

Can sub-penny pricing reduce trading costs?

Bidisha Chakrabarty^a and Kee H. Chung^{b,*}

^a*Department of Finance, John Cook School of Business, Saint Louis University
St. Louis, MO 63108, USA*

^b*Department of Finance and Managerial Economics, State University of New York (SUNY) at Buffalo,
Buffalo, NY 14260, USA*

Abstract

We examine the effect of tick size on quotation behavior in a naturally-controlled experimental setting. Of the top six Electronic Communications Networks (ECNs), three allow sub-penny quotes (group S) and three do not (group P). For a sample of stocks that trade on all six of these ECNs, we find that group S ECNs have narrower spreads than group P ECNs, especially for low-price stocks. Even after correcting for left-truncation and price discreteness, we find that spreads for the same stocks are tighter on group S ECNs, suggesting that a smaller tick size fosters greater price competition. We find that the one penny tick is frequently a binding constraint on the inside spread and the relaxation of the binding constraint would result in a 0.7 cent (16%) reduction in the inside spread.

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* Corresponding author. Tel.: 716-645-3262; fax: 716-645-3823.

E-mail address: keechung@buffalo.edu (K.H. Chung), Website: <http://www.acsu.buffalo.edu/~keechung/>.

1. Introduction

On April 9, 2001, all U.S. equity markets converted from fractional to decimal pricing. As a result, the minimum price variation (MPV) was narrowed from \$0.0625 (i.e., 1/16th of a dollar) to one cent. While the move to decimal pricing was designed to simplify pricing for investors and to make the U.S. securities markets more competitive internationally,¹ a number of issues related to market structure and investor protection have been raised by this change. The Securities and Exchange Commission (SEC) notes, “in particular, difficult issues have been raised in connection with the limited practice of pricing orders and trades in increments that are smaller than the MPV for quotations.”² This comment by the SEC pertains to what is commonly referred to as “sub-penny trading.”

Several Electronic Communications Networks (ECNs) have allowed their customers to place orders, and execute said orders, in increments finer than one cent since their proliferation in 1997. Before decimalization, these ECNs quoted in increments of 1/256th, which translates to \$0.0039. After decimalization, many ECNs disseminate quotes in three or four decimal places. Some broker-dealers also choose not to limit their order-entry and execution systems to two decimal places and often route sub-penny limit orders to ECNs for display and execution. They follow this practice to fulfill their obligations under the Securities Exchange Act of 1934, as amended with regard to the display of customer limit orders.³ However, the bulk of sub-penny quotation and trades occur on ECNs. The NASDAQ Decimalization Impact Study found that 84% of sub-penny executions involve ECNs on at least one side of the transaction and only 0.5% of sub-decimal limit orders are routed to and kept by market makers.

The SEC and various representatives of the investment community continue to debate the regulation of sub-penny pricing. On July 14, 2001, the SEC published concept release 43-44568 titled “Request for Comment on the Effects of Decimal Trading in Sub-pennies.” In this document, the SEC sought “comment on the impact on fair and orderly markets and investor protection of trading and potentially quoting securities in an increment of less than a penny.” Various market participants including

¹ See Securities Exchange Act Release No. 42360 (January 28, 2000), 65 FR 5004 (February 2000).

² See SEC Concept Release 17 CFR Part 240 [Release No. 34-44568: File No. S7-14-01].

³ See Rule 11Ac1-4 under the Exchange Act.

the Securities Traders Association, individual investors, institutional traders, and select ECNs responded to the SEC, some advocating a move to sub-penny trading and others pointing out potential problems of such a move.

Parties with opposing viewpoints cited the usual pros and cons. Those favoring a move to sub-penny pricing noted that the biggest gains would come from a lowering of the spread. An exchange-mandated MPV is an artificial floor on the spread and a smaller tick size can only lower this floor. Opponents of the move suggested that requiring the display of orders and quotes in sub-pennies would lead to investor confusion, a decrease in transparency, and increased “front running.” Because the size of the minimum price increment (tick) determines the cost of obtaining precedence through price priority, the tick size directly determines the profitability of front-running strategies. Moreover, requiring market centers to have facilities that can display and process orders at smaller increments could create a strain on their system capacity.

The debate came to the forefront once again on March 3, 2004, when the SEC published for comment its concept release 34-49325, a proposal to change certain national market system (NMS) rules, including one that pertained to sub-penny pricing. This proposal would prohibit market participants from accepting, ranking, or displaying orders, quotes, or indications of trading interest in pricing increments finer than one penny, except for securities priced under \$1. The response from the investment community to this proposal was unanimously negative. They pointed out that U.S. financial markets have historically been responsive to investors, and that the Commission’s intervention in fixing the MPV would only serve to cement the status quo and prevent marketplaces from making changes to pricing increments that benefit traders.⁴

⁴ The response of Edward Nicoll, the CEO of the Instinet Group is illustrative. He pointed out that when INET began quoting Sirius Radio (a stock that trades around \$4) in pennies instead of sub-penny increments, it immediately lost its market share to BRUT, which allows sub-penny quotes. INET itself prices QQQ in sub-pennies since the spread for QQQ is around \$0.003. Nicoll estimated that if all market centers traded QQQ in sub-pennies, the annual estimated savings to investors would be about \$150 million. (See www.sec.gov for the entire text of Nicoll’s testimony before the Commission.)

While the case for and against sub-penny pricing is still being argued in the popular press, there is little academic debate on this issue. In particular, there is no scientific study to back or refute either position. This lack of credible information regarding the effects of sub-penny quotes and trades is due partly to the fact that the SEC has approved sub-penny trading on a pilot basis only.⁵ U.S. equity markets as a whole have not been mandated to display quotes and prices in sub-penny increments. However, the SEC required NASDAQ and the Chicago Stock Exchange (CHX) to submit data/reports on their sub-penny trading. NASDAQ filed the required report with the SEC while CHX made its sub-decimal trading data available to the Commission. Neither of these is available to the public at the present. However, in a study commissioned for internal circulation, NASDAQ found that in one week of trading (August 2 through 8, 2001), 6% of all trades and 3% of trading volume were reported in sub-penny increments. The total amounts to over \$14.2 billion in sub-penny trades in one week.⁶

The existing debate on the potential merits and drawbacks of sub-penny pricing has been based on indirect inference from the literature on tick-size reduction. A number of studies examined the impact of tick size on market quality. Some compared pilot stocks that underwent decimalization with a matched sample of stocks that had yet to decimalize (see, e.g., Chakravarty et al., 2001). Others compared the same securities before and after decimalization (see, e.g., Bacidore, 1997; Chung, Chuwonganant, and McCormick, 2004). Neither of these approaches can achieve a complete match between the compared samples. In the former group, the firms that were compared were not identical, and in the latter group, the

⁵ On April 6, 2001, the SEC approved, on a pilot basis, a rule filed by the NASD specifying the protections NASDAQ market makers must provide to customer limit orders in sub-pennies. See Securities Exchange Act Release No. 44165 (April 6, 2001), 66 FR 19268 (April 13, 2001). On April 6, 2001, the Commission also granted the CHX, on a pilot basis, the flexibility to compete with ECNs (and NASDAQ market makers) by accepting orders in NASDAQ/NM securities priced in sub-penny increments while maintaining the uniform penny MPV for quotations. See letter to Paul O'Kelley, Chief Operations Officer, CHX, from Annette L. Nazareth, Director, Division of Market Regulation, Commission (April 6, 2001). This letter provided CHX specialists and market makers with the same flexibility in handling sub-penny orders that had been granted to ECNs. The NASDAQ and CHX proposals were originally approved as pilot programs until July 9, 2001 and then extended until November 5, 2001. This was then further extended and that is the status of the pilot at the time of writing. In March 2004, the SEC proposed an amendment of the NMS rule that would eliminate sub penny pricing for all stocks under \$1. The investment community was given until May 2004 to respond. No action has been taken on the proposal as of the time of writing (October, 2004). We would like to thank counselor Greg DuMark of the SEC for making some this information available.

⁶ We thank Frank Hatheway and Tim McCormick of NASDAQ for providing useful information regarding the report and for making available the sub-penny quotes data.

time period of comparison had to be, by definition, different. Moreover, none of the existing studies addresses the issue of sub-penny pricing.

In this paper we examine the effects of sub-penny pricing on market quality in a naturally-controlled experimental setting. Of the top six ECNs selected for both the frequency of quotes and trading volume, three allowed sub-penny quotes, while the other three did not (during the sample month of January 2002).⁷ ARCA, REDI, and BTRD are the ECNs that post quotes in two decimal places - we call them group P ECNs; INCA, ISLD, and BRUT post quotes in higher than two decimal places - we call them group S ECNs.⁸ Our sample comprises securities that trade on all six of these ECNs. Since these are the same securities, a significant part of the difference in their quotes should be attributable to the difference in the pricing grids imposed by the individual ECNs.

Using proprietary data provided by NASDAQ, we find that ECNs that allow sub-penny pricing have tighter spreads than ECNs that do not allow sub-penny pricing. The difference between the two ECN groups is especially pronounced for low-price stocks, indicating that the penny tick is more frequently a binding constraint for such stocks. Among the low-price stocks, those with higher trading volumes are more severely affected by the tick size constraint. We also find that front-running may not be a significant drawback of sub-penny pricing. For low-price stocks, ECNs that allow sub-penny quotes actually post larger depths than those ECNs that do not allow such quotes. This would not be the case if traders were wary of exposing their orders because of “pennying.”

More telling is the fact that the coarser price grid imposed by a mandated penny tick creates conditions that discourage quote competition. We use the Markov Chain Monte Carlo method to correct for the effects of price discreteness and left-truncation. We find that the true spreads are significantly lower for the ECNs that allow sub-penny pricing. We also find that the difference between the observed

⁷ In September 2002, Instinet and Island announced a merger and on October 27, 2003, batch migration of stocks to their common trading platform began, a move which eliminated sub-penny quotes for each group of pilot stocks.

⁸ The ECN id's are ARCA = Archipelago, REDI = Spear, Leeds and Kellogg, BTRD = Bloomberg TradeBook, INCA = Instinet, ISLD = Island and BRUT = Brass Utility LLC. INCA quotes three decimal places for all stocks under \$10, four places for all low-price stocks (under \$1) and this is revised every six months.

and true spreads is much smaller for the ECNs that allow sub-penny quotes than for those that do not allow such quotes. We interpret this result as evidence that the lack of quote aggressiveness fostered by a coarser pricing grid allows spreads to remain wider on the group P ECNs. This result is similar to the effect of the pricing grid that Ball and Chordia (2001) find for the seven large NYSE stocks before and after the reduction in tick size from 12.5 cents to 6.25 cents.

Although the analysis of ECN spreads is useful, ECN quotes are frequently competitive only on one side at any given time and hence do not reflect actual trading costs. A more meaningful metric for traders is the inside spread (the difference between the highest bid and lowest ask prices) since it captures the actual cost of trading. We find that the one penny tick is frequently a binding constraint on the inside spread and a complete relaxation of the binding constraint would result in a 0.7 cent (16%) reduction in the inside spread. We find that the greatest benefit of sub-penny pricing would accrue to low-price stocks. For example, our estimates show that for stocks priced below two dollars, a relaxation of the MPV would result in a spread reduction of one cent, which is over 36% of the inside spread for stocks in this price category. Overall, our results indicate that a finer pricing grid not only eliminates the effects of left-truncation and price discreteness, but more importantly, promotes quote competition.

The rest of the paper is organized as follows. In Section 2 we provide a brief survey of the literature on change in tick size and its impact on market quality. Section 3 explains data sources, sample selection methods, and summary statistics. Section 4 examines the effect of tick size on ECN spreads. Section 5 explains the Markov Chain Monte Carlo (MCMC) method and presents the results. Section 6 analyzes the effect of tick size on the inside spread, and Section 7 presents concluding remarks

2. Tick size and market quality

In January 1994, the SEC published the *Market 2000 Study of U.S. Equity Markets*, which concluded that the minimum price variation of $1/8^{\text{th}}$ of a dollar hinders competition. The SEC recommended an immediate change to $1/16^{\text{th}}$ pricing, to be followed by a transition to penny pricing. The immediate effect of a fall in the minimum price increment would be a lowering of the bid-ask spread.

Traders pay brokerage commissions and bid-ask spreads when they buy or sell securities. Although competition among a growing number of brokerages and the availability of efficient and cheap technology has reduced commissions, the exchange-mandated MPV puts a lower bound on the bid-ask spread. In a decimal trading environment, the minimum difference between the highest bid price and the lowest ask price has to be one cent because prices cannot be quoted in increments finer than one cent. Hence, the lowering of spreads is the biggest gain to investors from a reduction in the MPV.

However, as suggested by Harris (1994, 1996, 1997), a lowering of the MPV may result in a reduction in market depth. The argument is that, in the pre-decimal environment, the minimum cost of stepping ahead of an existing order was \$0.0625, while under decimal pricing it is reduced to a cent. This reduced cost of stepping ahead of existing orders may encourage what is called “front-running,” or jumping ahead of the queue. Investors wary of front-runners would more likely conceal their true trading interests (depths) in a market with a lower MPV. Harris argues that the minimum price increment should be economically significant in order to protect liquidity providers from quote matchers.

Others have construed an entirely different consequence of a lowering of the MPV. With a finer pricing grid, it is easier for institutional investors to jump to the front of the queue with limit orders, thereby increasing the supply of liquidity or “acting as pseudo-dealers.” If so, depth should not be adversely affected in a lower tick-size environment. Theory is not clear on which effect will dominate.⁹

Empirical evidence regarding the effect of tick size on market quality is large and growing. Most studies report that decimalization led to a reduction in quoted spreads. Comparing a sample of NYSE stocks trading in decimals with a matched control sample trading in fractions, Chakravarty, Harris, and Wood (2001) find lower effective spreads for the decimal sample. Chung, Charoenwong, and Ding (2004) show that this decline in spreads is due to a reduction in binding constraint and increased front-running. Bacidore (1997) finds that spreads decline significantly after decimal pricing in his study using a sample

⁹ There is some theoretical prediction regarding the effect of tick size reduction on volume. Ricker (1996) proposed that there would be an increase in volume, thereby offsetting the revenue loss to liquidity suppliers from reduced spreads. Wallman (1996) suggests that if trading volume increases, it would happen with a lag.

of stocks listed on the Toronto Stock Exchange. Bessembinder (1997) finds that smaller tick sizes lead to the largest reduction in spreads for stocks whose market makers avoid odd-eighth quotes. Ahn, Cao and Choe (1996) find a 10% decrease in spreads for stocks priced under \$5 that switched to “teenies.”

Evidence regarding the impact of smaller tick sizes on other measures of market quality is mixed. While Chan and Hwang (2000) find an increase in depths at best quotes, Bacidore (1997) finds a significant decrease in depths. Ronen and Weaver (2001) find significant decreases in both daily and transitory volatility following the American Stock Exchange’s market-wide adoption of \$1/16 ticks. They also find a higher incidence of “stepping ahead of the book” and suggest that this is a positive outcome since it provides price improvement for market orders.

Prior studies do not extend to include the impact of sub-decimal pricing; neither do they address the issue of left-truncation and price discreteness. We explicitly account for price discreteness and truncation by using the MCMC method applied to the case of sub-penny trading.

3. Data source and sample characteristics

We obtain data for this study from three sources. We obtain the sub-penny data on dealer (ECN) quotes from NASDAQ directly. The NASTRAQ database, which is publicly available from NASDAQ, round off dealer and ECN quotes at the second decimal place, and hence do not capture the effects of sub-penny pricing. The dataset used in this study is more comprehensive than the NASTRAQ data and reports higher than two decimal place quotes. However, we note that this dataset is also not complete. In many instances, data are reported to NASDAQ after the rounding off has been done. For those cases, we have no way to deduce whether a quote is rounded prior to being sent to NASDAQ, or if it actually falls on a penny increment. This implies that the difference between the two ECN groups should in reality be greater than what we find using partial data on sub-penny quotes. We obtain inside-quote data from the NASTRAQ database. We obtain data on firm characteristics from the COMPUSTAT database. The sample period is January 2002.

From the universe of all stocks that traded on NASDAQ in January 2002, we select only those securities that have four-digit ticker symbols¹⁰ and which trade on all of the top six ECNs, ranked by quote frequency and trading volume.¹¹ This leaves us with a universe of 1,817 securities from which we select our sample.

Because our study concerns the impact of tick size, we adopt a sample selection criterion that reflects our expectation in this regard. For example, Chan and Hwang (2000) show that the biggest improvement in market quality from a tick size reduction on the Hong Kong Stock Exchange is found in low-price stocks. Cao and Choe (1996) find a systematic relation between the impact of tick size change and trading activity for a sample of AMEX stocks. Based on these and other similar stylized facts in the literature, we use stock price and trading volume as the two metrics by which to select our study sample. Specifically, we rank the 1,817 stocks by these two metrics, which gives us four mutually exclusive groups: low-price, high-volume stocks form quadrant I, low-price, low-volume stocks form quadrant II, high-price, high-volume stocks form quadrant III, and high-price, low-volume stocks form quadrant IV. Stocks with average monthly price less than or equal to \$5 belong to the low-price quadrants, and the volume cut-off is the mid-point of average monthly trading range.

We select 66 stocks from each quadrant using a random number generator to make the final sample of 264 (66 x 4) securities. Of these, six stocks in quadrant I and six in quadrant III do not have complete information on firm characteristics and/or have missing data on some ECN quotes. These twelve stocks are dropped from the sample, which leaves us with a total of 252 securities.

We omit the following quotes and trades to minimize data errors: quotes if either the bid or the ask is less than or equal to zero, quotes if either the bid size or the ask size is less than or equal to zero, quotes if the bid-ask spread is less than zero or greater than \$15, and trades if the price or volume is less than or equal to zero.

¹⁰ In the NASDAQ market, securities with five digit ticker symbols represent American Depository Receipts and stocks with multiple share classes.

¹¹ The top six are the same by both metrics.

We measure share price by the mean value of the quote midpoints, return volatility by the standard deviation of quote-midpoint returns, and firm size by the average market value of equity. We measure turnover rate by the ratio of total share trading volume to the number of shares outstanding. Dollar volume of trade is the number of shares traded multiplied by share price. For each stock, PMIN is the proportion of group P ECN spreads that are equal to one penny and IPMIN is the proportion of inside spreads that are equal to one penny. We calculate both the dollar (absolute) and percentage (relative) spreads.

Table 1 presents the summary statistics of the variables. The mean and median values of share price are \$11.76 and \$4.77, respectively. The mean value of the inside spread is 6.2 cents. The mean values of ECN spreads are much larger: 41 cents for group S ECNs and 49 cents for group P ECNs. Similarly, the mean values of relative ECN spreads are much larger (0.0671 and 0.0858 for ECN groups S and P, respectively) than those of the relative inside spread (0.0105). The mean value (0.024) of IPMIN is much smaller than that (0.1686) of PMIN. This is because IPMIN is calculated from the highest bid and lowest ask of all market participants while PMIN is calculated from individual ECN quotes.

4. Effects of tick size on the spread and depth

As noted earlier, the MPV is the lower bound on the bid-ask spread. If the MPV is larger than the equilibrium spread of a stock, then a decrease in tick size would reduce the spread. However, if the MPV is already equal to or smaller than the equilibrium spread, then a decrease in tick size would not reduce the spread. In short, a decrease in the MPV leads to a fall in spreads only if the existing tick size is a binding constraint. In this section, we examine whether the two ECN groups post different spreads to determine whether the penny tick size is a binding constraint.

Table 2 shows the difference in spreads between the two ECN groups. Because the one-penny tick is more likely to be a binding constraint for lower priced stocks, we partition our study sample into

four price groups: Price \leq \$2, \$2 < Price \leq \$4, \$4 < Price \leq \$10, and Price > \$10.¹² For each price group, we report the mean quoted spread for group S and group P ECNs, respectively. The reported *t*-statistics are to test for difference in the mean between the two groups.

The results show that there is a significant difference in the mean spread between group S and group P ECNs for stocks trading under \$10. We find that the mean spreads for group P ECNs are significantly greater than those for group S ECNs for the first three price groups, regardless of whether we measure the spread in relative (%) or absolute (\$) term. The largest difference in relative spread between the two ECN groups is for the lowest price group, as expected, and it falls uniformly as price increases. For stocks priced higher than \$10, there is no significant difference in the mean spread between the two ECN groups. These results are consistent with our expectation that the mandated tick size of one penny (on group P ECNs) puts an artificially high floor on the spreads of low-price stocks.

Although our study sample of stocks that are traded on group P ECNs are identical to those traded on group S ECNs, the two ECN groups may have different volumes in a given security. Hence, it is possible that the difference in spreads is driven by the difference in trading volume between the two ECN groups (rather than the difference in tick size *per se*). For instance, if group S ECNs have greater trading volume than group P ECNs, we expect group S ECNs to exhibit lower spreads, given the negative relation between volume and the spread shown in prior research.

To test whether the difference in trading volume between the two ECN groups can explain the difference in spread, we regress the difference in spreads between group P and S ECNs on the difference in trading volume between the two groups. We obtain the following results (numbers in parenthesis are *t*-statistics):

$$\%Spread^P_i - \%Spread^S_i = 0.0208 - 0.0088 [\log(\text{Volume}^P_i) - \log(\text{Volume}^S_i)]_i;$$

(5.24)** (-1.54)

$$\text{Adjusted } R^2 = 0.01 \quad F = 2.38$$

¹² The price ranges are chosen such that there are at least 30 stocks in each group.

$$\text{\$Spread}_i^P - \text{\$Spread}_i^S = 0.0924 - 0.0175 [\log(\text{Volume}_i^P) - \log(\text{Volume}_i^S)];$$

(6.37) ** (0.83)

$$\text{Adjusted } R^2 = 0.01 \quad F = 0.69$$

where $\% \text{Spread}_i^P$ is the mean percentage spread of stock i on group P ECNs, $\% \text{Spread}_i^S$ is the mean percentage spread of stock i on group S ECNs, $\text{\$Spread}_i^P$ is the mean dollar spread of stock i on group P ECNs, $\text{\$Spread}_i^S$ is the mean dollar spread of stock i on group S ECNs, Volume_i^P is the mean dollar volume of stock i on group P ECNs, and Volume_i^S is the mean dollar volume of stock i on group S ECNs.

Note that while the estimated intercepts are significantly positive, the estimated coefficients for $[\log(\text{Volume}_i^P) - \log(\text{Volume}_i^S)]$ are not significantly different from zero. These results indicate that the difference in spreads between the two ECN groups cannot be accounted for by the difference in trading volume between the two ECN groups.

Table 2 shows that group S ECNs post significantly larger depths than group P ECNs for stocks selling under \$2.¹³ Directionally, the same results hold for the next two price groups although the differences are not statistically significant. For stocks priced higher than \$10, however, the ECNs quoting in two decimal places show slightly larger depths. However, the difference is not statistically significant.

Generally, high-volume stocks have large depths. Hence, one could argue that the differential volume of trading between the two ECN groups may explain the difference in depths. To test whether the difference in trading volume between the two ECN groups explains the depth difference, we regress the difference in depths between the two ECNs on the difference in volume and obtain the following results:

$$\text{Ask Depth}_i^P - \text{Ask Depth}_i^S = 66.12 - 249.16 [\log(\text{Volume}_i^P) - \log(\text{Volume}_i^S)];$$

(1.61) (4.21) **

¹³ We acknowledge that the comparison has a drawback. Consider the following situation as an example: a dealer is willing to supply 10,000 shares at \$10.00 and 10,000 shares at \$9.995 but is forced to display 20,000 shares at \$10.00 because the \$9.995 quote is infeasible under decimal pricing. Under sub-penny pricing, the depth at best quote will be 10,000 shares, ostensibly a 50% drop in liquidity. In reality, however, there is an improvement—10,000 shares at \$10.00 and 10,000 shares at \$9.995 instead of 20,000 shares at \$10.00. Chan and Hwang (2000) noted this and pointed out that in order to make a correct inference regarding the impact on depth, it is imperative to examine depths beyond the best quotes. However, for the NASDAQ market data obtained from the Consolidated Quotes, there is no provision for display of quotes higher than two decimal places. Hence it is not possible to actually examine the depth at price points between the existing one-cent MPV.

$$\text{Adjusted } R^2 = 0.06 \quad F = 17.72^{**}$$

$$\text{Bid Depth}_i^P - \text{Bid Depth}_i^S = 64.35 - 157.50 [\log(\text{Volume}_i^P) - \log(\text{Volume}_i^S)];$$

(1.47) (2.50)*

$$\text{Adjusted } R^2 = 0.02 \quad F = 6.26^*$$

Note that the estimated intercepts are not significantly different from zero in both regressions, indicating that there is no statistically significant difference in quoted depths between group P and S ECNs once we control for the effect of volume on depths. Overall, we find no evidence of quotation behavior that suggests investors may be wary of exposing their trading interests due to the possibility of front-running in a lower tick size regime.

5. The Monte Carlo Markov Chain (MCMC) method

The tick constrains security price to lie on a discrete grid; the finer the tick size, the finer the grid. The tick size also determines left-truncation in the distribution of the bid-ask spread. Prior studies (e.g., Harris, 1994; Chordia and Subrahmanyam, 1995) show that price discreteness also affects trading activity. In addition, Cho and Frees (1988) and Ball (1988) show that rounding-up of prices introduces model estimation bias. In the only work that is methodologically close to this study, Ball and Chordia (2001) show that the impact of this rounding is significant. They use the MCMC method on a sample of heavily traded U.S. stocks before and after the tick size change (from 1/8th to 1/16th of a dollar), and find that the largest component of quoted spreads is attributable to the rounding of prices. The study finds that the adverse selection component of the spread is relatively minor.

The left-truncation of the spread series due to tick size has not received much attention in finance literature.¹⁴ Yet, a truncated variable is neither a trivial nor a new issue in economics. Tobin (1958) first considered the problem and proposed an iterative solution using the maximum likelihood equation.

¹⁴ Harris (1994) is one of the few papers that discusses the implications of price discreteness and truncation using a switching model.

Takeshi (1973) refined Tobin's method and proposed an initial estimator, which performed better than Tobin's method for a larger sample. Numerous studies in labor, industrial, and health economics have extended the method to censored and missing observation data. [See Maddala (1986) for a comprehensive discussion.]

Although most studies model the bid-ask spread as a continuous variable, observed spreads are discrete variables. Moreover, observed spreads are left-truncated by the tick size. As Hasbrouck (1999) shows, a model in which true prices are rounded to the nearest tick size can be represented in the state space form, but the rounding destroys the Gaussian structure and time series independence of errors, rendering the Kalman filter estimation method inapplicable. One approach to estimating such a model could be numerical integration (see Kitagawa, 1987; Judd, 1998). Alternatively, one could use the MCMC method to estimate such a model.

In this study, we use the MCMC method to estimate a model of spreads. This method is essentially Monte Carlo integration using Markov Chains. Bayesians, and sometimes also frequentists, may need to integrate over possibly high dimensional probability distributions to make inferences about model parameters and/or to make predictions. Bayesians may need to integrate over the posterior distribution of model parameters, and frequentists may need to integrate over the distribution of observables given parameter values. Monte Carlo integration draws samples from the required distribution, and then calculates sample averages to approximate expectations. Markov Chain Monte Carlo draws these samples by running a Markov chain for a long time. What follows is a summary discussion of Monte Carlo integration.

5.1 MCMC Model

Let X be a vector of k random variables, comprising both model parameters and missing data with posterior distribution $\pi(\cdot)$. The task is to evaluate the expectation

$$E[f(X)] = \frac{\int f(x)\pi(x)dx}{\int \pi(x)dx} \quad (1)$$

for some function of interest $f(\cdot)$. Here we allow for the possibility that the distribution of X is known only up to a constant of normalization, i.e., $\int \pi(x)dx$ is unknown.

Monte Carlo integration evaluates $E[f(x)]$ by drawing samples $\{X_t, t = 1, \dots, n\}$ from $\pi(\cdot)$ and then approximating

$$E[f(x)] \approx \frac{1}{n} \sum_{t=1}^n f(X_t) \quad (2)$$

Thus, the population mean of $f(X)$ is estimated by a sample mean. When the samples $\{X_t\}$ are independent, the law of large numbers ensures that the approximation can be made as accurate as desired by increasing the sample size n . In general, drawing $\{X_t\}$ independently from $\pi(\cdot)$ is not feasible, as $\pi(\cdot)$ can be quite non-standard. However $\{X_t\}$ need not necessarily be independent. It can be generated by any process that draws samples throughout the support of $\pi(\cdot)$. One method of doing that is through a Markov chain having $\pi(\cdot)$ as its stationary distribution.

Suppose we generate a sequence of random variables, $\{X_0, X_1, X_2, \dots\}$ such that at each time $t \geq 0$, the next state in sample X_{t+1} is sampled from a distribution $Q(X_{t+1}/X_t)$ which depends only on the current state of the chain, X_t . That is, given X_t , the next state X_{t+1} does not depend further on the history of the chain $\{X_0, X_1, \dots, X_{t-1}\}$. Such a sequence is called a Markov chain and $Q(\cdot|\cdot)$ is the *transition kernel* of the chain.

The impact of the starting state X_0 on X_t concerns the distribution of X_t given X_0 . Let us denote this as $Q^{(t)}(X_t | X_0)$. Here we are not given the intervening variables $\{X_0, X_1, X_{t-1}, \dots\}$, so X_t depends directly on X_0 . Subject to regularity conditions, the chain will gradually forget its initial state and $Q^{(t)}(\cdot | X_0)$ will eventually converge to a unique *stationary* (or *invariant*) distribution which does not depend on t or X_0 . Let us denote this stationary distribution by $\phi(\cdot)$. As t increases, the sampled points $\{X_t\}$ will look increasingly like dependent samples from $\phi(\cdot)$. After a sufficiently long *burn-in* of say m iterations, points

$\{X_t; t = m+1, \dots, n\}$ will be dependent samples from approximately $\phi(\cdot)$. Thus, an estimator of $E[f(x)]$ will be given by

$$\bar{f} = \frac{1}{n-m} \sum_{t=m+1}^n f(X_t) \quad (3)$$

This is called an *ergodic average* and the convergence to the required expectation is ensured by the ergodic theorem. Constructing a Markov chain can be done using the Metropolis-Hastings algorithm, or the Gibbs Sampler, and we use the latter.¹⁵

In a world without ticks, let a_t (b_t) be the true ask (bid) price and so $s_t = a_t - b_t$. Let A_t (B_t) be the quoted ask (bid). For the market maker's trading profits to be nonnegative, the quoted ask, A_t , cannot be less than the true ask, a_t , and the quoted bid, B_t , cannot be greater than the true bid, b_t . Thus, the quoted ask A_t is the true ask a_t rounded up to the nearest tick and the quoted bid B_t is the true bid b_t rounded down to the nearest tick. The observed spread is $S_t = A_t - B_t$. Since $A_t \geq a_t$ and $B_t \leq b_t$, the true spread cannot be larger than the quoted spread. The true spread will not be constant; rather it will vary according to a stochastic process adjusting to micro information flows and possibly responding to large information-laden trades. Following Ball and Chordia (2001), we model the true spread, s_t , as a first-order logarithmic autoregressive process with additional structural variables as follows:

$$\ln(s_t) = \alpha + \beta \ln(s_{t-1}) + \gamma \ln \frac{V_{t-1}}{D_{t-1}} + e_t; \quad (4)$$

where V_{t-1} and D_{t-1} denote volume of the stock transacted at the previous price and quoted depth at time $t-1$, respectively, and e_t is an error term. This model allows the relative size of trade to depth at the last transaction to possibly impact current spread in order to capture any information that depth and volume adjustments may release. We construct the time series of spread from 9:30 a.m. to 4:00 p.m. even though

¹⁵ For a complete discussion of the Gibbs sampler, see Markov Chain Monte Carlo in Practice: Interdisciplinary Statistics (1998) and Best et. al (1995)

most ECNs accept orders from 8:00 a.m. and allow after hours trading. The model is estimated by the Gibbs sampling method, using WinBUGS software.¹⁶

To estimate Eq. (4), we assume near diffuse priors for the model parameters. We initialize s (for each ECN) with $\frac{1}{2}$ (the average quoted spread) on that ECN. The other model parameters are initialized with starting values of $\alpha = 0.05$, $\beta = 0.90$, and $\gamma = 0.005$. The starting values do not influence the final estimates because the adjustment period of the model is eliminated by choosing appropriate *burn-in* samples. For each security-ECN combination, *burn-in* iterations are decided by monitoring the mixing of the chains for each of the three nodes, with the minimum (default) burn-in being 10,000 iterations. The output is monitored for the mean, standard deviation, MC error, median, 2.5 and 97.5 percentile. The *burn-in* iterations that are to be discarded depend on the rate of convergence and varies from one security-ECN combination to another. Parameter estimates for α , β and γ are based on the next n iterations. For our sample, the smallest n is 16,000 iterations and the largest is 1,000,000. The model is estimated for all 252 sample securities. In all, we have 1,512 (252*6) MCMC runs.

5.2 Empirical results

Figure 1 shows snapshots of the sample output graphs for the coefficients of the model (called “nodes”) for stock ASPX at various iterations. The estimated nodes are α , β and γ . As is evident, after 1000 iterations, there is improper mixing of the chains. After 1,000 iterations, the node for β is essentially a flat line. As the number of iterations increases, the chains mix more. The output is also monitored so that the sample generating process reaches a stage where there is little reduction in the mean squared error from further iterations.

Figure 2 shows the cumulative distribution of true spreads for stock ABIZ (selected randomly), for two ECNs—ISLD and BTRD. ISLD allows sub-penny quotes and BTRD does not. As shown in the graph, there is a truncated area to the left of one penny, and true spreads that fall below a penny are

¹⁶ See Gilks et al. (1996) and Thomas (1994) for a detailed description of the BUGS (Bayesian Inference Using Gibbs Sampling) project.

rounded up to one penny in the case of BTRD. What is more striking is that the true spread series for the two ECNs diverge significantly even after the one-penny mark. The cumulative distribution function of the spread series quoted by ISLD stochastically dominates that of BTRD beyond the one-penny cutoff. In other words, the observed quotes placed by ISLD imply a tighter “true” spread series for security ABIZ than the quotes of BTRD. This result is true of the entire sample, but especially pronounced in securities that fall in the first quadrant - the high-volume low-price securities.

Having corrected for the impact of price discreteness and left-truncation of the spread series using the MCMC method, we now examine whether tick size affects quote competition itself. If the existence of a coarser pricing grid does not change the nature of the quotation process itself, then a methodological correction should remove the distortions caused by the pricing grid and the two ECN groups should show no difference in true spreads. On the other hand, if a coarser pricing grid changes the nature of the quotation process, then a methodological correction cannot eliminate all the difference between the spread series on the two ECN groups, and true spreads will differ.

The left half of Table 3 shows the results for relative spreads and the right half shows the results for absolute spreads. Spread^P_O and Spread^P_T denote the observed and true spreads, respectively, on group P ECNs, and Spread^S_O and Spread^S_T denote the observed and true spreads, respectively, on group S ECNs. As expected, the average true spreads for both groups of ECNs are significantly smaller than the average observed spreads, indicating that tick sizes are binding constraint on both groups of ECNs. We also find that the difference between the observed and true spreads is greater for group P than group S ECNs. For instance, the difference between the observed and true spreads is 1.26 cents for group P ECNs while it is only 0.35 cent for group S ECNs. This is not surprising given the fact that observed spreads are already much lower in group S ECNs, and thus there is less correction room left for the MCMC method.

More importantly, a significant difference exists in true spreads between the two ECN groups. For example, the difference in true dollar spreads between the two ECNs is 7.34 cents. This indicates that group S ECNs would exhibit narrower spreads than group P ECNs in the absence of any binding constraint. We attribute this result to the distortions introduced into the process of quoting security prices

by the granularity of the pricing grid. A finer grid permits more aggressive quotes, thereby reducing the spread. Considered collectively, the evidence in Table 3 suggests that the coarser pricing grid that group P ECNs impose not only affects the discreteness of the spread series, but actually changes the nature of quote competition.

6. Inside spread analysis

In the previous sections, we find that group P ECNs have wider spreads on average than group S ECNs; furthermore, this observation is more pronounced for low-price (under \$10) stocks. Although a comparison of spreads between the two ECN groups provides relevant perspective on the influence of pricing grid on spreads, we note that ECN spreads do not capture investors' trading costs accurately. The best execution rule requires that trades occur at the market inside, and inside spreads are generally much narrower than ECN spreads. Hence for traders, a more meaningful metric is the inside spread (the difference between the highest bid and lowest ask price) because it better captures the actual cost of trading. In this section, we extend our analysis to inside spreads and examine whether the penny tick size also constrains inside spreads.

6.1. Inside spread and share price

For each of the 252 stocks, we calculate both the absolute and relative spreads from data obtained from the inside quote files of the NASTRAQ database. We also estimate the true inside spreads using the MCMC method described in the previous section. Table 4 shows the difference between the observed and true inside spreads for the whole study sample as well as for each of the eight portfolios that are formed based on share price. We rank our sample of stocks according to share price and group them into eight portfolios. We then calculate, for each portfolio, the mean share price, the proportion of a stock's inside spreads that are equal to one penny (IPMIN), the difference between the observed absolute spread and the

true absolute spread ($\overline{\$I}_O - \overline{\$I}_T$), the difference between the observed relative spread and the true relative spread ($\% \overline{I}_O - \% \overline{I}_T$), and $(1/252) \sum_{s=1}^{252} (\$I_O^s - \$I_T^s) / \I_O^s where s denotes a sample security.

For the whole sample, the mean difference between the observed and true spreads is nearly 0.7 cent (t-value = 25.12).¹⁷ We find that for the lowest priced stocks (Portfolio 1), nearly 36% of all quoted spreads (IPMIN) are equal to one cent, and it is for this group that spread reduction is the greatest (0.9 cent). As a percentage of observed spread, this amounts to a 36.48% reduction (see the last column). As the average price of a portfolio increases, we find that the magnitude of spread reduction falls. In fact, all three measures of spread reduction - the reduction in the absolute spread, the reduction in the relative spread, and the percentage reduction in the absolute spread - decrease uniformly as price increases. This negative relation is expected because the lower the price of a stock, the lower its expected equilibrium spread. Since the tick size acts as a floor on spreads, a relaxation of the tick size is expected to have a greater (spread-reducing) effect on those stocks that find the tick size a binding constraint. The IPMIN metric corroborates this result: as the mean price of a portfolio increases, the average IPMIN decreases.

However, the relation between share price and IPMIN is non-linear. For the first five portfolios, there is a steady reduction in IPMIN, but the three highest-priced portfolios show a leveling off of IPMIN at around 12%. This is clearly evident in Figure 3, which graphs the relation between the various measures of spread reduction and IPMIN. The reason for this tapering off of IPMIN at higher prices is that for higher-priced stocks with high trading volume, the most popular quoted spread is one cent. Chakravarty et al. (2001) also report a similar finding in their decimalization impact study.

We also employ an alternative portfolio formation algorithm to check the robustness of the above results. We rank our sample of stocks according to IPMIN and group them into eight portfolios. The results are reported in Table 5. The highest IPMIN portfolio shows a severe binding constraint (IPMIN =

¹⁷ For the inside spread series we have no sub-decimal information and our estimates of $\overline{\$I}_O - \overline{\$I}_T$ may be upwardly biased. Thus, we interpret this 0.7cent reduction to be the maximum possible gain from a relaxation of the tick size.

0.529) and the average spread reduction for this group is over 31%. As expected, we find smaller spread reductions for portfolios with smaller IPMIN values.

6.2 *Inside spread and trading volume*

We now explore another dimension of a stock's attribute - trading volume - and investigate whether the spread reduction that could be achieved by relaxing the MPV varies systematically with a stock's trading volume. Our *a priori* expectation is that for higher volume stocks, the penny tick is more likely to be binding (because these stocks are likely to have lower equilibrium spreads), and hence, *ceteris paribus*, high-volume stocks would exhibit large differences between the observed and true spreads.

Table 6 shows the difference between the observed and true inside spreads for each of the eight portfolios formed based on dollar trading volume. Contrary to our expectations however, the difference between the observed and true spreads tends to be smaller for higher volume stocks. This result appears to be driven by the fact that stocks in higher volume portfolios have higher prices, for which the penny tick size is less likely to be a binding constraint. In contrast, low-volume portfolios include many low-price stocks, for which the penny tick size is more likely to be a binding constraint.

To uncouple the effects of trading volume and share price on spreads, we rank our sample of stocks according to share price and group them into five portfolios. Stocks in each price portfolio are then divided into five portfolios according to trading volume. We then calculate, for each price-volume portfolio, the mean share price, mean dollar volume, IPMIN, the difference between the observed and true spreads. Table 7 shows the results. As expected, the difference between the observed and true spreads becomes wider as price increases. Interestingly, within each price portfolio, the highest IPMIN is for the highest volume portfolio. For example, for portfolio (P1, V5) IPMIN is over 0.6, which is the highest of all the 25 price-volume portfolios. This confirms our earlier conjecture that trading volume and IPMIN should be positively correlated.

Within each price portfolio, we find that higher volume stocks tend to exhibit larger differences between the observed and true spreads. The last column of Table 7 shows that the higher the trading

volume within a price portfolio, the higher the percentage spread reduction. For three of the five portfolios, P2 through P4, the highest-volume portfolio exhibits the largest difference between the observed and true spreads. This is not the case for portfolio P1, which comprises of the lowest-priced stocks, where price is the biggest determinant of the difference between the observed and true spreads, and for portfolio P5, where the three highest-volume portfolios show nearly the same percentage reduction since these are all high-price stocks.

6.3. *Inside spread and sub-penny participation rate*

In this section, we examine how the inside spread is related to the sub-penny participation rate (SPPR), which is the ratio of the number of quotes placed by sub-penny ECNs to the total number of quotes placed by all market participants.¹⁸ We show in Section 4 that group S ECNs quote tighter spreads than group P ECNs. Hence, we expect that the inside spreads decrease with the sub-penny participation rate. Similarly, we conjecture that the difference between the observed and true inside spreads is smaller for stocks with higher SPPR because the observed spread of such stocks is likely to be closer to the true spread.

We obtain the following results when we regress the inside spread on both SPPR and a set of stock attributes (share price, return volatility, dollar trading volume, and turnover rate) that are known to determine the inside spread (numbers in parenthesis are t-statistics):

$$\begin{aligned} \% \overline{I_o} = & 0.0433 + 0.0106 (1/\text{Price}) - 0.0027 \text{Volatility} - 0.0026 \text{LnDoIVol} + 0.0005 \text{Turnover} - 0.0066 \text{SPPR} \\ & (13.92)** (14.70)** \quad (-0.45) \quad (-9.53)** \quad (2.26)* \quad (-2.23)* \\ & \text{Adjusted } R^2 = 0.74 \quad \text{F-value} = 145.66** \end{aligned}$$

$$\begin{aligned} \$ \overline{I_o} = & 0.1302 + 0.0017 \text{Price} + 0.1104 \text{Volatility} - 0.0052 \text{LnDoIVol} - 0.0013 \text{Turnover} - 0.0484 \text{SPPR} \\ & (6.95)** (9.88)** \quad (3.22)** \quad (-3.08)** \quad (-0.93) \quad (-2.77)** \end{aligned}$$

¹⁸ We obtain similar results when we use two alternative measures of sub-penny participation rate, i.e., (1) the number of inside quotes placed by sub-penny ECNs divided by the number of inside quotes placed by all market participants (all ECNs) and (2) the time a sub-penny ECN spends posting inside quotes as a fraction of total inside time.

Adjusted $R^2 = 0.36$ F-value = 28.78**

Note that the estimated regression coefficients for SPPR are negative and significant in both regressions. These results are consistent with our expectation that the inside spread is narrower when the sub-penny participation rate is higher.

Table 8 shows the results when we regress the difference between the observed and true inside spreads on SPPR. The estimated regression coefficients for SPPR are negative and significant for all three estimated models, indicating that higher sub-penny participation lowers the possibility of further inside spread reductions. This is because the aggressive nature of quotes placed by sub-penny ECNs already lowers the observed spread, and thus the true spread has less room for divergence from the observed spread.¹⁹

7. Conclusion

In this paper, we examine issues related to sub-penny pricing in a naturally controlled experimental setting. We look at the price quotes of a sample of securities that trade in the top six ECNs. Of these six, three ECNs allow sub-penny pricing and the other three do not. We find that ECNs that allow sub-penny quotes show tighter spreads than do ECNs that do not allow such quotes. The difference in spreads between the two ECN groups is especially pronounced for stocks that trade for less than \$10. We also find that the ECNs that allow sub-penny quotes actually exhibit larger depths than ECNs that do not allow sub-penny quotes.

Furthermore, the coarser price grid imposed by a mandated penny tick creates conditions that discourage quote aggressiveness. We use the Markov Chain Monte Carlo method to correct for the effects

¹⁹ We also regress the difference between the observed and true inside spreads on both SPPR and IPMIN. We estimate these regressions to determine whether the effect of SPPR on spread differences remains intact even after we control the effect of IPMIN on spread differences shown in Table 5. As expected, we find a strong and positive relation between spreads differences and IPMIN. More importantly, we find that spread differences are significantly and negatively related to SPPR even after controlling for the effect of IPMIN. These results indicate that the effect of sub-penny participation on spreads is above and beyond the effect of the tick-size induced binding constraint on spreads.

of price discreteness and left-truncation and estimate the true spreads for the sample securities on each of the six ECNs. We find that the true spread is much larger for the group P ECNs, and that the penny tick is frequently a binding constraint on the inside spread. Our results also show that increased participation of sub-penny ECNs in the quotation process leads to smaller spreads. Overall, our results indicate that a finer pricing grid not only eliminates the effects of left-truncation and price discreteness, but more importantly, promotes quote competition.

What do our findings imply for exchanges, trading platforms, and investors? In this age of cheap and efficient technology, citing strain on existing systems as a reason for keeping up an artificially high tick size cannot be justified. Since some trading platforms already offer sub-decimal quoting facilities, the demands of the marketplace will soon create conditions for the removal of the floor on prices that is now maintained by the penny tick size. Our estimates show that the spread reduction in the absence of binding constraints would be about 0.7 cent, which is roughly 16% of the average inside spread. Accounting for the inaccuracies of estimation and generalizing from a sample with 50% of the securities under \$5, we interpret this 16% reduction in inside spread as an upper bound. For high-volume stocks, that translates into savings of millions of dollars.

How do our sample estimates generalize to the universe of securities that are actually trading in the markets? Our evidence comes from a sample of stocks that trade on ECNs. ECNs conduct the bulk of NASDAQ listed securities trade (INET, the merged Island and Instinet, has 25% of the NASDAQ listed securities market). The fact that the average price of a NASDAQ stock is between \$10 and \$11 and the median stock price is around \$6 (see Chung and Chuwonganant, 2004), implies that our conclusions are relevant to at least half of all NASDAQ stocks, which is well over a thousand securities. We suggest that it is time more scientific research is brought to bear on the impact of the current tick size in U.S. equities markets.

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Table 1
Descriptive statistics

This table reports some summary statistics for the 252 sample securities that traded on all six ECNs in January 2002. We measure share price by the mean value of the quote midpoints, return volatility by the standard deviation of quote-midpoint returns, and firm size by the average market value of equity. We measure turnover rate by the ratio of total share trading volume to the number of shares outstanding. Dollar volume of trade is the number of shares traded multiplied by share price. Group P (S) refers to those ECNs that allow two (higher) decimal place quotes. We calculate both the dollar (absolute) and percentage (relative) spreads. Inside spread is the difference between the best bid and best offer. The PMIN is the proportion of group P ECN spreads that are equal to one penny and IPMIN is the proportion of inside spreads that are equal to one penny. Variable values are aggregated for each security for the sample month, and then averaged across the sample securities.

Variable	Mean	Standard deviation	Percentile					
			Minimum	5 th	25 th	50 th	75 th	Maximum
Share price (\$)	11.76	12.78	0.17	1.20	2.89	4.77	18.01	58.74
Return volatility	0.0682	0.0522	0.0184	0.0227	0.0368	0.0530	0.0771	0.3440
MVE (\$'000)	587875	1015129	6745	40612	99759	219178	520682	8732340
Turnover rate	1.8629	1.7732	0.0815	0.2490	0.6896	1.2958	2.4178	9.3606
Trading volume (\$)	1447479	3664056	4084	27033	94914	232557	1241009	37992662
\$ECN spread (Group S)	0.4148	0.2585	0.0058	0.0580	0.2154	0.3797	0.5494	1.3184
\$ECN spread (Group P)	0.4974	0.2618	0.0536	0.1188	0.3113	0.4612	0.6782	1.1581
%ECN spread (Group S)	0.0617	0.0445	0.0016	0.0117	0.0293	0.0504	0.0842	0.2484
%ECN spread (Group P)	0.0858	0.0676	0.0025	0.0143	0.0326	0.0664	0.1272	0.3907
\$Inside spread (in cents)	6.22	3.40	0.99	1.52	3.78	5.60	8.72	26.72
%Inside spread	0.0105	0.0078	0.0008	0.0016	0.0043	0.0093	0.0147	0.0609
PMIN	0.0240	0.0325	0	0	0.0039	0.0168	0.0310	0.2983
IPMIN	0.1686	0.1729	0.0004	0.0121	0.0579	0.1202	0.2143	0.9436

Table 2

Difference in spreads and depths between the group S and group P ECNs

This table shows the difference in spreads (depths) between the two ECN groups. Because the one-penny tick is more likely to be a binding constraint for lower priced stocks, we partition the sample into four price groups - Price \leq \$2, \$2 < Price \leq \$4, \$4 < Price \leq \$10, and Price > \$10. For each price group, we report the mean quoted spreads and depths for group S and group P ECNs. The reported *t*-statistics are to test for the difference in mean between the two groups. N denotes the number of stocks in each group. The numbers in parentheses are standard deviations.

	%Spread	\$Spread	Bid depth	Ask depth
Price \leq \$2 (N = 35)				
P	0.1501 (0.0925)	0.1925 (0.1255)	96.73	102.37
S	0.0736 (0.0518)	0.0982 (0.0749)	211.03	151.91
Difference	0.0765	0.0943	-114.3	-49.54
t-statistic	4.58**	4.50**	-8.07**	-3.35**
\$2 < Price \leq 4 (N = 73)				
P	0.1235 (0.0547)	0.3950 (0.1909)	15.71	13.85
S	0.0930 (0.0469)	0.2920 (0.1479)	20.17	19.07
Difference	0.0305	0.1029	-4.46	-5.22
t-statistic	5.19**	4.95**	-0.88	-1.30
\$4 < Price \leq \$10 (N = 46)				
P	0.0958 (0.0441)	0.5583 (0.2139)	10.11	9.88
S	0.0719 (0.0293)	0.4278 (0.1661)	14.03	15.42
Difference	0.0239	0.1304	-3.92	-5.54
t-statistic	4.67**	4.14**	-0.86	-1.37
Price > \$10 (N = 98)				
P	0.0316 (0.0177)	0.6473 (0.2420)	8.01	8.48
S	0.0297 (0.0170)	0.6062 (0.2411)	7.31	7.28
Difference	0.0019	0.0412	0.7	1.2
t-statistic	1.74	1.95	0.12	0.18
Whole sample				
P	0.0858 (0.0676)	0.4974 (0.2618)	32.64	33.65
S	0.0617 (0.0445)	0.4148 (0.2583)	63.13	48.42
Difference	0.0241	0.0826	-30.49	-14.77
t-statistic	7.22**	6.69**	-3.13**	-2.34*

**Significant at the 1% level

*Significant at the 5% level

Table 3
Observed and true spreads

This table reports the mean observed and true spreads, as well as the mean difference between observed and true spreads, of the two ECN groups, P (penny quotes) and S (sub-penny quotes). Spread^S_O , Spread^S_T , Spread^P_O , and Spread^P_T refer to the observed and true spreads of group S and the observed and true spreads of group P respectively. Absolute spread refers to dollar spread and relative spread is absolute spread divided by price.

Relative (Percentage) spreads		Mean	Absolute (Dollar) spreads		Mean
	$\% \text{Spread}^S_O$	0.0617		$\$ \text{Spread}^S_O$	0.4148
	$\% \text{Spread}^S_T$	0.0608		$\$ \text{Spread}^S_T$	0.4113
	$\% \text{Spread}^P_O$	0.0858		$\$ \text{Spread}^P_O$	0.4974
	$\% \text{Spread}^P_T$	0.0825		$\$ \text{Spread}^P_T$	0.4847
		Difference	t-stat		
	$\% \text{Spread}^P_O - \% \text{Spread}^P_T$	= 0.0033	7.57**	$\$ \text{Spread}^P_O - \$ \text{Spread}^P_T$	= 0.0126 21.77**
	$\% \text{Spread}^S_O - \% \text{Spread}^S_T$	= 0.0009	5.22**	$\$ \text{Spread}^S_O - \$ \text{Spread}^S_T$	= 0.0035 5.99**
	$\% \text{Spread}^P_O - \% \text{Spread}^S_O$	= 0.0241	7.22**	$\$ \text{Spread}^P_O - \$ \text{Spread}^S_O$	= 0.0826 6.69**
	$\% \text{Spread}^P_T - \% \text{Spread}^S_T$	= 0.0217	6.67**	$\$ \text{Spread}^P_T - \$ \text{Spread}^S_T$	= 0.0734 6.06**

**Significant at the 1% level.

Table 4

Difference between the observed and true inside spreads as a function of share price

This table shows the difference between the observed and true inside spreads for each of the eight portfolios that are formed based on share price. We rank our sample of stocks according to share price and group them into eight portfolios. We then calculate, for each portfolio, the mean share price, the proportion of a stock's inside bid-ask spread that equals one penny (PIMIN), the difference between the observed absolute (dollar) spread and the true absolute spread ($\overline{\$I_O} - \overline{\I_T}), the difference between the observed relative (percentage) spread and the true relative spread ($\overline{\%I_O} - \overline{\%I_T}$), and $(1/252) \sum_{s=1}^{252} (\$I_O^s - \$I_T^s) / \I_O^s , where s denotes a sample security. Numbers in parentheses are t-statistics.

Portfolio	Price	IPMIN	$\overline{\$I_O} - \overline{\I_T}	$\overline{\%I_O} - \overline{\%I_T}$	$(1/252) \sum_{s=1}^{252} (\$I_O^s - \$I_T^s) / \I_O^s
1	1.28	0.3597	0.0093** (18.59)	0.0090** (5.43)	0.3648
2	2.50	0.2145	0.0088** (11.09)	0.0032** (11.41)	0.2053
3	3.29	0.1623	0.0085** (9.54)	0.0024** (9.37)	0.1889
4	4.36	0.1285	0.0081** (10.52)	0.0017** (9.99)	0.1355
5	8.67	0.1072	0.0068** (9.39)	0.0007** (8.89)	0.0873
6	16.46	0.1262	0.0048** (8.73)	0.0003** (8.16)	0.0587
7	25.79	0.1119	0.0037** (8.18)	0.0001** (7.64)	0.0456
8	43.20	0.1209	0.0036** (5.77)	0.0001** (5.46)	0.0409
Whole sample	11.76	0.1686	0.0069** (25.12)	0.0022** (8.21)	0.1633

**Significant at the 1% level

Table 5

Difference between the observed and true inside spreads as a function of IPMIN

This table shows the difference between the observed and true inside spreads for each of the eight portfolios that are formed based on the proportion of a stock's inside bid-ask spread that equals one penny (IPMIN). We rank our sample of stocks according to IPMIN and group them into eight portfolios. We then calculate, for each portfolio, the mean IPMIN, share price, the difference between the observed absolute (dollar) spread and the true absolute spread ($\overline{\$I_O} - \overline{\I_T}), the difference between the observed relative (percentage) spread and the true relative spread ($\overline{\%I_O} - \overline{\%I_T}$), and $(1/252) \sum_{s=1}^{252} (\$I_O^s - \$I_T^s) / \I_O^s , where s denotes a sample security. Numbers in parentheses are t-statistics.

Portfolio	IPMIN	Price	$\overline{\$I_O} - \overline{\I_T}	$\overline{\%I_O} - \overline{\%I_T}$	$(1/252) \sum_{s=1}^{252} (\$I_O^s - \$I_T^s) / \I_O^s
1	0.5290	4.53	0.0067** (9.37)	0.0064** (3.59)	0.3111
2	0.2425	10.44	0.0064** (9.54)	0.0019** (4.56)	0.1513
3	0.1806	15.12	0.0072** (9.66)	0.0020 (5.24)	0.1376
4	0.1300	11.07	0.0073** (10.15)	0.0021** (4.01)	0.1332
5	0.0976	12.81	0.0069** (8.67)	0.0015** (5.35)	0.0959
6	0.0663	12.43	0.0074** (9.65)	0.0017 (5.17)	0.0919
7	0.0129	10.44	0.0077** (8.35)	0.0017** (4.99)	0.0941
8	0.0113	21.44	0.0042** (8.15)	0.0004** (3.97)	0.0404
Whole sample	0.1686	11.76	0.0069** (25.12)	0.0022** (8.21)	0.1633

**Significant at the 1% level

Table 6

Difference between the observed and true inside spreads as a function of trading volume

This table shows the difference between the observed and true inside spreads for each of the eight portfolios that are formed based on dollar trading volume. We rank our sample of stocks according to dollar trading volume and group them into eight portfolios. We then calculate, for each portfolio, mean dollar volume, mean share price, the difference between the observed absolute (dollar) spread and the true absolute spread ($\overline{\$I_O} - \overline{\I_T}), the difference between the observed relative (percentage) spread and the true relative spread ($\overline{\%I_O} - \overline{\%I_T}$), and $(1/252) \sum_{s=1}^{252} (\$I_O^s - \$I_T^s) / \I_O^s , where s denotes a sample security. Numbers in parentheses are t-statistics.

Portfolio	Dollar volume	Price	$\overline{\$I_O} - \overline{\I_T}	$\overline{\%I_O} - \overline{\%I_T}$	$(1/252) \sum_{s=1}^{252} (\$I_O^s - \$I_T^s) / \I_O^s
1	30829	3.83	0.0082** (11.19)	0.0059** (9.23)	0.2438
2	75840	4.60	0.0089** (9.93)	0.0035** (8.12)	0.1898
3	125594	5.73	0.0085** (11.38)	0.0024** (8.97)	0.1934
4	204230	7.44	0.0077** (9.95)	0.0027** (6.21)	0.1879
5	393892	14.17	0.0065** (9.15)	0.0017** (5.57)	0.1593
6	903944	13.88	0.0052** (8.21)	0.0008** (5.71)	0.1130
7	2707303	21.69	0.0048** (10.48)	0.0004** (5.89)	0.1101
8	10390041	29.05	0.0038** (5.83)	0.0002** (4.99)	0.0784
Whole sample	1447479	11.76	0.0069** (25.12)	0.0022** (8.21)	0.1633

**Significant at the 1% level

Table 7

Difference between the observed and true inside spreads for price-volume portfolios

This table shows the difference between the observed and true inside spreads for portfolios that are formed based on share price and dollar trading volume. We rank our sample of stocks according to share price and group them into five portfolios. Stocks in each price portfolio are grouped into five portfolios according to their dollar trading volume. We then calculate, for each price-volume portfolio, mean share price, mean dollar volume, IPMIN, the difference between the observed absolute (dollar) spread and the true absolute spread ($\overline{\$I}_O - \overline{\$I}_T$), the difference between the observed relative (percentage) spread and the true relative spread ($\overline{\%I}_O - \overline{\%I}_T$), and

$(1/252) \sum_{s=1}^{252} (\$I_O^s - \$I_T^s) / \I_O^s , where s denotes a sample security. Numbers in parentheses are t-statistics.

		Price	Dollar volume	IPMIN	$\overline{\$I}_O - \overline{\$I}_T$	$\overline{\%I}_O - \overline{\%I}_T$	$(1/252) \sum_{s=1}^{252} (\$I_O^s - \$I_T^s) / \I_O^s
P1	V1	1.43	19541	0.2155	0.0119** (15.63)	0.0133** (2.74)	0.3123
	V2	1.58	48222	0.1935	0.0077** (7.50)	0.0049** (6.78)	0.2460
	V3	1.61	97877	0.3027	0.0083** (8.12)	0.0067** (3.08)	0.2525
	V4	1.49	172123	0.3856	0.0093** (20.12)	0.0064** (5.83)	0.3894
	V5	1.90	1007467	0.6077	0.0061** (8.25)	0.0035** (3.85)	0.3066
							Mean = 0.3014
P2	V1	3.06	35545	0.0526	0.0064** (4.59)	0.0019** (4.77)	0.1319
	V2	3.05	84353	0.0944	0.0121** (6.38)	0.0037** (6.05)	0.2051
	V3	3.07	151840	0.1441	0.0085** (5.02)	0.0027** (5.04)	0.1968
	V4	3.14	237121	0.1173	0.0101** (7.47)	0.0030** (6.91)	0.2022
	V5	3.31	1709605	0.3265	0.0075** (4.82)	0.0021** (5.21)	0.2362
							Mean = 0.1944
P3	V1	4.88	48988	0.0687	0.0092** (6.00)	0.0019** (5.22)	0.1117
	V2	5.69	91247	0.0800	0.0076** (5.76)	0.0014** (4.83)	0.0924
	V3	5.12	139706	0.0786	0.0110** (7.81)	0.0020** (8.57)	0.1600
	V4	5.13	331396	0.1241	0.0064** (4.36)	0.0013** (3.74)	0.1128
	V5	5.86	1368682	0.2649	0.0062** (4.50)	0.0009** (5.39)	0.1785
							Mean = 0.1311
P4	V1	14.61	113578	0.0329	0.0051** (6.47)	0.0004** (4.79)	0.0486
	V2	14.55	295034	0.0396	0.0060** (9.00)	0.0004** (7.94)	0.0598
	V3	14.92	580390	0.0903	0.0063** (6.19)	0.0005** (4.98)	0.0692
	V4	15.09	1916681	0.1571	0.0043** (4.87)	0.0003** (3.86)	0.0607
	V5	15.28	7840797	0.2575	0.0039** (3.69)	0.0002** (3.96)	0.0804
							Mean = 0.0637
P5	V1	27.84	232485	0.0330	0.0021** (3.55)	0.0001** (3.57)	0.0179
	V2	34.79	753123	0.0545	0.0033** (3.23)	0.0001** (3.18)	0.0354
	V3	29.54	2039804	0.1228	0.0043** (5.70)	0.0002** (7.86)	0.0607
	V4	34.69	3446612	0.1778	0.0047** (5.50)	0.0001** (4.44)	0.0614
	V5	37.26	11428545	0.1887	0.0039** (4.78)	0.0001** (5.01)	0.0583
							Mean = 0.0467

**Significant at the 1% level

Table 8

Difference between the observed and true inside spreads as a function of SPPR

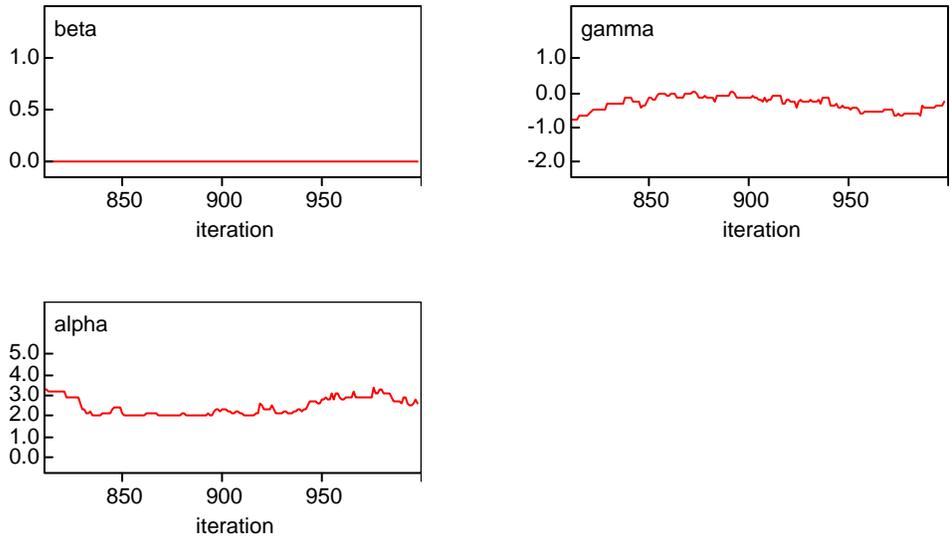
This table shows the results when we regress the difference between the observed and true inside spread on the sub-penny participation rate (SPPR), which is the ratio of the number of quotes placed by sub-penny ECNs to the total number of quotes placed by all market participants. We use three measures of spread difference: the difference between the observed absolute (dollar) spread and the true absolute spread ($I_O - I_T$), the difference between the observed relative (percentage) spread and the true relative spread ($\%I_O - \%I_T$), and $(\$I_O - \$I_T)/\$I_O$. Numbers in parentheses are t-statistics.

	β_0	β_1	Adjusted R ²	F-value
$\$I_O - \$I_T = \beta_0 + \beta_1 \text{SPPR} + \varepsilon$	0.0116** (15.01)	-0.0138** (-6.43)	0.14	41.40**
$\%I_O - \%I_T = \beta_0 + \beta_1 \text{SPPR} + \varepsilon$	0.0052** (6.24)	-0.0085** (-3.66)	0.05	13.41**
$(\$I_O - \$I_T)/\$I_O = \beta_0 + \beta_1 \text{SPPR} + \varepsilon$	0.3096** (10.48)	-0.4314** (-5.25)	0.10	27.53**

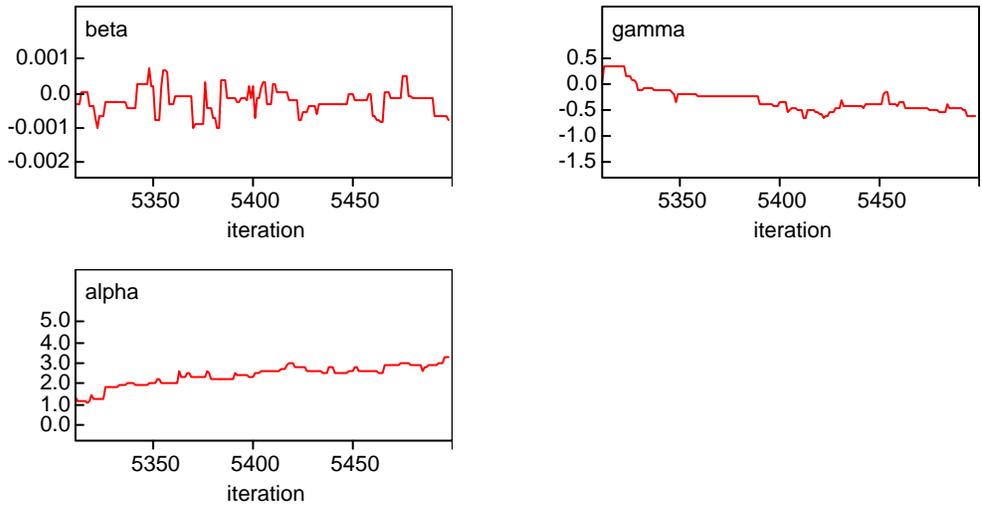
**Significant at the 1% level.

*Significant at the 5% level.

After 1,000 iterations



After 5,500 iterations



After 30,000 iterations

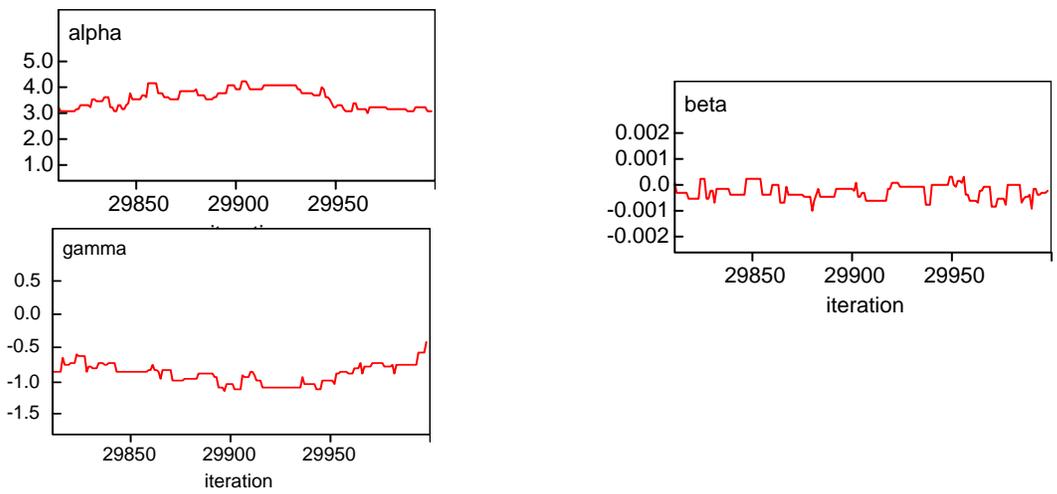


Figure 1: The dynamic trace for monitoring the 'nodes' of the model (ASPX quotes on ARCA)

Comparison of ISLD and BTRD for ABIZ

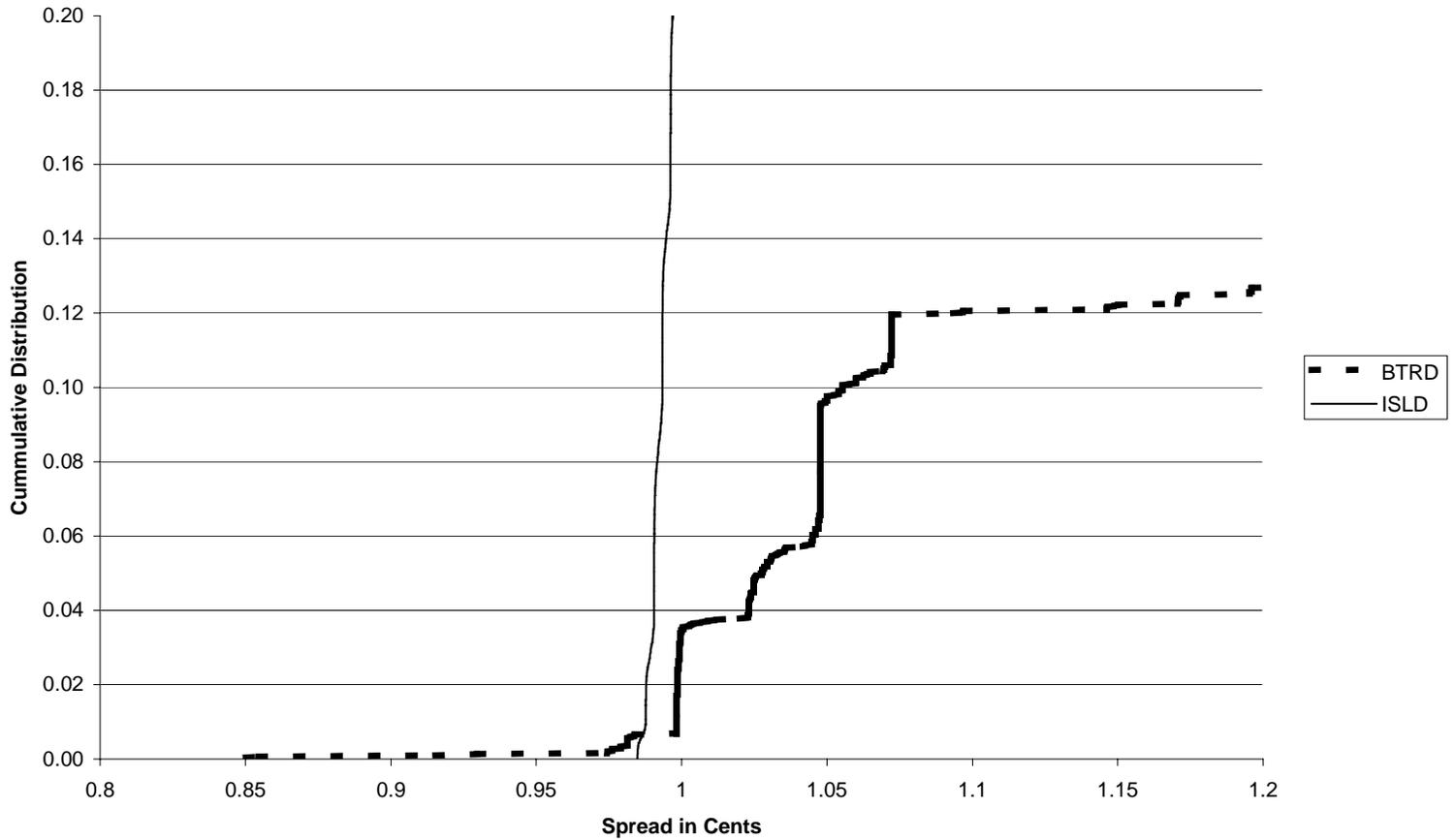


Figure 2: This figure shows a section of the cumulative distribution of true spreads for security ABIZ-Q (Adelphia Business Solutions Inc.) for the quotes of two ECNs – ISLD, which quotes in higher than two decimal places, and BTRD, which quotes in up to two decimal places. The plotted section zooms in around the binding constraint for spreads, the one cent mark. The darker (blue) line shows the true spread series for ECN BTRD and the lighter (pink) line is for ECN ISLD.

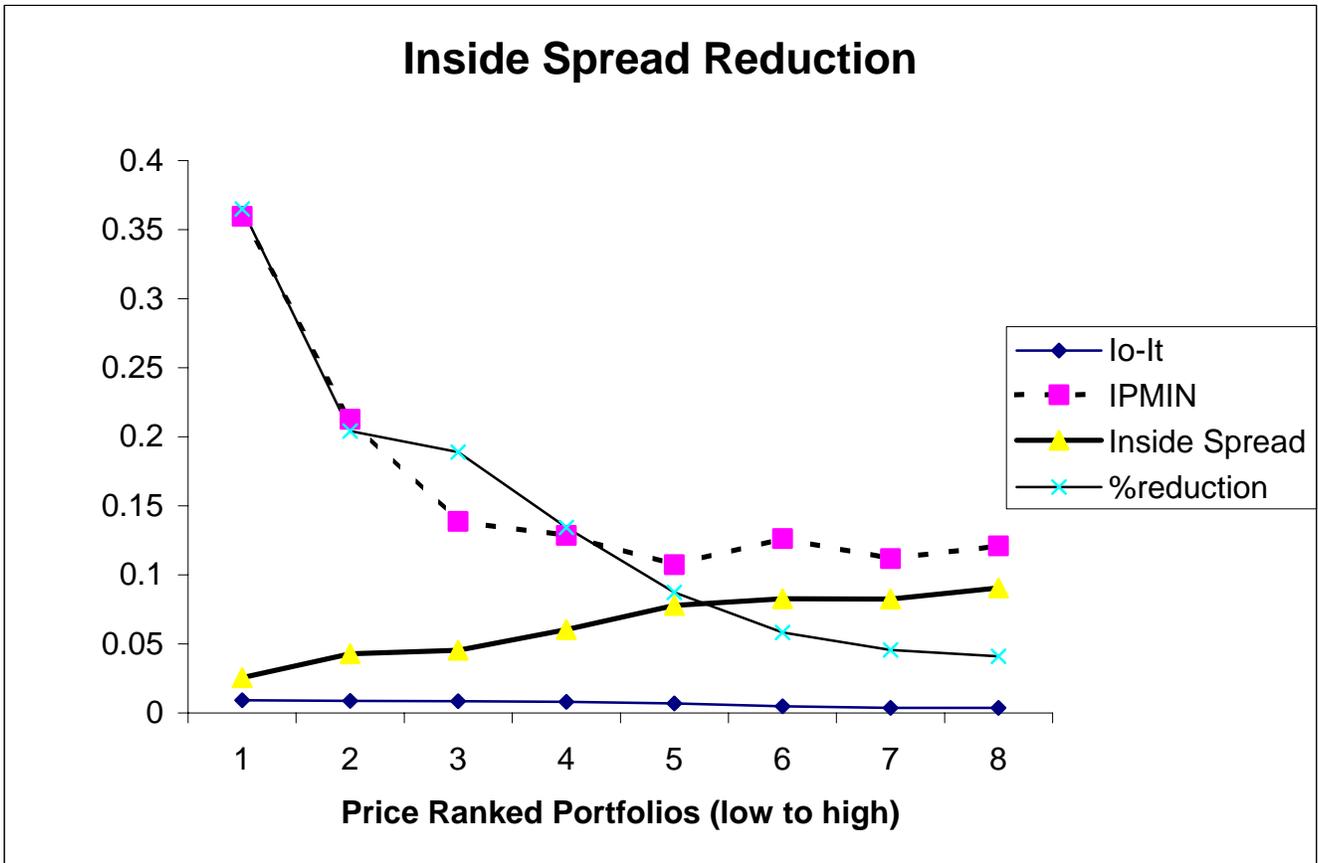


Figure 3: Inside spread reduction related to IPMIN