.38*	0.27	-3.42**	-1.76	-2.65**	-1.08	-2.36*	-0.86

Table 3: Univariate analysis for logarithmic trading volume in the KRX

This table reports the statistical summary of the changes in mean and median trading volume in logarithmic form for the Korean Stock Exchange for the full sample of 248 stocks and for subsamples stratified by volatility measured as the daily high-low volatility. The columns labeled '*Diff*' measure changes in trading volume, effectively in percentage form, from the pre-period to the post-period. The table presents the results of parametric *t*-tests and non-parametric Wilcoxon signed-rank tests to examine whether the means and medians change after the disclosure of broker ID. The *t*-Value and *Wil*-Value columns report the t-test and the Wilcoxon test statistics. "*Nobs*" is the number of observations. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

		Mean				**Median**				**Nobs**	
Quintile	**Session**	**pre-period**	**post-period**	**Diff**	***t*-Value**	**pre-period**	**post-period**	**Diff**	***Wil*-Value**	**pre-period**	**post-period**
Full Sample	Morning	9.61	9.83	0.23***	24.14	9.63	9.84	0.21***	22.86	41,443	42,220
	Afternoon	9.26	9.62	0.36***	33.84	9.35	9.67	0.32***	32.84	33,089	34,775
Quintile 1 (Lowest Volatility)	Morning	9.96	10.36	0.40***	18.12	9.99	10.40	0.41***	18.34	8,431	8,552
	Afternoon	9.75	10.25	0.49***	19.39	9.85	10.35	0.50***	19.92	6,914	7,124
Quintile 2	Morning	9.62	9.90	0.28***	13.81	9.66	9.89	0.23***	12.58	8,398	8,499
	Afternoon	9.30	9.68	0.38***	16.42	9.41	9.73	0.32***	15.88	6,748	7,021
Quintile 3	Morning	9.51	9.85	0.34***	16.84	9.50	9.87	0.36***	17.33	8,320	8,515
	Afternoon	9.16	9.63	0.48***	21.62	9.25	9.72	0.47***	21.82	6,620	7,070
Quintile 4	Morning	9.39	9.58	0.19***	9.31	9.41	9.60	0.18***	9.30	8,189	8,341
	Afternoon	8.99	9.31	0.32***	14.19	9.09	9.40	0.31***	14.47	6,470	6,807
Quintile 5 (Highest Volatility)	Morning	9.53	9.46	-0.07***	3.58	9.59	9.46	-0.13***	5.02	8,105	8,313
	Afternoon	9.04	9.19	0.15***	6.41	9.18	9.28	0.10***	5.67	6,337	6,753

Table 4: Multivariate analysis of logarithmic trading volume on the KRX

This table reports the results of the regression of the form:

$$Ln(Volume_{ijt}) = \alpha + \beta_1 Trend_{ijt} + \beta_2 VWAP\_Rel\_TkSize_{ijt} + \beta_3 Session_{ijt} + \\ + \beta_4 Brok_{ijt} + \beta Brok_{ijt} * Session_{ijt} + \sum_{i=2}^{i=n} \gamma_i D_i + \sum_{k=1}^{i=5} \theta_k Weekday_k + \varepsilon_{ijt},$$

where $Ln(Volume_{ijt})$ is the natural logarithm of volume in shares for stock *i*, trading session j at time *t*; $Trend_{ijt}$ is the time trend variable on trading day t; $VWAP\_Rel\_TkSize_{ijt}$ is the relative tick size to value-weighted average price in session j of trading day t; $Session_{ijt}$ is equal to 0 for morning trades and equal to 1 for afternoon trades in trading day t; $Brok_{ijt}$ is a dummy identifying the transparency event taking the value of 0 if anonymity and 1 otherwise; D_i represents the stock-specific dummy variable; and $Weekday_k$ represents the day-of-week specific dummy variables. n is 248 for the full sample, 50 for the first three quintiles and 49 for the two remaining individual quintiles. The table contains the stock fixed effect results of the regression for the full sample and for the five individual volatility-stratified quintiles. The results with and without day-of-week fixed effects are presented in Model 1 and Model 2, respectively. Standard errors are clustered by stocks, and hence are robust to both heteroskedasticity and correlation within stocks. The adjusted R^2 for the estimations is reported under Adj R2. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Trading Volume	
	Model 1	**Model 2**
Panel A: Full sample		
Intercept	7.518***	7.581***
	(117.3)	(117.8)
Trend	0.000	0.000
	(0.31)	(0.20)
VWAP Rel Tick Size	35.109*	34.970*
	(1.67)	(1.67)
Session	-0.381***	-0.370***
	(37.9)	(35.9)
Broker ID Transparency Dummy	0.222***	0.227***
	(5.11)	(5.23)
Broker ID*Session Interaction	0.139***	0.140***
	(14.07)	(14.09)
Stock Fixed Effects	Yes	Yes
Day-of-week Fixed Effects	Yes	No
Adj R-Square	30.86	30.73
N	151,527	151,527
Panel B: Quintile 1 (Lowest Volatility)		
Intercept	8.201***	8.357***
	(81.57)	(82.25)
Trend	-0.001	-0.001
	(1.15)	(1.23)
VWAP Rel Tick Size	6.566	6.373
	(0.16)	(0.16)
Session	-0.255***	-0.227***
	(12.2)	(11.1)
Broker ID Transparency Dummy	0.500***	0.507***
	(5.47)	(5.54)
Broker ID*Session Interaction	0.091***	0.090***
	(4.26)	(4.22)
Stock Fixed Effects	Yes	Yes
Day-of-week Fixed Effects	Yes	No
Adj R-Square	40.82	40.61
N	31,021	31,021

	Trading Volume	
	Model 1	**Model 2**
Panel C: Quintile 3		
Intercept	8.498***	8.540***
	(72.81)	(72.89)
Trend	0.000	0.000
	(0.35)	(0.32)
VWAP Rel Tick Size	48.087	48.175
	(0.93)	(0.93)
Session	-0.379***	-0.371***
	(18.9)	(18.6)
Broker ID Transparency Dummy	0.321***	0.324***
	(3.28)	(3.31)
Broker ID*Session Interaction	0.145***	0.145***
	(6.19)	(6.20)
Stock Fixed Effects	Yes	Yes
Day-of-week Fixed Effects	Yes	No
Adj R-Square	21.53	21.46
N	30,525	30,525
Panel D: Quintile 5 (Highest Volatility)		
Intercept	7.841***	7.826***
	(41.00)	(40.92)
Trend	0.001	0.001
	(0.95)	(0.92)
VWAP Rel Tick Size	-6.758	-6.996
	(0.11)	(0.11)
Session	-0.501***	-0.504***
	(30.3)	(30.7)
Broker ID Transparency Dummy	-0.179*	-0.175
	(1.68)	(1.64)
Broker ID*Session Interaction	0.225***	0.227***
	(10.80)	(10.88)
Stock Fixed Effects	Yes	Yes
Day-of-week Fixed Effects	Yes	No
Adj R-Square	27.16	27.03
N	29,508	29,508

Table 5: Univariate analysis of Spreads for Buyer-Initiated Trades on the KRX

This table reports the statistical summary of the changes in the mean and median of effective spreads and realized spreads after 10 trades on the Korean Stock Exchange for the full sample of 248 stocks and for subsamples stratified by daily range-based volatility. The columns '*Diff*' measure changes in the relative effective spread and the relative realized spread after 10 trades for buyer-initiated trades from the pre-period to the post-period. The table presents the results of parametric *t*-tests and non-parametric Wilcoxon signed-rank tests to examine whether the means and medians change after the disclosure of broker ID. The *t*-Value and *Wil*-Value columns report the *t*-test and the Wilcoxon test statistics. All measures are estimated separately for morning and afternoon sessions. "*Nobs*" is the number of observations. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

		Mean				**Median**				**Nobs**	
Quintile	**Session**	**pre-period**	**post-period**	**Diff**	***t*-Value**	**pre-period**	**post-period**	**Diff**	***Wil*-Value**	**pre-period**	**post-period**
Panel A: Effective Spreads (basis points)											
Full Sample	Morning	38.13	41.59	3.46***	70.08	32.36	35.09	2.73***	75.68	593,918	1,050,482
	Afternoon	31.01	33.99	2.98***	66.46	28.17	30.21	2.04***	63.98	354,101	671,312
Quintile 1 (Lowest Volatility)	Morning	30.80	34.59	3.79***	41.74	27.40	29.85	2.45***	43.96	106,169	237,757
	Afternoon	25.16	28.47	3.31***	40.81	22.78	25.54	2.76***	37.04	70,360	165,798
Quintile 2	Morning	37.13	42.48	5.35***	50.34	33.44	38.02	4.58***	52.16	107,891	196,979
	Afternoon	30.74	35.03	4.29***	44.87	29.50	33.67	4.17***	42.26	65,011	125,459
Quintile 3	Morning	39.43	42.09	2.66***	24.59	34.36	34.36	0.00	19.43	116,140	214,193
	Afternoon	32.45	34.68	2.23***	23.34	29.76	30.96	1.20***	19.60	66,755	135,603
Quintile 4	Morning	41.50	46.11	4.61***	37.47	34.84	37.78	2.93***	41.93	117,943	192,638
	Afternoon	33.62	37.37	3.75***	34.35	30.58	32.57	1.99***	32.23	68,586	117,241
Quintile 5 (Highest Volatility)	Morning	40.46	44.05	3.59***	31.26	32.36	35.84	3.48***	38.00	145,775	208,915
	Afternoon	32.88	36.32	3.44***	30.62	27.55	30.77	3.22***	33.83	83,389	127,211
Panel B: Realized Spreads (basis points)											
Full Sample	Morning	20.17	20.66	0.49**	2.55	27.05	28.01	0.97	0.46	593,918	1,050,482
	Afternoon	23.61	19.70	-3.91***	18.31	27.70	25.97	-1.73***	20.96	354,101	671,312
Quintile 1 (Lowest Volatility)	Morning	16.93	16.12	-0.81**	2.44	23.64	23.53	-0.11***	3.69	106,169	237,757
	Afternoon	19.16	16.33	-2.83***	8.20	23.20	21.73	-1.47***	10.26	70,360	165,798
Quintile 2	Morning	17.83	19.32	1.49***	3.52	28.41	30.21	1.80**	2.39	107,891	196,979
	Afternoon	24.87	20.70	-4.17***	9.08	30.14	27.55	-2.59***	10.29	65,011	125,459
Quintile 3	Morning	19.58	20.92	1.34***	3.07	27.10	28.99	1.89	1.54	116,140	214,193
	Afternoon	23.55	19.17	-4.38***	8.83	29.46	27.62	-1.83***	10.73	66,755	135,603
Quintile 4	Morning	22.70	23.49	0.79*	1.66	29.59	30.58	1.00	0.19	117,943	192,638
	Afternoon	24.05	21.68	-2.36***	4.36	29.50	28.20	-1.30***	5.33	68,586	117,241
Quintile 5 (Highest Volatility)	Morning	22.69	24.22	1.53***	3.34	26.35	29.33	2.98***	3.30	145,775	208,915
	Afternoon	26.08	21.85	-4.22***	7.96	27.23	27.10	-0.13***	7.83	83,389	127,211

Table 6: Univariate Analysis of Spreads for Seller-initiated Trades on the KRX

This table reports the statistical summary of the changes in mean and median relative effective spreads and the relative realized spread after 10 trades on the Korean Stock Exchange for the full sample of 248 stocks and for subsamples stratified by daily high-low volatility. Other notations are defined in Table 5. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

		Mean				Median				Nobs	
Quintile	**Session**	**pre-period**	**post-period**	**Diff**	***t-* Value**	**pre-period**	**post-period**	**Diff**	***Wil* -Value**	**pre-period**	**post-period**
Panel A: Effective Spreads (basis points)											
Full Sample	Morning	38.14	43.05	4.91***	101.27	32.79	36.10	3.31***	100.45	625,491	1,081,143
	Afternoon	30.34	34.93	4.60***	111.80	28.33	31.15	2.82***	96.96	384,647	705,168
Quintile 1 (Lowest Volatility)	Morning	31.55	35.44	3.88***	47.59	28.49	30.96	2.47***	48.76	135,730	252,238
	Afternoon	25.30	29.22	3.92***	58.10	23.31	26.86	3.55***	52.32	91,292	179,778
Quintile 2	Morning	38.09	43.52	5.42***	51.54	34.36	38.61	4.25***	52.88	118,199	208,867
	Afternoon	30.81	35.75	4.94***	54.79	30.21	34.60	4.39***	47.30	74,454	135,133
Quintile 3	Morning	39.80	43.95	4.15***	37.91	35.09	35.09	0.00	25.48	117,355	218,889
	Afternoon	32.05	35.88	3.83***	41.23	30.21	31.75	1.53***	28.42	71,095	140,500
Quintile 4	Morning	41.32	48.05	6.73***	54.41	35.09	39.53	4.44***	57.84	118,351	194,627
	Afternoon	32.46	38.98	6.52***	61.86	30.21	33.90	3.69***	55.20	69,621	121,145
Quintile 5 (Highest Volatility)	Morning	40.55	46.22	5.67***	47.47	33.11	37.45	4.34***	51.22	135,856	206,522
	Afternoon	32.31	37.22	4.90***	46.53	27.70	31.95	4.25***	43.42	78,185	128,612
Panel B: Realized Spreads (basis points)											
Full Sample	Morning	18.74	20.17	1.43***	7.66	22.34	24.21	1.88***	8.52	625,491	1,081,143
	Afternoon	7.09	12.94	5.85***	29.47	13.25	18.66	5.41***	31.74	384,647	705,168
Quintile 1 (Lowest Volatility)	Morning	17.24	18.94	1.69***	5.84	20.18	22.08	1.89***	7.01	135,730	252,238
	Afternoon	9.83	13.48	3.65***	12.31	16.05	18.28	2.23***	14.74	91,292	179,778
Quintile 2	Morning	18.97	20.29	1.32***	3.28	24.32	24.75	0.44***	3.31	118,199	208,867
	Afternoon	6.64	11.26	4.63***	11.07	15.06	18.60	3.54***	10.76	74,454	135,133
Quintile 3	Morning	18.08	19.50	1.42***	3.28	22.37	25.06	2.69***	3.47	117,355	218,889
	Afternoon	5.07	12.64	7.58***	16.22	8.53	20.17	11.65***	17.72	71,095	140,500
Quintile 4	Morning	18.51	20.68	2.17***	4.55	23.98	25.84	1.86***	4.97	118,351	194,627
	Afternoon	6.51	14.50	7.98***	15.11	11.04	21.32	10.28***	16.66	69,621	121,145
Quintile 5 (Highest Volatility)	Morning	20.80	21.77	0.97**	2.02	22.99	24.81	1.83	1.49	135,856	206,522
	Afternoon	6.68	12.81	6.13***	11.46	10.41	17.36	6.96***	11.12	78,185	128,612

Table 7: Multivariate analysis of effective spreads, realized spreads and market impact for buyer-initiated trades on the KRX

This table reports the results of regression of the form for buyer-initiated trades:

$$S\_M_{it} = \alpha + \beta_1 Trend_{it} + \beta_2 Rel\_TkSize_{it} + \beta_3 Ln(Trade\_Size_{it}) + \beta_4 Brok_{it} \times \left[Ln(Trade\_Size_{it}) - \mu_{tradesize} \right] +$$
$$+ \beta_5 Session_{it} + \beta_6 Brok_{it} + \beta Brok_{it} * Session_{it} + \sum_{i=2}^{i=n} \gamma_i D_i + \sum_{k=1}^{i=5} \theta_k Weekday_k + \varepsilon_{it},$$

where S_M_{it} is, alternatively, the relative effective spread, realized spread or the market impact for stock *i* at time *t*; $Ln(Trade\_Size_{it})$ is the logarithm of trade size for stock *i* at time *t*; and $\mu_{tradesize}$ is the mean of the logarithm of trade size for the full large trade sample and individual quintiles in corresponding regressions of S_M_{it}. Rel_TkSize_{it} is the minimum tick size relative to price; the remaining variables are defined in Table 4. The table contains the stock fixed effect results of the regression for the full sample and for the five individual volatility-stratified quintiles. The results with and without day-of-week fixed effects are presented in Models 1 and 2, respectively. Standard errors are clustered by stocks and, as a result, robust to both heteroskedasticity and correlation within stocks. *, **, and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

	Effective Spreads		Market Impact		Realized Spreads	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
Panel A: Full sample						
Intercept	41.841***	41.349***	-20.339***	-15.662***	62.180***	57.010***
	(30.52)	(30.47)	(8.50)	(6.53)	(25.21)	(23.22)
Trend	-0.018***	-0.018***	-0.040***	-0.040***	0.022***	0.022***
	(7.64)	(7.66)	(11.5)	(11.6)	(7.73)	(7.89)
Relative Tick Size	3,963***	3,962***	2,246***	2,240***	1,717***	1,722***
	(18.23)	(18.24)	(5.93)	(5.89)	(5.07)	(5.08)
Log Trade Size	-0.619***	-0.616***	1.904***	1.870***	-2.524***	-2.486***
	(9.78)	(9.74)	(14.77)	(14.46)	(18.6)	(18.3)
Broker ID*Trade Size	0.225**	0.224**	1.197***	1.211***	-0.972***	-0.987***
	(2.44)	(2.44)	(7.46)	(7.53)	(-5.75)	(-5.83)
Session	-6.276***	-6.341***	-10.606***	-9.994***	4.330***	3.654***
	(29.9)	(30.5)	(19.1)	(18.1)	(8.38)	(7.13)
Broker ID	6.932***	6.957***	11.158***	11.073***	-4.226***	-4.116***
	(13.51)	(13.57)	(14.30)	(14.13)	(-6.26)	(-6.08)
Broker ID*Session	-0.479**	-0.495**	3.579***	3.737***	-4.058***	-4.232***
	(2.26)	(2.35)	(6.02)	(6.28)	(6.97)	(7.27)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week Fixed Effects	Yes	No	Yes	No	Yes	No
Adj R-Square	11.38	11.37	0.61	0.58	0.42	0.39
N	2,669,813	2,669,813	2,669,813	2,669,813	2,669,813	2,669,813
Panel B: Quintile 1 (Lowest Volatility)						
Intercept	35.258***	34.593***	-6.894**	-5.725*	42.152***	40.318***
	(16.92)	(16.91)	(-2.29)	(-1.84)	(14.02)	(13.63)
Trend	-0.006	-0.006	-0.021***	-0.021***	0.015***	0.015***
	(1.40)	(1.40)	(3.85)	(3.87)	(3.32)	(3.34)
Relative Tick Size	5,231***	5,231***	2,057***	2,061***	3,175***	3,170***
	(15.97)	(15.96)	(4.40)	(4.41)	(8.36)	(8.36)
Log Trade Size	-0.249**	-0.247**	1.669***	1.667***	-1.917***	-1.913***
	(2.31)	(2.30)	(9.58)	(9.47)	(10.5)	(10.4)
Broker ID*Trade Size	0.349*	0.348*	1.019***	1.020***	-0.671**	-0.672**
	(1.93)	(1.94)	(4.27)	(4.26)	(2.47)	(2.47)
Session	-4.754***	-4.839***	-7.560***	-7.407***	2.805**	2.568**
	(10.9)	(11.2)	(6.97)	(7.01)	(2.58)	(2.45)
Broker ID	6.183***	6.207***	9.939***	9.896***	-3.756***	-3.689***
	(6.35)	(6.38)	(7.47)	(7.46)	(3.58)	(3.51)
Broker ID*Session	-0.578*	-0.599*	1.362	1.389	-1.940*	-1.988**
	(1.84)	(1.92)	(1.37)	(1.39)	(2.00)	(2.04)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week Fixed Effects	Yes	No	Yes	No	Yes	No
Adj R-Square	16.34	16.33	0.95	0.94	0.49	0.48

	Effective Spreads		Market Impact		Realized Spreads	
	Model 1	**Model 2**	**Model 1**	**Model 2**	**Model 1**	**Model 2**
N	580,084	580,084	580,084	580,084	580,084	580,084
Panel C: Quintile 3						
Intercept	51.363***	51.343***	-13.551**	-9.182	64.914***	60.526***
	(19.34)	(19.04)	(2.24)	(1.52)	(11.67)	(10.59)
Trend	-0.017***	-0.017***	-0.039***	-0.039***	0.022***	0.022***
	(3.45)	(3.50)	(4.61)	(4.59)	(3.50)	(3.44)
Relative Tick Size	3,722***	3,717***	3,483***	3,474***	240	242
	(8.49)	(8.51)	(3.01)	(3.00)	(0.23)	(0.23)
Log Trade Size	-0.747***	-0.748***	1.858***	1.817***	-2.606***	-2.565***
	(5.27)	(5.26)	(6.45)	(6.28)	(9.16)	(8.97)
Broker ID*Trade Size	0.113	0.115	1.560***	1.578***	-1.447***	-1.463***
	(0.47)	(0.48)	(3.85)	(3.89)	(3.62)	(3.66)
Session	-6.487***	-6.494***	-10.931***	-10.354***	4.444***	3.860***
	(17.7)	(17.9)	(10.1)	(9.61)	(4.20)	(3.72)
Broker ID	5.633***	5.683***	9.859***	9.710***	-4.226**	-4.027**
	(4.74)	(4.80)	(4.75)	(4.64)	(2.60)	(2.45)
Broker ID*Session	-0.604	-0.599	4.698***	4.848***	-5.302***	-5.447***
	(1.29)	(1.28)	(3.95)	(4.05)	(4.44)	(4.53)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week Fixed Effects	Yes	No	Yes	No	Yes	No
Adj R-Square	7.29	7.27	0.58	0.55	0.37	0.34
N	532,691	532,691	532,691	532,691	532,691	532,691
Panel D: Quintile 5 (Highest Volatility)						
Intercept	42.362***	41.928***	-30.834***	-25.654***	73.195***	67.582***
	(12.71)	(12.94)	(5.18)	(4.30)	(10.91)	(10.05)
Trend	-0.026***	-0.026***	-0.049***	-0.049***	0.023***	0.023***
	(4.97)	(4.99)	(5.69)	(5.67)	(3.24)	(3.25)
Relative Tick Size	4,015***	4,013***	3,104**	3,111**	911	902
	(7.65)	(7.64)	(2.47)	(2.46)	(0.75)	(0.74)
Log Trade Size	-0.570***	-0.566***	2.496***	2.455***	-3.065***	-3.021***
	(3.81)	(3.80)	(7.81)	(7.66)	(8.92)	(8.76)
Broker ID*Trade Size	0.008	0.008	0.481	0.497	-0.474	-0.489
	(0.04)	(0.04)	(1.09)	(1.12)	(0.93)	(0.96)
Session	-7.192***	-7.251***	-11.083***	-10.406***	3.891***	3.154***
	(14.8)	(15.3)	(9.36)	(9.05)	(3.45)	(2.89)
Broker ID	6.933***	6.949***	10.671***	10.564***	-3.737**	-3.615**
	(5.46)	(5.47)	(5.87)	(5.80)	(2.43)	(2.34)
Broker ID*Session	0.036	0.020	5.135***	5.435***	-5.099***	-5.415***
	(0.06)	(0.04)	(3.37)	(3.55)	(3.46)	(3.65)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week Fixed Effects	Yes	No	Yes	No	Yes	No
Adj R-Square	8.28	8.27	0.46	0.40	0.35	0.28
N	565,290	565,290	565,290	565,290	565,290	565,290

Table 8: Multivariate analysis for effective spreads, realized spreads and market impact for seller-initiated trades on the KRX

This table reports the results of regression of the form for seller-initiated trades:

$$S\_M_{it} = \alpha + \beta_1 Trend_{it} + \beta_2 Rel\_TkSize_{it} + \beta_3 Ln(Trade\_Size_{it}) + \beta_4 Brok_{it} \times \left[Ln(Trade\_Size_{it}) - \mu_{tradesize} \right] +$$
$$+ \beta_5 Session_{it} + \beta_6 Brok_{it} + \beta Brok_{it} * Session_{it} + \sum_{i=2}^{i=n} \gamma_i D_i + \sum_{k=1}^{i=5} \theta_k Weekday_k + \varepsilon_{it},$$

where S_M_{it} is alternatively the relative effective spread, realized spread or the market impact for stock *i* at time *t*; $Ln(Trade\_Size_{it})$ is the logarithm of trade size for stock *i* at time *t*; and $\mu_{tradesize}$ is the mean of the logarithm of trade size for the full large trade sample and individual quintiles in corresponding regressions of S_M_{it}. The remaining variables are defined in Table 7. The table contains the stock fixed effect results of the regression for the full sample and for the five individual volatility-stratified quintiles. Standard errors are clustered by stocks and, as a result, robust to both heteroskedasticity and correlation within stocks. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

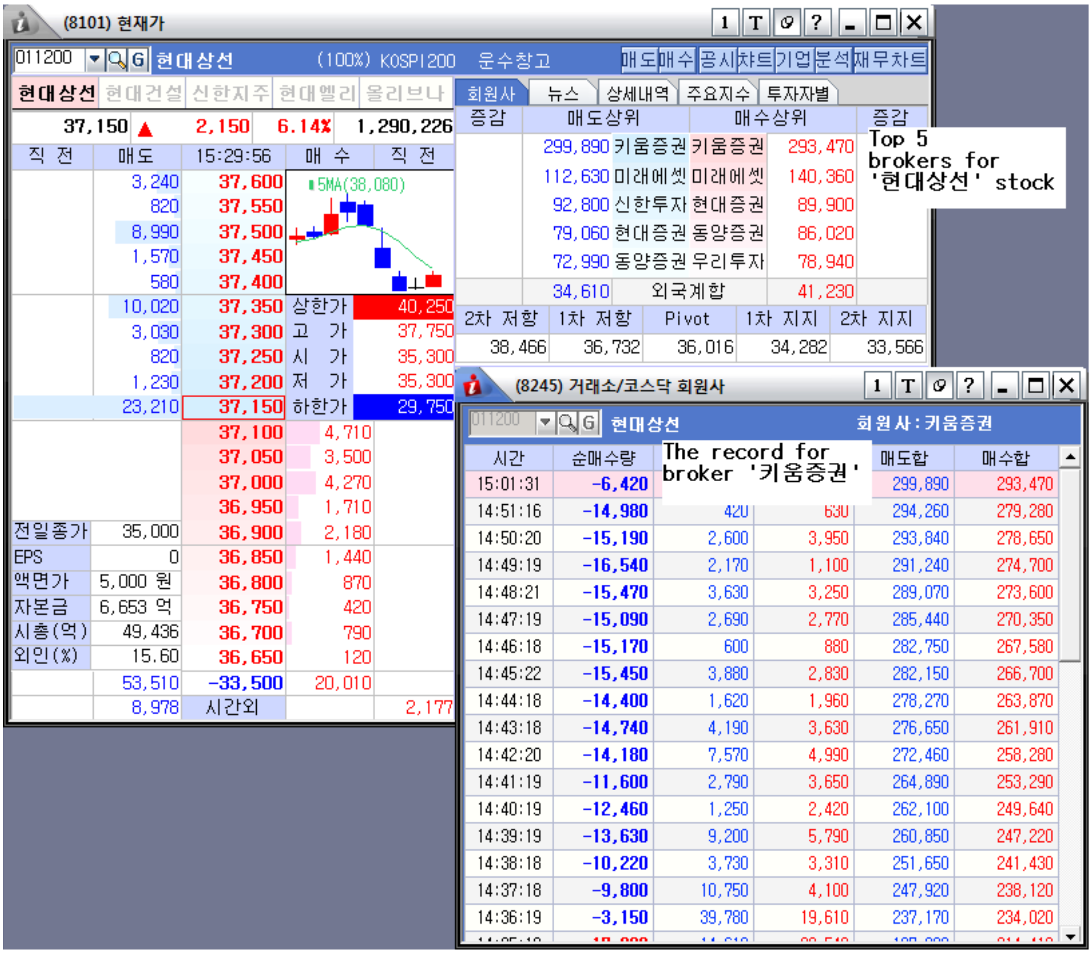
	Effective Spreads		Market Impacts		Realized Spreads	
	Model 1	Model 2	Model 1	Model 2	Model 1	Model 2
Panel A: Full sample						
Intercept	43.665***	44.284***	13.684***	12.371***	29.981***	31.913***
	(31.17)	(31.44)	(5.81)	(5.42)	(13.84)	(15.13)
Trend	-0.010***	-0.010***	0.022***	0.022***	-0.032***	-0.032***
	(3.81)	(3.80)	(6.70)	(6.85)	(9.69)	(9.78)
Relative Tick Size	4,143***	4,143***	2,165***	2,177***	1,978***	1,966***
	(16.00)	(16.01)	(8.82)	(8.89)	(6.09)	(6.04)
Log Trade Size	-0.656***	-0.660***	-0.458***	-0.450***	-0.198	-0.209*
	(10.3)	(10.4)	(3.48)	(3.42)	(1.59)	(1.69)
Broker ID*Trade Size	0.614***	0.616***	0.009	-0.005	0.605***	0.621***
	(6.55)	(6.58)	(0.07)	(0.04)	(4.34)	(4.45)
Session	-7.001***	-6.914***	4.597***	4.470***	-11.598***	-11.384***
	(30.3)	(30.6)	(9.76)	(9.58)	(22.2)	(21.9)
Broker ID	7.052***	7.027***	-0.023	-0.054	7.075***	7.081***
	(12.51)	(12.52)	(-0.04)	(-0.08)	(9.95)	(9.94)
Broker ID*Session	-0.432**	-0.419**	-4.664***	-4.767***	4.232***	4.348***
	(2.05)	(1.99)	(8.53)	(8.72)	(7.70)	(7.91)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week Fixed Effects	Yes	No	Yes	No	Yes	No
Adj R-Square	12.51	12.50	0.46	0.45	0.39	0.38
N	2,796,449	2,796,449	2,796,449	2,796,449	2,796,449	2,796,449
Panel B: Quintile 1 (Lowest Volatility)						
Intercept	35.521***	35.705***	0.470	0.893	35.051***	34.812***
	(20.48)	(20.60)	(0.17)	(0.32)	(12.22)	(12.01)
Trend	0.003	0.003	0.020***	0.020***	-0.017***	-0.017***
	(0.72)	(0.73)	(3.82)	(3.82)	(3.40)	(3.38)
Relative Tick Size	5,568.533***	5,566.426***	2,422.298***	2,420.393***	3,146.235***	3,146.034***
	(15.67)	(15.66)	(6.33)	(6.31)	(6.29)	(6.28)
Log Trade Size	-0.383***	-0.385***	0.866***	0.864***	-1.249***	-1.249***
	(4.40)	(4.41)	(4.97)	(4.95)	(6.74)	(6.73)
Broker ID*Trade Size	0.344**	0.347**	-0.453**	-0.450**	0.797***	0.796***
	(2.55)	(2.57)	(2.49)	(2.48)	(3.65)	(3.65)
Session	-5.439***	-5.415***	1.626*	1.682**	-7.065***	-7.097***
	(12.3)	(12.6)	(1.96)	(2.07)	(8.14)	(8.17)
Broker ID	4.367***	4.358***	-0.629	-0.616	4.996***	4.974***
	(4.84)	(4.84)	(0.60)	(0.58)	(4.51)	(4.49)
Broker ID*Session	-0.180	-0.175	-2.043**	-2.028**	1.863**	1.853**
	(0.61)	(0.60)	(2.34)	(2.33)	(2.20)	(2.19)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week Fixed Effects	Yes	No	Yes	No	Yes	No
Adj R-Square	19.34	19.33	0.62	0.62	0.56	0.56
N	659,038	659,038	659,038	659,038	659,038	659,038

	Effective Spreads		Market Impacts		Realized Spreads	
	Model 1	**Model 2**	**Model 1**	**Model 1**	**Model 2**	**Model 1**
Panel C: Quintile 3						
Intercept	50.469***	51.513***	36.150***	35.880***	14.319***	15.632***
	(18.59)	(19.02)	(8.86)	(8.37)	(3.07)	(3.32)
Trend	-0.006	-0.006	0.025***	0.025***	-0.031***	-0.031***
	(1.10)	(1.07)	(3.43)	(3.40)	(3.86)	(3.81)
Relative Tick Size	4,189***	4,1939***	2,2379***	2,2529***	1,952**	1,941**
	(8.23)	(8.26)	(4.13)	(4.14)	(2.51)	(2.49)
Log Trade Size	-0.875***	-0.882***	-0.961***	-0.959***	0.086	0.077
	(5.87)	(5.90)	(4.08)	(4.03)	(0.35)	(0.31)
Broker ID*Trade Size	0.847***	0.852***	0.112	0.102	0.736**	0.749**
	(3.50)	(3.52)	(0.39)	(0.36)	(2.19)	(2.22)
Session	-7.449***	-7.294***	5.558***	5.531***	-13.007***	-12.825***
	(16.8)	(17.0)	(6.68)	(6.63)	(14.3)	(14.0)
Broker ID	5.932***	5.874***	-1.165	-1.147	7.097***	7.021***
	(4.63)	(4.61)	(0.77)	(0.76)	(3.96)	(3.91)
Broker ID*Session	-0.408	-0.383	-6.355***	-6.434***	5.947***	6.052***
	(0.83)	(0.77)	(6.13)	(6.27)	(5.56)	(5.73)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week Fixed Effects	Yes	No	Yes	No	Yes	No
Adj R-Square	7.91	7.88	0.30	0.28	0.37	0.34
N	547,839	547,839	547,839	547,839	547,839	547,839
Panel D: Quintile 5 (Highest Volatility)						
Intercept	41.401***	42.327***	34.878***	34.291***	6.523	8.036
	(10.78)	(11.23)	(5.61)	(5.71)	(1.08)	(1.33)
Trend	-0.017***	-0.017***	0.031***	0.032***	-0.049***	-0.050***
	(2.77)	(2.77)	(3.32)	(3.48)	(5.25)	(5.40)
Relative Tick Size	4,242***	4,246***	1,162	1,183	3,080***	3,063***
	(6.73)	(6.73)	(1.25)	(1.29)	(3.13)	(3.13)
Log Trade Size	-0.475***	-0.483***	-1.756***	-1.765***	1.281***	1.282***
	(2.88)	(2.94)	(6.40)	(6.41)	(4.58)	(4.54)
Broker ID*Trade Size	0.710***	0.712***	0.817*	0.815*	-0.107	-0.103
	(2.88)	(2.89)	(1.91)	(1.91)	(0.29)	(0.28)
Session	-7.877***	-7.746***	5.861***	5.865***	-13.739***	-13.611***
	(14.7)	(14.9)	(4.89)	(5.07)	(11.8)	(12.0)
Broker ID	7.825***	7.803***	-0.626	-0.770	8.451***	8.573***
	(5.64)	(5.64)	(0.38)	(0.47)	(4.51)	(4.58)
Broker ID*Session	-0.731	-0.709	-5.513***	-5.705***	4.782***	4.996***
	(1.24)	(1.21)	(3.92)	(4.06)	(3.54)	(3.69)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week Fixed Effects	Yes	No	Yes	No	Yes	No
Adj R-Square	8.82	8.81	0.26	0.22	0.47	0.42
N	549,175	549,175	549,175	549,175	549,175	549,175

Appendices

Appendix 1: Screen-shot of broker ID information available on the KRX

This screen-shot shows the information available to all investors trading on the KRX. The top right screen shows the top five selling brokers in the blue column and the top five buying brokers in the red column in descending order for stock KS.011200. (Hyundai Merchant Marine Co). The exchange allows investors to view a detailed record of each of the top broker's trades in each stock if they are one of the top five brokers on either side of the market in that particular stock. The bottom right-hand-side screen provides an example of the display of all individual trades, blue sales and red buys for one of the top five selling brokers. This screen reports the cumulative buy and sell volume and the difference between the two at the time of the screenshot. Specifically, the second column shows the net aggregate trade amount at the time stated in the first column. The third and fourth columns present incremental aggregate ask and bid amounts for the incremental time interval. The fifth and sixth columns contain cumulative ask and bid amounts during the day until the time of the screenshot. In this example, the broker has sold 6,420 more shares than they have purchased at the time of the screenshot, 15:01.



Appendix 2: Impact of the real-time disclosure of broker IDs to the public on market quality in the KRX

Following the November 25, 1996 event, the KRX took a further step toward post-trade transparency by starting to display broker IDs in real-time to the public since August 15, 1997. To provide a robustness check on the role of post-trade transparency of broker IDs, we investigate this August 1997 event. Using the same set of stocks with an extended time period, we aim to answer two critical questions: (1) Does the improvement in market efficiency following the first event continues after this further reform? (2) Is volume higher once the bias towards afternoon trading is removed with continuous disclosure?

We use variance ratio tests and a parametric test for trading volume to address the two questions, respectively. The investigated period spans from 01 January 1996 to 31 December 1998 that covers the time around the first post-trade transparency reform to make a comparison with the impact of the first broker IDs disclosure event and also to provide a robustness check for our analysis in the main part of the paper. Since the immediate time following the full disclosure event of August 1997 overlaps the Asian financial crisis 1997, we split the examined period into six windows based on the two event dates and the Asian financial crisis timeline[27]. The six windows are presented as follows:

January 1, 1996 - November 24, 1996

Anonymous Pre-period:
No broker IDs was displayed.

November 25, 1996 – July 1, 1997

Broker IDs were disclosed at the end of trading session.

July 1, 1997 – August 14, 1997

The Asian Financial Crisis starts.
Broker IDs were disclosed at the end of trading session.

August 16, 1997 – October 30, 1997

[27] The timeline of the Asian financial crisis 1997 follows a report by the International Monetary Fund (IMF). Source: http://www.pbs.org/wgbh/pages/frontline/shows/crash/etc/cron.html

Broker ID transparent in real-time to the public
November 1, 1997 – March 31, 1998

The Asian Financial Crisis deepens. Broker IDs were displayed in real-time to the public.

April 8, 1998 – December 31, 1998

The Asian Financial Crisis ended Broker IDs were displayed in real-time to the public.

The variance ratio tests described in Section 3 is used to examine whether the market continues to be informationally efficient following the real-time disclosure of broker IDs event. Appendix 2.1 reports the variance ratios and the test statistics for one-to-two day returns for a given windows. Under the random walk null hypothesis, the value of the variance ratio for 1-day to 2-day returns is one. The results show that the null hypothesis may be rejected at 1% significance levels for the anonymous pre-period with no broker IDs available to the public. The rejection of the random walk hypothesis disappears in the second investigated window Nov 25, 1996 to July 1, 1997 once market participants could observe broker IDs at the end of each trading session during the day. Naturally, these results are consistent with the findings around the first broker ID event presented in Section 3.

During the third investigated window, which is marked by the commencement of Asian financial crisis with no change in transparency of broker IDs, the KRX stocks experience negative serial correlation returns (0.899) with the significance level of 5%. The introduction of real-time disclosure of broker IDs during the crisis show a positive impact on market efficiency, which is evidenced by a statistically insignificant variance ratio for 1-day to 2-day returns for the period of August 16, 1997 to October 30, 1997. The test results over the next two time windows indicate that stock prices cease to follow a random walk once the financial crisis deepens with downgrade of South Korea sovereign debt in November and December. Once the crisis is over, the market becomes efficient with broker IDs displayed in real-time to the public. In summary, our variance ratio tests results provide evidence that the market becomes informationally efficient each time transparency is improved, in November 25, 1996 and in August 15, 1997.

Appendix 2.1: Results for variance ratios test around the two changes in displaying broker IDs on the KRX

This table reports the number of daily returns, variance ratio and t-statistics for the ratio of 1 to 2 day returns for periods impacted by transparency changes and the Asian financial crisis. *** denotes statistical significance at 1% level.

Time Period Analyzed		**Number of daily returns**	**Variance Ratio for 1- to 2-day returns**	**Heteroskedastic Robust Test Statistic**
Jan 1 ,1996 to Nov 24, 1996	Anonymous pre-period	62,197	0.949	-11.705***
Nov 25 ,1996 to July 1, 1997	Broker ID transparent end of session	42,083	1.006	1.171
July 1, 1997 to August 14, 1997	Financial Crisis starts	9,210	0.899	-8.546***
August 16, 1997 to October 30, 1997	Broker ID transparent real time	13,235	1.002	0.221
November 1, 1997 to March 31, 1998	Financial Crisis deepens	27,636	0.954	-6.907***
April 8, 1998 to December 31, 1998	Financial Crisis over	45,913	0.99	-0.803

We then examine whether there is a difference in the average number of shares traded across 248 stocks between periods with different broker ID transparency, and periods more and less impacted by the Asian financial crisis. We test the significance of the difference in trading volume between two consecutive investigated windows in a parametric *t*-test. The results are reported in Appendix 2.2. Column "Difference" measure changes in trading volume from the last time window (*t-1*) to the current time window *t*. For example: on average, the number of shares traded in the period November 15, 1996 to July 1, 1997 is 88,163 shares, which is 9,814 shares higher than in the anonymous pre-period and the difference is statistically significant at the 5% level. Examining all of the time windows, our results show that the second transparency reform does not induce more volume immediately, perhaps due to crisis impact. However, volume sharply increases when the crisis deepens (firesales) and when the economy returns to its normal state. Overall, our analysis indicate that the higher volumes are facilitated by a more transparent market.

Appendix 2.2: Univariate Analysis for trading volume around the two changes in displaying broker IDs on the KRX

This table reports the statistical summary of the changes in mean trading volume for the Korean Stock Exchange for the full sample of 248 stocks. The columns labeled '*Difference*' measure the change in trading volume between the two consecutive time periods analyzed. The table presents the results of a parametric *t*-tests to examine whether the means change after the disclosure of broker IDs at both times with and without the impact of the Asian financial crisis. *, **, *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Time Period Analyzed		**Mean Volume**	**Difference**
Jan 1 ,1996 to Nov 24, 1996	Anonymous pre-period	78,349	
Nov 25 ,1996 to July 1, 1997	Broker ID transparent end of session	88,163	9,814*
July 1, 1997 to August 14, 1997	Financial Crisis starts	82,747	-5,416
August 16, 1997 to October 30, 1997	Broker ID transparent real time	81,648	-1,099
November 1, 1997 to March 31, 1998	Financial Crisis deepens	206,335	124,687**
April 8, 1998 to December 31, 1998	Financial Crisis over	275,272	68,938**

Appendix 3: Distribution of minimum tick size as a function of the stock price in the KRX

Stock price levels (won)	Tick sizes (won)
Less than 5000	5
5000 or more to less than 10,000	10
10,000 or more to less than 50,000	50
50,000 or more to less than 100,000	100
100,000 or more to less than 500,000	500
Over 500,000	1000