Tick size and trading costs on the Korea Stock Exchange

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Abstract

The Korea Stock Exchange (KSE) imposes larger mandatory tick sizes on higher priced stocks. In this study, we examine the effects of tick size on spreads, depths, and quote clustering using trade and quote data for a large sample of KSE-listed stocks. Our results indicate that large tick sizes imposed on high-price stocks are significant binding constraints on absolute spreads, resulting in large spreads for these stocks. We do not find any convincing evidence of larger market depths associated with larger tick sizes. On the contrary, we find stocks that move to smaller tick categories actually exhibit an increase in market depths. Our results also show that quote clustering on the KSE is negatively related to the tick size. Overall, our findings indicate that step-increasing tick sizes are detrimental to market quality, although the adverse effect of binding tick sizes is somewhat mitigated by lower negotiation costs.

Key words: Spreads; Depths; Tick size; Quote clustering; Execution cost

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1. Introduction

The Korea Stock Exchange (KSE) imposes larger mandatory tick sizes on higher priced stocks. In contrast, U.S. securities markets use a uniform tick size of one cent across all price levels.[1] The tick size has important consequences on market quality for several reasons. If the tick size is too large, it imposes a binding constraint on the width of quotable bid-ask spreads, leaving the spread wide. If the tick size is too small, it may decrease market depth and increase negotiation costs, thus delaying the price-discovery process. In addition, a small tick size may shift market power from public investors to professional traders by making it easier for professionals to step in front of public limit orders. In this study, we examine the effects of tick size on execution costs and quote clustering using a large sample of stocks listed on the KSE.

Numerous studies analyze the effect of tick size on market quality. Harris (1994, 1997, 1999) and Ronen and Weaver (2001) hold that large tick sizes may hurt traders as they could be binding constraints on spreads. Grossman et al. (1997) hold that small tick sizes may hurt traders because small tick sizes could result in large negotiation costs. Harris (1997) also notes that smaller tick sizes may reduce the depth because of the higher risk of front running imposed upon public liquidity suppliers by professional traders and specialists. The smaller cost of stepping in front of existing orders and greater price competition may also lead to narrower spreads even when the minimum price variation is not the binding constraint. Anshuman and Kalay (1998) show that large tick sizes reduce the value of private information. Their model endogenizes the

[1] U.S. securities markets employed multiple tick sizes in the past. For example, the NYSE had the following tick sizes in 1994: $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. The Amex used the same tick rule as the NYSE until September 1992 when it was changed to $1/16 for stocks under $5. 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, in 1994.

technology of information acquisition by allowing informed traders to choose the precision of their private signals. Anshuman and Kalay compare the expected utility of informed traders under continuous pricing with the expected utility under discrete pricing. They show that informed traders invest more to acquire accurate signals under continuous pricing.

Ahn, Cao, and Choe (1996, 1998), Chung and Chuwonganant (2003), Chung, et al. (2004) examine changes in market quality associated with changes in tick size and show that smaller tick sizes lead to narrower spreads. Copeland (1979), Angel (1997), and Schultz (2000) show that relative spreads widen following stock splits and splits provide brokers with additional incentives to promote the newly split stock. Harris (1996), Bessembinder (2000), and Chan and Hwang (2001) examine the spread changes when a stock belonging to one tick group moves to another tick group.

In this study, we shed further light on the effect of tick size on market quality using data from the KSE. Although most securities markets in the world employ multiple tick sizes (e.g., Paris Bourse, Tokyo Stock Exchange, Hong Kong Stock Exchange, and Singapore Stock Exchange), there are only few studies of such markets. The multiple tick structure seems to build upon a belief that the tick size, relative to share price, should not be too small. Although this view seems popular worldwide, it is a notion that is not shared by some markets. Despite these different views, existing studies provide only limited evidence regarding the effectiveness of using step-increasing tick sizes. The KSE offers an excellent opportunity to analyze the effect of multiple tick sizes on market quality because it uses six different tick sizes.

To examine how the tick size affects spreads and depths, we first look at whether stocks that are subject to larger tick sizes exhibit wider spreads and greater depths, after controlling for the effects of other stock attributes that are believed to be associated with spreads and depths. We also examine whether stocks that moved from one tick category to another exhibit concurrent changes in spreads or depths using an event study.

We find that stocks that are subject to larger mandatory tick sizes have larger relative spreads, indicating that the KSE's stepwise tick system unnecessarily imposes larger execution costs on traders for higher priced stocks. We find no convincing evidence of larger market depths associated with larger tick sizes. Our results also suggest that the multiple tick structure diminishes the need for traders to employ their own price grids, reducing quote clustering for high priced stocks. Overall, our findings indicate that step-increasing tick sizes are detrimental to market quality as they exacerbate the binding-constraint problem, although the adverse effect of binding tick sizes is somewhat mitigated by lower negotiation costs.

The rest of the paper is organized as follows. Section 2 highlights institutional details of the KSE. Section 3 describes the data and presents descriptive statistics. Section 4 shows how the spread is related to tick sizes, share price, and other stock attributes using cross-sectional regression analyses. Section 5 provides additional evidence on the relation between tick sizes and spreads using an event study. Section 6 examines the determinants of quote clustering on the KSE and its effect on spreads. The paper ends with a brief summary and concluding remarks.

2. The Korea Stock Exchange

The KSE is a purely order-driven market where buyers and sellers interact and find best prices without a participation of market makers. Bids and offers received from investors are executed according to a set of priority rules. The whole trading procedures, including order placement, order matching, order execution, and trade confirmation, are fully automated. Trading on the KSE takes place five days a week from Monday through Friday. The KSE has three trading sessions. The regular session is from 9:00 am to 3:00 pm, the pre-hour session is from 7:30 am to 8:30 am, and the after-hour session is from 3:10 pm to 16:00 pm. Trading unit is 10 shares and odd lots can be traded in the pre-hour and after-hour sessions.

Orders submitted by investors are matched according to the price and time priority and are executed according to either periodic call auction or continuous action. Periodic call auction is used to determine a fair price after a period of trade suspension or in cases where relevant information is lacking or unavailable. This method brings together all bids and offers during a given period of time and matches them at a single price that maximizes trading volume. The KSE uses call auction to determine the opening and closing prices as well.

The KSE uses continuous auction to determine price during regular trading hours after the opening price has been determined. This method matches a bid and offer bilaterally; and when a new bid or offer enters into the system, it is matched with any of the existing offers or bids compiled in the order book according to price priority and time priority.

A step-function tick size system is one of the key institutional features of the KSE. Six different quotation price units are used depending on the price of shares. Order should be placed using a price in accordance with quotation price unit. Table 1 shows the tick size for each price range.

[Insert Table 1 Here]

3. Data source, variable measurement, and descriptive statistics

Our data come from the KSE. The data file contains trade and quote data for all stocks traded on the KSE. Our study covers a three-month period from April 2003 through June 2003. We use trades and quotes during the regular hours between 9:00 am and 3:00 pm. We omit the following to minimize data errors: (1) quotes if either the ask or the bid is less than or equal to zero; (2) quotes if either the ask size or the bid size is less than or equal to zero; (3) quotes if the bid-ask spread is greater than 20% of share price or less than zero; (4) trades if the price or volume is less than or equal to zero; (5) trade price, p_t, if $|(p_t - p_{t-1})/p_{t-1}| > 0.2$; (7) ask quote, a_t, if $|(a_t - a_{t-1})/a_{t-1}| > 0.2$; and (8) bid quote, b_t, if $|(b_t - b_{t-1})/b_{t-1}| > 0.2$.

We calculate daily mean values of share price (quote midpoint), the absolute spread (the ask price – the bid price), the relative spread (the absolute spread/share price), the number of trades (NTRADE), and trade size (TSIZE) using all quotes and trades within each day. We measure return volatility by the standard deviation of quote midpoint returns in each day. Table 2 shows select stock attributes for the whole study sample and for stocks in each tick size category. For the whole sample, the mean (median) value of share price is 11,013 (4,670) won, the mean (median) trade size is 1,964,000 (1,264,000) won, and the mean (median) number of transactions is 470 (63), respectively. The mean (median) value of absolute and relative spreads are 121 (45) won and 0.0136 (0.0088), respectively, and the mean (median) value of quoted depth is 10,895 (726).[2] The mean (median) value of the standard deviation of quote midpoint returns is 0.0203 (0.0058).

[Insert Table 2 Here]

To assess the extent to which larger tick sizes could be binding constraints, we estimate the probability that a given tick size is a binding constraint on absolute spreads. For this, we calculate the percentage of spread quotes that are equal to the tick size. Because the observed spread is equal to one tick whenever the equilibrium spread is smaller than the tick size, the percentage of spread quotes that are equal to one tick (PMIN) is a reasonable proxy for binding probability.

Table 3 shows the mean PMIN value for each tick size group as a whole, and also for each volume (i.e., number of trades) quintile within each tick size group. Because there are only two stocks that belong to the largest tick size category (i.e., 1,000 won), we combine them with stocks in the 500-won tick category. The results show that the percentage of spread quotes that are equal to one tick is substantial and varies with the tick size. For example, the percentage of spreads that are equal to one tick is 54.13% for those stocks that belong to the 50-won tick category. It is interesting to note that the corresponding figure is 48.1% even for the group of stocks that belong to the 5-won tick category.[3] These results indicate that tick sizes are significant binding constraints on the KSE, regardless of the level of share price.

Finally, the results show that PMIN increases with trading activity (number of trades) within each tick size group. For example, for stocks that belong to the 10-won tick category, the mean PMIN for least active stocks (V1) is 16.77% whereas the corresponding figure for most active stocks (V5) is 76.11%. This likely reflects the fact that the equilibrium spread of active stocks is smaller than that of less active stocks.

[Insert Table 3 Here]

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[2] We observe the maximum spread of 17,500 won for a stock selling at 486,250 won.

[3] We calculate the mean value of PMIN for each stock and then obtain its mean value across stocks. When we calculate the mean value of PMIN using all observations within each tick category without first calculating its mean value for each stock, the mean PMIN value for each tick category are 71.03 for the 5-won tick, 65.95 for the 10-won tick, 81.96 for the 50-won tick, 70.64 for the 100-won tick, and 91.93 for the 500-won tick, respectively. Mean PMIN values are greater according to the second method because stocks with larger number of trades generally have higher PMIN values.

4. Empirical findings

4.1. *Effect of step-function tick sizes on spreads*

Harris (1994) finds a strong positive correlation between the relative bid-ask spread and the inverse of share price using U.S. data. Harris interprets this finding as evidence that U.S. tick sizes (which were primarily \$1/8 at the time) are so large that they impose binding constraints on the absolute spreads of low-price stocks. For instance, consider the following regression model:

$$\text{Spread}_{i,t} = \beta_0 + \beta_1 (1/\text{Price}_{i,t}) + \varepsilon_{i,t}; \tag{1}$$

where $\text{Spread}_{i,t}$ is the relative bid-ask spread of stock i at time t, i.e., $(\text{Ask price}_{i,t} - \text{Bid price}_{i,t})/\text{Price}_{i,t}$, $\text{Price}_{i,t}$ is the midpoint of the bid and ask prices for stock i, β_0 and β_1 are regression coefficients, and $\varepsilon_{i,t}$ is an error term. If the numerator of the dependent variable, i.e., $(\text{Ask price}_{i,t} - \text{Bid price}_{i,t})$ does not vary because the equilibrium absolute spread (i.e., the spread that would prevail if the tick size were infinitesimally small) is smaller than the tick size (i.e., the tick size is a binding constraint), then any variation in the dependent variable is entirely due to variation in the denominator, i.e., $\text{Price}_{i,t}$. Hence, the extent to which the relative spread can be explained by $1/\text{Price}_{i,t}$ measures the extent to which the tick size is a binding constraint on spread widths. In an extreme case where the tick size is always a binding constraint on the absolute spread, we expect that $\beta_1 > 0$ and $R^2 = 1$.

As discussed earlier, a key feature of the KSE is the multiple tick system in which higher priced stocks are subject to larger tick sizes. To examine whether larger mandatory tick sizes for higher priced stocks are binding constraints on spread widths and thereby widen spreads, we add a dummy variable for each tick size in regression model (1). Also included in the regression are the control variables that are believed to have an effect on the spread. They are the log of average trade size (TSIZE), the log of the number of trades (NTRADE), and the standard deviation of quote midpoint returns in each day. Prior studies [see, e.g., Stoll (1978, 2000) and Chung, Van Ness, and Van Ness (1999)] show that the relative spread is negatively related to TSIZE and NTRADE, and positively related to return volatility. Based on these considerations, we estimate the following regression model:

$$\text{Spread}_{i,t} = \beta_0 + \beta_1 (1/\text{Price}_{i,t}) + \beta_2 \log(\text{TSIZE}_{i,t}) + \beta_3 \log(\text{NTRADE}_{i,t}) + \beta_4 \text{ Return volatility}_{i,t} + \beta_5 \text{ D10} + \beta_6 \text{ D50} + \beta_7 \text{ D100} + \beta_8 \text{ D500} + \varepsilon_{i,t}; \quad (2)$$

where D10, D50, D100, and D500 are the dummy variables for 10-won tick, 50-won tick, 100-won tick, and 500-won tick, respectively. We take the logarithmic transformation of TSIZE and NTRADE because these variables are highly skewed.

The estimated coefficients (β_5 through β_8) for the tick size dummy variables measure the difference in the relative spread between the 5-won tick stocks and the 10-, 50-, 100-, and 500-won tick stocks, respectively. Hence, by looking at the sign and statistical significance of β_5 through β_8, we can determine whether stocks with larger mandatory tick sizes have larger spreads, relative to the mean spread of stocks with the 5-won tick size, after controlling for the effects of other stock attributes.

We estimate regression model (2) using the pooled data of cross-sectional and daily time-series observations during our three-month study period. We report regression results in Table 4. The results show that the spread is negatively related to TSIZE and NTRADE, and positively related to return volatility. These results are consistent with the finding of prior studies. More importantly, we find that the estimated coefficients for all tick dummy variables are not only positive and significant but also directly related to the tick size (i.e., the regression coefficients are greater for larger tick sizes). These findings suggest that as tick sizes get bigger, so do the spreads, indicating that the KSE's progressive tick sizes induce larger spreads.

We find that the regression coefficients for 1/Price are positive and highly significant. This result indicates that lower priced stocks have larger relative spreads because tick sizes are more likely to be binding constraints on spread widths for these stocks. This result suggests that high-price KSE stocks would have smaller relative spreads were there not mandatory increases in tick size. However, because the KSE uses a step-wise tick structure, even higher priced stocks are subject to binding constraints and thus exhibit larger relative spreads.

4.2. Effect of step-function tick sizes on the binding probability

To determine whether the larger relative spreads for stocks with larger tick sizes are indeed driven by binding constraints, we examine the relation between PMIN and log(Price), the tick dummy variables, and other control variables. Because PMIN will be *greater* for stocks with smaller equilibrium spreads, we expect our control variables to have regression coefficients that are opposite to those from the previous spread regressions. Indeed, Table 4 shows that PMIN is positively related to TSIZE and NTRADE, and negatively related to return volatility. More importantly, estimated coefficients for the tick size dummy variables are not only all positive and significant but also directly related to the tick size, indicating that larger tick sizes are more likely to be binding constraints on spread widths. In addition, PMIN is negatively related to log(Price), indicating that the tick size is more binding on lower priced stocks. These results support the idea that the positive relation between spreads and tick sizes is indeed driven by the fact that larger ticks are more likely binding.

4.3. Effect of step-function tick sizes on depths

Although larger spreads associated with larger tick sizes show a detrimental effect of large tick sizes on market quality, the net effect of larger tick sizes on market quality is unclear if larger tick sizes result in greater depths. To examine the effect of tick size on depths, we estimate the following regression model:

$$\log(\text{Depth}_{i,t}) = \beta_0 + \beta_1 \log(\text{Price}_{i,t}) + \beta_2 \log(\text{TSIZE}_{i,t}) + \beta_3 \log(\text{NTRADE}_{i,t}) + \beta_4 \text{ Return volatility}_{i,t} + \beta_5 \text{ D10} + \beta_6 \text{ D50} + \beta_7 \text{ D100} + \beta_8 \text{ D500} + \varepsilon_{i,t}; \quad (3)$$

where $\text{Depth}_{i,t}$ is the total number of shares at the ask and at the bid, and all other variables are the same as previously defined in Eq. (1). We take the logarithmic transformation of Depth, Price, TSIZE, and NTRADE because these variables are highly skewed.

Table 4 shows that the depth is positively related to TSIZE, NTRADE, and PMIN, and negatively to share price. These results are consistent with the findings of Harris (1994). We find that the tick size dummy variables are not only all positive and significant but also directly related to the tick size, indicating that the depth increases with tick size. Hence, liquidity providers on the KSE quote larger depths for stocks with larger tick sizes. These results are in line with the finding of prior studies in other markets that an increase in tick size generally results in an increase in quoted depth.

Although the positive regression coefficients for the tick size dummy variables reported in Table 4 could be interpreted to imply that market depths increase with tick sizes, the finding should be interpreted with some caution. As Goldstein and Kavajecz (2000) showed earlier, accurate comparison of market depths between stocks with different tick sizes should consider depths at adjacent quotes as well as the depth at the inside market. Because the regression results in Table 4 are based on the depth at the inside market only, they do not offer a definitive answer as to whether larger tick sizes indeed result in greater market depths. In the next section, we shed further light on this issue using an event-study methodology.

5. Changes in spreads and depths associated with changes in tick size

In this section we perform an alternative test of the effect of tick sizes on spreads and depths. Instead of looking at the cross-sectional relation between spreads (depths) and tick sizes, we analyze inter-temporal changes in the spread (depth) for stocks that moved from one tick category to another tick category. Our binding constraint hypothesis predicts that the spread narrows (widens) when stocks move to a smaller (larger) tick category. For each stock, we identify all the two consecutive quotes between which the tick size changed from one category to another. We then compare the spread before and after the tick size change. We perform similar analyses for the depth.

Table 5 shows the results of our event study when we measure market depth using only the depth at the inside market. Panel A shows the results for stocks that moved to larger tick categories and Panel B shows the results for stocks that moved to smaller tick categories. There are 7,117 cases where a stock experienced an increase in tick size. Panel A shows that, across all tick categories, both the dollar and relative spreads increase significantly when stocks move to larger tick categories. For example, the absolute spread increases on average by 53 won when stocks move from the 10-won tick category to the 50-won tick category. Similarly, the absolute spread increases by 113 won when stocks move from the 50-won tick category to 100-won tick category. We obtain qualitatively similar results for the relative spread. Panel A also shows that depths increase when stocks move to larger tick categories. The depth change is significant at the 1% level when stocks move from the 10-won tick category to the 50-won tick category and from the 100-won tick category to 500-won tick category.

Panel B shows that both the absolute and dollar spreads decline when stocks move to smaller tick size categories, although the results are somewhat weaker (i.e., smaller t-statistics) than when stocks move to larger tick size categories. For example, changes in both the absolute and relative spreads are not significant when stocks move from the 100-won tick category to the 50-won tick category. Similarly, we find a significant decrease in depths when stocks move to smaller tick size categories, except for the move from the 10-won tick to 5-won tick categories.

Overall, our results show that an increase in tick size leads to an increase in both relative and absolute spreads and a decrease in tick size generally leads to a decrease in both relative and absolute spreads. Similarly, an increase in tick size leads to an increase in depths at the inside market and a decrease in tick size leads to a decrease in depths at the inside market.

[Insert Table 5 Here]

As pointed out earlier, however, comparing depths at the inside market could be problematic when the comparison is made between two tick categories. To examine the sensitivity of our results to different measurement methods, we re-examine changes in depths that are associated with the tick size reduction. Specifically, we subtract the depth at the inside market before the tick-size reduction from the sum of the depth at the inside market and the total depth at "adjacent quotes" after the tick-size reduction.

We define adjacent quotes as those quotes that belong to the price range covered by the bid and ask quotes before the tick size reduction. For example, suppose that the inside market quote at time t is: bid price = 10,450 won, bid size = 1,000 shares, ask price = 10,500 won, and ask size = 1,000 shares. Here, we assume that the inside spread is equal to the tick size (50 won) that applies to stocks priced between 10,000 won and 50,000 won (see Table 1). Now suppose that the inside market quote at time t+1 changed to: bid price = 9,470 won, bid size = 500 shares, ask price = 9,480 won, and ask size = 500 shares. Here again, we assume that the inside spread is equal to the new tick size of 10 won that applies to stocks priced between 5,000 won and 10,000 won. Also suppose that at time t+1, we have the following adjacent quotes (within 50 won): bid quotes of 300 shares each at both 9,450 won and 9,460 won, and ask quotes of 300 each at both 9,490 won and 9,500 won. In this case, we measure the change (200 shares) in depth between t and t+1 by subtracting the depth at the inside market (2,000 shares) before the tick-size reduction from the sum of the depth at the inside market (1,000 shares) and the total depth at adjacent quotes (1200 = 300 x 4) after the tick-size reduction.

Table 6 shows the depth-comparison results based on the above measure of depth changes. The results show that there is a significant increase in depths when stocks moved to smaller tick size categories. For example, we find an average depth increase of 3,687 shares when stocks moved from the 50-won tick category to 10-won tick category. The observed changes are all statistically significant at the 1% level.

[Insert Table 6 Here]

Overall, our results suggest that larger tick sizes mandated by the KSE for higher priced stocks inadvertently widen spreads without concurrent increases in market depths. Our regression and event study results show that the step-increasing tick sizes of the KSE induce binding constraints on quotable spread widths. This finding exposes a cost to adopting a step-function tick system. However, any costs associated with a multiple tick system must be weighed against its potential benefits. In the next section, we consider a commonly contended benefit of having larger tick sizes.

6. Effects of tick sizes on quote clustering and spreads

In this section, we analyze the effect of step-increasing tick sizes on quote clustering. We perform regression analyses to assess the extent to which the usual explanations advanced to explain quote clustering applies to the KSE and, more importantly, to determine whether the KSE's multiple tick system lowers the extent of quote clustering for higher priced stocks. To examine whether larger tick sizes for higher priced stocks reduce the extent of quote clustering, we regress a standardized measure of quote clustering on our tick dummy variables and other stock attributes that are shown to affect quote clustering in prior studies (see Ball, Torous, and Tschoegl, 1985; Harris, 1991; and Grossman et al., 1997). These stock attributes include share price, trade size, number of trades, return volatility, and the spread.

We also examine how quote clustering affects spreads on the KSE. Prior studies show that stocks with higher degrees of quote clustering exhibit wider spreads on the NYSE and NASDAQ after controlling for the effects of other stock attributes.[4] To reflect the endogeneity of quote clustering in the spread model and the endogeneity of the spread in the quote-clustering model, we estimate the following structural model using three-stage least squares (3SLS):

$$\begin{aligned} SQC_{i,t} = {} & \alpha_0 + \alpha_1 \log(Price_{i,t}) + \alpha_2 \log(TSIZE_{i,t}) + \alpha_3 \log(NTRADE_{i,t}) + \alpha_4 \text{ Return volatility}_{i,t} \\ & + \alpha_5 \text{ Spread}_{i,t} + \alpha_6 \text{ D10} + \alpha_7 \text{ D50} + \alpha_8 \text{ D100} + \alpha_9 \text{ D500} + \upsilon_{i,t}\,; \qquad (4) \end{aligned}$$

[4] See, for example, Christie and Schultz (1994), Godek (1996), Barclay (1997), and Chung, Van Ness, and Van Ness (2001, 2004).

$$\text{Spread}_{i,t} = \beta_0 + \beta_1 (1/\text{Price}_{i,t}) + \beta_2 \log(\text{TSIZE}_{i,t}) + \beta_3 \log(\text{NTRADE}_{i,t}) + \beta_4 \text{ Return volatility}_{i,t} + \beta_5 \text{ SQC}_{i,t} + \beta_6 \text{ D10} + \beta_7 \text{ D50} + \beta_8 \text{ D100} + \beta_9 \text{ D500} + \varepsilon_{i,t}; \quad (5)$$

where $SQC_{i,t}$ is a standardized quote clustering measure and all other variables are the same as previously defined in regression model (2). For stocks in the 5-won tick category, SQC is the percentage of quotes that end with 0. For stocks in the 50-won tick category, SQC is the percentage of quotes that end with 00. For stocks in the 10-won tick category, SQC is 2.5 x (the percentage of quotes that end with 50 or 100). For stocks in the 100-won tick category, SQC is 2.5 x (the percentage of quotes that end with 500 or 1,000). For stocks in the 1,000-won tick category, SQC is 2.5 x (the percentage of quotes that end with 5,000 or 10,000). These adjustments make the SQC measure comparable across all tick categories.

Table 7 shows the 3SLS results from the pooled data of cross-sectional and daily time-series observations during our study period. The results show that the estimated coefficients for the three largest tick size dummy variables in the SQC equation are not only negative and significant but also larger (in absolute values) for stocks with larger tick sizes, indicating that larger tick sizes reduce the extent of quote clustering. We interpret this result as evidence that the traders' desire to use coarser (than all available) price grids diminishes (i.e., quote clustering declines) as the tick size becomes larger because larger tick sizes make price discovery easier. The results also show that quote clustering is negatively related to NTRADE and positively related to share price, trade size, and the spread. These results are generally consistent with the findings of Ball, Torous, and Tschoegl (1985), Harris (1991), and Chung, Van Ness, and Van Ness (2004).

[Insert Table 7 Here]

Table 7 also shows that the estimated coefficient for SQC is positive and significant in the spread equation. The positive relation between the spread and quote clustering is consistent with a finding of Chung, Van Ness, and Van Ness (2004).[5] The positive relation between spreads and quote clustering may largely be an unintended outcome of investor preference towards coarse quotes. The results for the other variables in the spread equation are similar to those reported earlier in Table 4.

7. Summary and concluding remarks

Some securities markets use a uniform tick size across all stocks and other markets impose larger tick sizes on higher priced stocks. The U.S. stock markets use the uniform tick size while most Asian and European stock markets use the multiple tick system. The Korea Stock Exchange follows the latter practice. In the U.S. markets, only those stocks with very low prices were subject to smaller tick sizes before decimalization in 2001. This reflects the belief of U.S. market regulators that the tick size was too large for some (e.g., low-price) stocks before decimalization. In contrast, regulators in securities markets that employ a multiple tick system seem to believe that "too small" tick sizes may be harmful. In the present study, we analyze the efficacy of a multiple tick system using data from the Korea Stock Exchange, where stocks are subject to six different tick sizes.

Our empirical results indicate that the imposition of larger mandatory tick sizes on higher priced stocks may adversely affect market liquidity on the KSE. We find that stocks that are subject to larger mandatory tick sizes have larger relative spreads. Our results also indicate that

[5] This result contradicts the finding of Huang and Stoll (1996) that after controlling for differences in economic factors, no relation exists between quoted spreads and the frequency of odd-eighth quotes. However, our result is consistent with the finding of Barclay (1997), Bessembinder (1997), and Kandel and Marx (1997) that the spread is positively related to quote clustering.

larger tick sizes do not necessarily result in larger market depths. However, we find that the extent of quote clustering decreases with the tick size. On the whole, our findings suggest that the KSE's stepwise tick system unnecessarily imposes larger execution costs on traders for higher priced stocks, although its adverse effect on market quality may be somewhat mitigated by reduced negotiation costs.

An interesting area for future research would be the comparison of informational efficiency of share price across stocks with different tick sizes. We conjecture that all things being equal, investors with private information are more likely to trade when tick sizes are smaller because smaller tick sizes increase the probability that the true value of an asset is higher than the quoted ask price or lower than the quoted bid price. To the extent that smaller tick sizes encourage information-based trading and because it is the information-based trading that makes asset prices efficient, prices of stocks that belong to small tick size categories are more likely to be efficient than prices of stocks that belong to large tick size categories. It would be of significant interest to both market regulators and investors to find out whether this is indeed the case.

Another area for future research may be the comparison of stock split frequencies between small- and large-tick category stocks. To the extent that larger tick sizes impose greater execution costs on traders, companies that belong to large tick size categories may have an incentive to move to a small tick size category by splitting their stocks. It would be interesting to find out whether stocks that belong to larger tick categories exhibit greater frequencies of stock splits and, more importantly, whether stock splits actually lead to changes in tick categories. This line of inquiries could shed further light on the economics of stock splits.

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Table 1
Share price and tick size on the Korea Stock Exchange

A step-function tick size system is one of the key institutional features of the KSE. Six different quotation price units are used depending on the price of shares. Order should be placed using a price in accordance with quotation price unit.

Price range	Tick size
1 won – 5,000 won	5 won
5,000 won – 10,000 won	10 won
10,000 won – 50,000 won	50 won
50,000 won – 100,000 won	100 won
100,000 won – 500,000 won	500 won
500,000 won +	1,000 won

Table 2
Descriptive statistics

We calculate daily mean values of share price (quote midpoint), the absolute spread (the ask price – the bid price), the relative spread (the absolute spread/share price), the number of trades (NTRADE), and trade size (TSIZE) using all quotes and trades within each day. We measure return volatility by the standard deviation of quote midpoint returns in each day.

Panel A: Whole sample

Variable	Mean	Std. deviation	Min	25th percentile	50th percentile	75th percentile	Max
Share price (won)	11,013	28,337	76	2,212	4,670	9,868	701,166
Absolute spread (won)	121	454	5	14	45	100	17,500
Relative spread	0.0136	0.0156	0.0006	0.0045	0.0088	0.0163	0.1898
Number of trades	470	1,761	1	16	63	302	76,205
Trade size (1,000 won)	1,964	6,646	3	700	1,264	2,217	792,718
Depth	10,895	104,155	10	296	726	2,179	5,531,886
Return Volatility	0.0203	0.2613	0.0001	0.0031	0.0058	0.0104	19.6958

Panel B: Tick size = 5 won

Variable	Mean	Std. deviation	Min	25th percentile	50th percentile	75th percentile	Max
Share price (won)	2,370	1,319	76	1,310	2,307	3,393	4,999
Absolute spread (won)	34	46	5	8	17	42	785
Relative spread	0.0142	0.0141	0.0006	0.0058	0.0101	0.0170	0.1898
Number of trades	394	1,899	1	14	52	219	76,205
Trade size (1,000 won)	1,275	3,134	3	565	990	1,534	224,288
Depth	18,418	138,537	10	392	1,035	3,164	5,531,886
Return Volatility	0.0157	0.0918	0.0004	0.0039	0.0068	0.0119	6.8768

Panel C: Tick size = 10 won

Variable	Mean	Std. deviation	Min	25th percentile	50th percentile	75th percentile	Max
Share price (won)	7,016	1,431	5,000	5,699	6,855	8,230	9,999
Absolute spread (won)	100	121	10	26	61	126	1,390
Relative spread	0.0146	0.0170	0.0010	0.0037	0.0090	0.0183	0.1648
Number of trades	445	1,513	1	14	51	320	54,642
Trade size (1,000 won)	1,938	6,701	49	799	1,422	2,365	89,789
Depth	1,224	3,118	11	232	456	1,048	106,912
Return Volatility	0.0154	0.1565	0.0001	0.0025	0.0048	0.0090	10.2393

Table 2 (Continued)

Panel D: Tick size = 50 won

Variable	Mean	Std. deviation	Min	25th percentile	50th percentile	75th percentile	Max
Share price (won)	20,763	10,070	10,000	12,590	17,689	26,338	49,992
Absolute spread (won)	252	471	50	63	106	250	7,850
Relative spread	0.0119	0.0163	0.0011	0.0040	0.0064	0.0130	0.1793
Number of trades	664	1,559	1	25	113	534	24,859
Trade size (1,000 won)	3,173	3,906	102	1,570	2,527	4,004	235,001
Depth	1,612	3,347	10	216	513	1,398	48,198
Return Volatility	0.0389	0.5240	0.0005	0.0025	0.0048	0.0086	19.6958

Panel E: Tick size = 100 won

Variable	Mean	Std. deviation	Min	25th percentile	50th percentile	75th percentile	Max
Share price (won)	65,594	13,769	50,065	54,550	61,562	73,940	99,993
Absolute spread (won)	616	1,715	100	136	198	298	15,400
Relative spread	0.0090	0.0225	0.0012	0.0022	0.0031	0.0048	0.1642
Number of trades	660	821	1	198	313	751	5,103
Trade size (1,000 won)	4,735	3,016	540	2,897	3,953	5,771	27,926
Depth	503	544	10	203	307	582	4,356
Return Volatility	0.0086	0.0477	0.0005	0.0019	0.0036	0.0061	1.0409

Panel F: Tick size = 500 won

Variable	Mean	Std. deviation	Min	25th percentile	50th percentile	75th percentile	Max
Share price (won)	183,027	120,427	100,100	119,477	134,359	179,919	701,166
Absolute spread (won)	1,175	2,383	500	515	550	688	17,500
Relative spread	0.0069	0.0144	0.0013	0.0032	0.0044	0.0057	0.1841
Number of trades	1,313	1,773	1	240	673	1,630	11,805
Trade size (1,000 won)	12,387	34,907	946	5,538	8,140	12,187	792,718
Depth	1,242	1,343	10	315	716	1,819	10,241
Return Volatility	0.0111	0.1328	0.0001	0.0015	0.0024	0.0052	3.2466

Table 3
Relation between the percentage of one tick spreads and number of trades

To assess the extent to which larger tick sizes could be binding constraints, we estimate the probability that a given tick size is a binding constraint on absolute spreads. For this, we calculate the percentage of spread quotes that are equal to the tick size. Because the observed spread is equal to one tick whenever the equilibrium spread is smaller than the tick size, the percentage of spread quotes that are equal to one tick (PMIN) is a reasonable proxy for binding probability. This table shows the mean PMIN value for each tick size group as a whole, and also for each volume (i.e., number of trades) quintile within each tick size group. Because there are only two stocks that belong to the largest tick size category (i.e., 1,000 won), we combine them with stocks in the 500-won tick category.

Tick size (won)	PMIN (%)	Number of trades					Number of observations
		V1	V2	V3	V4	V5	
5	48.10	27.70	33.87	45.85	60.55	72.57	17,512
10	38.71	16.77	17.16	30.25	53.23	76.11	5,956
50	54.13	28.19	31.94	49.30	71.92	89.19	7,834
100	56.31	35.06	46.63	48.99	64.66	85.51	618
500	79.15	39.62	78.25	88.27	93.72	96.28	650

Table 4
OLS results for spreads, depths, and PMIN

This table shows how the spread, depth, and PMIN are related to stock attributes and tick sizes. Spread is the relative bid-ask spread, Price is the midpoint of the bid and ask prices, Depth is the total number of shares at the ask and at the bid, PMIN is the percentage of spreads that are equal to tick size, TSIZE is the average trade size, NTRADE is the number of trades, Return volatility is the standard deviation of quote midpoint returns in each day, and D10, D50, D100, and D500 are the dummy variables for 10-won tick, 50-won tick, 100-won tick, and 500-won tick, respectively. We estimate the regression models using the pooled data of cross-sectional and daily time-series observations of these variables during our three-month study period.

Variable	Spread	Spread	log(Depth)	log(Depth)	PMIN	PMIN
Intercept	0.0743**	0.1121**	0.8691**	2.9084**	-215.5234**	5.3524*
	(68.91)	(92.31)	(12.90)	(40.61)	(-77.35)	(2.02)
1/Price	4.0035**	4.4282**				
	(72.05)	(81.09)				
log(Price)			-1.0232**	-1.3430**	-11.7128**	-27.9142**
			(-338.06)	(-230.16)	(-97.79)	(-184.91)
log(TSIZE)	-0.0027**	-0.0060**	0.9433**	0.9469**	22.0338**	13.3089**
	(-31.49)	(-60.47)	(145.75)	(155.75)	(83.34)	(62.56)
log(NTRADE)	-0.0048**	-0.0038**	0.0589**	0.1523**	8.0142**	10.7628**
	(-111.48)	(-83.19)	(21.62)	(52.12)	(70.19)	(119.15)
Return	0.0069**	0.0063**	0.0067	0.0072	-0.8580	-1.1139
	(23.71)	(22.57)	(0.39)	(0.45)	(-1.11)	(-1.87)
PMIN			0.0222**	0.0158**		
			(180.09)	(105.74)		
D10		0.0032**		0.3085**		22.4565**
		(18.85)		(31.26)		(65.35)
D50		0.0074**		0.9058**		60.3885**
		(39.69)		(60.06)		(135.00)
D100		0.0215**		1.2075**		84.3197**
		(41.68)		(44.01)		(93.42)
D500		0.0248**		1.9746**		119.4670***
		(50.72)		(61.57)		(121.13)
F-value	8,586**	5,179**	71,075**	45,535**	8,981**	10,331**
Adjusted R^2	0.4055	0.4514	0.9160	0.9264	0.5243	0.7173

**Significant at the 1% level.
*Significant at the 5% level.
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Table 5
Spread and depth changes (after – before) associated with changes in the tick size

For each stock, we identify all the two consecutive quotes between which the tick size changed from one category to another. We then compare the spread before and after the tick size change. We perform similar analyses for the depth. This table shows the results of our event study when we measure market depth using only the depth at the inside market. Panel A shows the results for stocks that moved to larger tick categories and Panel B shows the results for stocks that moved to smaller tick categories. Numbers in parenthesis are t-statistics.

Panel A: Increase in tick size

	Number of observations	Change in absolute spreads	Change in relative spreads	Change in depths
Whole sample	7,097	65** (8.51)	0.0037** (18.79)	557** (11.56)
5 won → 10 won	3,537	18** (9.77)	0.0027** (9.77)	119 (1.68)
10 won → 50 won	2,793	53** (18.63)	0.0050** (19.52)	1,235** (15.31)
50 won → 100 won	468	113* (1.97)	0.0024* (2.04)	104* (2.02)
100 won → 500 won	299	659** (4.41)	0.0059** (3.97)	102** (4.04)

Panel B: Decrease in tick size

Whole sample	7,079	-34** (-5.51)	-0.0010** (-7.04)	-574** (-15.06)
10 won → 5 won	3,525	-2 (-1.45)	-0.0010* (-2.42)	-5 (-0.10)
50 won → 10 won	2,785	-36** (-12.96)	-0.0030** (-12.17)	-1,395** (-21.08)
100 won → 50 won	465	-23 (-0.40)	-0.0003 (-0.05)	-255** (-4.23)
500 won → 100 won	304	-400** (-3.78)	-0.0030* (-2.41)	-129** (-3.78)

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

Table 6
Depth changes (after – before) after considering the original minimum tick sizes

To examine changes in depths that are associated with the tick size reduction, we subtract the depth at the inside market before the tick-size reduction from the sum of the depth at the inside market and the total depth at "adjacent quotes" after the tick-size reduction. We define adjacent quotes as those quotes that belong to the price range covered by the bid and ask quotes before the tick size reduction. For example, suppose that the inside market quote at time t is: bid price = 10,450 won, bid size = 1,000 shares, ask price = 10,500 won, and ask size = 1,000 shares. Here, we assume that the inside spread is equal to the tick size (50 won) that applies to stocks priced between 10,000 won and 50,000 won (see Table 1). Now suppose that the inside market quote at time t+1 changed to: bid price = 9,470 won, bid size = 500 shares, ask price = 9,480 won, and ask size = 500 shares. Here again, we assume that the inside spread is equal to the new tick size of 10 won that applies to stocks priced between 5,000 won and 10,000 won. Also suppose that at time t+1, we have the following adjacent quotes (within 50 won): bid quotes of 300 shares each at both 9,450 won and 9,460 won, and ask quotes of 300 each at both 9,490 won and 9,500 won. In this case, we measure the change (200 shares) in depth between t and t+1 by subtracting the depth at the inside market (2,000 shares) before the tick-size reduction from the sum of the depth at the inside market (1,000 shares) and the total depth at adjacent quotes (1200 = 300 x 4) after the tick-size reduction.

Change in tick size	Number of observations	Change in depths	Standard deviation	t-statistic
Whole sample	1,805	6,937	11,361	25.94**
10 won → 5 won	585	14,209	15,279	22.49**
50 won → 10 won	1,056	3,687	6,792	17.64**
100 won → 50 won	69	2,402	4,249	4.70**
500 won → 100 won	95	1,578	1,973	7.80**

** Significant at the 1% level.

Table 7
Spreads and quote clustering: 3-stage least squares (3SLS) results

This table shows how quote clustering affects spreads on the KSE. To reflect the endogeneity of quote clustering in the spread model and the endogeneity of the spread in the quote-clustering model, we estimate the following structural model using three-stage least squares (3SLS). We use the pooled data of cross-sectional and daily time-series observations of these variables.

$$SQC_{i,t} = \alpha_0 + \alpha_1 \log(Price_{i,t}) + \alpha_2 \log(TSIZE_{i,t}) + \alpha_3 \log(NTRADE_{i,t}) + \alpha_4 \text{ Return volatility}_{i,t} + \alpha_5 \text{ Spread}_{i,t} + \alpha_6 D10 + \alpha_7 D50 + \alpha_8 D100 + \alpha_9 D500 + \upsilon_{i,t};$$

$$Spread_{i,t} = \beta_0 + \beta_1 (1/Price_{i,t}) + \beta_2 \log(TSIZE_{i,t}) + \beta_3 \log(NTRADE_{i,t}) + \beta_4 \text{ Return volatility}_{i,t} + \beta_5 SQC_{i,t} + \beta_6 D10 + \beta_7 D50 + \beta_8 D100 + \beta_9 D500 + \varepsilon_{i,t};$$

where $SQC_{i,t}$ is a standardized quote clustering measure and all other variables are the same as previously defined in regression model (2). Numbers in parenthesis are t-statistics.

Variable	Spread	SQC
Intercept	0.0829**	-32.9370**
	(53.48)	(-10.79)
1/Price	5.5865**	
	(45.81)	
log(Price)		8.4018**
		(73.26)
log(TSIZE)	-0.0065**	2.5967**
	(-61.79)	(15.60)
log(NTRADE)	-0.0027**	-1.0882**
	(-42.40)	(-11.36)
Return volatility	0.0038**	
	(15.84)	
Spread		298.6979**
		(13.26)
SQC	0.0004**	
	(25.31)	
D10	-0.0007**	1.2154**
	(-3.18)	(5.80)
D50	0.0103**	-24.6736**
	(43.46)	(-71.41)
D100	0.0202**	-28.8582**
	(39.83)	(-35.12)
D500	0.0271**	-41.7188**
	(53.18)	(-52.50)

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