Shining a Spotlight on Counterparty Identity in the World's Best-Lit Market*

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Abstract

We study the impact of post-trade broker identity disclosure on market efficiency, trading volume and bid ask spreads in a unique South Korean Korea Exchange experiment that created the World's best-lit market. Using a broad panel dataset of Korea Stock exchange listed stocks we find that simply revealing the ex-post order flow of the major brokers to the entire market improves market efficiency and increases trade volume both economically (24%) and statistically. Accounting for the variety of trade characteristics and stock liquidity levels in the sample, we measure liquidity providers' profits and information-effect component of spreads using trade-time benchmarked realized spreads and corresponding trade-time market impact. We find that both effective and realized spreads fall indicating greater competition between market makers and liquidity suppliers, and higher liquidity in the transparent period. These results suggest that transparency of counterparty identity post-trade is a viable policy for markets that wish to improve market efficiency and liquidity.

Keywords: transparency, anonymity, market efficiency, market quality

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1. Introduction

This paper is the first to examine the effect of a significant change in the trading protocol at the Korea Exchange [KRX].[1] This event gives us a unique opportunity to investigate how increased post-trade transparency of counterparty identity affects market quality; does post-trade transparency speed up information dissemination as expected based on Pagano and Roell (1996) or does it deter market participants from information acquisition, as in the least favorable of Rindi (2008) two scenarios. Starting November 25, 1996[2], the trades of the top-five brokers (cumulative buy and sell volume in each stock) were revealed to the public at the end of the morning and the afternoon trading sessions[3], while before this date the identity of brokers [broker ID] was not known to market participants. Appendix 1 shows a screenshot of how the most active broker IDs and their cumulative trade balances are presented to the public. The KRX increased transparency while other exchanges have typically altered their partially transparent markets in the opposite direction[4], which makes the Korean experiment particularly interesting. The KRX has in fact emphasized transparency as central to its business model.

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[1] The KRX in Seoul, South Korea is a result of a merger of the Korean Stock Exchange, the subject of this investigation, and the derivatives exchange in 2005.

[2] An official document from KRX confirms this date as the introduction of post-trade broker identity information.

[3] From the middle of August 1997 this information was provided to the public in real time.

[4] 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 identity of 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 June 2nd,

Our study contributes to the literature with several novel findings. First, this is the first empirical paper to examine the impact of the post-trade broker identity disclosure on market efficiency. Employing the variance ratio test (Lo and MacKinlay, 1988)[5] on two-day, ten-day, fifteen-day and twenty-day horizons returns over one-day returns, we document that previously negatively serially correlated returns at the daily level instead follow a random walk over the three longer horizons after post-trade transparent broker IDs. Our findings are supported by theoretical predictions made by Campbell, Grossman and Wang (1993) who predicted that informed trades do not result in serial correlation. Avramov, Chordia and 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 implication for exchanges indicating that any return predictability of future stock price based on today's prices is possibly simply due to an anonymous trading protocol. The transparency level is particularly important in a market dominated by uninformed noise traders as these rely on information from the order flow.

2008, NASDAQ OMX Nordic introduced post-trade anonymity on the Helsinki market and the five most heavily traded shares in Stockholm, but in April 2009 the decision regarding Stockholm was reversed and ex-post transparency 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.

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

Second, we find that trading volume increases by 24% for all stocks when the public has access to the broker identities even after controlling for the determinants of trading volume and inclusion of a trend factor. The volume of the largest and least volatile stocks increase the most (50%), while there is no change in the trading volume of the smallest and most volatile stocks. Hollifield, Miller, Sandås and Slive (2006) establish that traded volume is a natural indicator of gains from trade. While some of the traded volume is liquidity driven (often classified as noise trading) and some of the volume is information driven, 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 of current studies just include volume as a control variable in their analysis.

Third, we examine liquidity providers' profit using different intervals of trades, not calendar-time as in conventional measure to mitigate potential biases due to vastly differences in stock liquidity levels and trade rapidity since our data includes most of stocks in the KRX. We find that when broker IDs are public post-trade, the effective spread is significantly lower as a result of a large reduction in realized spreads. This is a strong indication that the higher competition between liquidity providers and a more informed order flow in transparent markets lead to lower costs of transacting per se. The effect is stronger in the low volatility stocks which are larger and where most trading interest manifests itself. By definition, the changes in effective and realized spreads must be offset by the change in market impact, see Boehmer (2005), Boehmer, Saar and Yu (2005) and Hendershott and Jones (2005).

As continuous limit order markets are becoming more dominant an understanding of the effects of transparency in this setting is important. Some theoretical models of transparency are equally relevant for limit order (order-driven) markets and can help explain our results. In Pagano and Roell (1996) price setters (who can be market makers or limit order providers) widen the bid-ask spread so as to protect themselves against an adverse selection problem potentially generated by insiders rather than to cover 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, as the more uninformed traders learn about the order flow, the better they can protect themselves against losses to insiders. Hence these models predict that more transparency is associated with higher liquidity as a consequence of lower asymmetric information.

Foucault, Moinas, and Theissen (2007) and Rindi (2008) develop models, which include informational differences between agents and where transparency allows uninformed agents to observe the order placement of the informed. Rindi's (2008) model can also be applied to form 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, ID transparency reduces the incentive to buy information and so reduces the number of informed traders. If information acquisition is sufficiently costly, it follows that ID transparency could lower the number of informed agents who enter the market and thus reduces liquidity (Rindi

(2008)). In a market where broker IDs are pre-trade anonymous such that limit orders do not reveal the identity of the liquidity provider and post-trade transparent, then any adverse impact on information acquisition should be lower compared with markets are pre-trade transparent, as information is private until it is traded on. 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 effects of a significant increase in post-trade transparency in a pure automated limit order market has not been investigated before.[6] We argue that the distinction between intermediated and order driven markets is important. Public broker identities in an order driven market allows a categorization of all market participants conditional on how informed they are about a particular security at a particular time, so that less informed participants can discover

[6] Comerton-Forde, Frino and Mollica (2005) find that the KSE introduced broker identifiers on October 25, 1999, and that "the reduction in anonymity on the KSE is associated with a decline in liquidity" with an increase in relative and effective bid ask spreads." However, the records from the Exchange show that this change actually occurred about three years earlier on the KSE and the trading protocol change in 1999 was actually for the uninvestigated KOSDAQ market, not for the larger KSE. Pham (2013) examines the later introduction of post-trade broker ID information on the far smaller KOSDAQ market to show that it lead to 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. The two Korean exchanges are the only ones to ever provide post-trade transparency to all participants. Prior to November 2005 the ASX provided pre-and post-transparency to brokers only while banning the provision of this data to their clients. In contrast to the ASX, the Toronto Stock Exchange makes display of broker identities purely voluntary. One might expect from findings in the literature adverse to broker ID transparency that if participants are given a choice that 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.

price information from the transactions of more informed participants. In contrast for an intermediated market the argument is about 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.[7] Based on the current literature, we expect that liquidity and price discovery will improve once broker IDs are reported post-trade, as the orderflow will contain more information. We expect that making broker IDs transparent only post-trade will be particularly beneficial for liquidity and price discovery, since any negative effects of revealing trader identities pre-trade are eliminated.

In summary this paper analyzes the impact of the post-trade broker identity disclosure on market efficiency, trading volume and all three components of the bid ask spread (effective spreads, realized spreads and market impact). We find that market efficiency improves, volume of trade increases, effective spreads fall indicating improved liquidity, realized spreads fall indicating higher competition between market makers, while market impact increases which we attribute to more information contained in trades.

2. Previous literature

2.1 Anonymity and transparency

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

A large body of the theoretical work on transparency is concerned with pre-trade identification of liquidity demanders in intermediated market structures with dealers, 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), and Green, Hollifield and Schürhoff (2007)). In summary this literature documents that knowing the identity of the counterparty of a trade is important for market quality. The effect is dependent on the number of dealers such that bid-ask spreads may increase if dealers' incentives to compete for order flow are reduced in a more transparent market. On the other hand, it is found that dealers' exercise substantial market power in an opaque system and hence anonymity may increase transaction costs for their customers. Since we are in this study focusing on a limit order book market, we use predictions from those models that are also applicable 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.

2.2 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) point out that markets cannot reflect all available information as there would be no reward for costly information gatherers. Pagano and Roell (1996), show that immediate trade reporting significantly improves market efficiency. We expect to observe an improvement in market efficiency as a result of increased transparency provided that private information in the Korean market is close to costless as would be expected in a liquid widely traded equities market.

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 existing 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 since transparency ameliorates the effect of information asymmetry[8], 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. Madhavan (1995), Pagano and Roell (1996), and Rindi (2008) demonstrate these efficiency gains analytically. 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

[8] 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 the asset. Thus, it models partial information acquisition and finds empirical support for the greater role for 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 rather the broker identity of the new component of typically a 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 addresses empirically this important extension of Foucault, Moinas and Theissen (2007).

market efficiency. We expect that the informational efficiency of stock prices improves with the introduction of post-trade transparent broker identities.

2.3 Post-trade Transparency and Trading Activity

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 trade are dependent on the valuations for the security they trade. Using observable orderflow and payoffs from alternative order submission strategies that the traders could have made, Hollifield, Miller, Sandås and Slive (2006) work out the gains from trade. Hence this could be interpreted as empirical evidence that traders indeed benefit from trade. Trading volume is often decomposed into informed and uniformed trading. Wang (1994) and Karpoff (1997) show that volume is positively correlated with absolute returns and that informational and noninformational trading lead to different dynamic relations between trading volume and stock returns. An increase in informed volume means more rapid price discovery since informed volume is expected to move prices while increase in uninformed volume would lead to improved liquidity since uninformed volume cushions the effect of informed trades on stock price. Johnson (2008) points out that in the classic Kyle (1985) model of asymmetric information informed demand moves proportional 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 have simultaneously absolutely more informed trade volume and, at the same time, are more liquid. Ex-post transparency means that uninformed traders are more likely to know their counterparty and, because of more immediate price discovery, face less informational asymmetry. Higher uninformed demand enables more informed trading, giving rise to both higher trade volume and liquidity.

2.4 Post-trade Transparency and Liquidity

Flood, Huisman, Koedijk and Mahieu (1999) 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 happens when transparency increases. a) As uninformed traders can discover price information from the trades executed by informed traders, an overall decrease in average transaction costs occurs as every transaction contains more information. b) The increase in transaction information significantly enhances the price discovery process. 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 lower transaction costs in the longer run as more information will be disseminated with each transaction when the counterparties are publicly identified.

3. Data and Descriptive Statistics

The initial dataset consists of 1,885 companies, which are all the available common stocks in the KSE for the period from February 1, 1996 to November 30, 1997, 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 sizes.

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 30, 1997[9]. Our final sample includes 236 actively traded stocks.

In keeping 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 post the event and further split the event window into two 173-trading-day periods: Pre- and Post- periods. The Pre-period is from March 21, 1996–September 29, 1996 and the Post-period is from December 19, 1996–July 30, 1997 and is chosen so as not to overlap with any other significant design changes.

We implement analysis for capturing the changes in trading volume using intraday data that includes only transactions occurring at each time-stamp (detailed to milliseconds). We

[9] 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 was taken in effect in mid-August 1997, we exclude August 1997 onward from our sample.

aggregate multiple trades occurring at the same time (stamped to millisecond) in the same direction into a single trade, for which the trade size becomes the aggregated total of value of the individual aggregated trades, and price becomes the volume-weighted average price, following Gouriéroux, Jasiak and Le Fol (1999).

We also create a dataset of large trades to examine the changes in liquidity and the information-related price impact of transactions. Based on the average trade value per stock over the Pre-period, we delete trades whose values are below these stock specific averages from the dataset to form this intraday large trade dataset. All analyses of liquidity proxies in the paper are on the large trade dataset. Both the full and the large trade samples are stratified by daily range-based volatility[10] to control for potentially different impact of the market design change on stocks with different volatility. When we stratify the large trade sample into quintiles we include the same stocks as in the original dataset.

Before we go into the details of market efficiency, volume and liquidity changes around the event, it is important consider the general development of the Korea Exchange and its environment during the investigated period and beyond. Figure 1 shows the year-by-year market capitalization in Korean Won, the number of listed domestic companies and concentration of market capitalization in the top 5% of companies during the 1995-2013 period. The market capitalization of Korean shares was relatively stable during the investigated event period from March 21, 1996 to July 30, 1997 in the early part displayed in Figure 1, and most of the growth

[10] 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 highest and lowest transaction price.

occurs after 2004. There was a drop due to the Asian financial crisis leading to a lower market capitalization at the end of 1997, from which the market recovered by end of 1998.

A more detailed look at the monthly statistics for the 1996 to 1997 period provided by the World Federation of Stock Exchanges[11] reveals that the investigated period precedes a significant fall in market capitalization due to the Asian crisis, widely reported to have an effect on the market mostly during the period September to November 1997. There was very little change in the number of listed companies during the investigated period with a decline from 727 to 769, while the concentration of capitalization within the top 5 % of companies rose from 47 to 62 percent. Figure 2 shows the day-by-day value traded during the investigated period March 21, 1996 to July 30, 1997. This figure indicates that there was no significant secular trend in trading activity during this period. In fact the first and the second half of the sample period are balanced. To capture any remaining trend in the investigated variables we include a trend variable in our regression models.

<Insert Figure 1 and Figure 2 about here>

4. The effect of the 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

[11] For space reasons we do not report these monthly statistics obtained from the World Federation of Stock Exchanges.

(1988). This test exploits the underlying property of the random walk process, where the 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[12]. 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 a price series' deviation 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 in the Pre-period and the 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 returns variance ratios. These are robust to heteroskedasticity and consistent with Lo and MacKinlay (1988).

[12] We estimate how closely stock prices follow a random walk using a simple specification test based on variance estimators stretching from a two-day; ten-day; fifteen-day and twenty-day horizons. Since the transparency change only affects the market when the limit-order book is open, we derive each $one-day$ returns 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.

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

The Post-period with public broker ID shows the opposite results for the three longer time horizons. The absolute level of the z* statistic ranges from 0.09 to 1.77, reducing drastically from the anonymity to the transparency period, suggesting that we cannot reject the null hypothesis of random walk at the usual significance levels for the full sample (see Panel 2 – Panel 4). However, we do not observe an improvement in market efficiency for the short-term horizon of up to two day following the revelation of broker IDs (see Panel A). This is to be expected as it takes formerly uninformed noise traders in the anonymous regime a relatively short while, here up to two days, to either copycat informed traders or learn in the now informationally rich regime. These results suggest a remarkable improvement in market efficiency after the introduction of transparency in the market for the long-term measures.

<Insert Table 1 about here>

In Table 2 we report variance ratio test results for sub-samples based on volatility using the various intervals: (1, 2); (1, 10); (1, 15) and (1, 20) days. The results of the impact of ID disclosure on market efficiency are consistent in most of the time horizons. The tests results in

Panel A and Panel B show no statistical evidence that the variance ratios in all of the four interval combinations are significantly different from unity for the two least volatility-sorted quintiles in both the periods. These findings suggest that prices of these low volatile stocks follow a random walk regardless of the degree of market transparency.

However, looking at the test statistics in Panel C, D and E in the Pre-period columns, we observe the variance ratios of 1-day to 2-days, 1-day to 10-days, 1-day to 15-days and 1-day to 20-days returns are significantly different from one. The evidence indicates a strong rejection of the null hypothesis of random walk in the three most volatile stock quintiles when traders are unable to identify their counterparties. The test statistics of these three quintiles fall outside of the interval of ±1.96 in the Post-period for the three longest time horizons (see the last three columns in Panel C, D and E), indicating that we cannot reject the random walk for all of these volatility quintiles at the usual significance levels with transparent broker IDs. The 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 provide evidence that the market is inefficient during the period when broker IDs are hidden, and becomes efficient during the post-period when the public can access to broker IDs. This argument is strongly supported in the long-term horizons, but also observable in short-term variance ratio estimations. 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. These results are to be expected as large capitalization firms are more widely followed and expected to have higher price efficiency from the outset.

5. The effect of the post-trade transparency on Volume

5.1 Univariate Tests

Traded volume is computed as the sum of number of shares traded during the day excluding opening trade volume. We examine whether there is statistically significant difference in means and medians of trading volume between the Pre- and Post-event periods using Student *t* and non-parametric Wilcoxon sign-rank tests, respectively.

Table 3 reports the difference between mean and median traded volume for the full 236 stocks and the volatility-stratified quintiles surrounding the event of November 25, 1996. All figures document highly significant increase in trading activity, with the exception of the most volatile stocks, after displaying the broker identities to the public.

<Insert Table 3 about here>

We observe the largest increase of 39% in the average of volume traded for the least volatile quintile of stocks (see Panel B). These are typically the largest stocks. We document that the greater the volatility, the less the trading volume rise in the more transparent market. There is no significant change in trading volume for the most volatile quintile of stocks (see Panel D), suggesting these shares were unaffected by the introduction of public broker IDs. Overall, the increase in the number of shares traded of the top four quintiles leads to a remarkable economically and statistically significant improvement in the trading activity of 21% for the whole market. Examining the Wilcoxon tests' results, we also find the same patterns in all of the quintiles and the full sample.

5.2 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 prevent 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[13] for each stock as a proxy for the price level. The daily relative tick size per stock is the minimum absolute tick size scaled by the value-weighted average price for each day. A broker dummy variable is included in all regressions to examine whether there is a change resulting from the switch to displayed broker IDs *ex post*.

We estimate a regression model in which volume depends on control variables including relative tick size, a transparency dummy and a time trend to correct for a potentially increasing trend in volume over time. Following Foucault, Moinas and Theissen (2007), we apply stock fixed effects to control for some of the heterogeneity across stocks. Our regression model is

[13] Appendix 2 provides the distribution of minimum tick size as a function of the stock price in the KRX during the investigated period.

$$Ln(Volume_{it}) = \alpha + \beta_1 Trend_{it} + \beta_2 Vwap\_Rel\_TkSize_{it} + \beta Brok_t + \sum_{i=2}^{i=n} \gamma_i D_i + \varepsilon_{it} \qquad (1)$$

where $Ln(Volume_{it})$ is the natural logarithm of daily volume in shares for stock i at time t; $Trend_{it}$ is the time trend variable, $Vwap\_Rel\_TkSize_{it}$ is the relative tick size to daily value-weighted average price, $Brok_t$ is a dummy identifying the transparency event taking the value 0 if anonymity and 1 otherwise;, and $\sum_{i=2}^{n} \gamma_i D_i$ represents the $n-1$ estimates for the stock-specific dummies allowing for the stock fixed effect. If we find the event dummy coefficient β differs significantly from zero, it provides evidence that the change in the policy of disclosure of broker IDs affects daily trading volume after we control for other potential determinants.

Table 4 reports the stock fixed effect results for regressions on the full sample and on five volatility-stratified quintiles. The reported standard errors are Rogers (1993) clustered by stock, and hence are robust to both heteroscedasticity and correlation within stocks. We do not report the coefficients of stock dummies to save space. The adjusted R-squares lie in the range of 0.223 to 0.426, depending on volatility-stratified quintiles examined. The coefficient of the broker ID dummy is 0.505, which is highly significant and positive for the least volatile quintile, suggesting an increase of 50.5% trading volume in these stocks. For the second most and mid-volatile quintiles, we also find significant increases but less in magnitude at 40.7% and 24%, respectively, in trading volume during the period with public broker IDs, after controlling for the trend and relative tick size. However, there is no evidence of a change in trading volume for the two most volatile stock quintiles after disclosing the broker identities to the public.

These findings are consistent with our univariate results with the exception of quintile 4. The statistically significant intercept and stock dummies coefficients (non-reported) for quintiles 4 imply that the documented changes in the univariate analysis may be associated with individual stock effect only for this quintile. The coefficients of trend variable, β_1 are insignificant for all stocks and most of volatility quintiles, suggesting that the changes in trading volume are not attributed to a trend over the investigated period. Overall, although the two most volatile stock quintiles are not affected by the introduction of the post-trade transparency, the policy results in significant increase in trading volume in the three less volatile stock quintiles, which leads to a growth of 24% in trading volume in the entire transparent market.

<Insert Table 4 about here>

6. The effect of the 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), then 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 they occur in the market.

The effective spread for buys (sells) is the difference between the execution price of buy (sell)-initiated trades and the prevailing mid-point price, where 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 decompose the effective spread into temporary and permanent components. The former 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 in trades. The more information trades contain, the more prices will move in the direction of the trade (up following purchases and down following sales). The traders incorporate the information in the order flow imbalance by permanently adjusting his quotes upwards (downwards) 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, respectively[14]. The relative realized spread for buys (sells) computes as the realized spread scaled by the initial midpoint price. Our measure is consistent with Boehmer (2005), who defines realized spreads using the midpoint 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,

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

i.e., trade-time, not calendar-time as in the literature, to mitigate possible biases caused by the differences in stock liquidity and trade speed.[15] We compute market impact for buys (sells) as the change in the midpoint prices of 1, 2, 4, 6, 8 and 10 trades later, respectively, 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 as the liquidity measures involve trade time horizons.

Easley, Kiefer and O'Hara (1997) find that trade size introduces an adverse selection problem into security trading. Given that they wish to trade, informed traders prefer sizeable trades prior to information-induced price changes taking place. Easley, Kiefer and O'Hara (1997) show that large trades have approximately twice the informational content of small trades, and Lin, Sanger and Booth (1995) find that price impacts increase with trade size. These studies 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, in this paper we examine changes in effective spreads, realized spreads and market impact of large trades only.

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[15] Our data includes most of 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.

6.1 Univariate Analysis – Transaction Costs and Liquidity Providers' Compensation

Tables 5 and 6 report the statistical change in mean and median of relative effective spread – measure of transaction cost; 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. As the results for all of these three proxies are identical for all of the examined trade horizons, we report those for the 8-post-trade horizon only.

<Insert Tables 5 and 6 about here>

The univariate outcomes consistently present effective spreads and realized spreads that decline signficantly for both buyer- and seller-initiated trades. The buyer-initiated traders benefit more than seller-initiated traders by a greater reduction in transaction cost; but also earn less for liquidity provision than seller-initiated traders. Our results are in contrast to Comerton-Forde, Frino and Mollica (2005) where they find increased transaction cost in a more transparent market but, as noted above, their study mistook the timing of the event by approximately three years. Our results are also in contrast to Comerton-Forde and Tang (2009) who find that spreads decreased when broker IDs were no longer displayed on the ASX. Our findings imply that liquidity providers gain lower compensation for liquidity provision in a transparent environment, as the competition between liquidity providers is fiercer. Increased competition is likely to arise from the ability of liquidity suppliers to gain information by observing informed trader direction. We observe that market impact is higher after the change to public broker IDs, which is consistent with the fact that realized spreads fall by more than the fall in effective spreads and the ability of previously uninformed traders under the former regime to mimic the trades of those they identify as being informed.

6.2 Model about 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 public broker IDs on transaction cost' components:

$$S\_M = \alpha + \beta_1 Trend_{it} + \beta_2 Rel\_TkSize_{it} + \beta_3 Ln\left(Trade\_Size_{it}\right) + \beta_4 Brok_t \times Ln\left(Trade\_Size_{it}\right) + \\ + \beta Brok_t + \sum_{i=2}^{i=n} \gamma_i D_i + \varepsilon_{it}, \tag{2}$$

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

$$\frac{\Delta S\_M_{it}}{\Delta Brok_t} = \beta_4 Ln\left(Trade\_Size_{it}\right) + \beta . \tag{3}$$

Equation (3) shows that β is the effect of broker dummy on S_M_{it} conditional on the logarithm of trade size equal to zero, which is not of interest. Thus, we reparameterize equation (2) using mean centering for the logarithm of trade size such that the coefficient of broker dummy reflects the direct effect of transparency reform on S_M_{it} at the mean value of the logarithm of trade size. This method of centering the regressors reduces latent multi-collinearity and improves the reliability of the resulting regression equations. As a result, the mean-centered equation (2) becomes:

$$\begin{aligned} S\_M_{it} &= \alpha + \beta_1 Trend_{it} + \beta_2 Rel\_TkSize_{it} + \theta_1 Ln\left(Trade\_Size_{it}\right) + \\ &\beta_4 Brok_t \times (Ln\left(Trade\_Size_{it}\right) - \mu_{tradesize}) + \theta_2 Brok_t + \sum_{i=2}^{i=n} \gamma_i D_i + \varepsilon_{it} , \end{aligned} \tag{4}$$

in which $m_{tradesize}$ 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}**.** Now the coefficient on broker dummy, θ_2 , is the effect of transparency on the effective spread, realized spread and market impact at the mean value of the logarithm of trade size. The impact of the logarithm of trade size on the three proxies is conditional on opacity and transparency, which are θ_1 and $\theta_1 + \beta_4$, respectively. In other words, $\beta_4 > 0\,(\beta_4 < 0)$ implies a higher (lower) effect of the logarithm of trade size on spreads and market impact in the more transparent market.

6.2.1 Impact of Large Buyer-Initiated Trades

Table 7 estimates Model (4) on large buyer-initiated[16] trades only. The coefficient θ_2 is significantly negative in the effective spread regression for the full large-trade sample, implying that more post-trade transparency is associated with a lower effective spread for buyer-initiated trades. We also observe the same pattern for all quintiles in which stock quintiles 1 and 5 experience a greater increase in this coefficient. Specifically, the magnitudes of the coefficients of the transparency dummy indicate that the switch to public broker identities has produced a decline in the effective spread by 213% and 258% for the least and the most volatile stocks in the Post-period respectively (see Panel B and Panel F). Overall, the measure for buyer-initiated trades increased by 177% after broker IDs became public.

<Insert Table 7 about here>

Because effective spreads can be decomposed into realized spread and market impact, narrower effective spreads associated with much lower realized spreads reflect higher market

[16] We focus on large (i.e., above average sized) trades only as we conclude in preliminary tests that the economic significance of transaction cost changes is only relevant for these trades, while smaller trades have very little market impact.

impact implying more informative order flow (see Boehmer (2005)). One can interpret realized spreads as liquidity providers' earnings. The changes in realized spreads are qualitatively identical to the changes in effective spreads. Realized spreads reduce by the range of 117% and 260% in different volatility quintiles, leading to the overall fall of 179% in the full large-trade sample. The changes in market impact follow the same pattern as in the univariate results, which experience an increase of 2%-3% for the quintiles and 2% for the full large trade sample in the Post-period compared to the Pre-period.

6.2.2 Impact of Large Seller-Initiated Trades

The results for the seller-initiated trades in Table 8 are generally consistent with the results for buyer-initiated trades presented in Table 7. Estimating the model specified by equation (4) on large seller-initiated trades, the coefficient θ_2 is significantly positive at 41.6% in the effective spread regression for the full large-trade sample. The results imply that more post-trade transparency is associated with a lower effective spread for seller-initiated trades, bearing in mind that the price impact of sales is negative. We observe that less volatile stocks experience a slightly higher fall in this coefficient. Specifically, the magnitudes of the coefficients indicate that the switch to public broker identities has reduced the effective spread by 50% for the least volatile stocks; 39% for medium quintile stocks, and 28% for the most volatile stocks in the Post-period. There is a discrepancy between buys and sells in that the effective spreads of less volatile stocks appear more affected by sales, as opposed to buys, with the least and most volatile stocks more affected. Typically sales are more often liquidity driven and buys are more often information driven (see e.g., Saar (2001)) which may also explain the smaller coefficients for sales as well as the asymmetry. Realized spreads are significantly lower for seller-initiated trades that are similar for buys for all volatility stocks.

<Insert Table 8 about here>

Market impacts are also greater (i.e. more negative) for seller-initiated trades with public broker ID display, with the size of the coefficients smaller for sells than for buys, e.g., −0.14% for the full sample of large seller-initiated trades, which is more than half the impact for similar buys. Market impact is higher in all of volatile stocks quintiles.

7. Conclusions

This paper investigates the impact of changes in post-trade transparency on market quality when the Korea Stock Exchange started 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. Ours is the first analysis of this experiment, the first and only case in which a major exchange has adopted post-trade transparency. We use the variance ratio, traded volume, effective spread, realized spread and market impact to measure market quality, while market capitalization and volatility are accounted for using firm fixed effects and by stratifying the sample into quintiles by range-based volatility.

Our variance ratio test shows that the prices of Korean shares do not follow a random walk during the period of anonymous broker IDs and start following a random walk when the investors can observe signed trades and trade imbalances ex-post. Our findings indicate that access to information in Korea must be close to costless as otherwise prices in the transparent period would not appear to reflect all available information. Ex-post revelation of broker IDs attached to orderflow 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, we find that our results lead to a reinterpretation of the conclusions from previous research, which are typically adverse to transparent regimes.

Our study finds when broker IDs are publicly displayed, volume increases by 50% for the 173-day Post-transparency period in the least volatile quintile, compared with the similar Pre-event period, with the lower transaction cost and liquidity providers' earnings and higher market impact. The results imply fiercer competition between informed traders and increased market impact caused by a more informative order flow.

Regarding trading volume, we find that in a more transparent environment, the least volatile stocks experience the greatest increase in shares traded. Thus, in relatively liquid markets neither the Grossman and Stiglitz (1980) problem of costly endogenous information acquisition nor the Milgrom and Stokey (1982) problem of markets entirely dominated by risk averse investors with rational expectation leads to market closure. In contrast, the number of shares traded for most volatile stocks were not affected following the introduction of public broker IDs. Prior to the reform, informed and uninformed traders alike partake in the same spreads. Averaging occurs since there is no means to distinguish heterogeneously informed players. In highly volatile and relatively illiquid markets dominated by informed traders with rational expectations, transparency may make it difficult for informed traders to hide with price changes instantly reflective of private information, hence closing down the market more frequently as in Milgrom and Stokey (1982). Thus, our empirical findings on trading volume provide positive indications of overall gains from trade following the introduction of broker IDs to the public since the larger stocks dominate trading.

Finally, effective spreads decrease significantly with the making public of broker identities for both buyer- and seller- initiated trades. Typically, the realized spread measures compensation for liquidity providers. Uninformed traders may become “quasi-informed” in a more transparent market. Hence, they may become more willing to offer liquidity by placing more aggressive limit orders to take the other side of noise trader demands. As a result, competition in liquidity provision could become stronger, resulting a fall in liquidity providers’ profits which is what we find.

This study supports the current policy of the Korea Stock Exchange 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 of orders pre-trade, while it provides transparency as to who the active market participants are post-trade. Since 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 Korean Exchange appears to have benefited from transparency, the turnover rate in stocks is significantly higher than for example in Tokyo and its share index future KOSPI 200 is one of the most actively traded stock index futures of the world.

Our results indicate that exchanges should consider providing more limit order book or especially 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 subsidizes paid for by uninformed traders in anonymous markets. As we have shown, such policy comes at the expense of a less efficient and far less liquid market. Fully transparent broker ID's post-trade 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 where they are active.

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

The table reports number of observations, variance ratios for combination of a 1-day to 2-day; a 1-day to 10-day; a 1-day to 15-day and a 1-day to 20-day returns and heteroskedasticity robustness test statistics for the pre- and post- November 25, 1996 periods for the full sample. The Pre-period and Post-period is defined as March 21st 1996 – October 29th 1996 and November 19th 1996 - July 30th 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 two-day returns is 1 and the test statistics follow a standard normal distribution (asymptotically). * denotes significance at the 5% level. ** denotes significance at the 1% level.

	Pre-Period	**Post-Period**
Panel A: 1-day to 2-day return ratio		
Number of observations	40553	40812
Variance ratio	0.98	1.01
Heteroskedastic robust test statistic	-4.48**	2.15*
Panel B: 1-day to 10-day return ratio		
Number of observations	40553	40812
Variance ratio	0.880	1.000
Heteroskedastic robust test statistic	-6.59**	-0.09
Panel C: 1-day to 15-day return ratio		
Number of observations	40553	40812
Variance ratio	0.87	1.02
Heteroskedastic robust test statistic	-5.67**	1.03
Panel D: 1-day to 20-day return ratio		
Number of observations	40553	40812
Variance ratio	0.840	1.050
Heteroskedastic robust test statistic	-6.09**	1.77

Table 2: Results for variance ratio tests for a 1-day to 2-day returns combination in the KRX – Volatility Quintiles

The table reports number of observations, variance ratios for combination of a 1-day to 2-day; a 1-day to 10-day; a 1-day to 15-day and a 1-day to 20-day returns and the heteroskedasticity-robust z* statistics for the pre- and post- November 25, 1996 periods for five volatility quintiles. * denotes significance at the 5% and ** at the 1% level.

	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 (lowest)								
Number of observations	8250	8300	8250	8300	8250	8300	8250	8300
Variance ratio	1.004	0.999	1.015	1.019	1.019	1.003	0.966	1.002
Heteroskedastic robust test statistic	0.285	-0.065	0.346	0.443	0.353	0.065	-0.561	0.036
Panel B: Quintile 2								
Number of observations	8078	8129	8078	8129	8078	8129	8078	8129
Variance ratio	0.99	0.988	0.981	1.009	0.968	1.028	0.913	1.065
Heteroskedastic robust test statistic	-0.812	-0.938	-0.468	0.221	-0.644	0.538	-1.502	1.07
Panel C: Quintile 3								
Number of observations	8070	8127	8070	8127	8070	8127	8070	8127
Variance ratio	0.967	1.023	0.858	0.981	0.819	1.019	0.765	1.049
Heteroskedastic robust test statistic	-2.901**	1.832	-3.629**	-0.454	-3.69**	0.366	-4.124**	0.822
Panel D: Quintile 4								
Number of observations	8074	8128	8074	8128	8074	8128	8074	8128
Variance ratio	0.962	1.024	0.783	1.014	0.755	1.043	0.715	1.069
Heteroskedastic robust test statistic	-3.295**	1.997*	-5.595**	0.348	-5.049**	0.836	-5.038**	1.163
Panel E: Quintile 5 (highest)								
Number of observations	8081	8128	8081	8128	8081	8128	8081	8128
Variance ratio	0.972	1.017	0.846	0.967	0.856	1.006	0.85	1.023
Heteroskedastic robust test statistic	-2.492*	1.388	-3.981**	-0.81	-2.969**	0.111	-2.646**	0.382

Table 3: Univariate analysis for trading volume in the KRX

The table reports the statistical summary of changes in mean and median trading volume for the Korean Stock Exchange for the full sample of 236 stocks and for subsamples stratified by volatility measured as the daily high-low volatility. The rows 'Difference' measure changes in trading volume from the Pre-period to the Post-period. The *t*-statistic and Wilcoxon sign-rank test examine whether means and medians change after the disclosure of broker identity. *, **, ***denotes significance at the 5%, 1% and 0.1% level respectively.

	Mean	Median	t-statistic	Wilcoxon
Panel A: All Stocks				
Pre-Period	10.36	10.36		
Post-Period	10.57	10.55		
Difference	0.21	0.18	24.94***	23.39***
Panel B: Volatility Quintile 1 (lowest)				
Pre-Period	10.8	10.82		
Post-Period	11.19	11.18		
Difference	0.39	0.36	19.53***	18.55***
Panel C: Volatility Quintile 2				
Pre-Period	10.39	10.38		
Post-Period	10.63	10.63		
Difference	0.25	0.24	13.45***	13.44***
Panel D: Volatility Quintile 3				
Pre-Period	10.3	10.27		
Post-Period	10.52	10.52		
Difference	0.23	0.25	12.91***	13.19***
Panel E: Volatility Quintile 4				
Pre-Period	10.17	10.13		
Post-Period	10.33	10.33		
Difference	0.16	0.19	9.47***	9.47***
Panel D: Volatility Quintile 5 (highest)				
Pre-Period	10.16	10.21		
Post-Period	10.19	10.18		
Difference	0.03	-0.03	1.43	0.25

Table 4: Multivariate analysis of trading volume in the KRX

This table reports the results of regression of the form:

$$Ln(Volume_{it}) = \alpha + \beta_1 Trend_{it} + \beta_2 Vwap\_Rel\_TkSize_{it} + \beta Brok_t + \sum_{i=2}^{i=n} \gamma_i D_i + \varepsilon_{it},$$

where for stock i at time t, $Ln(Volume_{it})$ is the natural logarithm of daily volume; $Trend_{it}$ is the time variable; $Brok_t$ is the dummy variable for broker ID transparency taking the value 0 if opaque and 1 otherwise; $Vwap\_Rel\_TSize_{it}$ is the natural logarithm of relative tick size to daily value-weighted average price; D_i is the stock-specific dummy variables. n is 236 for the full sample, 48 for the first quintile and 47 for the four remaining individual quintiles. The table contains the stock fixed effect results of regression for the full sample and for individual five volatility-stratified quintiles. Standard errors are clustered by stocks, and hence are robust to both heteroscedasticity and correlation within stocks. The adjusted R^2 for the estimations is reported under Adj R2. . *, **, ***denotes significance at the 5%, 1% and 0.1% level respectively.

	Intercept	**Trend**	**Vwap_Rel_Ts**	**Brok**	**Adj R2**
All Stocks	8.243***	-0.0001	41.346*	0.24***	0.34
Quintile 1 (lowest)	10.122***	-0.0007	23.228	0.505***	0.426
Volatility Quintile 2	10.205***	-0.0009*	67.69	0.407***	0.288
Volatility Quintile 3	9.485***	-0.0001	14.367	0.24**	0.223
Volatility Quintile 4	10.117***	0.0003	77.701	0.131	0.236
Quintile 5 (highest)	8.334***	0.0006	16.025	-0.081	0.301

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

The table reports the statistical summary of changes in mean and median of effective spreads, realized spreads and market impact after 8 trades in the Korean Stock Exchange for the full sample of 236 stocks and for subsamples stratified by daily range-based volatility. The rows 'Difference' measure changes in relative effective spread, relative realized spread after 8 trades, and relative market impact after 8 trades for buyer-initiated trades from the Pre-period to the Post-period. The *t*-statistic and Wilcoxon sign-rank test examine whether means and medians change after the disclosure of broker identity. *, **, ***denotes significance at the 5%, 1% and 0.1% level respectively.

	Relative effective spread (%)		**Relative realized spread after 8**		**Relative market impact**	
	Mean	Median	Mean	Median	Mean	Median
Panel A: Full sample						
Pre-Period	2.31	1.193	2.31	1.193	0	0
Post-Period	0.09	0.004	0.07	0.003	0.02	0
Difference	-2.22***	-1.19***	-2.24***	-1.19***	0.02***	0
Panel B: Volatility Quintile 1 (lowest)						
Pre-Period	3.026	1.173	3.026	1.173	0	0
Post-Period	0.056	0.003	0.048	0.002	0.009	0
Difference	-2.97***	-1.17***	-2.978***	-1.171***	0.009***	0
Panel C: Volatility Quintile 2						
Pre-Period	1.903	1.276	1.903	1.276	0	0
Post-Period	0.08	0.004	0.065	0.003	0.015	0
Difference	-1.823***	-1.273***	-1.838***	-1.273***	0.015***	0
Panel D: Volatility Quintile 3						
Pre-Period	1.48	0.824	1.48	0.824	0	0
Post-Period	0.083	0.004	0.067	0.003	0.017	0
Difference	-1.397***	-0.821***	-1.414***	-0.821***	0.017***	0
Panel E: Volatility Quintile 4						
Pre-Period	2.033	1.25	2.033	1.25	0	0
Post-Period	0.101	0.004	0.08	0.003	0.021	0
Difference	-1.932***	-1.245***	-1.953***	-1.246***	0.021***	0
Panel F: Volatility Quintile 5 (highest)						
Pre-Period	3.031	1.539	3.031	1.539	0	0
Post-Period	0.116	0.004	0.092	0.003	0.025	0
Difference	-2.915***	-1.535***	-2.939***	-1.536***	0.025***	0

Table 6: Univariate analysis of Spreads for Seller-Initiated Trades in the KRX

The table reports the statistical summary of changes in mean and median relative effective spreads, relative realized spread and relative market impact after 8 trades in the Korean Stock Exchange for the full sample of 236 stocks and for subsamples stratified by daily high-low volatility. Other notations are defined in Table 5. *, **, ***denotes significance at the 5%, 1% and 0.1% level respectively.

	Relative effective spread		**Relative realized spread**		**Relative market impact**	
	Mean	Median	Mean	Median	Mean	Median
Panel A: Full sample						
Pre-Period	-0.44	-0.451	-0.44	-0.451	0	0
Post-Period	0	-0.004	0.01	-0.002	-0.01	0
Difference	0.43***	0.448***	0.44***	0.449***	-0.01***	0
Panel B: Volatility Quintile 1 (lowest)						
Pre-Period	-0.506	-0.59	-0.506	-0.59	0	0
Post-Period	-0.004	-0.003	0.002	-0.002	-0.005	0
Difference	0.503***	0.587***	0.508***	0.588***	-0.005***	0
Panel C: Volatility Quintile 2						
Pre-Period	-0.435	-0.448	-0.435	-0.448	0	0
Post-Period	-0.005	-0.004	0.005	-0.003	-0.009	0
Difference	0.43***	0.444***	0.44***	0.446***	-0.009***	0
Panel D: Volatility Quintile 3						
Pre-Period	-0.423	-0.42	-0.423	-0.42	0	0
Post-Period	-0.005	-0.003	0.005	-0.003	-0.01	-0.001
Difference	0.419***	0.416***	0.429***	0.417***	-0.01***	-0.001***
Panel E: Volatility Quintile 4						
Pre-Period	-0.448	-0.499	-0.448	-0.499	0	0
Post-Period	-0.005	-0.004	0.008	-0.003	-0.013	-0.001
Difference	0.443***	0.495***	0.456***	0.496***	-0.013***	-0.001***
Panel F: Volatility Quintile 5 (highest)						
Pre-Period	-0.393	-0.375	-0.393	-0.375	0	0
Post-Period	-0.005	-0.004	0.011	-0.002	-0.016	-0.002
Difference	0.388***	0.371***	0.404***	0.372***	-0.016***	-0.002***

Table 7: Multivariate analysis for effective spreads, realized spreads and market impact for buy-initiated trades in the KRX

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

$$S\_M_{it} = \alpha + \beta_1 Trend_{it} + \beta_2 Rel\_TSize_{it} + \theta_1 Ln\left(Trade\_Size_{it}\right) + \beta_4 Brok_t * (Ln\left(Trade\_Size_{it}\right) - \mu_{tradesize}) + \theta_2 Brok_t + \sum_{i=2}^{i=n} \gamma_i D_i + \varepsilon_{it},$$

where S_M_{it} is alternatively the relative effective spread, realized spread or the market impact for stock *i* at time *t*; $Ln\left(Trade\_Size_{it}\right)$ is the logarithm of trade size for stock *i* at time *t*; $\mu_{tradesize}$ 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 4. The last column presents $\theta_1 + \beta_4$ if both are significant at the conventional levels, or equal to either of θ_1 or β_4 if only one of these is significant and assigned "." otherwise. The table contains the stock fixed effect results of regression for the full sample and for individual five volatility-stratified quintiles. Standard errors are clustered by stocks, and hence robust to both heteroscedasticity and correlation within stocks.

	Intercept	Trend	Rel_TkSize	Log_trade_ size	Brok*log_trade _size	Brok	Adj-R2	Log_trade_size conditional on Brok=1
Panel A: Full sample								
Relative effective spread	3.565	0.0004	-68.519	0.4*	-0.702	-1.771***	0.78	0.4
Relative realized spread 8 trades	3.647	0.0004	-68.343	0.395*	-0.715*	-1.792***	0.78	-0.315
Relative market impact 8 trades	-0.083***	-0.00002*	-0.175	0.005***	0.013***	0.02***	0.01	0.018
Panel B: Volatility quintile 1 (lowest)								
Relative effective spread	-9.02	-0.0002	-61.82	0.73	-1.64	-2.13*	0.79	.
Relative realized spread 8 trades	-9.003	-0.0002	-60.62	0.72	-1.65	-2.13*	0.79	.
Relative market impact 8 trades	-0.01	-0.000001	-1.198	0.001*	0.01***	0.01***	0.004	0.011
Panel C: Volatility quintile 2								
Relative effective spread	-3.21*	-0.002	15.68	0.23**	-0.31*	-1.19***	0.78	-0.11
Relative realized spread 8 trades	-3.13*	-0.002	17.99	0.22**	-0.32*	-1.22***	0.79	-0.1
Relative market impact 8 trades	-0.07**	-0.00002	-2.31	0.004**	0.01*	0.02*	0.01	0.014

(Continues)

	Intercept	Trend	Rel_TkSize	Log_trade_ size	Brok*log_trade _size	Brok	Adj-R2	Log_trade_size conditional on Brok=1
Panel D: Volatility quintile 3								
Relative effective spread	-1.81	-0.0007	-137.3	0.22***	-0.37*	-1.15**	0.72	-0.17
Relative realized spread 8 trades	-1.77	-0.0007	-138.29	0.22***	-0.38*	-1.17**	0.73	-0.16
Relative market impact 8 trades	-0.04*	-0.00002	0.99	0.002*	0.02***	0.02***	0.01	0.022
Panel E: Volatility quintile 4								
Relative effective spread	-4.06	0.001	65.06	0.29**	-0.41*	-1.58***	0.81	-0.21
Relative realized spread 8 trades	-3.97	0.001	66.08	0.29*	-0.42*	-1.59***	0.82	-0.13
Relative market impact 8 trades	-0.09**	0.00001	-1.02	0.006***	0.02***	0.01**	0.01	0.026
Panel F: Volatility quintile 5								
Relative effective spread	3.62	0.003*	-167.15	0.4**	-0.63*	-2.58***	0.78	-0.23
Relative realized spread 8 trades	3.74	0.003*	-170.75	0.4*	-0.65*	-2.6***	0.78	-0.25
Relative market impact 8 trades	-0.11***	-0.00002	3.6*	0.006***	0.02***	0.03***	0.01	0.026

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

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

$$S\_M_{it} = \alpha + \beta_1 Trend_{it} + \beta_2 Rel\_TSize_{it} + \theta_1 Ln\left(Trade\_Size_{it}\right) + \beta_4 Brok_t * (Ln\left(Trade\_Size_{it}\right) - \mu_{tradesize}) + \theta_2 Brok_t + \sum_{i=2}^{i=n} \gamma_i D_i + \varepsilon_{it},$$

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*; $\mu_{tradesize}$ 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 4. The last column presents $\theta_1 + \beta_4$ if both are significant at the conventional levels, or equal to either of θ_1 or β_4 if only one of these is significant and assigned "." otherwise. The table contains the stock fixed effect results of regression for the full sample and for individual five volatility-stratified quintiles. Standard errors are clustered by stocks, and hence robust to both heteroscedasticity and correlation within stocks.

	Intercept	Trend	Rel_TkSize	Log_trade_ size	Brok*log_trade_ size	Brok	Adj-R2	Log_trade_size conditional on Brok=1
Panel A: All of 440 stocks								
Relative effective spread	-0.735***	-0.00002	7.687	0.018	-0.024	0.416***	0.84	.
Relative realized spread 8 trades	-0.774***	-0.00003	7.658	0.02*	-0.022	0.43***	0.82	0.02
Relative market impact 8 trades	0.038***	0.00001*	0.029	-0.002***	-0.002**	-0.014***	0.02	-0.004
Panel B: Volatility quintile 1 (lowest)								
Relative effective spread	-1.01**	-0.00005	7.76	0.03	-0.04	0.5***	0.84	.
Relative realized spread 8 trades	-1.02**	-0.00005	7.5	0.03	-0.03	0.5***	0.84	.
Relative market impact 8 trades	0.005	-0.000002	0.26	-0.0004	-0.002	-0.01***	0.01	.
Panel C: Volatility quintile 2								
Relative effective spread	-0.98*	-0.0003*	10.07	0.04	-0.06	0.49***	0.85	.
Relative realized spread 8 trades	-1.002*	-0.0003*	10.32	0.04	-0.06	0.495***	0.83	.
Relative market impact 8 trades	0.027**	-0.00001	-0.25	-0.001**	-0.002*	-0.008***	0.02	-0.003

(Continues)

	Intercept	Trend	Rel_TkSize	Log_trade_ size	Brok*log_trade_ size	Brok	Adj-R2	Log_trade_size conditional on Brok=1
Panel D: Volatility quintile 3								
Relative effective spread	-0.837**	-0.00006	-5.26	0.03	-0.05	0.39***	0.86	.
Relative realized spread 8 trades	-0.851**	-0.00006	-5.15	0.03	-0.04	0.41***	0.84	.
Relative market impact 8 trades	0.014	0.000005	-0.11	-0.001	-0.003**	-0.014***	0.02	.
Panel E: Volatility quintile 4								
Relative effective spread	-0.719**	-0.0001	7.65	0.02	-0.03	0.45***	0.88	.
Relative realized spread 8 trades	-0.751***	-0.0002*	7.39	0.02	-0.03	0.47***	0.84	.
Relative market impact 8 trades	0.032*	0.00001	0.26	-0.002*	-0.004**	-0.02***	0.02	-0.006
Panel F: Volatility quintile 5 (highest)								
Relative effective spread	-0.51	0.0004*	10.47	0.007	-0.013	0.28***	0.84	.
Relative realized spread 8 trades	-0.55	0.0003*	10.8	0.009	-0.006	0.3***	0.8	.
Relative market impact 8 trades	0.041**	0.00002*	-0.33	-0.002**	-0.007***	-0.021***	0.03	-0.009

Figure 1 Market Capitalization, Listings and Concentration 1995 to 2013

The figure provides annual statistics for the Korea Exchange reporting year-by-year the market capitalization of domestic stocks in Korean Won (first *y*-axis), number of domestic listed companies (second *y*-axis) and the concentration of market capital to the top 5% of companies (scaled to the first *y*-axis). Source: World Federation of Stock Exchanges.

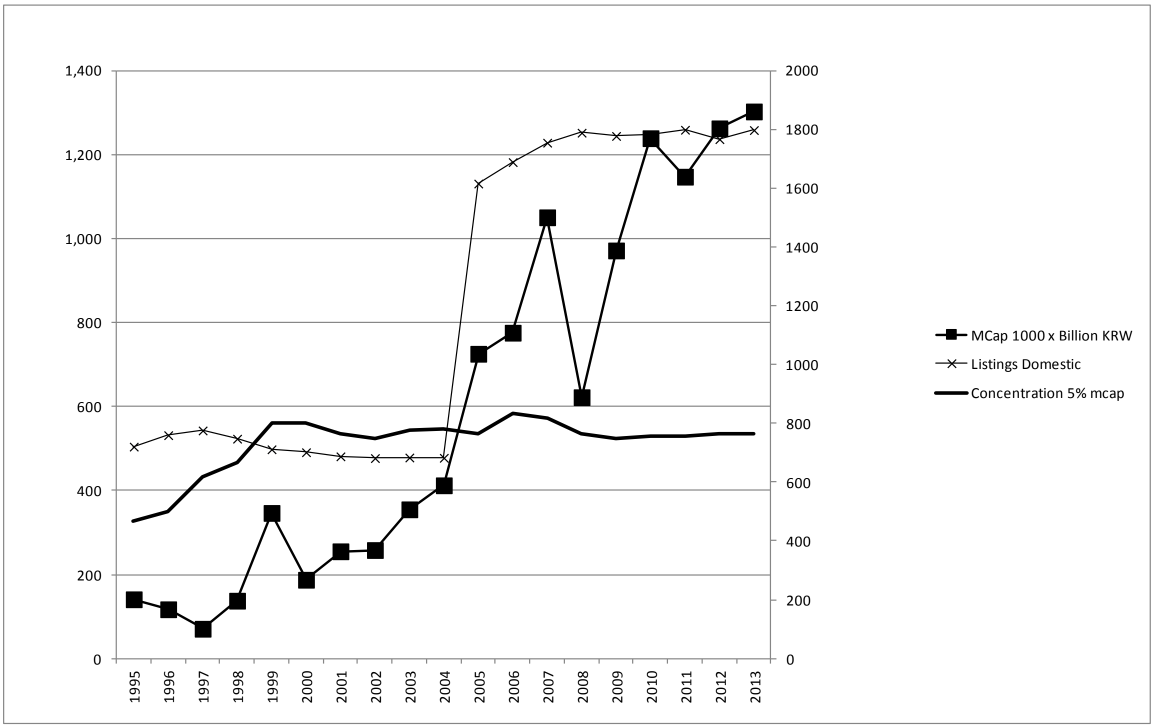
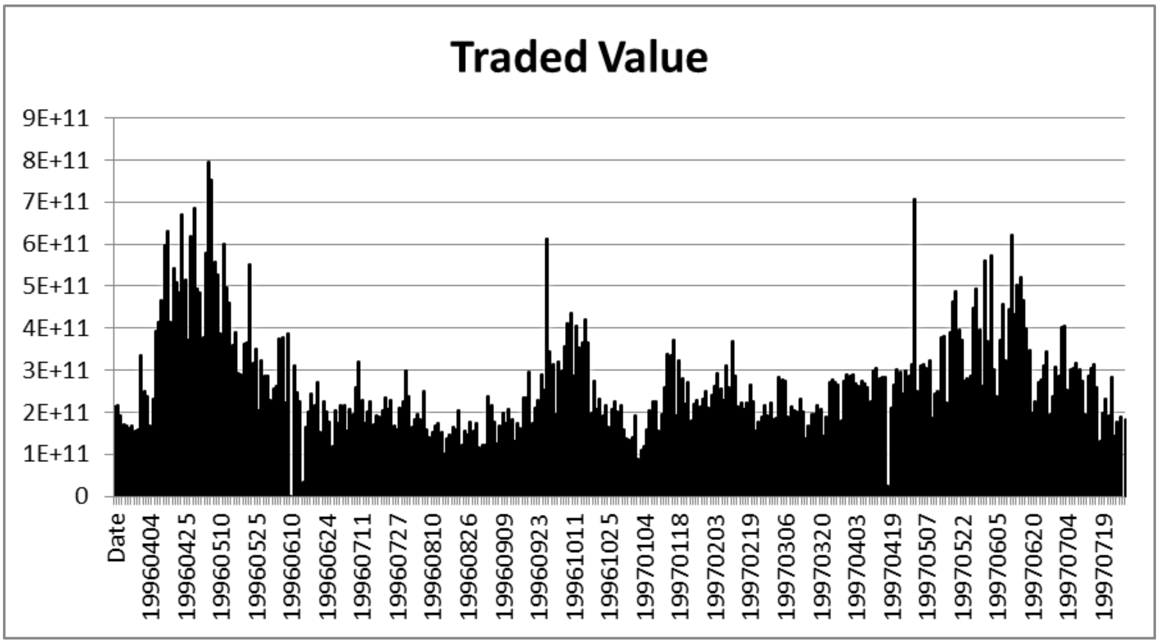


Figure 2 Market Capitalization, Traded Value March 21, 1996 to July 30, 1997

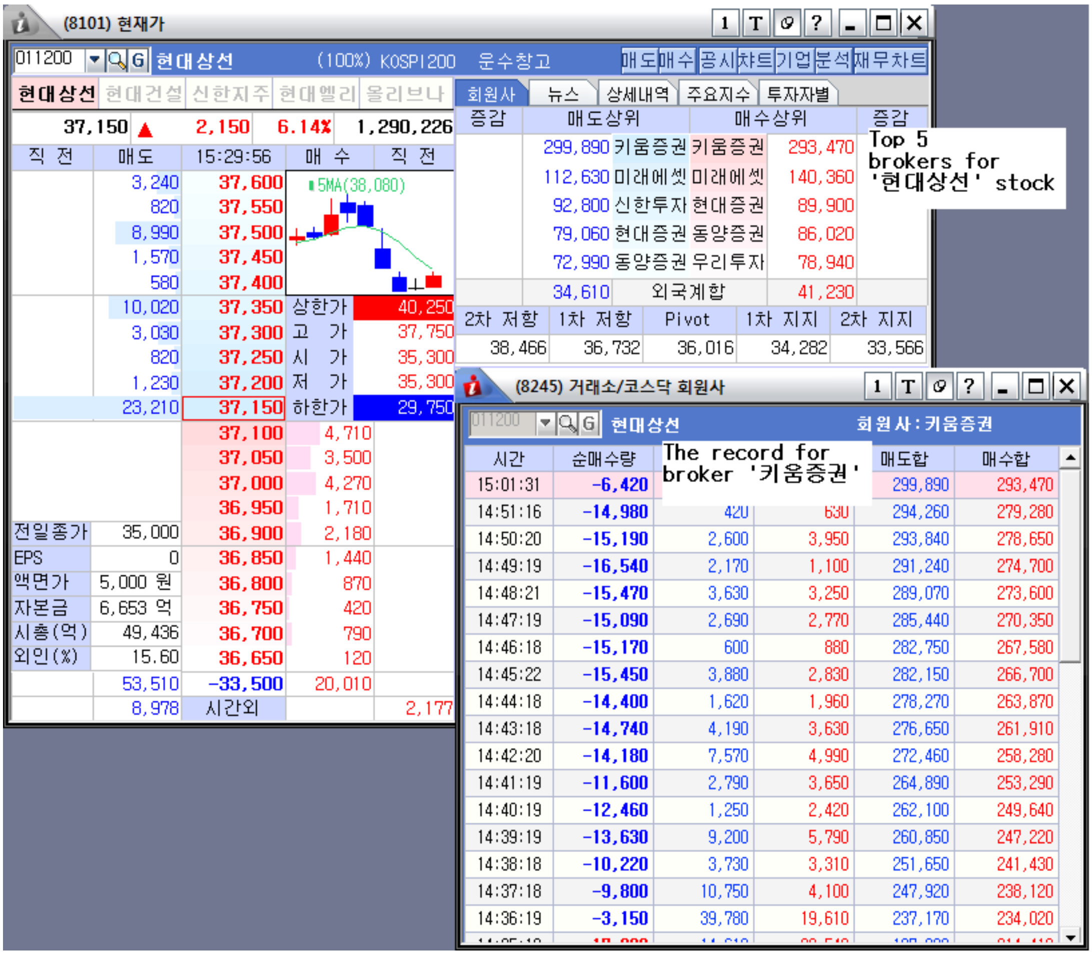
The figure provides daily traded value for the complete sample of stocks from Korea Exchange during the investigated period March 21, 1996 to July 30, 1997, (before applying our requirement that all common stocks have at least five hundred transactions per month during the investigated period).



Appendices

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

The screen-shot shows information available to all investors trading in the KRX. The top right screen shows the top five selling brokers in the blue 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 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 sells 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 more 6,420 more shares than they have purchased at the time of the screenshot, 15:01.



Appendix 2: 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