Tick size, market structure, and trading costs[#]

Kee H. Chung,[a,*] Jangkoo Kang,[b] Joon-Seok Kim[b]

[a] *Department of Finance and Managerial Economics, State University of New York (SUNY) at Buffalo, Buffalo, NY 14260, USA*
[b] *Graduate School of Finance, Korea Advanced Institute of Science and Technology, Chungnyangni-dong, Dongdaemoon-gu, Seoul, Korea*

[#]The authors thank Hao Zhang and Daisy E. Chung for valuable comments and suggestions.
[*]Corresponding author. Tel.: +1-716-645-3262; Fax: +1-716-645-2131.
E-mail addresses: keechung@buffalo.edu (Kee H. Chung), jkkang@business.kaist.ac.kr (Jangkoo Kang), joonseok.kim@gmail.com (Joon-Seok Kim).

Tick size, market structure, and trading costs

Abstract

Large tick sizes imposed on high-price stocks on the Korea Stock Exchange (KSE) are significant binding constraints on bid-ask spreads. Nearly 60% of quoted spreads are equal to the tick size for stocks with the largest tick size. The average spread of KSE stocks is smaller than that of the matched sample of New York Stock Exchange (NYSE) stocks, although the average spread of KSE stocks that belong to larger tick size groups is greater than that of matched NYSE stocks. These results suggest that the KSE's electronic limit order market provides cheaper executions than the NYSE's specialist system for our matched sample of stocks, and the KSE could further reduce trading costs if the large tick sizes imposed on high-price stocks are replaced with smaller ones.

JEL classification: G18; G19

Key words: bid-ask spreads, depths, execution costs, minimum price variation, informational efficiency, market structure

1. Introduction

An important protocol of securities markets is the size of minimum permissible price variation (i.e., tick size). There is significant variation in tick structure across markets. Some markets use a stepwise tick system in which the tick size varies with share price, while others use a single tick size for all stocks. Most stock markets in Asia and Europe use the stepwise tick system in which larger tick sizes are imposed on higher priced stocks. For example, the Kuala Lumpur Stock Exchange uses seven tick sizes and the Korea Stock Exchange (KSE) uses six tick sizes that vary with share price. In these markets, market regulators seem to believe that the tick size should not be too small in proportion to the share price.

Stock markets in the United States have also employed the stepwise tick structure in the past. For example, in 1994, the New York Stock Exchange (NYSE) used the tick size of $1/8 for stocks priced at or above $1, $1/16 for stocks under $1 and at or above $0.25, and $1/32 for stocks under $0.25. Similarly, quotes in the NASDAQ system were at multiples of $1/8 if the bid was above $10 and $1/64 if the bid was under $10. Both the NYSE and NASDAQ completed decimalization in 2001 and have used a uniform tick size of one penny for all stocks since then. Market regulators in the U.S. seem to believe that the tick size should not be too large.

Financial economists have recognized the potential benefits and costs of different tick sizes. Harris (1994, 1997) suggests that large tick sizes increase execution costs because the tick size constitutes a lower bound for the quotable spread. If the tick size is too large, it would frequently be a binding constraint on the bid-ask spread and thus impose unnecessarily large execution costs on traders. Harris notes that small tick sizes are not without cost. If the tick size is too small, it may reduce market liquidity because it lowers the cost of front running. That is, small tick sizes may make liquidity providers less willing to supply liquidity because of the high risk of front running. Small tick sizes may also imply large negotiation costs and thereby delay price discovery (Grossman et al., 1997).

A number of studies have examined the effect of tick sizes on market quality in the U.S. and Canadian stock markets. Ahn, Cao, and Choe (1996, 1998), Bessembinder (1999, 2003), Van Ness, Van Ness, and Pruitt (2000), Chung, Charoenwong, and Ding (2004), and Chung, Chuwonganant, and McCormick (2004) examine changes in market quality around a market-wide change in tick size. These studies show that a reduction in tick size generally leads to smaller depths and narrower spreads. Bessembinder (2000) shows that both quoted and effective spreads are smaller for NASDAQ stocks selling below \$10 and attributes the result to their smaller tick size. Despite the ubiquity of stepwise tick systems across continents (e.g., Korea Stock Exchange, Kuala Lumpur Stock Exchange, Paris Bourse, Swiss Exchange, and Tokyo Stock Exchange), the efficacy of these tick systems and their ramifications for both trading costs and the information efficiency of asset price have not been well understood.

In this study we examine the effects of tick size and market structure on trading costs using data from the KSE and the NYSE. We first analyze the effect of tick size on the spread and depth of KSE stocks. We use the discrete spread model of Harris (1994) to estimate the expected reduction in spreads that can result from a decrease in tick size. We also examine the effect of tick sizes on the information efficiency of asset price by analyzing whether larger tick sizes discourage information-based trading. We measure the extent of information-based trading using the method in Easley, Hvidkjaer, and O'Hara (2002). Finally, we perform matched sample comparisons of KSE and NYSE stocks to determine whether the difference (if any) in spreads between the two markets can be attributed to their differences in tick structure, market structure, or both.

Our study makes an important contribution to the literature in three dimensions. First, we provide new evidence of the efficacy of the stepwise tick system using data from one of the world's largest stock markets. Despite the widespread use of the stepwise tick system in many countries, related empirical evidence is rather scanty. We provide such evidence. Second, to the best of our knowledge, the present study is the first attempt to assess the effect of the stepwise tick system on market quality through an inter-market comparison of underlying variables (e.g., spreads and binding probability). Prior research typically performs either a before-and-after comparison of market quality around the tick size change in a market (see, e.g., Bessembinder, 2003) or a cross-sectional comparison of market quality across stocks with different tick sizes in a market (see, e.g., Chung, Kim, and Kitsabunnarat, 2005; Chung and Shin, 2005). We consider our approach meaningful because the analysis of the effect of a given tick system on market quality (in a given market) provides only partial information regarding the ultimate efficacy of the tick system. Third, our study adds further evidence to the existing literature on the effect of market structure on execution quality (see Huang and Stoll, 1996; Venkataraman, 2001) through comparative analyses of trading costs between the electronic limit order market (i.e., the KSE) and the hybrid specialist system of the NYSE.

Our empirical results show that the large tick sizes imposed on high-price stocks on the KSE are significant binding constraints on bid-ask spreads. For example, nearly 60% of quoted spreads are equal to the tick size for stocks with the largest tick size, and more than 87% of quoted spreads are equal to the tick size for stocks in the largest firm-size portfolio. These results indicate that traders on the KSE (especially those who buy and sell shares of large companies) are paying large trading costs because of the artificially imposed large tick sizes. Our results indicate that if the tick size were reduced from ₩5 to ₩1, the percentage quoted spread would decrease from 0.8941% to 0.4542% for our study sample of stocks. Likewise, if the tick size were reduced from ₩50 to ₩10, we expect the spread to decrease from 0.8060% to 0.3475%. We find that the probability of information-based trading increases with the tick size, suggesting that informed traders on the KSE are not discouraged by the additional trading costs imposed on high-price stocks through larger tick sizes.

The average spread of KSE stocks is significantly smaller than that of the matched sample of NYSE stocks as a whole. When we compare spreads of stocks within each tick size group, the mean spread of KSE stocks that belong to the smaller tick size groups is significantly smaller than that of matched NYSE stocks, whereas the mean spread of KSE stocks that belong to the larger tick size groups is significantly larger than that of matched NYSE stocks. On the whole, these results suggest the KSE's electronic limit order market provides cheaper executions than the NYSE's hybrid system for our study sample of stocks, and that the advantage of the KSE system could further be enhanced if the larger tick sizes imposed on high-price stocks were replaced with smaller ones.

The paper is organized as follows. Section 2 describes data sources and error filtering methods. Section 3 explains our variable measurement procedures and examines the effect of tick sizes on the spread of KSE stocks. Section 4 uses the discrete spread model to estimate the expected effect of tick size changes on spreads. Section 5 compares the spread of KSE stocks to the spread of NYSE stocks using the matched sample. Section 6 presents a brief summary and concluding remarks.

2. Data sources and error filters

We obtain trade and quote data for KSE-listed stocks from the KSE, and trade and quote data for NYSE-listed stocks from the NYSE's TAQ database. We produce national best bid and offer (NBBO) from the TAQ database using the program provided by the Wharton Research Data Services (WRDS). We use trades and quotes during regular trading hours from April 2003 to June 2003. We exclude from our study sample preferred stocks, lower-class common stocks, and stocks that undergo stock splits or reverse splits during the three-month study period.

To minimize data error, we omit a trade if (i) TAQ error correction indicator is greater than one; (ii) TAQ sales condition code is A, C, D, N, O, R, or Z; (iii) it is not preceded by a valid same-day quote; and (iv) price is non-positive or price change is greater than 10%. We omit a quote if (i) the bid or ask price is non-positive; (ii) the bid-ask spread is non-positive or larger than $4; (iii) change in quote midpoints exceeds 10%; and (iv) TAQ quote condition code is 4, 7, 9, 11, 13, 14, 15, 19, 20, 27, or 28. On the KSE, a large market buy (sell) order can exhaust the quoted depth at the best quote and walk up (down) the limit order book. The KSE database reports multiple trade prices with an identical time stamp when the size of a market order is greater than the inside depth. We reclassify these simultaneous trades as one trade, calculate the share-weighted average price, and use it as the execution price of the order.

3. Tick sizes and trading costs on the Korea Stock Exchange

In this section we examine the effect of tick sizes on trading costs using a large sample of stocks listed on the KSE.

3.1. Variable measurement

To measure the trading cost of orders that are executed at the quoted price, we calculate the percentage quoted spread using the following formula:

$$Quoted\ spread_{it} = \frac{100 \cdot (ASK_{it} - BID_{it})}{MID_{it}}, \tag{1}$$

where ASK_{it} is the ask price of stock i at time t, BID_{it} is the bid price for stock i at time t, and MID_{it} is the mean value of ASK_{it} and BID_{it}. For each stock, we then calculate the time-weighted mean percentage quoted spread.

To measure the trading cost of orders that are executed with price improvement, we calculate the percentage effective spread using the following formula:

$$Effective\ spread_{it} = \frac{200 \cdot D_{it} \cdot (P_{it} - MID_{it})}{MID_{it}}, \tag{2}$$

where D_{it} is a binary variable that equals 1 for buyer-initiated trades and -1 for seller-initiated trades, P_{it} is the transaction price, and MID_{it} is the most recent quote midpoint prior to the trade executed at time t. We determine D_{it} using the Lee and Ready (1991) algorithm by comparing the trade to the quote in effect one second earlier. For each stock, we then calculate the trade-weighted mean percentage effective spread.

Although the quoted and effective spreads measure execution costs borne by traders, they are not necessarily the revenues earned by liquidity providers. Liquidity providers earn less than the quoted or effective spread when price moves in the adverse direction after a trade (i.e., when the price impact of a trade is positive). To measure the net revenue earned by liquidity providers, we calculate the percentage realized spread using the following formula:

$$\text{Re}\,alized\ spread_{it} = \frac{200 \cdot D_{it} \cdot (P_{it} - P_{it+n})}{MID_{it}}, \tag{3}$$

where P_{it+n} denotes the quote midpoint five minutes after the trade. We calculate the trade-weighted mean realized spread for each stock.

We estimate the probability of information-based trading (PIN) using the model in Easley, Hvidkjaer, and O'Hara (2002). The model assumes that a news event occurs with the probability of α before each trading session. The news event is a good one with the probability of δ and a bad one with the probability of 1– δ. The daily arrival of traders follows independent Poisson processes. Informed traders arrive at the rate of μ and uninformed liquidity buyers (sellers) arrive at the rate of ε_b (ε_s). The likelihood function of this trade process on a given day is given by

$$L(\theta \mid B,S) = (1-\alpha)e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!} + \alpha\delta e^{-\varepsilon_b}\frac{\varepsilon_b^B}{B!}e^{-(\mu+\varepsilon_s)}\frac{(\mu+\varepsilon_s)^S}{S!}$$

$$+\alpha(1-\delta)e^{-(\mu+\varepsilon_b)}\frac{(\mu+\varepsilon_b)^B}{B!}e^{-\varepsilon_s}\frac{\varepsilon_s^S}{S!}, \tag{4}$$

where B(S) is the number of buyer- (seller-) initiated trades on a given day. Using the series of buy and sell trades over our study period, we estimate model parameters by maximizing the likelihood function. We then measure the probability of information-based trading by PIN = $\alpha\mu/(\alpha\mu+\varepsilon_b+\varepsilon_s)$.

3.2. *Tick sizes and trading costs*

The tick size on the KSE varies with share price in the following manner (where ₩ denotes Korean Won): ₩5 if share price is below ₩5,000; ₩10 if share price is between ₩5,000 and ₩10,000; ₩50 if share price is between ₩10,000 and ₩50,000; ₩100 if share price is between ₩50,000 and ₩100,000; ₩500 if share price is between ₩100,000 and ₩500,000; and ₩1,000 if share price is above ₩500,000. Note that the largest tick size on the KSE is equivalent to about one U.S. dollar and the second largest is equivalent to about 50 cents.

Table 1 shows the mean value of spreads for our entire sample of 651 stocks, for stocks within each tick size group, and for stocks within each firm size and tick size group. The number (percentage) of stocks within each tick size group (₩5, ₩10, ₩50, and ₩50+) are 322 (49.46%), 149 (22.89%), 158 (24.27%), and 22 (3.38%), respectively.[1] For the whole sample, the mean quoted spread is 1.0445% and the mean effective spread is 1.0510%. The mean effective spread is slightly greater than the mean quoted spread, indicating that at least some orders were larger than the quoted depth at the inside market.

We find no clear pattern in the relation between the mean spread and tick size for the whole sample. For example, the mean quoted spread of stocks with the tick size of ₩5, ₩10, ₩50, and ₩50+ are 1.0503, 1.1306, 1.0158, and 0.5829, respectively. We find qualitatively similar results for the effective and realized spreads. It is unlikely, however, that we can observe the true relation between the spread and tick size from the whole sample, because both trading volume (and thus the spread) and share price (and thus the tick size) are highly correlated with firm size.

The second panel of Table 1 shows the relation between the spread and tick size after controlling for firm size. For this result, we first cluster our study sample of stocks into three portfolios according to their market capitalizations. We then calculate the mean spread of stocks within each tick-size group for each firm-size portfolio. The results show that the mean quoted, effective, and realized spreads of stocks with large tick sizes tend to be greater than those of stocks with small tick sizes. For example, for stocks in the smallest firm-size portfolio, the mean quoted spread of stocks with the tick size of ₩5, ₩10, and ₩50 are 1.1459, 1.3637, and 1.4324, respectively. We find similar results for the effective and realized spreads.

Table 1 also shows estimates of the binding probability (BND) for the whole sample and for each tick size group. The binding probability is the probability that the tick size is a binding constraint on absolute spreads, measured by the percentage of quoted spreads that are equal to the tick size. The results show that about 40% of quoted spreads are equal to the tick size for the whole sample, and nearly 60% of quoted spreads are equal to the tick size for stocks with the largest tick size. More importantly, about 30% of quoted spreads are equal to the tick size for stocks in the smallest firm-size portfolio as a whole, and more than 87% of quoted spreads are equal to the tick size for stocks in the largest firm-size portfolio as a whole. These results indicate that traders on the KSE (especially those who buy and sell shares of large companies) are paying unnecessarily large trading costs because of the artificially imposed large tick sizes.

To further examine the effect of tick sizes on the quoted spread, we regress the quoted spread on three dummy variables, D_{10}, D_{50}, and D_{50+} for different tick sizes (₩10, ₩50, and

[1] The tick size group ₩50+ includes all stocks with a tick size larger than ₩50.

₩50+) and the control variables that have been shown to explain cross-sectional variation in the spread (see, e.g., Harris, 1994). These variables include market value of equity (MVE), dollar trading volume (VOLUME), return volatility (VOLATILITY), the probability of information-based trading (PIN), and the inverse of share price (INVPRICE). We measure return volatility by the standard deviation of daily closing quote-midpoint returns.

The results (see Table 2) show that the regression coefficients on D_{10}, D_{50}, and D_{50+} are all positive and significant, indicating that the mean spreads of stocks with ₩10, ₩50, and ₩50+ tick are all larger than the mean spread of stocks with ₩5 tick. In addition, the regression coefficients on D_{10}, D_{50}, and D_{50+} increase with the tick size and the differences are statistically significant according to the F-test (see the bottom rows). The regression results for the control variables are similar to those reported in prior research: the spread is positively related to return volatility, PIN, 1/Price, and firm size, and negatively to trading volume. We obtain similar results when we replicate the above analyses with the percentage effective spread.

To determine whether the binding probability differs across stocks with different tick sizes, we regress the percentage of quoted spreads that are equal to the tick size (i.e., BND) on D_{10}, D_{50}, and D_{50+}, and the control variables that are likely to determine the binding probability, such as firm size, trading volume, return volatility, PIN, and quoted depth. The results (see the second column in Table 2) show that the binding probability monotonically increases with the tick size. The results of the F-test show that there are significant differences in regression coefficients between adjacent tick size dummy variables. On the whole, these results indicate that the large tick sizes imposed on high-price stocks are significant binding constraints on spreads and thus the positive and significant regression coefficients on D_{10}, D_{50}, and D_{50+} in the quoted spread regression model can be attributed, at least in part, to these binding constraints.

4. Projection of trading costs

Harris (1994) projects the spreads that would be quoted if traders could use a finer price grid using a discrete model of bid-ask spreads. In this section, we use the same method to examine the effect of tick size changes on the spread and binding probability.

4.1. Discrete spread model

The frequency of the discrete spread in the n^{th} tick size step can be expressed in terms of the cumulative distribution of the unrounded spread:

$$P(SP = RT \cdot n) = \Phi(RT \cdot \sqrt{n(n+1)};\theta) - \Phi(RT \cdot \sqrt{(n-1)n};\theta), \tag{5}$$

where SP is the observed (discrete) spread, RT is the ratio of tick size to share price, Φ is the cumulative distribution function of the unrounded spread, and θ is a set of distributional parameters. Following Harris (1994), we assume that the unrounded spread follows a gamma distribution. The gamma distribution is a reasonable approximation of the distribution of the unrounded spread because it is defined over positive numbers and it could accommodate a rich family of distributional shapes.

The mean unrounded spread (in log), MSP, is specified by the following model:

$$\begin{aligned} MSP = \beta_0 + \beta_1 MVE + \beta_2 VOLUME + \beta_3 VOLATILITY + \beta_4 PIN + \beta_5 INVPRICE\bullet D_5 \\ + \beta_6 INVPRICE\bullet D_{10} + \beta_7 INVPRICE\bullet D_{50}\,, \end{aligned} \tag{6}$$

where MVE, VOLUME, VOLATILITY, PIN, and INVPRICE denote the market value of equity (in log), dollar trading volume (in log), return volatility, the probability of information-based trading, and the inverse of average share price (in log), respectively. We drop stocks with ₩50+ tick size because of the small sample size.

We estimate the parameters of the gamma distribution and betas of equation (6) using the maximum likelihood estimation method. The multinomial log likelihood is given by the following equation:

$$ln\,L(\theta) = \sum_{i=1}^{K}\sum_{n=1}^{N}\hat{P}(SP_i = n \cdot RT_i)\,ln(P(SP_i = n \cdot RT_i)), \tag{7}$$

where $\hat{P}$ is the observed frequency of spreads in the n[th] tick size step, N is the maximum number of tick size steps under consideration, and K is the number of stocks. In the estimation, we use only those stocks that remained in the same tick size group during our study period. The number of stocks in each tick size group in the final sample is 243 for ₩5, 34 for ₩10, and 101 for ₩50, respectively.

Table 3 shows the maximum likelihood estimation results. The estimated coefficients on independent variables are similar to those reported in Table 2. The effect of (inverse) share price on the unrounded spread varies with the tick size, which is consistent with Harris's prediction. The shape parameter is in the neighborhood of one.

The fitted gamma distribution is determined by the spread model in Table 3. To project the spread under a new tick size, we obtain the projected gamma distribution using the coefficient on the dummy variable for the new tick size. For example, for a tick size change from ₩50 to ₩10, we use the estimated coefficient on the ₩10 tick size dummy to obtain the projected unrounded spread. We then discretize the projected distribution by the new tick size and calculate the projected spread.

Panel A of Table 4 shows the quoted, fitted, and projected spreads for each of the three tick size groups, together with the results of the t-test on whether the difference between the quoted and fitted (or projected) spreads is statistically significant. We show the results for the entire study sample as well as for each of the three firm-size portfolios.

The results show that a reduction in the tick size would lead to a significant decrease in the spread. For instance, if the tick size is reduced from ₩5 to ₩1, the percentage quoted spread is projected to decrease from 0.8941% to 0.4542% for the whole sample, and the difference is statistically significant at the 1% level. For the same tick size change, the percentage quoted spread is expected to decrease from 0.9558%, 0.3717%, and 0.1821% to 0.4853%, 0.1939%, and 0.0648% for stocks of small, medium, and large companies, respectively. Likewise, if the tick size is reduced from ₩50 to ₩10, the spread is projected to decrease significantly from 0.8060% to 0.3475% for the whole sample. Overall, our results suggest that the existing tick sizes are significant binding constraints on bid-ask spreads on the KSE and that the relaxation of these constraints would reduce trading costs.

To confirm whether the projected decrease in spreads is indeed largely due to the reduction in the binding probability, we apply the above procedure to obtain the fitted and projected binding probabilities. Panel B of Table 4 shows that if the tick size is reduced from ₩5 to ₩1, the binding probability would decrease from 49.97% to 24.99% for the whole sample. For the same tick size change, the binding probability would decrease from 48.25%, 62.94%, and 88.23% to 23.99%, 31.79%, and 55.31% for stocks of small, medium, and large companies, respectively. Likewise, if the tick size is reduced from ₩50 to ₩10, the binding probability would decrease from 46.50% to 26.14% for the whole sample. Overall, these results confirm our conjecture that the existing tick sizes on the KSE are indeed significant binding constraints on spreads.[2]

4.2. Quoted depths and binding probability

If the tick size is larger than the equilibrium spread, liquidity providers are likely to quote larger depths than they would otherwise because they find liquidity provision a profitable enterprise (Harris, 1994). Hence, we expect larger depths for stocks with larger tick sizes or greater binding probabilities. Stocks with larger tick sizes are also likely to have larger depths because liquidity providers are subject to lower risks of front running with such stocks. In addition, Seppi (1997) shows that the limit order book's cumulative depth decreases as the tick size decreases. Indeed, prior research finds smaller depths after tick size reductions on various exchanges (Bacidore, 1997; Porter and Weaver, 1997; Goldstein and Kavajectz, 2000).

To examine the effect of tick sizes on the quoted depth, we regress the quoted depth (DEPTH) on D_{10}, D_{50}, and D_{50+}, as well as on the control variables that have been shown to explain cross-sectional variation in depths (see Harris, 1994). These variables include market value of equity (MVE), dollar trading volume (VOLUME), the bid-ask spread (SPREAD), the probability of information-based trading (PIN), and return volatility (VOLATILITY). We also estimate the model using our empirical proxy for the binding probability (BND) instead of D_{10}, D_{50}, and D_{50+}.

---

[2] Our projection is based on the assumption that the tick size change does not affect stock attributes, such as number of trades, trade size, and return volatility. If the tick size reduction results in greater trading volume and/or lower return volatility, our projection would be inaccurate.

As discussed above, we expect a positive relation between the depth and binding probability, and positive, larger regression coefficients on dummy variables for lager tick sizes. We expect a positive relation between the depth and spread because the liquidity supply schedule has a positive slope (see Harris, 1994). We expect a negative relation between the depth and PIN if liquidity providers are less willing to commit large depths when adverse selection risks are higher. Likewise, to the extent that adverse selection problems are greater for riskier stocks, liquidity providers are likely to quote smaller depths for stocks with higher return volatility. We conjecture that the depth is positively related to both MVE and VOLUME because stocks of larger companies tend to have lower adverse selection risks and high volume stocks would require greater depths.

The first and second columns of Table 5 show the regression results. Consistent with our expectation, the depth is positively and significantly related to the binding probability. The results also show that the estimated coefficients on D_{50} and D_{50+} are significant and positive, indicating that liquidity providers post larger depths for stocks with larger tick sizes. The regression coefficient on D_{10} is negative and significant, indicating that the average depth of stocks with the second smallest tick size (₩10) is slightly smaller than the average depth of stocks with the smallest tick size (₩5). This result is at odds with our expectation and it is unclear what drives the result. Consistent with our expectation, the depth is positively related to MVE, VOLUME, and SPREAD, and negatively related to VOLATILITY in both regression models. Contrary to our expectations, however, the depth is positively and significantly related to PIN. A possible explanation for the positive relation between the depth and PIN is that, all things being equal, informed traders have a greater incentive to trade stocks with larger depths because the price impact of a trade is smaller for such stocks. Indeed, we show in the next section that PIN is positively related to the depth, after controlling for other determinants of information-based trading.

Although we find evidence of larger spreads associated with larger tick sizes in Section 3, the net effect of the tick size on liquidity is unclear because larger tick sizes also accompany larger depths. Unless we have a clearly defined trade-off function between spreads and depths, it is difficult to measure the net effect of smaller tick sizes on liquidity. To shed some light on the net effect, we calculate the following market quality index (MQI) suggested by Bollen and Whaley (1998):[3]

$$MQI_{it} = \frac{(1/2)Quoted\ depth_{it}}{Quoted\ spread_{it}}. \tag{8}$$

We then regress MQI on D_{10}, D_{50}, and D_{50+}, and the control variables (i.e., MVE, VOLUME, and VOLATILITY, PIN).

The results (see Table 5) show that the regression coefficients on D_{10}, D_{50}, and D_{50+} are all negative and significant, indicating that the market quality indices of stocks with ₩10, ₩50, or ₩50+ tick are all smaller than the market quality index of stocks with ₩5 tick. In addition, the regression coefficients on D_{10}, D_{50}, and D_{50+} decrease with the tick size and the differences are statistically significant according to the F-test. These results indicate that larger tick sizes generally have detrimental effects on liquidity on the KSE.

[3] This measure assumes a linear liquidity supply schedule (i.e., a linear tradeoff between the spread and depth), which may not correctly capture actual preferences of liquidity providers.

4.3. Do large tick sizes discourage information-based trading?

Informed traders make asset markets informationally efficient because private information is impounded into asset price through their trading. If the trading cost imposed by large tick sizes were greater than the value of private information they possess, informed traders would not trade. Anshuman and Kalay (1998) consider an analytical model in which they show that large tick sizes reduce the value of private information. Hence, the tick size may affect market quality not only through its impact on spreads, depths, and binding probabilities, but also through its impact on the informational efficiency of asset price.

In this section, we examine the effect of tick sizes on the informational efficiency of asset price by comparing the probability of information-based trading across stocks with different tick sizes. We conjecture that all things being equal, informed traders are more likely to trade those stocks that have a smaller tick size because the smaller the tick size, the higher the probability that the value of private information is greater than the trading cost. To the extent that smaller tick sizes encourage information-based trading, prices of stocks with small tick sizes would be more informative than prices of stocks with large tick sizes (because it is the information-based trading that makes asset prices efficient). To test this conjecture, we regress PIN on D_{10}, D_{50}, and D_{50+}, and select control variables that are likely to be related to PIN, such as MVE, VOLUME, SPREAD, DEPTH, and VOLATILITY.

Column 3 of Table 5 shows that contrary to our expectation, PIN tends to increase with the tick size. The regression coefficient on D_{10} is significant and positive, and the regression coefficient on D_{50} is significantly greater than the regression coefficient on D_{10}. The regression coefficient on D_{50+} is not significantly different from that on D_{50}. These results suggest that information-based trading is more frequent in stocks with larger tick sizes. Apparently, informed traders on the KSE are not discouraged by the additional trading cost imposed on high-price stocks.

A possible explanation for the positive relation between PIN and the tick size is that there may be more frequent information events as well as more informed traders for stocks with larger tick sizes, because they tend to be stocks of large companies (with high share prices) that are followed and monitored by more analysts and traders. Note that a stock can have a large PIN value in two ways: more frequent occurrence of information events (i.e., large α) and/or more frequent arrival of informed traders (i.e., large μ). Indeed, our (unreported) results indicate that both α and μ increase with share price (and thus the tick size). These results support the idea that stocks with larger tick sizes have larger PIN values because they are typically highly priced, large company shares with more frequent information events and greater trader interest.

Finally, we find that there is more information-based trading in stocks with larger market capitalizations, larger spreads and depths, larger return volatility, and smaller trading volume. The positive relation between PIN and MVE may be explained by the fact that larger companies are likely to have more frequent information events and greater trading interest. Spreads and return volatility are positively related to PIN perhaps because stocks with larger spreads and higher return volatility are likely to have greater information asymmetry problems. The positive relation between PIN and the depth may reflect the fact that informed traders are more likely to trade stocks with larger depths because larger depths imply smaller price impacts of trades.

5. Comparison of the spreads of KSE and NYSE stocks

In the previous sections, we perform inter-stock comparisons of spreads using a sample of stocks listed on the KSE to determine the effect of the stepwise tick structure on trading costs. In this section, we further examine the effect of the stepwise tick system on spreads by comparing the spreads of KSE and NYSE stocks. In particular, we examine whether there is a significant difference in spreads between KSE and NYSE stocks and whether the difference (if it exists) can be explained by their differential tick structure.

While the KSE imposes larger mandatory tick sizes on higher priced stocks, the NYSE has used a uniform tick size of one cent across all price levels since its decimalization in 2001. Figure 1 compares the tick structure of the two markets. Note that tick sizes on the KSE are at least 0.1% of share price at all price levels, whereas the ratio of tick size to price declines monotonically on the NYSE.

The KSE differs significantly from the NYSE in market structure. The KSE is a pure electronic limit order market where buyers and sellers interact directly to find best prices without a participation of market makers. In contrast, the NYSE is a hybrid market in which the specialists play a significant role as 'the liquidity provider of last resort' in compliance with their affirmative obligation. The specialists have an affirmative obligation to maintain a market presence as well as a fair and orderly market. This obligation requires the specialist to provide liquidity when the level of liquidity provided by public traders is inadequate.

In what follows, we compare the spreads of KSE and NYSE stocks to determine whether the difference in spreads between the two groups of stocks can be explained by their differences in tick structure, market structure, or both. If the difference in spreads between KSE and NYSE stocks is systematically related to their tick structure, the difference is likely due to tick structure. If the difference in spreads cannot be accounted for by tick structure, it may be due to market structure.

5.1. Matching procedure and sample characteristics

To compare the spreads of KSE and NYSE stocks after controlling for differences in their attributes, we obtain a matched sample of KSE and NYSE stocks that are similar in trading volume, price, return volatility, and market capitalization. To obtain the matched sample, we calculate the following matching score for all possible pairs of KSE and NYSE stocks:

$$Matching\ score = \sum_{i=1}^{K}\left(\frac{2(X_i^K - X_i^N)}{X_i^K + X_i^N}\right)^2 \tag{9}$$

where X_i represents one of the four stock attributes and superscripts K and N refer to the KSE and the NYSE, respectively. For each KSE stock, we select the best matched NYSE stock. If a NYSE stock is matched with multiple KSE stocks, we keep the pair with the lowest matching score. Finally, we drop the pairs for which the matching score exceeds one. This procedure yields 160 pairs of KSE and NYSE stocks that are similar in their attributes.

Table 6 shows descriptive statistics on the entire study sample and the matched sample, respectively. For the entire study sample, KSE stocks have smaller market capitalizations, higher return volatility, and smaller trading volume than NYSE stocks. The relative tick size (tick size/price) is larger on the KSE, as is the percentage of quoted spreads that are equal to the tick size, indicating that the tick size is more frequently a binding constraint on the KSE. The probability of information-based trading is higher on the KSE. The mean value of PIN for KSE stocks is 20.1% whereas the corresponding figure for NYSE stocks is 13.5%.

For the matched sample, KSE and NYSE stocks are much more similar in their attributes. The average market capitalization of KSE and NYSE stocks are $736 and $738 million, respectively. The average price of KSE stocks is $13.95 and the average price of NYSE stocks is $12.73. The average trading volume of KSE stocks is $5,450,000 whereas the corresponding value for NYSE stocks is $5,306,000. The average standard deviation of daily closing quote-midpoint returns for KSE and NYSE stocks are 2.81% and 3.03%, respectively.

5.2. Comparison of trading costs between matched KSE and NYSE stocks

Table 7 compares the spreads of KSE and NYSE stocks. The table also shows the results of the t-test and the Wilcoxon signed rank test. We show the results for the entire matched sample, for each firm size group, and for each tick size group. Panel A shows that for the entire sample of matched stocks, the average quoted spread of KSE stocks (0.73%) is smaller than that of NYSE stocks (0.87%) and the difference is statistically significant at the 1% (5%) level according to the t-test (the Wilcoxon signed rank test). This result suggests that the KSE's electronic limit order market provides cheaper executions than the NYSE's hybrid market for our matched sample of stocks as a whole.

When we compare the spreads of KSE and NYSE stocks within each firm size group, the mean quoted spread of KSE stocks is significantly smaller than that of NYSE stocks for stocks in the smallest firm size group. In contrast, the mean quoted spread of KSE stocks is significantly larger than that of NYSE stocks for stocks in the largest firm size group. These results are at odds with our initial expectations. To the extent that shares of smaller companies are traded less actively, our initial expectation was that the performance of the pure limit order market (the KSE) relative to that of the hybrid market (the NYSE) would be poorer for smaller companies (because liquidity provision by limit order traders increases with trading activity). If this were the case, the KSE would exhibit larger spreads than the NYSE for thinly traded stocks of small companies. However, our results do not support this line of thought. Apparently, the observed pattern of differential spreads between KSE and NYSE stocks cannot be explained by the difference in market structure between the KSE and the NYSE.

A possible explanation for these results is the differential tick structure between the two markets. Perhaps the larger quoted spread of large KSE stocks (relative to that of large NYSE stocks) may be attributed to the fact that they are typically high-price stocks that are subject to larger tick sizes. These KSE stocks may have larger spreads because they have large tick sizes that are frequently a binding constraint on the spread. To test this conjecture, we cluster our matched sample of KSE and NYSE stocks according to the tick size and compare the mean spread of KSE stocks to that of NYSE stocks within each tick size group.

Panel B of Table 7 shows the results. The results show that the mean quoted spreads of KSE stocks that belong to smaller tick size groups (₩5 and ₩10) are significantly smaller than the mean quoted spreads of matched NYSE stocks. In contrast, the mean quoted spreads of KSE stocks that belong to larger tick size groups (₩50 and ₩50+) are significantly larger than the mean quoted spreads of matched NYSE stocks. Similarly, the mean effective spreads of KSE stocks that belong to smaller (larger) tick size groups are significantly smaller (larger) than the mean effective spreads of matched NYSE stocks. These results support our conjecture that large tick sizes imposed on high-price stocks on the KSE are significant binding constraints on absolute spreads, resulting in larger spreads for these stocks.

Indeed, Panel C shows that the binding probability on the KSE is significantly higher than the binding probability on the NYSE across all tick sizes. More importantly, the binding probability increases monotonically with the tick size (from 30.80%, 42.81%, 58.45%, and to 74.24%) on the KSE. Interestingly, the binding probability tends to decrease for the matched NYSE stocks. The lowest mean binding probability (13.78%) of those NYSE stocks that are matched with the KSE stocks with the largest tick size reflects that these NYSE stocks are likely to be high priced, large volume stocks. In the same vein, Panel C also shows that the relative tick size (tick size/price) of KSE stocks does not decrease with the tick size, whereas it declines monotonically with the tick size on the NYSE.

To shed some light on the effect of the stepwise tick structure on market liquidity, we also compare the market quality index (MQI) of KSE and NYSE stocks. The results (see Panel D) show that the average market quality index of NYSE stocks is significantly smaller than the average market quality index of KSE stocks that belong to the first three tick size groups (i.e., ₩5, ₩10, and ₩50). In contrast, the average market quality index of NYSE stocks is greater than the average market quality index of KSE stocks that belong to the largest tick size group (₩50+). Although these results support the idea that the large tick size imposed on highly priced KSE stocks has a detrimental effect on market liquidity, they should be interpreted with caution because the validity of MQI depends critically on its underlying assumption of the linear liquidity supply function.

On the whole, our results suggest that the KSE's electronic limit order market provides cheaper executions than the NYSE's hybrid system. Our results also suggest that the efficiency of the KSE system could be further enhanced if the larger tick sizes imposed on high-price stocks were replaced with smaller ones.

It is important to note that our study is not a general comparative analysis of trading costs between the KSE and the NYSE because our study sample includes only those KSE stocks that can be matched with a NYSE stock based on the four stock attributes. Many stocks on the KSE are not included in our study sample because they are generally much smaller (in terms of MVE) or less active (in terms of VOLUME) than any of the available NYSE stocks. Likewise, many stocks on the NYSE are not included in our study sample because they are much larger or more active than any of the available KSE stocks. To the extent that these non-matched KSE (NYSE) stocks are likely to have larger (smaller) spreads than any of the remaining NYSE (KSE) stocks, our study does not provide evidence as to the overall performance of the KSE and the NYSE.

6. Summary and concluding remarks

A number of stock markets across continents use the stepwise tick system in which the tick size increases with share price. These markets impose larger tick sizes on higher priced stocks based on the belief that the tick size relative to share price should not be too small because, for example, smaller tick sizes may lead to low liquidity due to the higher risk of front running. Despite the prevalence of the stepwise tick systems, the efficacy of these systems is not well understood. In this study we examine the effects of the stepwise tick structure on trading costs and other measures of market quality using data from the Korea Stock Exchange and the New York Stock Exchange.

Our results indicate that large tick sizes imposed on high-price stocks have detrimental effects on market quality because they are frequently a binding constraint on bid-ask spreads. We find evidence that relaxation of large tick sizes imposed on high-price stocks could significantly reduce the trading costs on the KSE. Using the matched sample of KSE and NYSE stocks that are similar in price, return volatility, trading volume, and market capitalization, we find that the average spread of KSE stocks is smaller than the average spread of NYSE stocks. We interpret this result as evidence that the electronic limit order market provides cheaper executions than the NYSE's specialist system, although the generality of this claim is yet to be established because of the limited nature of our study sample.

Despite the overall superior performance of the KSE's electronic limit order market, the mean quoted and effective spreads of KSE stocks that belong to larger tick size groups are significantly larger than those of matched NYSE stocks. Hence, our results suggest that the efficacy of the KSE system could be further enhanced if the larger tick sizes imposed on high-price stocks were replaced with smaller ones.

Although the results of our study underscore the benefit of smaller tick sizes in terms of smaller trading costs, there are multiple dimensions (such as the speed of price discovery) of market quality that need to be addressed for a comprehensive evaluation of a given tick system. Similarly, although we find that the average spread of KSE stocks is smaller than that of NYSE stocks, the result should be interpreted with great caution with respect to the relative performance of the electronic limit order market and the hybrid-specialist market because our study sample of matched KSE and NYSE stocks includes only a small subset of the entire population and there are other dimensions of market quality that are not examined in our study.

References

Ahn, H., Cao, C., Choe, H., 1996. Tick size, spread, and volume. Journal of Financial Intermediation 5, 2-22.

Ahn, H., Cao, C., Choe, H., 1998. Decimalization and competition among stock markets: Evidence from the Toronto Stock Exchange cross-listed securities. Journal of Financial Markets 1, 51-87.

Anshuman, V., Kalay, A., 1998. Market making with discrete prices. Review of Financial Studies 11, 81-109.

Bacidore, J., 1997. The impact of decimalization on market quality: an empirical investigation of the Toronto Stock Exchange. Journal of Financial Intermediation 6, 92-120.

Bessembinder, H., 1999. Trade execution costs on NASDAQ and the NYSE: a post-reform comparison. Journal of Financial and Quantitative Analysis 34, 387-407.

Bessembinder, H., 2000. Tick size, spreads, and liquidity: an analysis of Nasdaq securities trading near ten dollars. Journal of Financial Intermediation 9, 213-239.

Bessembinder, H., 2003. Trade execution costs and market quality after decimalization. Journal of Financial and Quantitative Analysis 38, 747-777.

Bollen, N., Whaley, R., 1998. Are 'teenies' better? Journal of Portfolio Management 25, 10-24.

Chung, K.H., Charoenwong, C., Ding, D., 2004. Penny pricing and the components of spread and depth changes. Journal of Banking and Finance 28, 2981–3007.

Chung, K.H., Chuwonganant, C., McCormick, D.T., 2004. Order preferencing and market quality on NASDAQ before and after decimalization. Journal of Financial Economics 71, 581-612.

Chung, K.H., Kim, K., Kitsabunnarat, P., 2005. Liquidity and quote clustering in a market with multiple tick sizes. Journal of Financial Research 28, 177-195.

Chung, K.H., Shin, J.S., 2005. Tick size and trading costs on the Korea Stock Exchange. Asia-Pacific Journal of Financial Studies 34, 165-193.

Easley, D., Hvidkjaer, S., O'Hara, M., 2002. Is information risk a determinant of asset returns? Journal of Finance 57, 2185-2221.

Goldstein, M., Kavajecz, K., 2000. Eighths, sixteenths and market depth: changes in tick size and liquidity provision on the NYSE. Journal of Financial Economics 56, 125-149.

Grossman, S., Miller, M., Fischel, D., Cone, K., Ross, D., 1997. Clustering and competition in dealer markets. Journal of Law and Economics 40, 23-60.

Harris, L., 1994. Minimum price variations, discrete bid-ask spreads, and quotation sizes. Review of Financial Studies 7, 149-178.

Harris, L., 1997. Decimalization: A review of the arguments and evidence. Working Paper, University of Southern California.

Huang, R., Stoll, H., 1996. Dealer versus auction markets: a paired comparison of execution costs on NASDAQ and the NYSE. Journal of Financial Economics 41, 313-357.

Lee, C., Ready, M., 1991. Inferring trade direction from intraday data. Journal of Finance 46, 733-746.

Porter, D., Weaver, D., 1997. Tick size and market quality. Financial Management 26, 5-26.

Seppi, D., 1997. Liquidity provision with limit orders and a strategic specialists. Review of Financial Studies 10, 103-150.

Van Ness, B., Van Ness, R., Pruitt, S., 2000. The Impact of the reduction in tick increments in major U.S. markets on spread, depth, and volatility, Review of Quantitative Finance and Accounting 15, 153-169

Venkataraman, K., 2001. Automated versus floor trading: an analysis of execution costs on the Paris and New York Exchange. Journal of Finance 54, 1445-1484.

Table 1
The bid-ask spread and binding probability on the Korea Stock Exchange

This table shows the mean bid-ask spread and binding probability for our study sample of 651 KSE stocks during the three months period from April 2003 to June 2003. We obtain the percentage quoted (effective) spread for each quote (trade) and then calculate the time-weighted (trade-weighted) mean percentage quoted (effective) spread for each stock. Similarly, we obtain the percentage realized spread using the quote midpoint five minutes after the trade. We then calculate the trade-weighted mean realized spread for each stock. The binding probability is the probability that the tick size is a binding constraint on absolute spreads, measured by the percentage of quoted spreads that are equal to the tick size. A firm is categorized as small, medium, or large if its market capitalization is smaller than $100 million, between $100 million and $1 billion, or greater than $1 billion. We convert Korean Won into U.S. dollars using the exchange rates during the study period.

	Whole sample	Tick size			
		₩5	₩10	₩50	₩50+
Number of stocks	651 (100%)	322 (49.46%)	149 (22.89%)	158 (24.27%)	22 (3.38%)
Quoted spread (%)	1.0445	1.0503	1.1306	1.0158	0.5829
Effective spread (%)	1.0510	1.0925	1.0824	1.0052	0.5580
Realized spread (%)	0.2981	0.2579	0.3589	0.3482	0.1150
Binding probability (%)	38.64	41.42	24.82	43.29	58.17
Quoted spread by firm size					
Small	1.2513	1.1459	1.3637	1.4324	-
Medium	0.4344	0.3508	0.2516	0.5057	0.7350
Large	0.2422	0.1688	0.1852	0.2605	0.2567
Binding probability by firm size (%)					
Small	30.07	38.45	13.56	25.35	-
Medium	59.89	61.59	66.68	59.82	43.97
Large	87.08	86.85	74.14	89.27	88.62

Table 2

Effects of tick sizes and stock attributes on the quoted spread and binding probability

To examine the effect of tick sizes on the quoted spread, we regress the quoted spread on three tick size dummy variables, D_{10}, D_{50}, and D_{50+}, and the following control variables: market value of equity (MVE), dollar trading volume (VOLUME), return volatility (VOLATILITY), the probability of information-based trading (PIN), and the inverse of share price (INVPRICE). We measure return volatility by the standard deviation of daily closing quote-midpoint returns. We estimate the probability of information-based trading (PIN) using the model in Easley, Hvidkjaer, and O'Hara (2002). To examine the effect of tick sizes on the binding probability, we regress the binding probability on D_{10}, D_{50}, D_{50+}, MVE, VOLUME, VOLATILITY, PIN, and DEPTH, where DEPTH denotes the quoted depth. We use log of MVE and VOLUME in the regressions. Numbers in parenthesis are t-statistics. The bottom two rows show the F-statistics for testing the equality of two regression coefficients on respective tick size dummy variables.

	Quoted spread	Binding probability
Market value of equity (MVE)	0.1458*** (5.60)	-1.0024* (-1.93)
Dollar trading volume (VOLUME)	-0.4069*** (-17.56)	4.7959*** (8.50)
Return volatility (VOLATILITY)	0.1783*** (8.58)	-1.1046** (-2.56)
Probability of information-based trading (PIN)	0.0186*** (5.00)	-0.2944*** (-3.87)
1/Price (INVPRICE)	0.2708*** (8.79)	
Market depth (DEPTH)		15.2945*** (36.91)
D_{10}	0.1914*** (3.60)	7.5011*** (6.56)
D_{50}	0.3006*** (5.11)	23.9063*** (17.90)
D_{50+}	0.3527*** (2.97)	39.7818*** (14.68)
Constant	2.4397*** (7.83)	-113.2699*** (-17.92)
Number of stocks	651	651
Adjusted R^2	0.6541	0.9103
Test for $D_{10} = 0$	12.98***	43.03***
Test for $D_{50} = D_{10}$	3.73*	195.22***
Test for $D_{50+} = D_{50}$	0.22	46.14***

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Table 3

Maximum likelihood estimation of the discrete spread model

This table shows the results of maximum likelihood estimation of the discrete spread model. We use only those KSE stocks that remain in the single tick size category throughout the study period. The spread model includes the following variables: D_5, D_{10}, D_{50}, market value of equity (MVE), dollar trading volume (VOLUME), return volatility (VOLATILITY), the probability of information-based trading (PIN), and the interaction variable between each tick size dummy variable and the inverse of share price (INVPRICE). We measure return volatility by the standard deviation of daily closing quote-midpoint returns. We estimate the probability of information-based trading (PIN) using the model in Easley, Hvidkjaer, and O'Hara (2002). We use log of MVE, VOLUME, and INVPRICE in the regression.

	Unrounded quoted spread
Market value of equity (MVE)	0.0371 (0.85)
Dollar trading volume (VOLUME)	-0.3383*** (-9.55)
Return volatility (VOLATILITY)	0.1375*** (14.44)
Probability of information-based trading (PIN)	0.0110 (1.06)
INVPRICE·D_5	0.5588*** (8.47)
INVPRICE·D_{10}	0.5002*** (8.50)
INVPRICE·D_{50}	0.4225*** (10.24)
Constant	8.9539*** (19.8360)
Shape parameter	1.0848*** (97.4931)
Number of stocks	378

***Significant at the 1% level.

Table 4
Projected spreads and binding probability by the discrete spread model

Panel A shows the quoted, fitted, and projected spread by the discrete spread model. We obtain the projected spread based on the assumption that the current tick size is reduced to the next smaller tick size. Hence, for stocks with the tick size of ₩5, we obtain the projected spread under the assumption that the new tick size is ₩1. Likewise, for stocks with the tick size of ₩10 (₩50), we obtain the projected spread under the assumption that the new tick size is ₩5 (₩10). A firm is categorized as small, medium, or large if its market capitalization is smaller than \$100 million, between \$100 million and \$1 billion, or greater than \$1 billion. Panel A also shows two t-statistics for each tick size group. The first t-statistic is for testing the equality of mean between the quoted and fitted spreads. The second t-statistic is for testing the equality of mean between the quoted and projected spreads. We repeat the above tests using the binding probability (BND) and show the results in Panel B. The binding probability is the probability that the tick size is a binding constraint on absolute spreads, measured by the percentage of quoted spreads that are equal to the tick size.

	Tick size = ₩5					Tick size = ₩10					Tick size = ₩50				
Firm size	Quoted	Fitted	t-statistic	Projected (₩1)	t-statistic	Quoted	Fitted	t-statistic	Projected (₩5)	t-statistic	Quoted	Fitted	t-statistic	Projected (₩10)	t-statistic
Panel A. Quoted spread															
All	0.8941	1.0239	-6.03 ***	0.4542	22.76 ***	0.5806	0.5576	0.63	0.3290	6.15 ***	0.8060	0.7887	0.86	0.3475	13.94 ***
Small	0.9558	1.0900	-5.66 ***	0.4853	22.98 ***	0.7803	0.7183	1.13	0.4262	6.90 ***	1.1498	1.0939	1.50	0.4978	13.54 ***
Medium	0.3717	0.4689	-2.89 ***	0.1939	10.26 ***	0.2287	0.2753	-7.29 ***	0.1581	9.10 ***	0.5269	0.5437	-0.91	0.2266	11.52 ***
Large	0.1821	0.1996	n/a	0.0648	n/a	0.1717	0.2259	n/a	0.1284	n/a	0.2513	0.2882	-6.44 ***	0.1016	10.47 ***
Panel B. Binding probability															
All	49.97	48.06	1.86 *	24.99	17.67 ***	34.68	36.30	-0.76	31.68	1.30	46.50	49.17	-2.30 **	26.14	11.75 ***
Small	48.25	46.85	1.26	23.99	15.69 ***	16.76	25.49	-4.82 ***	21.72	-2.74 **	27.22	36.52	-7.12 ***	17.18	5.21 ***
Edium	62.94	56.68	2.84 ***	31.79	12.05 ***	64.64	55.11	4.92 ***	48.97	7.48 ***	58.52	56.33	1.24	30.42	10.99 ***
Large	88.23	81.52	n/a	55.31	n/a	76.20	59.12	n/a	52.96	n/a	87.93	78.43	21.13 ***	49.13	66.21 ***

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Table 5

Determinants of the quoted depth, market quality index, and the probability of information-based trading

To examine the effect of tick sizes on the quoted depth, we regress the quoted depth on market value of equity (MVE), dollar trading volume (VOLUME), quoted spread (SPREAD), return volatility (VOLATILITY), the probability of information-based trading (PIN), and either the binding probability (BND) or the three tick size dummy variables. We estimate the probability of information-based trading (PIN) using the model in Easley, Hvidkjaer, and O'Hara (2002). We measure return volatility by the standard deviation of daily closing quote-midpoint returns. The binding probability is the probability that the tick size is a binding constraint on absolute spreads, measured by the percentage of quoted spreads that are equal to the tick size. To examine the effect of tick sizes on the market quality index (MQI), we regress MQI on D_{10}, D_{50}, D_{50+}, MVE, VOLUME, PIN, and VOLATILITY. To examine the effect of tick sizes on PIN, we regress PIN on D_{10}, D_{50}, D_{50+}, MVE, VOLUME, VOLATILITY, and SPREAD. We use log of MVE, VOLUME, and MQI in the regression. Numbers in parenthesis are t-statistics. The bottom two rows show F-statistics for testing the equality of two regression coefficients on respective tick size dummy variables.

	Quoted depth (DEPTH)	Quoted depth (DEPTH)	Market quality index (MQI)	PIN
Market value of equity (MVE)	0.1367***	-0.0440*	-0.2626***	0.5366**
	(7.34)	(-1.83)	(-6.35)	(2.11)
Dollar trading volume (VOLUME)	0.3622***	0.7292***	1.1183***	-2.3307***
	(14.12)	(38.73)	(30.14)	(-5.95)
Quoted spread (SPREAD)	0.2104***	0.3307***		1.8896***
	(7.20)	(19.42)		(4.66)
Probability of information-based	0.0169***	0.0064*	-0.0005	
trading (PIN)	(6.04)	(1.73)	(-0.08)	
Return volatility (VOLATILITY)	-0.1557***	-0.2356***	-0.3252***	1.5555***
	(-9.42)	(-11.19)	(-9.29)	(6.59)
Binding probability (BND)	0.0186***			
	(22.38)			
Quoted depth (DEPTH)				0.7226*
				(1.73)
D_{10}		-0.1291***	-1.1758***	1.9002***
		(-2.62)	(-13.84)	(3.66)
D_{50}		0.2527***	-1.8442***	3.9618***
		(4.61)	(-19.55)	(6.96)
D_{50+}		0.5032***	-3.3240***	4.1998***
		(4.33)	(-16.60)	(3.39)
Constant	0.7930***	0.3285	-7.2076***	25.6737***
	(3.52)	(1.04)	(-14.20)	(8.03)
Number of stocks	651	651	651	651
Adjusted R^2	0.9188	0.8675	0.8503	0.4146
Test for $D_{10} = 0$		6.89***	191.49***	13.42***
Test for $D_{50} = D_{10}$		47.14***	48.57***	11.60***
Test for $D_{50+} = D_{50}$		5.26**	61.62***	0.04

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.

Table 6

Descriptive statistics on the whole and matched samples

This table show descriptive statistics on the whole and matched samples of KSE and NYSE stocks. To obtain the matched sample, we calculate the following matching score for all possible pairs of KSE and NYSE stocks:

$$Matching\ score = \sum_{i=1}^{K}\left(\frac{2(X_i^K - X_i^N)}{X_i^K + X_i^N}\right)^2$$

where X_i represents one of the four stock attributes (market value of equity, share price, dollar trading volume, and return volatility) and superscripts K and N refer to KSE and NYSE, respectively. For each KSE stock, we select the best matched NYSE stock. When a NYSE stock is matched with multiple KSE stocks, we keep the pair with the lowest matching score. Finally, we drop the pairs for which the matching score exceeds one. This procedure yields 160 pairs of KSE and NYSE stocks that are similar in the four matching variables. Return volatility is the standard deviation of daily closing quote-midpoint returns, PIN is the probability of information-based trading, Binding probability is the percentage quoted spreads that are equal to the tick size, Quoted depth is the number of shares available at the best bid and ask, and Tick size/price is the ratio of tick size to share price. We convert Korean Won into U.S. dollars using the exchange rates during the study period.

	Whole sample		Matched sample	
	KSE	NYSE	KSE	NYSE
Number of stocks	651	1325	160	160
Market value of equity ($1,000,000)	312.9	5814.2	735.6	738.9
Price ($)	10.62	24.24	13.95	12.73
Trading volume ($1,000)	2,658	26,130	5,450	5,306
Trading volume (1,000 shares)	764.87	998.52	558.17	478.00
Return volatility (%)	3.04	2.24	2.81	3.03
PIN (%)	20.11	13.48	19.11	20.59
Binding probability (%)	38.64	28.86	48.29	20.90
Quoted depth (shares)	11,554	1,560	2,455	1,766
Tick size/price (%)	0.3015	0.0806	0.2211	0.1815

Table 7

Matched sample comparisons of trading costs between KSE and NYSE stocks

Panels A and B compare the mean spreads of KSE and NYSE stocks. In each panel, we show the results of the t-test (t) and the Wilcoxon signed rank test (z) for testing the equality of two means. We show the results for the entire matched sample, for each firm size group, and for each tick size group. A firm is categorized as small, medium, or large when its market capitalization is smaller than $100 million, between $100 million and $1 billion, or greater than $1 billion. Panel C compares the mean tick/price ratio and the binding probability between KSE and NYSE stocks for each tick size group. Binding probability is the probability that the tick size is a binding constraint on absolute spreads, measured by the percentage of quoted spreads that are equal to the tick size. Panel D compares the quoted depth and the market quality index between KSE and NYSE stocks for each tick size group.

Panel A. Spreads by firm size

	Quoted spread (%)			Effective spread (%)		
Firm size	KSE	NYSE	T[z]	KSE	NYSE	t[z]
All	0.7302	0.8714	-2.63***[-1.94*]	0.7441	0.8172	-1.50[-1.52]
Small	1.2544	1.5748	-2.64**[-2.86***]	1.2313	1.3765	-1.35[-2.07**]
Medium	0.4119	0.4595	-1.30[-0.51]	0.4541	0.5053	-1.13[-0.20]
Large	0.2390	0.1739	2.66**[2.38**]	0.2727	0.2238	1.69[2.04**]

Panel B. Spreads by tick size

	Quoted spread (%)			Effective spread (%)		
Tick size (₩)	KSE	NYSE	T[z]	KSE	NYSE	t[z]
5	0.9009	1.6391	-6.11***[-4.98***]	0.9315	1.4743	-5.91***[-4.72***]
10	0.6462	0.8256	-2.75***[-3.54***]	0.6564	0.8801	-2.75***[-3.04***]
50	0.7225	0.5200	3.50***[5.79***]	0.7268	0.4710	4.33***[6.37***]
50+	0.3210	0.1633	3.88***[2.67***]	0.3454	0.1495	5.32***[2.67***]

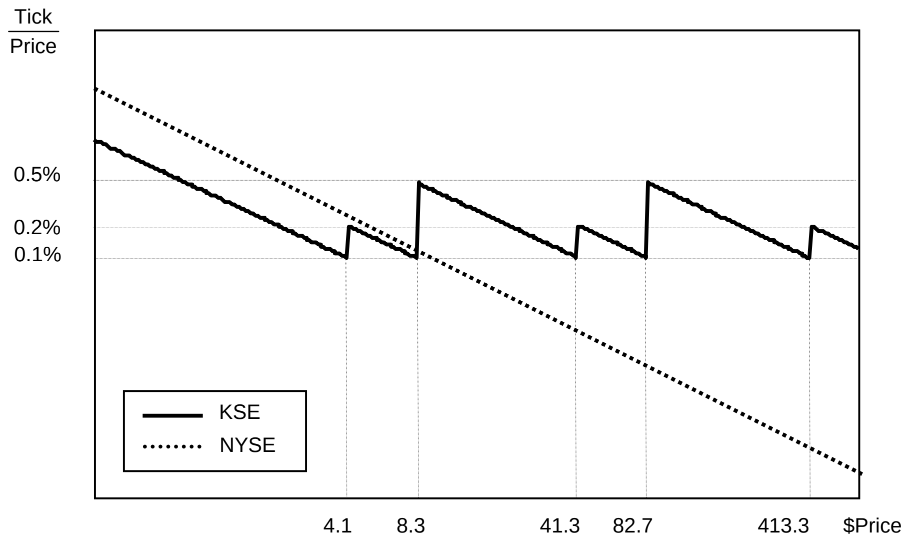
Panel C. Relative tick size and binding probability by tick size

	Tick/price (%)			Binding probability (%)		
Tick size (₩)	KSE	NYSE	T[z]	KSE	NYSE	t[z]
5	0.1823	0.4062	-12.11***[-5.70***]	30.80	23.33	4.74***[4.35***]
10	0.1552	0.1691	-1.80*[-1.94*]	42.81	24.07	8.96***[5.11***]
50	0.2769	0.0723	23.12***[7.32***]	58.45	18.69	17.61***[7.32***]
50+	0.2366	0.0205	5.63***[2.67***]	74.24	13.78	11.41***[2.67***]

Panel D. Quoted depth and market quality index (MQI) by tick size

	Quoted depth			MQI		
Tick size (₩)	KSE	NYSE	T[z]	KSE	NYSE	t[z]
5	6,568	9,516	-2.82***[-5.02***]	8,471	4,389	1.89*[3.15***]
10	13,416	11,417	0.93[-1.25]	11,355	4,873	2.42**[3.89***]
50	41,930	15,216	4.67***[5.25***]	9,029	4,638	3.98***[3.14***]
50+	80,044	26,777	1.91*[2.31**]	3,681	4,699	-1.81[-1.60]

***Significant at the 1% level.
**Significant at the 5% level.
*Significant at the 10% level.


Tick
Price
0.5%
0.2%
0.1%
KSE
NYSE
4.1
8.3
41.3
82.7
413.3
$Price

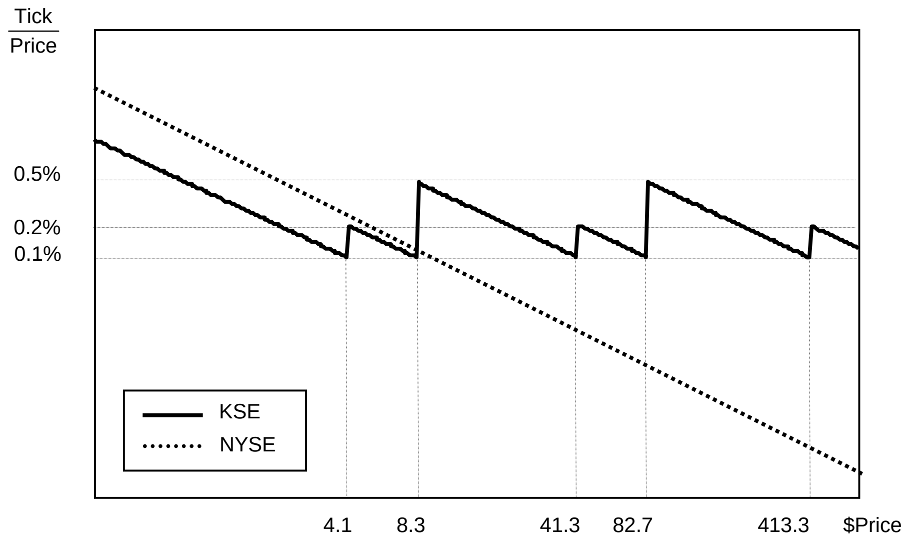


Figure 1. This figure shows the structure of tick size on the KSE and the NYSE. Both axes are log-transformed and based on dollar value. The solid line depicts the relative tick size (i.e., tick size/share price) as a function of share price on the Korea Stock Exchange and the dashed line depicts the relative tick size as a function of share price on the New York Stock Exchange.