5-1999

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Published in Journal of Futures Market, May 1999, 19 (3), 307-324.

DOI: 10.1002/(SICI)1096-9934(199905)19:3<307::AID-FUT4>3.0.CO;2-5

Abstract

This paper investigates and analyzes the intraday and daily determinants of bid-ask spreads (BASs) in the foreign exchange futures (FXF) market. It is found that the number of transactions and the volatility of FXF prices are the major determinants. The number of transactions is negatively related to the BAS, whereas volatility in general is positively related to it. The study also finds that there are economies of scale in trading FXF contracts. The intraday BAS follows a U-shaped pattern, and they tend to be higher on Mondays and Tuesdays than on other days of the week. Higher spreads at the beginning and end of a trading day are consistent with the presence of adverse selection and the avoidance of the possibility of carrying undesirable inventory overnight, respectively. Seasonal differences in BASs that are related to the delivery date of a contract are also found.

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The author gratefully acknowledges the helpful comments of the editor and two anonymous referees.

INTRODUCTION

This article examines the determinants of bid-ask spreads (BAS) in the foreign exchange futures (FXF) market using the bid-ask spread estimator advanced by Chu, Ding, and Pyun (CDP, 1996). Many previous studies concerning bid-ask spreads have focused their analyses on the determinants, components, and behavior of BASs in the equity markets (see, for example, George, Kaul, and Nimalendran, 1991; McInish and Wood, 1992; Glosten and Milgrom, 1985; Glosten, 1987; Glosten and Harris, 1988; Copeland and Galai, 1983; Haller and Stoll, 1989; and Stoll, 1989, among others). A few researchers have examined BASs in the financial futures market (for example, Wang, Michalski, Jordon, & Moriarty, 1994; Ma, Peterson, & Sears, 1992; and Laux & Senchack, 1992). These studies deal mainly with the estimation and intraday behavior of the BAS.

There are some studies that analyze the BASs in the foreign exchange spot market (Overturf, 1982; Boothe, 1988; Glassman, 1987; Fieleke, 1975; Allen, 1977; and Bossaerts & Hillion, 1991). But hardly any study has been done to examine the determinants of BASs in the FXF market. The most closely related research is that by Harvey and Huang (1991), who study the volatility in the FXF market. Essentially, they find that increases in price volatility coincide with announcements of macroeconomic news and recognize that the variance is affected by the BAS.

The bid-ask spread represents a major component of a trader's transaction cost. In an order-driven market, such as in the futures market of the Chicago Mercantile Exchange (CME), the spread can only be implied. There are no specific quotes by official market makers. It is therefore imperative, in such a market, for a serious trader to have an understanding of the various factors that can have a significant impact on the BAS. A trader in the FXF market would want to know what drives the spread: (i) what is the impact of trading activity and price volatility on the BAS; (ii) whether there are any macroeconomic variables that can explain the size of the spread; and (iii) whether there is a particular period within the trading day, week, or contract month that represents higher or lower spreads and, hence, higher or lower transaction costs. The effect of the various factors on BASs in the FXF market may not necessarily be the same as those that drive the spreads in the foreign exchange spot market. Thus it is important for traders in the FXF market to appreciate the underlying factors that can contribute to their transaction costs and the timing of their transactions.

TRADING ON THE CHICAGO MERCANTILE EXCHANGE AND OTHER INSTITUTIONAL DETAILS

The Chicago Mercantile Exchange (CME) trades futures contracts in six currencies, including the deutsche mark (DM) and Japanese yen (JY) contracts. The trading hours are from 7:20 AM to 2:00 PM daily. A standard delivery schedule of March, June, September, and December is followed. Trading on the floor is through a system of open outcry where bid and offer prices are made known verbally in a trading pit. The actual trading of futures contracts on the exchange floor is done by *floor traders* or *floor brokers*, who are members of the exchange. Floor traders are those who trade for their own account, whereas floor brokers trade on behalf of their brokerage firm or for their firm's customers. Both floor traders and brokers are granted equal access to the market. However, brokers are required to trade for their customers before trading for their own account.

In the trading process, orders to buy or sell futures are sent to a member firm's representative on the trading floor through the telephone or a computerized order-entry system. The orders are then time-stamped and taken to the trading pit by an appointed runner. The floor broker, who handles a firm's trades in a specific contract or delivery month, takes responsibility for executing the order. All bids and offers must be announced through open outcry. Trading in a particular contract can only take place in a designated trading pit and within the officially established trading times. When an order is executed, it is again time-stamped, together with its price and trade size. Confirmation of the transaction is then transmitted to the firm's originating office and the customer. At the same time, a *pit observer* records the price of the trade for immediate entry into the CME's computerized price-reporting system for immediate transmission of the information to market participants globally.

In FXF markets, there are no official market makers such as the dealer-specialists of organized stock markets. Scalpers provide liquidity by quoting bid and ask prices against which market orders can be executed. This is as close as it can get to certain equity markets (such as the NYSE), where specialists make the market by buying and selling from their own inventory—but fundamentally different from a screen-based computerized market (such as in Singapore and Malaysia), where no designated market makers exist and transactions occur only when buy and ask orders match. In the screen-based equity markets, all trades are effected through computer matching of buy and sell quotes by strict price and time priority, and all transactions occur at posted prices. This means that there can be no difference between posted and effective spreads.

On the NYSE, also, the opening procedure is different from that of the futures market. The NYSE procedure involves a price discovery process in which the market is called to determine the best price that will effect the greatest number of transactions. In contrast, transaction prices in the futures market are determined through an open outcry process of bid and ask quotes on the trading floor. This means that even a pseudo-market maker such as the scalper does not simultaneously reveal both bid and ask quotes even though he may stand ready to buy from or sell to the market. This is very different from the specialist system of the NYSE, wherein the market makers (specialists) provide immediacy to the market by standing ready to buy and sell through quoting their bid and ask prices simultaneously. Because of the way prices are quoted, there can be some fundamental differences in the way bid-ask spreads are determined in the futures and equity markets. The implicit BASs of the futures contracts are not directly observable, but can be estimated using the covariance of price changes. These will be discussed later in this article.

FXF contracts trade primarily on the International Monetary Market (IMM) of the Chicago Mercantile Exchange (CME) with deutsche mark (DM) and Japanese yen (JY) futures contracts being the most actively traded of all currency contracts. FXF contracts also trade on the London International Financial Futures Exchange (LIFFE) and the smaller Singapore International Monetary Exchange (SIMEX), the Philadelphia Board of Trade, and some South American exchanges. However, interest on the LIFFE tapered off and trading was suspended in 1990. The CME had a mutual offset arrangement with the Singapore International Monetary Exchange (SIMEX) during 1990 (it was in operation from 1984 to 1995), whereby traders on the CME can offset their positions on the SIMEX without incurring any additional transaction costs. Thus, conceivably, a trader on the CME can react to new information and offet his position on the SIMEX during Chicago's closing hours.

LITERATURE REVIEW AND HYPOTHESES

In the equity market, McInish and Wood (1992) show that intraday BASs depend negatively on the level of activity and market competition, and positively on the level of risk and information. In the foreign exchange market, Boothe (1988) finds that different measures of risk and transactions volume have an impact on BASs. Specifically, he provides evidence for a positive relationship between the level of uncertainty regarding future prices and BASs. The relationship between trading volume and BASs is found to be negative.

In the futures market, Ma, Peterson, and Sears (1992) examine various measures of BASs on different futures contracts and find that spread levels are significantly higher at the beginning and end of a trading session. They provide the explanation of higher levels of trading noise and information uncertainty during those periods. However, these phenomena can be caused by infrequent trading.

Wang, Michalski, Jordan, and Moriarty (1994) investigate the determinants of the bid-ask spread and price volatility of S&P 500 index futures that are traded on the Chicago Mercantile Exchange. They find that the major factors affecting BASs are the price risk, trade volume, and market competition. They also find a U-shaped pattern in BASs. However, they realize that this pattern is not significant after adjusting for the effects of price volatility, transaction volume, and market competition.

I utilize the findings in the equity and foreign exchange markets to investigate the forces driving BASs in the FXF market. Activity measures usually encompass two main components—the number of transactions and the trading volume per transaction. As trading activity increases, the market becomes more liquid. Scalpers in the FXF market provide liquidity by quoting bid and ask prices against which market orders can be executed. Garbade and Silber (1979) find that the actions of scalpers reduce the volatility of price movements. Hence, an increase in the number of transactions and trading volume can lead to scale economies, resulting in lower BASs. However, Easley and O'Hara (1987), Glosten (1989), and Kyle (1985) suggest that adverse selection should increase with order size.

Similarly, according to inventory models of the BAS, order processing costs also increase with trade size. Thus an increase in BASs due to both adverse selection and order processing costs should be due to an increase in the order size. But Haller and Stoll (1989) find an inverse relationship between BASs and trading volume in the German auction equity market. Copeland and Galai (1983) maintain that market activity is a negative function of BASs. Based on the results of previous studies, I do not expect to see any significant difference, if any, in the way trading activity affects the BAS among the equity, spot foreign exchange, and futures markets. The following hypothesis is therefore investigated.

Hypothesis 1: BASs in the FXF market are negatively related to trading activity.

McInish and Wood (1992) use a transformed ratio of the number of shares traded on regional exchanges to the number of shares traded on the New York Stock Exchange (NYSE) to establish an inverse relationship between BASs and the level of competition. In the FXF market, contracts trade primarily on the International Monetary Market (IMM) of the CME with deutsche mark (DM) and Japanese yen (JY) futures contracts being the most actively traded. Competition from other exchanges is slight and any effects from the competition should be minimal. Consequently, this study does not attempt to establish such a relationship in the FXF market.

The uncertainty regarding future exchange rates subjects dealers to the risk of holding onto a contract. There are a number of possible measures of risk in the FXF market, such as those investigated by Fieleke (1975) and Overturf (1982). Overturf finds a positive BAS relation to price volatility measured by its standard deviations, whereas Fieleke reports a positive relationship between the rate of change in the exchange rate and the cost of transacting in the foreign exchange market. Overturf further suggests that the uncertainty regarding the rate of change in exchange rates tends to widen the BAS. In the FXF market, BASs are not directly observable but can be estimated using the covariance of price changes. Wang et al. (1994) demonstrate that OLS estimates of the BAS equation are inconsistent if the standard deviation of transaction price changes is found in the regression. Thus, in order to avoid a misspecification of the BAS regression model [such as eq. (3)], a measure of volatility other than the standard deviation, which is related to the covariance, should be applied.

Garman and Klass (1980) provide a volatility measure that does not contain the standard deviation but rather takes into account the open, high, low, and closing prices of each time period. Their estimator has been found to be more efficient than the traditional close-to-close estimators. The specification of the Garman-Klass estimator is detailed later in this article. In line with prior expectations, the following hypothesis is anticipated to hold.

Hypothesis 2: The volatility of FXF prices has a direct relationship with the BAS.

The presence of asymmetric information exposes a trader to the problem of adverse selection. The trader expects a loss, a priori, due to uninformed trading. Copeland and Galai (1983) show that, all else being equal, informational uncertainty is positively related to the BAS. They report that the BAS is a positive function of the price level and the return variance. If high price levels result from informed trading, then the relationship between price levels and BASs should be positive. In most empirical studies of BASs in the stock markets, a positive price–BAS relation has been found (for example, Demsetz, 1968; Benston & Hagerman, 1974; Stoll, 1976; and Copeland & Galai, 1983). These studies generally attribute their findings of large dealer spreads to the risk of adverse selection or uninformed trading. However, McInish and Wood (1992) find a negative BAS–price relationship. They ascribe their finding to the presence of economies of scale in trading. When prices are high, the dollar volume of transactions rises. This leads to a lowering of dealers' required BAS to cover their costs.

In FXF markets, however, there are no official market makers such as the dealer-specialists of organized stock markets. Therefore, the relationship between price levels and BASs, if any, may not be obvious. A positive BAS-price relationship supports an asymmetric information hypothesis, whereas a negative relationship lends support to the presence of scale economies in trading in the FXF market. Hence this study examines the information conveyed through price levels in the framework of the FXF market. The following null hypothesis is examined.

***Hypothesis* 3**: There is no relationship between BASs in the FXF market and price levels.

This article further postulates that there are intraday, weekday, and seasonal patterns in the BAS, reflecting the changing underlying structure of the market. Admati and Pfleiderer (1988) suggest that trades will be concentrated during certain times of the day. In particular, discretionary liquidity traders are thought to concentrate their trades during the periods near the opening and closing of the market. McInish and Wood (1992) report a reversed J-shaped pattern in intraday BASs that is inversely related to trading activity. This means that BASs are higher at the beginning and end of a trading day than the rest of the day. In addition, they find that weekday patterns, though mostly significant, are weaker than intraday patterns. Weekday patterns are also found to be unstable over time. In the FXF market, traders are possibly faced with a greater degree of the adverse selection problem at the start of a trading day than the rest of the day. There is also an increase in the likelihood of carrying undesirable inventory overnight toward the end of the trading day. Hence spreads are expected to be higher at the beginning and end of a trading day.

Bossaerts and Hillion (1991) have developed an asymmetric information model of BASs in the foreign exchange market and they document evidence of asymmetric information for all days of the week. However, spreads on Fridays are found to be more pronounced. Information asymmetry is thought to be accompanied by an increase in the BAS. Because governments usually reveal their intention to intervene in the currency market during weekends when the foreign exchange markets are closed, BASs may be expected to increase on Fridays. This may be explained by the increased uncertainty from the possibility of having informed traders transact on the Friday before the government's announcement. McInish and Wood (1992) also present evidence of larger spreads on Fridays in the equity market. Moreover, because futures contracts can have different delivery dates, a seasonal pattern that reflects the various maturities is also expected and is investigated. This article represents one of the first to study the existence of a maturity pattern.

DATA AND METHODOLOGY

Data

The study uses the time-stamped transaction-by-transaction data of the deutsche mark (DM) and Japanese yen (JY) futures contracts that are traded on the International Monetary Market of the Chicago Mercantile Exchange (CME) for the year 1990. Time series of transaction prices and price changes for the March, June, September, and December delivery dates of each FXF are constructed. Close-to-open (that is, overnight, weekend, and holiday) price changes, from the market's closing time to the its next opening session, and trades after the market's official closing time are excluded from the data. In order to avoid a possible maturity effect and the necessity to adjust for a time-varying volatility in price changes (Laux & Senchack, 1994), observations are collected for each contract until two weeks prior to its delivery date. Data for the March contract begin 2 January; for the June contract, 8 March; for the September contract, 7 June; and for the December contract, 6 September. The series of data are then chronologically appended to each other to form a long time series of prices and price changes for 1990. The total number of price change observations for the DM futures over the four contract dates is 294,502; for the JY futures, it is 281,980.

Deutsche mark and Japanese yen futures prices are selected for this study for two main reasons: (i) They are the two most actively traded currency futures contracts on the CME that are chosen in order to avoid a possible bias caused by infrequent trading as pointed out by Ma et al. (1992); (ii) the BAS estimator used in this study follows that advanced by Chu, Ding, and Pyun (CDP, 1996) and it is judicious to use a similar data set as that employed by CDP in the development of their model. In the current analysis, as in CDP, the trading period from 7:20 AM to 2:00 PM within each trading day is divided into thirteen time intervals: The first interval has 40 minutes, whereas the remaining twelve intervals consist of 30 minutes each for a total of 400 minutes in each trading day.

The CDP Estimator for Bid-Ask Spreads

The CDP spread estimator shown in eq. (1) considers the intraday Markovian bid-ask bounce process, which leads to a desirable equilibrium condition of reaching a bid or an ask transaction type with equal chances. Based upon a second-order Markov process, the derived estimator is shown to be a more generalized estimator of BASs than in previous studies, such as those of Roll (1984) and Choi, Salandro, and Shastri (1988). It considers the conditional probability of a subsequent transaction's being the same type as that of the current transaction (δ), and the conditional probability of the next transaction's being the same as the current type but different from the previous type (α). CDP's results show that the average implied BAS is about \$10, which is less than the value of one tick size of \$12.50. The small BAS reveals the low trading cost and high operational efficiency in the FXF market.

Methodology

Various models have been advanced for the estimation of the BAS and its components (for example, Roll, 1984; Choi, Salandro, & Shastri, 1988; George, Kaul, & Nimalendran, 1991; Laux & Senchack, 1994; and Chu, Ding, & Pyun, 1996). Because BASs are not directly observable in the FXF market, they need to be estimated first. The model derived by Chu, Ding, and Pyun (1996) is used for this purpose. The CDP model builds on both the Roll (1984) and Choi, Salandro, and Shastri (1988) models and is intended to be an improvement over the two models. CDP have shown that these two previous models are a special case of their new model. As shown by Laux and Senchack (1992), Roll's estimator is more suited for futures prices, because it mainly measures order processing costs that form the bulk of the transaction costs in the futures market where adverse selection problems are less pronounced. It follows, therefore, that BAS estimators that are Roll-based are more applicable to the futures market rather than the equity market.

The approach of George, Kaul, and Nimalendran (1991) is largely applicable to equity prices where the components of the BAS are estimated separately. Laux and Senchack (1992) provide an alternative estimate for the BAS of currency futures in a heteroskedastic market in which more weight is assigned to observations in periods of light trading. The CDP model, however, assumes a second-order Markov process to derive a more general BAS estimator that is Roll-based but has less restrictive assumptions than Roll's estimator. It utilizes only the transaction price data to estimate BASs and is specified as:

$$s = \sqrt{\frac{-Cov(\Delta p_t, \ \Delta p_{t+1})}{(1 - \delta)(1 - \alpha)}} \tag{1}$$

where s is the implied BAS; Δp_t is the price change at time t; Cov refers to the covariance between two consecutive price changes; δ is the conditional probability that the next transaction type (bid or ask) is the same as the current transaction type; and α is the conditional probability that the next transaction type is the same as the current type but different from the previous type. Eq. (1) has been derived using a second-order Markov chain transition matrix model where α and δ are maximum likelihood estimates. If $\alpha = \delta$, eq. (1) reduces to the Choi, Salandro, and Shastri (1988) model. If $\alpha = \delta = 0.5$, it reduces to Roll's (1984) model. Thus, eq. (1) is a more generalized BAS estimator and both the Roll and Choi et al. estimators are special cases of the CDP model.

The implied BASs are first estimated for each time interval and trading day by the CDP method.[1] In order to ascertain the determinants of the BAS, the implied spread is regressed against variables that represent the level of activity, risk, information, and interest rate differential, together with three sets of dummy variables (D1, D2, D3) that serve to measure intraday, weekday, and seasonal effects, respectively. The intraday and weekday effects are readily understood. The seasonal effects are those that exhibit differences in spreads for the different delivery months in a year. It should be pointed out that spread values, rather than percentages spreads (as in McInish & Wood, 1992), are measured in this study for two reasons. First, the results where the spread value, rather than the relative spread, is used as the dependent variable would convince that the significance of the regression coefficients is not spurious. Sec-

[1]It should be noted that the CDP estimator is Roll (1984) based and utilizes the covariance of price changes in each time interval of a trading day. There are, however, some intervals where the covariance is positive, rendering it impossible to estimate a BAS for those intervals. If this occurs, then observations for the affected intervals will not be included in the analysis. The author recognizes that the exclusion of data in this manner is a fundamental weakness of all Roll-based spread estimators. But, in this study, no more than a third of the observations have been excluded in any time interval. In Roll's study, however, his sample included up to a 51% occurrence rate of positive covariances.

ond, unlike McInish and Wood's study, no averaging of the spreads is required. The regression for each contract is a time series one and there is no motivation to measure relative spreads.

Because data for the trading volume per transaction are not available, activity levels can only be measured by the number of transactions (NTRANS) in each time interval t and trading day d together with the trading volume per day. The variable NTRANS therefore serves as a proxy measure for intraday activity levels. Differential risk over the thirteen time intervals in each day are captured through the Garman-Klass (1980) volatility measure (GK) in each time interval. The GK estimator is specified as

$$GK = 0.511(a + b)^2 - 0.019[x(a - b) + 2ab] - 0.383x^2 \quad (2)$$

where x = ln(close/open); a = ln(high/open); and b = −ln(low/open). It is recognized that the GK estimator is susceptible to the effects of outliers. To check for the possible existence of outliers, the basic statistics in each time interval are examined for any inconsistencies and the transaction prices are visually inspected to identify any unusual prices. This procedure resulted in the elimination of one observation that was peculiarly large in the JY December contract on October 5, 1990.[2]

Information effects are evaluated by a price dummy variable (PRDUM) in each time interval.[3] The median transaction price is first identified from the entire time series. The average price within each interval is then computed and compared to the overall median price. If the average price is greater than the median price, then the variable PRDUM is assigned a value of one. Otherwise, a value of zero is assigned.

The empirical analysis is performed through the use of a regression model. The model, which is an interval analysis of transaction prices, is specified as

$$\begin{aligned} s_{t,d} = \beta_0 &+ \beta_1 NTRANS_{t,d} + \beta_2 NGK_{t,d} + \beta_3 PRDUM_{t,d} \\ &+ \sum_{i=4}^{15} \beta_i D1_{i,t,d} + \sum_{i=16}^{19} \beta_i D2_{i,t,d} + \sum_{i=20}^{22} \beta_i D3_{i,t,d} + e_{t,d} \quad (3) \end{aligned}$$

where $s_{t,d}$ is the interval BAS; NTRANS is the number of transactions in

[2]Caution was taken not to arbitrarily eliminate legitimate large price change observations, because, other than the one already eliminated, the next "big" price change has many occurrences and they cannot be prudently regarded as outliers.

[3]Although the price level, rather than a price dummy, may generally provide more information, the regression with the dummy shows a stronger relationship with the BAS, and only the results containing the dummy variable are reported here. Moreover, the intention is to find out if there is a BAS-price relationship, rather than the magnitude of such a relationship.

TABLE I

Intraday Implied Bid-Ask Spreads and Volatility (Amounts in US$ Per Contract)

		Bid-Ask Spread		*Std Dev of BAS*		*% of Neg. Cov.*	
Time Interval		*DM*[a]	*JY*[b]	*DM*	*JY*	*DM*	*JY*
1.	7:20–8:00	12.89	12.27	3.68	3.71	95	87
2.	8:00–8:30	11.14	11.88	3.91	4.31	92	81
3.	8:30–9:00	10.62	10.85	3.78	4.08	87	79
4.	9:00–9:30	10.35	10.26	3.91	4.00	82	72
5.	9:30–10:00	9.35	9.82	3.40	3.96	81	69
6.	10:00–10:30	9.19	9.85	3.52	4.03	79	72
7.	10:30–11:00	8.61	9.83	3.65	3.78	77	68
8.	11:00–11:30	9.31	9.85	3.65	4.82	83	74
9.	11:30–12:00	9.96	10.29	3.73	4.31	84	69
10.	12:00–12.30	9.78	10.84	3.82	4.66	77	72
11.	12:30–13:00	10.10	10.52	3.88	4.20	78	70
12.	13:00–13:30	10.77	10.23	3.82	4.18	83	76
13.	13:30–14:00	12.87	12.32	3.78	4.36	92	89

Notes: BASs for each time interval and trading day over the four delivery dates are computed for those intervals where a negative covariance in price changes exist. Positive covariances are ignored. BASs are then averaged across all days for each time interval to obtain the mean BAS and the standard deviation for that interval. The percentage of days with a negative covariance of price changes is reported in the last two columns. There are 294,502 price change observations for DM futures and 281,980 price change observations for JY futures.

[a]Deutsche mark futures contracts. Each contract trades for DM125,000.

[b]Japanese yen futures contracts. Each contract trades for ¥12.5 million.

the time interval; NGK is 10,000 times the value of GK; PRDUM is the price dummy described above; D1, D2, and D3 capture the intraday, weekday, and seasonal effects, respectively; and $e_{t,d}$ is a random error term.

EMPIRICAL RESULTS

Results are presented for the intraday analysis for each of the DM and JY contracts. A pooled data analysis of both contracts was also done but the results are not reported here. Overall, the findings from the pooled analysis support the individual analysis.

Utilizing the 294,502 price change observations of the DM contracts and the 281,980 price change observations of the JY contracts, the maximum likelihood estimates of α and δ are found to be 0.4447 and 0.4372, respectively, for the DM contract; and 0.4941 and 0.4748, respectively, for the JY contract. Substituting the values of these estimates into eq. (1) yields the average intraday BASs and their standard deviations reported in Table I. It should be pointed out that, whereas the values of α and δ

for the JY contracts are close to 0.5 [which could justify simply using the Roll (1984) model], the corresponding values for the DM contracts deviate sufficiently from 0.5 to support the use of the CDP model in estimating bid-ask spreads. Applying Roll's model would have over estimated the size of the spread. The estimated spreads shown in Table I are largely within one tick size of $12.50 except during the first and last time interval of DM trading. This is consistent with efficient estimators of the BAS.

Although it is observed that the BAS for both contracts is higher during the first 40 minutes and last 30 minutes of trading, the corresponding volatility, as measured by their daily standard deviation in each time interval, does not reveal any particular pattern. However, it is interesting to see that the BASs of the JY contracts are, in general, more volatile than those of the DM contracts. The last two columns of Table I report the percentage of negative covariances in each time interval. It is noted that the lowest value for the DM contract is 77%, whereas that for the JY contract is 68%. These figures provide a sense for the validity of using eq. (1) in estimating the implied BASs.

The regression model of eq. (3) is run to examine the determinants of intraday BASs in the FXF market. Results of this regression are presented in Table II. The strength of this regression is supported by the F-statistics of 58.44 for the DM contracts and 38.17 for the JY contracts. These values are statistically significant at the 0.01 level. The adjusted R-squares of 0.3296 for the DM and 0.2616 for the JY show that, respectively, 32.96% and 26.16% of the variation in intraday BASs are explained by the independent variables.

As expected, the level of trading activity, as measured by the variable NTRANS, is significantly negative at the 0.01 level for both the DM and JY contracts. The result confirms Hypothesis 1 that the number of transactions in an intraday time interval is negatively related to the size of the BASs in the interval. One inference from this result is that there are economies of scale in trading. The interval risk in FXF prices has been found to be directly related to the intraday BAS, confirming Hypothesis 2. This is supported by the strong coefficients of the Garman-Klass volatility measure (NGK) that are statistically significant at the 0.01 level. These results are consistent with findings from the existing microstructure literature that show a positive relationship between risk and the size of spreads.

The price dummy variable (PRDUM), on the other hand, is found to be negatively significant at the 0.01 level for both contracts. This finding dominates the presence of any asymmetric information trading. It is therefore consistent with the presence of trading economies in the FXF

TABLE II

Results for the Regression of Interval Bid-Ask Spreads per Contract Against Activity, Risk, and Information Variables

	Deutsche Mark		Japanese Yen	
Independent Variables	*Coefficients*	*t-statistics*	*Coefficients*	*t-statistics*
Intercept	11.6002	29.88[b]	11.6965	22.93[b]
NTRANS	−0.0446	−22.07[b]	−0.0475	−19.67[b]
NGK	15.8543	6.21	30.4039	9.51[b]
PRDUM	−0.853	−4.11[b]	−0.7435	−2.72[b]
Interval 1	7.3781	21.24[b]	6.2545	14.60[b]
Interval 2	3.2195	9.96[b]	2.9005	7.33[b]
Interval 3	2.2179	6.78[b]	1.6857	4.24[b]
Interval 4	1.9434	5.85[b]	1.0087	2.48[b]
Interval 5	1.0061	3.02[b]	0.3092	0.76
Interval 6	0.8143	2.43[a]	0.3570	0.88
Interval 8	0.4380	1.32	0.2077	0.52
Interval 9	1.0759	3.26[b]	0.5215	1.27
Interval 10	0.3515	1.04	0.7018	1.73
Interval 11	0.6546	1.94	0.4386	1.07
Interval 12	1.2178	3.65[b]	0.2675	0.67
Interval 13	4.6912	14.45[b]	3.8241	9.82[b]
Monday	1.1251	5.51[b]	0.9853	3.99[b]
Tuesday	0.4407	2.19[a]	0.5287	2.16[a]
Wednesday	0.2799	1.38	0.0479	0.20
Thursday	0.3947	1.90	0.3529	1.40
March	0.6131	2.13[a]	1.8801	6.91[b]
June	1.1975	4.79[b]	1.5719	4.38[b]
September	0.4991	2.56[b]	0.1052	0.31
N	2572		2309	
Adjusted R^2	0.3296		0.2616	
F-Statistic	58.44[b]		38.17[b]	

Notes: The trading period from 7:20 AM to 2:00 PM within each trading day is divided into thirteen time intervals: The first interval has 40 minutes and the remaining twelve intervals consist of 30 minutes each for a total of 400 minutes. BASs are first estimated for each time interval and trading day. They are then regressed against variables that represent the level activity, risk, information, and interest parity together with three sets of dummy variables (D1, D2, D3) that serve to measure intraday, weekday, and seasonal effects, respectively. Activity level is measured through the number of transactions (NTRANS) in each time interval. Differential risk across time intervals in each day is captured through the German-Klass (1980) volatility measure (GK) that takes into account the open, high, low, and closing prices. The variable NGK is 10,000 times GK. Information effects are evaluated by a price level dummy variable (PRDUM) for each time interval. The median transaction price is first identified from the entire time series. The average price within each interval is then computed and compared to the overall median price. If the average price is greater than the median price, then the variable PRDUM is assigned a value of one. Otherwise, a value of zero is assigned.
[a]Significant at the 0.05 level.
[b]Significant at the 0.01 level.

market and supports the results of McInish and Wood (1992) for the stock market. Copeland and Galai (1983) had argued that higher price levels in the stock market are associated with larger spreads because of a higher informational uncertainty due to the bidding up of prices by informed traders. But my finding of lower spread levels when prices increase supports the notion of the presence of economies of scale in trading futures contracts. Thus Hypothesis 3, which states that there is no relationship between BASs and prices, does not hold.

The existence of intraday patterns in BASs implies that the size of the BAS depends on the time interval in a trading day. The first five and last two intervals of trading for the DM contract contribute positively and significantly to BASs at the 0.01 level. These are evidenced by the statistically significant interval dummy variables at the 99% confidence level. These intervals encompass the time from 7:20 AM to 10:00 AM, and from 1:00 PM to 2:00 PM, respectively. For the JY contract, BASs are positively significant at the 0.01 level during the first four and the last intervals of trading. These occur during the trading times from 7:20 AM to 9:30 AM, and from 1:30 PM to 2:00 PM, respectively. The results demonstrate that, except in interval 9 for the DM contract, it may be less costly to trade during the interior time periods of a trading day.

Higher spreads at the beginning of a trading day may be due to certain traders having less information and their uncertainty about the behavior of the market. It can also be attributed to some traders having private or superior information that are not available to others. The higher BASs serve to compensate the unofficial market makers for assuming the risk of uninformed trading. The higher price risk at the end of the trading day and the resultant increase in spreads may be caused by the uncertainty related to an increase in the possibility of carrying undesirable inventory overnight. There are also weekday trading patterns in the FXF market. Both the DM and JY contracts portray significantly positive coefficients in the weekday dummy variables on Monday (at the 0.01 level) and on Tuesday (at the 0.05 level). This phenomenon reveals a weekday preference for trading that may be related to a varying cost of transaction.

The coefficients of the dummy variables for each contract delivery month are all positive. They are significant at the 0.01 level for the June and September DM contracts, and the March and June JY contracts. In addition, the March DM contract is significantly related to BASs at the 0.05 level. These results indicate that there are differences in BASs by delivery months, suggesting the presence of a seasonal effect in BASs. The findings reveal that it may be less costly, in terms of the BAS, to transact in the FXF market for nearby December DM and JY contracts, and more costly to execute trades in nearby June DM and March JY contracts. The lower BAS for December contracts is consistent with a higher trading activity which saw 85,299 price changes for the DM contracts and 102,553 price changes for the JY contracts. This contrasts with

70,538 and 48,228 observations for the March DM and JY contracts, respectively; 65,837 and 66,113 for the June contracts; and 72,828 and 65,086 for the September contracts.

SUMMARY AND CONCLUSIONS

This article has investigated and analyzed the intraday determinants of BASs in the FXF market. It has been found that the number of transactions and the volatility of FXF prices are major determinants of intraday BASs. The number of transactions is negatively related to BASs, whereas volatility in general is positively related. These variables proxy for activity level and risk and are consistent with findings from previous studies. This study also finds that there are economies of scale in trading FXF contracts.

Intraday and weekday patterns in BASs have been found. BASs exhibit a U-shape pattern during the trading day, whereas BASs are higher during Mondays and Tuesdays than during other days of the week. Higher spreads at the beginning and end of a trading day reflect the presence of adverse selection and the possibility of carrying undesirable inventory overnight, respectively. There are also seasonal differences in BASs that have been found in the analysis.

Although this paper has investigated and identified some key determinants of BASs in the FXF market, it recognizes the possibility that others may exist. The identification of such other determinants is best left to future research to examine the stability of the present determinants over time and contract type. In general, however, activity levels and risk are thought to be stable determinants and are found to support those of previous studies. Moreover, the patterns of BASs should also prove to be time and contract invariant.

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Penny pricing and the components of spread and depth changes

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Published in Journal of Banking & Finance, December 2004, 28 (12), 2981-3007.

DOI: 10.1016/j.jbankfin.2003.11.001

Abstract

Recent studies show that decimal pricing led to significant reductions in the spread and depth on the NYSE. In this paper, we examine how the observed changes in the spread and depth can be attributed to different factors. We show that stocks with higher proportions of one-tick spreads and odd-sixteenth quotes, and more frequent trading before decimalization experienced larger declines in the spread and depth afterwards. We interpret this result as evidence of reduced binding constraints and increased price competition under decimal pricing. We also find that decimal pricing led to nontrivial changes in select stock attributes, and that these changes exerted an additional impact on spreads and depths. Our results suggest that sub-penny pricing may further reduce the spreads of high-volume, low-risk, or low-price stocks.

Keywords

Binding constraint, tick size, stepping ahead, spreads, depths, decimal pricing

1. Introduction

The New York Stock Exchange (NYSE) moved from fractional pricing to dollars-and-cents pricing with the goal of making prices more easily understood by investors and bring the US securities markets into conformity with international practices. It

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initiated a pilot program on August 28, 2000 with seven listed issues trading in dollars and cents, followed by 57 issues on September 25, 2000, and 94 issues on December 4, 2000. The NYSE completed the conversion on January 29, 2001 by trading all remaining issues in decimals.

In this study, we investigate principal factors that led to the changes in the spread and depth from decimal pricing. Specifically, we examine how much of the inter-stock differences in spread and depth changes that are associated with decimal pricing can be explained by the inter-stock differences in the percentages of one tick spreads and odd-sixteenth quotes, trading frequency, and share price before decimalization. Our study helps assess how much of the observed changes in the spread and depth can be attributed to binding constraint, front running, price competition, quote rounding, and concurrent changes in stock attributes. Our results show which stocks benefited most from decimalization and help assess the likely effect of sub-penny pricing for different stocks.

Numerous studies analyse the impact of decimalization on trading costs and market quality. Chakravarty et al. (2001a,b) show that decimal pricing resulted in lower quoted and effective spreads. They also find that the available depths at the best bid and ask prices are significantly smaller after decimalization. The authors conclude that their findings deliver a mixed verdict on the net effect of decimal pricing on market quality. Similarly, Bacidore et al. (2001) and the NYSE (2001a,b) show that NYSE stocks exhibit smaller spreads and depths after decimalization. NASDAQ (2001a), Chung et al. (in press), and Bessembinder (2003b) compare trading costs between the NYSE and NASDAQ after decimalization.

Chakravarty et al. (in press) isolate the effects of decimalization using a matched sample of decimal and non-decimal stocks on the NYSE. They find that the quoted depth as well as the quoted and effective spreads decline significantly following decimalization. Bacidore et al. (2003) use NYSE system order data to examine changes in trader behavior, displayed liquidity supply, and execution quality around decimalization. They find that although traders do not reduce the use of limit orders in favor of market orders or non-displayed orders, they decrease limit order size and cancel limit orders more frequently after decimalization. However, the study shows that the lower displayed liquidity does not result in poor execution quality.

Although prior studies show that both spreads and depths declined after decimalization, they provide limited evidence on why such changes occurred. Thus, the main causes of these declines have not been well understood. Most studies (see Bacidore et al., 2001; Bessembinder, 2003b) find larger declines in spreads for large-capitalization or high-volume stocks and interpret the result as evidence that the pre-decimalization tick size ($1/16) was more likely a binding constraint on spread widths for these stocks. None of these studies, however, provides evidence regarding how much of the decline in the spread and depth can actually be attributed to the reduced binding constraint, and how much to other factors such as front running, stepping ahead (price improvement), quote rounding, and changes in stock attributes. In the present study we provide such evidence.

It is useful to note the difference between front running by sell-side intermediaries (e.g. specialists, market makers, and brokers) and stepping ahead of the existing queue by buy-side traders (e.g. pension funds, mutual funds, and hedge funds). The former is unethical if not illegal if it is undertaken with the knowledge of customer order flow that will move price. The latter is simple price competition that is done with no knowledge of order flow for the purpose of improving the likelihood of getting an execution.

Theory suggests at least four possible causes of spread and depth changes that are associated with decimalization (see Harris, 1994, 1997, 1999; Ronen and Weaver, 2001). Decimal pricing is likely to narrow the spread because a smaller tick size reduces the probability that the minimum price variation is a binding constraint on spread widths. The relaxation of the binding constraint is also likely to reduce the depth because sell-side liquidity providers may slide down the liquidity supply schedule along with the smaller spread. Although prior studies provide indirect evidence on this issue by showing that decimal pricing has a greater impact on high-volume and/or large-capitalization stocks, no direct evidence exists in support of this hypothesis.

Decimal pricing may reduce the depth because of the higher risk of front running imposed upon buy-side traders by specialists. The smaller tick size may narrow spreads even when the minimum price variation is not a binding constraint because both buy-side traders and specialists are more likely to improve existing quotes. Decimal pricing may narrow spreads because the smaller tick size reduces quote rounding. Finally, decimal pricing is likely to change the spread and depth because the smaller tick size can alter the factors that influence the spread and depth. For example, the smaller tick size may lead to higher trading activity and, consequently, narrower spreads. Similarly, it may result in lower return volatility and thus narrower spreads. For example, Ronen and Weaver (2001) find significant decreases in both daily and transitory volatility after the tick size reduction on the American Stock Exchange.

The spread and depth reduction due to the relaxation of the binding constraint is expected to be a positive function of the probability that the minimum price variation was a binding constraint before decimal pricing. In contrast, the spread and depth changes triggered by the increased risk of front running and price competition are likely to be related to the probability of front running and price competition after decimal pricing. In this study, we measure the binding-constraint probability by the proportion of spread quotes that are equal to the minimum price variation ($1/16) before decimalization. We measure the front-running probability and price competition by the proportion of odd-sixteenth quotes and the intensity of trading before decimalization. We consider changes in five stock attributes – share price, number of trades, trade size, return volatility, and market capitalization – as additional sources of spread and depth changes after decimal pricing. [1]

Our results show that the observed reductions in the spread and depth are positively correlated with the pre-decimalization proportions of one-tick spreads

[1] Prior studies suggest these variables as determinants of spreads and depths. See, e.g. Stoll (1978), McInish and Wood (1992), Harris (1994), and Bessembinder (1999).

and odd-sixteenth quotes, indicating that stocks with the most one-tick spreads and the least quote clustering benefited the most from decimal pricing. We also find that stocks with a greater number of trades before decimalization exhibited larger reductions in the spread and depth after decimal pricing. These results are consistent with the notion that relaxation of the binding constraint and the increased price competition and front running led to smaller spreads and depths after decimal pricing. Decimal pricing led to nontrivial changes in select stock attributes and these changes exerted an additional impact on spreads and depths. The intraday pattern of the observed changes in spreads and depths is highly correlated with the intraday variation in the proportion of one-tick spreads, suggesting that the extent to which the pre-decimalization tick size was a binding constraint varied across different times of the day. Finally, our results suggest that sub-penny pricing may further reduce the spreads of high-volume, low-risk, or low-price stocks.

The paper is organized as follows. In Section 2, we discuss the likely effects of decimal pricing on the spread and depth and establish our hypotheses. Section 3 explains our data source, the measurement of key variables, and sample characteristics. Section 4 presents the empirical results. Section 5 addresses the question of whether the penny tick size is a binding constraint for certain stocks. Section 6 provides a brief summary and concluding remarks.

2. The effects of decimal pricing on the spread and depth of NYSE stocks

In this section, we describe how decimal pricing can affect the spread and depth in different ways.

2.1. Probability that the minimum price variation is a binding constraint on spread widths

The minimum price variation limits the prices that liquidity providers can quote. Liquidity providers cannot narrow the bid–ask spread when the spread is equal to one tick. Decimal pricing will narrow spreads when the minimum price variation was a binding constraint on spread widths before decimalization. Because sell-side liquidity providers are likely to quote smaller depths at narrower spreads (i.e. the liquidity-supply schedule is positively sloped), decimal pricing would also lower the depth through its effect on the spread.

The probability that the minimum price variation is a binding constraint on spread widths is likely to be positively related to the proportion of spreads equal to one tick. This is because the observed spread will be one tick whenever the equilibrium spread (i.e. the spread that liquidity providers would have quoted had there been no binding constraint) is less than one tick. Hence, we employ the proportion of spread quotes that are equal to the pre-decimal tick size ($1/16) as our empirical proxy for the probability that the tick size was a binding constraint on spread widths. This leads to the following hypothesis:

Hypothesis 1. Decimal pricing leads to larger declines in spreads and depths for stocks with higher proportions of spread quotes that are equal to \$1/16 before decimal pricing.

2.2. Front running and price competition

The NYSE uses price and time priority rules to determine which orders will be filled first. The price priority rule requires that orders with the highest bid and lowest ask prices must be filled before those with inferior prices. The time priority rule requires that, among public orders, the first order at a given price must be filled before other orders are filled. [2] The time priority rule is meaningful only if the minimum price variation is nontrivial. The minimum price increment determines the cost of obtaining precedence through price priority when a trader does not have time precedence at a given price. If the increment is very small, the cost of obtaining precedence is negligible because traders can obtain precedence simply by bettering the existing quotes by insignificant amounts. Hence, the minimum price variation determines the probability (and also profitability) of stepping in front of existing orders.

Decimal pricing greatly reduces the cost of front running by the sell side (e.g. specialists), and thus specialists are more likely to engage in front running at the expense of the buy side (e.g. institutional and retail traders). In turn, buy-side traders (e.g. institutional traders, in particular) are likely to defend themselves from front runners by using floor brokers to hide their orders, breaking up their orders, and switching from limit order strategies to market order strategies (Harris, 1999). [3] In addition, because smaller tick increments imply a smaller barrier to competition for buy-side traders, they are likely to compete more actively with price while offering a smaller quantity at a given price. Based on these considerations, we expect decimal pricing to reduce displayed depths. [4]

The effect of the reduced cost of front running on spreads is less obvious. The reduced cost of front running may result in wider spreads because of an increase in the adverse selection risk faced by buy-side traders. If limit orders are disadvantaged frequently enough, buy-side traders may alter order submission strategies and reduce their use of limit orders, resulting in wider spreads. Conversely, the smaller tick size may narrow spreads because both buy-side traders and specialists are more likely to improve existing quotes. Both the buy- and sell-sides are more able and willing to

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[2] On the NYSE, Rule 2072 requires that the time priority rule be strictly enforced for the first public bid (or offer) at a given price. The NYSE enforces price priority and uses a combination of order size and order placement time to determine priority for limit orders that are tied on price. Price and time priority rules are not enforced, however, across the markets that trade NYSE-listed stocks. For example, limit orders left with Boston, Pacific, or Cincinnati Exchanges do not have time priority over limit orders left with the NYSE. In the present study, we exclude off-NYSE quotes and trades from the study sample.

[3] As some of the recent NYSE scandals have highlighted, front running oftentimes involves floor brokers as well.

[4] We recognize that this line of arguments may not hold on NASDAQ, considering the ongoing growth of Electronic Communications Network (ECN) and the failure of Supermontage.

improve the quote when it costs only one penny instead of 6.25 cents to do so. Hence, the net effect of the reduced tick size is likely to be determined by the relative strengths of these forces.

Bacidore et al. (2001) find a significant decrease in the distance between limit order prices and the contemporaneous spread midpoint after decimalization and conclude that limit order traders are more aggressive under penny pricing. In a similar vein, Jennings (2001) finds that the proportion of one-tick quote updates that improved both sides of the National Best Bid or Offer increased from 1% of the quote updates before decimalization to 5% after decimalization, indicating the increased competitiveness of the quoting environment. [5] Hence, it appears that traders use the increased flexibility of decimals to compete more intensely on price. These considerations suggest that decimal pricing is likely to reduce spreads even when the pre-decimalization tick size was not a binding constraint on spread widths (i.e. spreads were larger than $1/16).

Sell-side intermediaries (specialists, in particular) are more likely to engage in front running when there is less uncertainty about asset value because the profitability of front running depends on the accuracy of their prediction of future price movements. Similarly, buy-side traders are more likely to improve existing quotes when asset value uncertainty is lower. Harris (1991) and Grossman et al. (1997) show that coarser price grids are used more frequently when underlying asset values are uncertain. As a result, the extent of front running and price competition under decimal pricing is likely to be higher (lower) for stocks that exhibited finer (coarser) price grids before decimalization. Hence, finer price grids that resulted from decimal pricing are likely to have greater front-running and price competition effects on stocks that exhibited lower quote clustering around even-sixteenths before decimalization. These considerations lead to our next hypothesis:

Hypothesis 2. Decimal pricing leads to larger declines in spreads and depths for stocks with higher proportions of odd-sixteenth quotes before decimal pricing.

2.3. *Quote rounding*

Bid–ask spreads in markets with small tick sizes would be narrower than those in markets with large tick sizes (even when the equilibrium spread is greater than the minimum price variation) if market makers tend to round up their quoted spreads. For example, suppose that the equilibrium spread is 10 cents. If the tick size were $1/16 and the spread were rounded up to the next available level, the observed spread would be $2/16 (12.5 cents). However, the observed spread would be 10 cents if the tick size were only one penny. Hence, we expect bid–ask spreads to decline after decimal pricing even when the tick size was not a binding constraint on spread widths

[5] Consistent with Harris' (1997, 1999) conjecture, Jennings (2001) also finds that the primary source of one-tick quote improvements changed from agency orders to principal orders in the months following decimal pricing, indicating that the smaller tick size plays into the hands of professional traders.

before decimalization. Because quote rounding is equally likely to occur across stocks with different attributes, we expect to observe a decline in the spread that is independent of stock attributes (such as the proportion of spread quotes that are equal to $1/16 and the proportion of odd-sixteenth quotes).

2.4. Changes in stock attributes and their impact on the spread and depth

To the extent that decimal pricing accompanied changes in stock attributes which have an effect on the spread and depth, the observed changes in the spread and depth may be attributed, at least in part, to the changes in stock attributes. Prior studies suggest that a decrease in tick size generally results in a greater number of trades, smaller trade sizes, and lower return volatility. For example, NYSE (2001b) reports a significant increase in the number of trades and a decrease in trade size after decimalization. The study also finds that the degree of price change associated with executing a given number of shares is considerably lower after decimalization. Bessembinder (2003b) shows that intraday return volatility declined after decimalization. He finds that the median return volatility declined from 2.04% in the pre-decimalization sample to 1.56% in the post-decimalization sample using a sample of NYSE stocks.

Our study design involves a "before and after" comparison and uses data during two time periods: 30 trading days immediately before and after the implementation of decimal pricing. To the extent that there are any changes in stock attributes between these two time periods, they are likely to have an effect on the spread and depth. For example, the spread as a percentage of share price will be affected by changes in share price as well as changes in the dollar spread. In addition, there may be some exogenously determined shifts in market volatility between the two periods.

In our study, we include the changes in five stock attributes (i.e. share price, number of trades, trade size, return volatility, and market capitalization) in the regression model to determine how much of the observed changes in the spread and depth can be attributed to changes in these stock attributes.

3. Data source, variable measurement, and descriptive statistics

We obtain data used in this study from the NYSE's Trade and Quote (TAQ) database. Our initial sample consists of 2,629 NYSE-traded common stocks available in the TAQ database. From the initial sample, we omit 19 stocks that have a minimum price variation smaller than $1/16 before decimalization. In addition, we drop seven stocks that do not have sufficient data during either the pre- or post-decimalization period. This leaves us with the final study sample of 2,603 stocks – seven stocks from the first pilot (August 28, 2000), 49 stocks from the second pilot (September 25, 2000), 81 stocks from the third pilot (December 4, 2000), and 2,466 stocks from the full implementation (January 29, 2001) of decimal pricing.

To examine the effects of decimalization on the spread and depth, we use trade and quote data during 30 trading days immediately before and after the date on which each implementation group was subject to decimal pricing. We omit the following to minimize data errors: (1) quotes if either the ask price or the bid price 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 price is greater than or equal to the ask price; (3) quotes if the bid–ask spread is greater than $5; (4) before-the-open and after-the-close trades and quotes; (5) trades if the price or volume is less than or equal to zero; and (6) out-of-sequence trades and quotes.

Table 1 shows select attributes of our study sample of 2,603 stocks during the pre- and post-decimalization study periods for each pilot as well as the full implementation. We measure share price by the average daily closing quote midpoint and return volatility by the standard deviation of daily returns calculated from the daily closing quote midpoints. The table also reports the results of paired comparison *t*-tests on the mean absolute and mean relative differences in stock attributes between the pre- and post-decimalization study periods. The mean absolute difference is the mean difference in the stock attribute between the pre- and post-decimalization study periods. The mean relative difference is the cross-sectional mean of the ratio of the absolute difference to the pre-decimalization value of the stock attribute.

Consistent with the results reported in prior studies (e.g. NYSE, 2001b; Bessembinder, 2003b), we find that decimal pricing led to an increase in the number of trades for all three pilots and the full implementation group. We find mixed results, however, for other stock attributes. Decimal pricing led to a significant decrease in return volatility for the full implementation group. In contrast, return volatility is higher after decimalization for the second and third pilots and remains the same for the first pilot. Similarly, trade size is smaller after decimal pricing for the full implementation group but larger for the first pilot. We observe significant increases in both share price and market capitalization after decimalization for the full implementation group. On the whole, these results indicate that at least some part of the observed changes in the spread and depth after decimal pricing may be due to concurrent changes in stock attributes.

3.1. Execution costs

We employ four measures of execution cost in this study: the quoted spread in dollars $[(A_{i,t} - B_{i,t})]$, the quoted spread as a proportion of share price $[(A_{i,t} - B_{i,t})/M_{i,t}]$, the effective spread in dollars $[2 \cdot D_{i,t} \cdot (P_{i,t} - M_{i,t})]$, and the effective spread as a proportion of share price $[2 \cdot D_{i,t} \cdot (P_{i,t} - M_{i,t})/M_{i,t}]$, where $A_{i,t}$ is the quoted ask price for stock i at time t, $B_{i,t}$ is the quoted bid price for stock i at time t, $M_{i,t}$ is the midpoint of $A_{i,t}$ and $B_{i,t}$, $P_{i,t}$ is the transaction price for stock i at time t, and $D_{i,t}$ is a binary variable which equals +1 for buyer-initiated trades and −1 for seller-initiated trades. Bessembinder (2003a) suggests that making no allowance for trade reporting lags is optimal when assessing whether trades are buyer or seller initiated, but comparing trade prices with earlier quotations is optimal when assessing trade execution costs. In this study, we estimate $D_{i,t}$ using the algorithm suggested

Table 1
Descriptive statistics before and after decimalization

	Before decimalization			After decimalization			Mean difference			
	Mean	Median	SD	Mean	Median	SD	Absolute	t-Statistic	Relative	t-Statistic
Panel A: August 28, 2000 Pilot (N = 7)										
Number of trades	229	39	270	274	42	319	45	2.32	0.3538	2.93*
Trade size ($1000)	53.63	14.93	60.30	62.43	18.90	68.58	8.80	2.73*	0.2129	3.29*
Share price	36.50	37.32	17.56	38.19	37.11	19.35	1.69	0.92	0.0389	1.15
Return volatility	0.0193	0.0184	0.0058	0.0240	0.0218	0.0163	0.0047	1.02	0.1592	0.77
Market value of equity ($ million)	6,056	689	7,664	6,954	705	8,339	898	0.90	0.1112	1.06
Panel B: September 25, 2000 Pilot (N = 49)										
Number of trades	245	69	439	302	99	511	58	3.30**	0.3104	5.74**
Trade size ($1000)	52.48	35.73	46.77	50.94	32.85	52.44	−1.536	−0.53	−0.0430	−1.11
Share price	48.51	28.86	72.35	39.76	29.13	36.85	−8.75	−1.39	−0.0660	−3.35**
Return volatility	0.0212	0.0184	0.0141	0.0328	0.0278	0.0277	0.0116	2.88**	0.7261	3.34**
Market value of equity ($ million)	9,318	1,020	24,442	8,902	901	22,899	−415	−1.47	−0.0479	−3.30**
Panel C: December 4, 2000 Pilot (N = 81)										
Number of trades	161	35	312	198	53	337	37	5.96**	0.4587	10.35**
Trade size ($1000)	30.42	17.64	33.03	30.16	16.72	35.68	−0.263	−0.16	0.0154	0.42
Share price	18.49	13.48	14.15	18.94	14.07	14.69	0.45	1.84	0.0070	0.49
Return volatility	0.0267	0.0231	0.0165	0.0292	0.0268	0.0169	0.0025	1.95	0.2341	4.24**
Market value of equity ($ million)	3,529	368	11,042	3,483	396	10,703	−46	−0.58	−0.0040	−0.25
Panel D: January 29, 2001 Full (N = 2466)										
Number of trades	195	59	360	210	61	369	15	11.34**	0.0664	8.71**
Trade size ($1000)	35.18	22.24	37.06	30.87	19.27	35.09	−4.310	−10.61**	−0.0530	−3.03**
Share price	23.99	17.87	23.35	24.55	19.02	23.14	0.56	8.58**	0.0602	13.55**
Return volatility	0.0321	0.0272	0.0249	0.0243	0.0203	0.0350	−0.0078	−10.53**	−0.1912	−13.50**
Market value of equity ($ million)	4,578	518	20,825	4,533	549	20,421	−45	−0.92	0.0650	13.01**

This table shows select attributes of the study sample of stocks during the pre- and post-decimalization study periods for each pilot as well as the full implementation group. We measure share price by the average daily closing quote midpoint and return volatility by the standard deviation of daily returns calculated from the daily closing quote midpoints. The table also reports the results of paired comparison t-tests on the mean absolute and mean relative differences in stock attributes between the pre- and post-decimalization study periods. The mean absolute difference is simply the mean difference in the stock attribute between the pre- and post-decimalization study periods. The mean relative difference is the cross-sectional mean of the ratio of the absolute difference to the pre-decimalization value of the stock attribute. N denotes the sample size.
* and ** statistically significant at the 1% and 5% levels, respectively.

by Lee and Ready (1991) and modified by Bessembinder (2003a). The effective spread measures the actual cost paid by the trader. We measure the quoted depth in both dollars and round lots. [6]

For each stock, we first calculate the time-weighted quoted spread, the trade-weighted effective spread, and the time-weighted quoted depth during the pre- and post-decimalization study periods, respectively. We then calculate the cross-sectional means of these variables during each period. The results (see Table 2) show that decimal pricing led to a significant decrease in both the quoted and effective spreads across all four implementation groups. For example, the quoted dollar spread declined by 3.2–7.1 cents after decimalization across different groups. These are equivalent to a decline of about 24–31% in relative terms. Similarly, the effective dollar spread declined by 2.8–5 cents across different groups, which are equivalent to 29–40% declines in relative terms. The results show that decimal pricing led to 30–36% declines in the quoted depth, except for the first pilot. Overall, these results are qualitatively identical to those reported in Chakravarty et al. (2001a,b), Bacidore et al. (2001), NYSE (2001a,b), NASDAQ (2001b), and Bessembinder (2003b).

3.2. Binding constraint on spread widths

We measure the probability that the minimum price variation is a binding constraint on spread widths by the proportion of quoted spreads that are equal to $1/16 (PQMIN_QS hereafter) before decimalization. To assess the sensitivity of our results to different measurement methods, we also calculate the proportion of trading time during which the quoted spread is equal to $1/16 (PTMIN_QS). In addition, we calculate the proportion of effective spreads that are equal to one tick (PQMIN_ES). Both PQMIN_QS and PTMIN_QS measure the probability that liquidity providers could not have narrowed existing quotes due to the binding constraint.

Panel A of Table 3 shows that the mean (median) values of PQMIN_QS, PTMIN_QS, and PQMIN_ES are 0.31 (0.30), 0.32 (0.31), and 0.44 (0.45), respectively, with standard deviations of 0.20, 0.21, and 0.18. More than 50% of our sample stocks have PQMIN_QS, PTMIN_QS, and PQMIN_ES values that are greater than 30%, indicating that the minimum price variation is a significant binding constraint on liquidity providers' quote decisions for many stocks.

We expect the probability that the minimum price variation is a binding constraint on spread widths to be negatively related to the equilibrium spread – the spread that liquidity providers would have quoted had there been no binding constraint (i.e. when the minimum price variation is infinitesimally small). To the extent that the equilibrium spread is a function of stock attributes, we expect PQMIN_QS, PTMIN_QS, and PQMIN_ES to be related to the stock attributes. In particular, because high-volume, low-risk, or low-price stocks are likely to have smaller equilibrium spreads, we expect PQMIN_QS, PTMIN_QS, and PQMIN_ES to be positively

[6] The share depth is measured by the sum of bid and ask sizes. The dollar depth is the product of the share depth and the quote midpoint.

Table 2
Spreads and depths before and after decimalization

	Before decimalization			After decimalization			Mean difference			
	Mean	Median	SD	Mean	Median	SD	Absolute	t-Statistic	Relative	t-Statistic
Panel A: August 28, 2000 Pilot ($N = 7$)										
Quoted spread ($)	0.2071	0.1646	0.1126	0.1360	0.1215	0.0548	−0.0712	−3.13*	−0.3081	−7.39**
Quoted spread (%)	0.0078	0.0084	0.0059	0.0050	0.0054	0.0038	−0.0028	−3.29*	−0.3320	−7.50**
Effective spread ($)	0.1244	0.0884	0.0811	0.0741	0.0475	0.0460	−0.0503	−3.69*	−0.3998	−15.93**
Effective spread (%)	0.0047	0.0045	0.0039	0.0028	0.0023	0.0025	−0.0019	−3.55*	−0.4191	−15.28**
Quoted depth ($1000)	212	63	241	138	66	132	−74	−1.76	−0.0107	−0.07
Quoted depth (round lots)	49	39	41	33	39	18	−16	−1.63	−0.0309	−0.19
Panel B: September 25, 2000 Pilot ($N = 49$)										
Quoted spread ($)	0.2007	0.1460	0.2789	0.1485	0.1204	0.1205	−0.0522	−2.13*	−0.1968	−7.47**
Quoted spread (%)	0.0068	0.0051	0.0052	0.0059	0.0042	0.0048	−0.0009	−2.96**	−0.1271	−4.59**
Effective spread ($)	0.1163	0.0839	0.1220	0.0808	0.0719	0.0587	−0.0355	−3.30**	−0.2872	−9.65**
Effective spread (%)	0.0044	0.0029	0.0036	0.0035	0.0020	0.0031	−0.0009	−3.81**	−0.2261	−7.22**
Quoted depth ($1000)	376	186	578	186	122	247	−189	−3.53**	−0.3604	−9.74**
Quoted depth (round lots)	138	59	257	61	37	79	−77	−2.94**	−0.3075	−7.73**
Panel C: December 4, 2000 Pilot ($N = 82$)										
Quoted spread ($)	0.1523	0.1321	0.0717	0.1177	0.1028	0.0681	−0.0346	−13.29**	−0.2452	−13.39**
Quoted spread (%)	0.0163	0.0101	0.0199	0.0125	0.0080	0.0139	−0.0038	−4.09**	−0.2385	−11.06**
Effective spread ($)	0.0926	0.0825	0.0355	0.0644	0.0534	0.0425	−0.0283	−15.38**	−0.3440	−15.91**
Effective spread (%)	0.0104	0.0064	0.0130	0.0072	0.0045	0.0083	−0.0033	−4.95**	−0.3380	−14.24**
Quoted depth ($1000)	187	91	234	86	70	73	−100	−4.83**	−0.3174	−8.32**
Quoted depth (round lots)	135	70	243	56	48	37	−79	−3.26**	−0.3141	−8.05**
Panel D: January 29, 2001 Full ($N = 2466$)										
Quoted spread ($)	0.1621	0.1339	0.1445	0.1301	0.1001	0.1480	−0.0320	−26.30**	−0.2412	−62.79**
Quoted spread (%)	0.0132	0.0081	0.0168	0.0097	0.0055	0.0134	−0.0034	−26.25**	−0.2781	−74.46**
Effective spread ($)	0.0979	0.0784	0.0935	0.0688	0.0490	0.0909	−0.0290	−38.10**	−0.3529	−83.94**
Effective spread (%)	0.0084	0.0051	0.0111	0.0054	0.0029	0.0078	−0.0029	−27.72**	−0.3846	−94.97**
Quoted depth ($1000)	223	114	614	104	71	140	−118	−11.79**	−0.3138	−41.35**
Quoted depth (round lots)	140	64	510	55	39	94	−85	−9.83**	−0.3490	−49.78**

For each stock we first calculate the time-weighted quoted spread, the trade-weighted effective spread, and the time-weighted quoted depth during the pre- and post-decimalization study periods, respectively. We calculate both the dollar and proportional quoted and effective spreads and the depth in dollars and in round lots. We then calculate the cross-sectional means of these variables during each period. The table also reports the results of paired t-tests on the equality of the mean between the two periods. N denotes the sample size.

* and ** statistically significant at the 1% and 5% levels, respectively.

Table 3
Determinants of the proportion of one-tick spreads during the pre-decimalization period

	PQMIN_QS	PTMIN_QS	PQMIN_ES
Panel A: Descriptive statistics			
Mean	0.3140	0.3230	0.4416
Standard deviation	0.1959	0.2094	0.1839
Minimum	0.0000	0.0000	0.0000
1st percentile	0.0030	0.0002	0.0243
5th percentile	0.0310	0.0241	0.1142
10th percentile	0.0654	0.0585	0.1852
25th percentile	0.1614	0.1535	0.3178
50th percentile	0.3005	0.3053	0.4523
75th percentile	0.4358	0.4602	0.5619
90th percentile	0.5780	0.6141	0.6630
95th percentile	0.6737	0.7142	0.7398
99th percentile	0.8462	0.8606	0.8779
Maximum	0.9744	0.9729	0.9840
N	2,603	2,603	2,603
Variable			
Panel B: Logit regression results			
Intercept	−5.3575 (−58.24)**	−6.1743 (−49.97)**	−3.5148 (−44.93)**
Pilot 1 dummy	−0.4133 (−1.78)	−0.8210 (−2.63)**	−0.1445 (−0.73)
Pilot 2 dummy	0.1707 (1.92)	0.1495 (1.25)	0.0317 (0.42)
Pilot 3 dummy	−0.1319 (−1.89)	−0.0968 (−1.03)	−0.1233 (−2.08)*
Log(share price)	−1.4580 (−66.53)**	−1.6233 (−55.15)**	−1.0385 (−55.73)**
Log(number of trades)	0.8801 (42.61)**	1.0542 (37.99)**	0.6333 (36.05)**
Log(trade size)	0.2889 (10.50)**	0.2510 (6.79)**	0.1105 (4.72)**
Log(return volatility)	−1.1437 (−47.05)**	−1.3361 (−40.92)**	−0.8752 (−42.33)**
Log(market value of equity)	−0.0392 (−2.27)*	−0.0459 (−1.97)*	0.0018 (0.13)
F-statistic	989.07**	731.66**	712.76**
Adjusted R^2	0.7538	0.6936	0.688

We measure the probability that the minimum price variation is a binding constraint on spread widths by the proportion of quoted spreads that are equal to \$1/16 (PQMIN_QS) during the pre-decimalization study period. To assess the sensitivity of our results to different measurement methods, we also calculate the proportion of trading time during which the quoted spread is equal to \$1/16 (PTMIN_QS). In addition, we calculate the proportion of effective spreads that are equal to one tick (PQMIN_ES). Panel A reports the descriptive statistics of the three measures of the binding constraints. Panel B presents the Logit regression results showing how these variables are related to stock attributes (share price, number of trades, trade size, return volatility, and market value of equity). To determine whether the relation between the logits and stock attributes differs across decimalization implementation groups, we include three pilot dummy variables in the regressions. Numbers in parenthesis are t-statistics. N denotes the sample size.
* and ** statistically significant at the 1% and 5% levels, respectively.

related to the number of trades and trade size, and negatively to share price and return volatility.

Indeed, when we regress PQMIN_QS, PTMIN_QS, and PQMIN_ES against a common set of explanatory variables (i.e. log of share price, number of trades, trade size, return volatility, market capitalization, and three dummy variables for the decimal pricing pilots), we find that the results are consistent with our expectation (see Table 3). [7] We also find that these explanatory variables account for about 70% of the cross-sectional variation in PQMIN_QS, PTMIN_QS, and PQMIN_ES.

4. Empirical findings

In the previous section, we show that decimal pricing led to significant reductions in the spread and depth. We also find evidence that the minimum price variation was a binding constraint on spreads before decimal pricing. In addition, we find significant differences in stock attributes between the pre- and post-decimalization study periods. In this section, we examine how the observed changes in the spread and depth are related to the proportion of one-tick spreads, the proportion of odd-sixteenth quotes, and the changes in stock attributes.

4.1. Spread and depth changes as a function of the binding probability and quote clustering

To assess how the relaxation of the binding constraint affected the spread and depth, we first cluster our study sample of 2603 stocks into 10 portfolios (each with an approximately equal number of stocks) according to the proportion of one-tick quoted spreads before decimalization (PQMIN_QS). [8] We then calculate the percentage changes in the quoted spread and depth within each portfolio. Similarly, we cluster our sample into 10 portfolios according to the proportion of one-tick effective spreads (PQMIN_ES) and calculate the percentage changes in the effective spread within each portfolio.

We show the results in Panel A of Table 4. Notice that there is a strong positive correlation between the observed reduction in the spread and depth and PQMIN_QS. For example, stocks that belong to decile 1 experienced on average a 7.78% (11.66%) decline in the quoted dollar (proportional) spread whereas the corresponding figure for stocks that belong to decile 10 is 40.68% (44.45%). Similarly, stocks that belong to decile 1 experienced a 12.93% (16.19%) decline in the effective dollar (proportional) spread whereas the corresponding figure for stocks that belong to decile 10 is 50.65% (54.22%). For the quoted depth in dollars (round lots), we find a 3.65% (0.71%) increase (decline) for decile 1 and a 68.10% (70.20%) decline for decile 10. The magnitudes of spread and depth reductions increase almost linearly across portfolios. Overall, these results are consistent with Hypothesis 1.

Earlier we showed (see Section 3.2) that both PQMIN_QS and PQMIN_ES are positively related to the number of trades and trade size, and negatively to share

[7] Because the dependent variables are bound to lie between zero and one, we estimate the model using Logit regressions. We obtain qualitatively similar results from Probit regressions.

[8] We obtain qualitatively identical results when portfolios are formed based on PTMIN_QS. Hence we report only the results from the PQMIN_QS-based portfolios for brevity.

Table 4

Changes in the spread and depth and the proportions of one-tick spreads and odd-sixteenth quotes

Deciles	1 (smallest)	2	3	4	5	6	7	8	9	10 (largest)
Panel A: Deciles are based on the proportion of one-tick spreads (PQMIN_QS or PQMIN_ES)										
ΔQuoted spread ($)	−0.0778	−0.1601	−0.1828	−0.2215	−0.2238	−0.2613	−0.2709	−0.2863	−0.3149	−0.4068
	(−5.10)**	(−14.08)**	(−15.66)**	(−23.94)**	(−27.10)**	(−30.98)**	(−30.79)**	(−31.66)**	(−28.94)**	(−39.95)**
ΔQuoted spread (%)	−0.1166	−0.1786	−0.2183	−0.2401	−0.2531	−0.2900	−0.3108	−0.3234	−0.3659	−0.4445
	(−8.66)**	(−14.97)**	(−20.09)**	(−24.72)**	(−29.69)**	(−32.78)**	(−33.76)**	(−34.63)**	(−42.02)**	(−43.67)**
ΔEffective spread ($)	−0.1293	−0.2366	−0.2753	−0.3320	−0.3468	−0.4079	−0.4210	−0.4251	−0.4350	−0.5065
	(−8.02)**	(−17.60)**	(−23.40)**	(−32.04)**	(−32.64)**	(−43.99)**	(−48.66)**	(−47.89)**	(−41.70)**	(−53.75)**
ΔEffective spread (%)	−0.1619	−0.2651	−0.3004	−0.3513	−0.3712	−0.4302	−0.4547	−0.4520	−0.4736	−0.5422
	(−10.83)**	(−20.91)**	(−26.13)**	(−33.36)**	(−37.22)**	(−47.44)**	(−52.14)**	(−49.07)**	(−54.12)**	(−56.94)**
ΔQuoted depth ($)	0.0365	−0.0934	−0.1639	−0.2536	−0.2888	−0.3486	−0.3974	−0.4379	−0.5113	−0.6810
	(1.45)	(−3.72)**	(−4.54)**	(−16.52)**	(−19.75)**	(−22.99)**	(−31.68)**	(−30.44)**	(−38.72)**	(−72.08)**
ΔQuoted depth (#)	−0.0071	−0.1171	−0.2035	−0.2763	−0.3200	−0.3806	−0.4378	−0.4721	−0.5465	−0.7020
	(−0.30)	(−5.00)**	(−6.49)**	(−20.01)**	(−23.39)**	(−27.57)**	(−42.01)**	(−35.60)**	(−44.83)**	(−78.72)**
Panel B: Deciles are based on the proportion of odd-sixteenth quotes (PODD)										
ΔQuoted spread ($)	−0.0859	−0.1375	−0.1810	−0.2273	−0.2175	−0.2717	−0.2855	−0.3113	−0.3419	−0.3465
	(−5.64)**	(−12.25)**	(−16.50)**	(−22.81)**	(−19.20)**	(−30.90)**	(−34.93)**	(−36.48)**	(−39.75)**	(−30.58)**
ΔQuoted spread (%)	−0.1315	−0.1741	−0.2072	−0.2628	−0.2579	−0.3004	−0.3144	−0.3405	−0.3764	−0.3762
	(−10.00)**	(−14.62)**	(−18.36)**	(−25.11)**	(−26.01)**	(−32.76)**	(−34.63)**	(−40.12)**	(−40.57)**	(−32.88)**
ΔEffective spread ($)	−0.1329	−0.2297	−0.2819	−0.3411	−0.3504	−0.3939	−0.4217	−0.4438	−0.4777	−0.4423
	(−8.37)**	(−19.38)**	(−23.18)**	(−32.22)**	(−29.43)**	(−44.61)**	(−41.38)**	(−50.44)**	(−57.43)**	(−37.75)**
ΔEffective spread (%)	−0.1754	−0.2638	−0.3067	−0.3724	−0.3840	−0.4165	−0.4453	−0.4672	−0.5046	−0.4668
	(−11.93)**	(−22.23)**	(−25.83)**	(−34.98)**	(−35.28)**	(−44.42)**	(−43.22)**	(−53.46)**	(−58.21)**	(−39.96)**
ΔQuoted depth ($)	−0.0278	−0.1563	−0.2010	−0.2183	−0.3145	−0.3663	−0.3977	−0.4732	−0.4864	−0.4976
	(−1.21)	(−8.20)**	(−11.47)**	(−5.53)**	(−20.05)**	(−18.63)**	(−25.92)**	(−41.31)**	(−25.34)**	(−24.69)**
ΔQuoted depth (#)	−0.0727	−0.1907	−0.2298	−0.2631	−0.3492	−0.3982	−0.4269	−0.4948	−0.5159	−0.5214
	(−3.25)**	(−10.20)**	(−13.68)**	(−7.68)**	(−23.42)**	(−23.54)**	(−29.70)**	(−43.75)**	(−28.37)**	(−27.06)**

To assess how the relaxation of the binding constraint affected spreads and depth, we first cluster our study sample of 2603 stocks into 10 portfolios according to PQMIN (PQMIN_QS for the quoted spread and depth and PQMIN_ES for the effective spread). We then calculate the mean percentage changes in the quoted spread, effective spread, and depth within each portfolio. To assess how the pre-decimalization quote coarseness affected spread and depth changes, we also cluster our study sample into 10 portfolios according to the proportion of odd-sixteenth quotes (PODD) and calculate mean percentage spread and depth changes within each portfolio. In each cell, we report the mean percentage change in the variable (Δvariable) and the corresponding *t*-statistic. Each portfolio contains 260 or 261 stocks.

* and ** statistically significant at the 1% and 5% levels, respectively.

price and return volatility. Hence, the above results suggest that high-volume, low-risk, or low-price stocks benefited most from decimal pricing.

To assess how the pre-decimalization quote coarseness affected spread and depth changes, we cluster our study sample into 10 portfolios according to the proportion of odd-sixteenth quotes (PODD). We then calculate the percentage changes in the spread and depth within each portfolio. We show the results in Panel B of Table 4. As in Panel A, we find a strong positive correlation between the observed reduction in the spread and depth and PODD. For example, stocks that belong to decile 1 experienced on average an 8.59% (13.15%) decline in the quoted dollar (proportional) spread whereas the corresponding figure for stocks that belong to decile 10 is 34.65% (37.62%). For the quoted depth in dollars (round lots), we find a 2.78% (7.27%) decline for decile 1 and a 49.76% (52.14%) decline for decile 10. These results indicate that stocks with coarser price grids before decimalization experienced smaller declines in the spread and depth after decimal pricing, supporting Hypothesis 2.

4.2. Regression result

Although the previous section shows that the proportions of one-tick spreads and odd-sixteenth quotes are highly correlated with spread and depth changes, there are other factors that are likely to have an impact on the spread and depth. It is also possible that the observed correlations in Table 4 may be spurious. For example, if stocks with higher quote clustering have wider spreads, the observed correlation between spread changes and PODD may simply reflect the fact that stocks with larger spreads before decimal pricing experienced greater reductions in spreads after decimalization.

To examine how the observed changes in the spread and depth can be explained by the binding constraint and quote clustering after controlling for the effects of other factors, we estimate the following regression models:

$$\Delta\mathrm{SPREAD}_i = \alpha_0 + \sum_{k=1}^{3}\alpha_k D_k + \sum_{k=4}^{8}\alpha_k\left\{\mathrm{Log}\left(A_{k,i}^{\mathrm{Post}}\right) - \mathrm{Log}\left(A_{k,i}^{\mathrm{Pre}}\right)\right\} + \alpha_9\mathrm{PQMIN}_i + \alpha_{10}\mathrm{SPREAD}_i + \alpha_{11}\mathrm{PODD}_i + \varepsilon_{1i}, \tag{1}$$

$$\Delta\mathrm{DEPTH}_i = \beta_0 + \sum_{k=1}^{3}\beta_k D_k + \sum_{k=4}^{8}\beta_k\left\{\mathrm{Log}\left(A_{k,i}^{\mathrm{Post}}\right) - \mathrm{Log}\left(A_{k,i}^{\mathrm{Pre}}\right)\right\} + \beta_9\mathrm{PQMIN}_i + \beta_{10}\mathrm{DEPTH}_i + \beta_{11}\mathrm{PODD}_i + \varepsilon_{2i}, \tag{2}$$

where $\Delta\mathrm{SPREAD}_i$ and $\Delta\mathrm{DEPTH}_i$ denote the percentage changes in the spread and depth, respectively, between the pre- and post-decimalization periods, (post-value − pre-value)/pre-value; D_k $(k = 1,\ldots,3)$ is the dummy variable for each decimalization pilot; $A_{k,i}$ $(k = 4,\ldots,8)$ represents one of the five stock attributes – share price, the number of trades, trade size, the standard deviation of daily stock returns, and the market value of equity; PQMIN_i, SPREAD_i, DEPTH_i, and PODD_i are the pre-decimalization values of the proportion of spreads that are equal to the minimum price variation, the spread, the depth, and the proportion of odd-sixteenth quotes, respectively; αs and βs are the regression coefficients; and ε_{1i} and ε_{2i} are the error terms. We calculate ΔSPREAD_i and ΔDEPTH_i using the proportional spread and dollar depth. Likewise, SPREAD_i and DEPTH_i are the pre-decimal proportional spread and dollar depth, respectively. [9]

We include SPREAD_i and DEPTH_i in the model to determine whether stocks with larger spreads or depths before decimalization experienced greater reductions in these variables. We include the dummy variables D_k ($k = 1, \ldots, 3$) in the model to determine whether decimal pricing exerted different impacts between the first three pilots and the full implementation group. According to Hypothesis 1, we expect α_9 and β_9 to be significantly negative. Similarly, we expect α_{11} and β_{11} to be negative according to Hypothesis 2.

We show the regression results in Table 5. The first three columns show the results when the dependent variable is the change in the quoted spread, the next three columns show the results when the dependent variable is the change in the effective spread, and the last three columns show the results when the dependent variable is the change in the quoted depth. For each dependent variable, we report the results of the three regression models.

The first model uses only the changes in the five stock attributes and three dummy variables for pilots as the explanatory variables. In this case, the estimates of α_0 measure the changes in the spread and depth that cannot be explained by concurrent changes in the five stock attributes for the full implementation group of 2466 stocks. Similarly, $\alpha_0 + \alpha_1$, $\alpha_0 + \alpha_2$, and $\alpha_0 + \alpha_3$ measure the changes in the spread and depth that cannot be explained by the changes in the stock attributes for decimal pilots 1, 2, and 3, respectively. Because the majority (94.7%) of our sample stocks belong to the full implementation group and also because the majority of α_1, α_2, and α_3 estimates are not significantly different from zero (see below), we focus our discussion on the results of the full implementation group. [10] In the second model, we add the proportion of spreads that are equal to the minimum price variation in the regression. The third regression model incorporates two additional variables: the pre-decimal spread (or depth) and the proportion of odd-sixteenth quotes.

The regression results show that a majority of the estimated coefficients for the pilot dummy variables are not significant, suggesting that decimal pricing has similar effects on the spread and depth between the pilots and the full implementation group. The results of regression model (1) indicate that a significant portion of the cross-sectional variation in spread and depth changes can be explained by the cross-sectional differences in the changes in stock attributes. For example, these stock attributes (together with pilot dummies) explain about 26% and 22% of the cross-sectional variation in the quoted and effective spread changes, respectively.

The results of regression model (2) show that the estimated coefficients for PQMIN are significant and negative in all three regressions, indicating that stocks

[9] The results using the dollar spread and share depth are qualitatively identical to those presented here.

[10] The signs and significance of the α_1, α_2, and α_3 estimates tell us whether the effects of decimal pricing on spreads and depths differ between the full implementation and respective pilot samples.

Table 5
Determinants of the changes in the spread and depth

Independent variable	Change in quoted spread			Change in effective spread			Change in depth		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	−0.2080	−0.0914	−0.0224	−0.3137	−0.0979	−0.0262	−0.2616	−0.0067	0.0406
	(−47.29)**	(−16.72)**	(−1.42)	(−63.96)**	(−12.33)**	(−1.57)	(−27.88)**	(−0.58)	(1.28)
Pilot 1 dummy	−0.0635	−0.0918	−0.0858	−0.0450	−0.0832	−0.0707	0.1693	0.1073	0.1147
	(−1.04)	(−1.74)	(−1.64)	(−0.66)	(−1.44)	(−1.24)	(1.30)	(0.96)	(1.03)
Pilot 2 dummy	0.0477	0.0670	0.0630	0.0698	0.0797	0.0770	−0.0558	−0.0137	−0.0123
	(2.00)*	(3.25)**	(3.07)**	(2.63)**	(3.54)**	(3.45)**	(−1.10)	(−0.31)	(−0.28)
Pilot 3 dummy	0.0165	0.0325	0.0272	0.0320	0.0460	0.0341	−0.0454	−0.0105	−0.0139
	(0.89)	(2.02)	(1.69)	(1.54)	(2.61)**	(1.95)	(−1.14)	(−0.31)	(−0.41)
ΔLog(share price)	−0.3737	−0.2980	−0.3049	−0.2725	−0.1816	−0.2120	0.1202	0.2855	0.2722
	(−13.64)**	(−12.51)**	(−12.57)**	(−8.92)**	(−6.97)**	(−8.04)**	(2.06)*	(5.67)**	(5.37)**
ΔLog(number of trades)	−0.1939	−0.1740	−0.1680	−0.2188	−0.1837	−0.1679	0.0056	0.0492	0.0538
	(−17.77)**	(−18.40)**	(−17.12)**	(−17.98)**	(−17.71)**	(−15.71)**	(0.24)	(2.46)*	(2.67)**
ΔLog(trade size)	0.0227	−0.0368	−0.0398	0.0575	−0.0151	−0.0183	0.4476	0.3176	0.3158
	(2.26)*	(−4.14)**	(−4.49)**	(5.15)**	(−1.55)	(−1.90)	(20.95)**	(16.90)**	(16.78)**
ΔLog(return volatility)	0.1391	0.1207	0.1183	0.1379	0.1142	0.1089	−0.0038	−0.0440	−0.0497
	(19.08)**	(19.07)**	(18.61)**	(16.97)**	(16.49)**	(15.76)**	(−0.25)	(−3.29)**	(−3.65)**
ΔLog(market value of equity)	−0.0419	−0.0310	−0.0313	−0.0758	−0.0644	−0.0650	−0.0763	−0.0525	−0.0527
	(−3.38)**	(−2.89)**	(−2.94)**	(−5.49)**	(−5.50)**	(−5.61)**	(−2.89)**	(−2.32)*	(−2.33)*
Proportion of one-tick spreads (PQMIN)	–	−0.4277	−0.3690	–	−0.5379	−0.4329	–	−0.9351	−0.8736
		(−29.67)**	(−19.91)**		(−31.90)**	(−17.85)**		(−30.67)**	(−21.08)**
SPREAD or DEPTH	–	–	0.0278	–	–	1.0104	–	–	-1.87×10^{-5}
			(0.16)			(3.52)**			(−1.80)
Proportion of odd sixteenths (PODD)	–	–	−0.2120	–	–	−0.3045	–	–	−0.1529
			(−4.93)**			(−5.80)**			(−1.69)

Table 5 (*continued*)

Independent variable	Change in quoted spread			Change in effective spread			Change in depth		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
F-statistic	116.03**	235.89**	193.69**	92.78**	227.87**	195.26**	63.77**	181.72**	149.39**
Adjusted R^2	0.2613	0.4483	0.4489	0.2201	0.4397	0.4509	0.1618	0.3846	0.3855

To examine how the observed changes in spreads and depths can be explained by the binding constraint together with these other factors, we estimate the following regression models:

$$\Delta\text{SPREAD}_i = \alpha_0 + \sum_{k=1}^{3}\alpha_k D_k + \sum_{k=4}^{8}\alpha_k\left\{\text{Log}\left(A_{k,i}^{\text{Post}}\right) - \text{Log}\left(A_{k,i}^{\text{Pre}}\right)\right\} + \alpha_9\text{PQMIN}_i + \alpha_{10}\text{SPREAD}_i + \alpha_{11}\text{PODD}_i + \varepsilon_{1i},$$

$$\Delta\text{DEPTH}_i = \beta_0 + \sum_{k=1}^{3}\beta_k D_k + \sum_{k=4}^{8}\beta_k\left\{\text{Log}\left(A_{k,i}^{\text{Post}}\right) - \text{Log}\left(A_{k,i}^{\text{Pre}}\right)\right\} + \beta_9\text{PQMIN}_i + \beta_{10}\text{DEPTH}_i + \beta_{11}\text{PODD}_i + \varepsilon_{2i},$$

where ΔSPREAD_i and ΔDEPTH_i denote the percentage change in the spread and depth, respectively, between the pre- and post-decimalization periods, (post-value − pre-value)/pre-value; D_k ($k = 1, \ldots, 3$) is the dummy variable for each decimalization pilot; $A_{k,i}$ ($k = 4, \ldots, 8$) represents one of the five stock attributes – share price, the number of trades, trade size, the standard deviation of daily stock returns, and the market value of equity; PQMIN_i, SPREAD_i, DEPTH_i, and PODD_i are the pre-decimalization values of the proportion of spreads that are equal to the minimum price variation, the spread, the depth, and the proportion of odd sixteenth quotes, respectively; αs and βs are the regression coefficients; and ε_{1i} and ε_{2i} are the error terms. We calculate ΔSPREAD_i and ΔDEPTH_i using the proportional spread and dollar depth. Likewise, SPREAD_i and DEPTH_i are the pre-decimal proportional spread and dollar depth, respectively. We include SPREAD_i and DEPTH_i in the model to determine whether stocks with larger spreads or depths before decimalization experienced greater reduction in these variables. We include the dummy variables D_k ($k = 1, \ldots, 3$) in the model to determine whether decimal pricing exerted different impacts between the first three pilots and the full implementation group. Numbers in parenthesis are t-statistics.
* and ** statistically significant at the 1% and 5% levels, respectively.

with higher proportions of one-tick spreads experienced larger reductions in the quoted and effective spreads as well as in the quoted depth. These results are consistent with our Hypothesis 1. The inclusion of PQMIN alone increased the adjusted R^2 value by 18.70%, 21.96%, and 22.28%, respectively, in each of the three regression models, reflecting the importance of the binding constraint as a possible source of larger (smaller) spreads and depths before (after) decimal pricing.

The estimated coefficients for the proportion of odd-sixteenth quotes are significant and negative in the quoted and effective spread models, respectively, indicating that stocks with higher proportions of odd-sixteenth quotes experienced larger reductions in the quoted and effective spreads. [11] The result is in line with Hypothesis 2 and supports the notion that finer price grids, which became available as a result of decimal pricing, may have a greater front-running effect on stocks whose liquidity providers (e.g. specialists) did not avoid odd-sixteenth quotes before decimal pricing. [12] The estimated coefficient for the proportion of odd-sixteenth quotes is negative but not significant in the depth model. Hence, although decimal pricing led to greater reductions in quote depths for stocks that are likely to have a greater front-running effect, the results are not as strong as we anticipated. [13]

The estimated coefficient for SPREAD in the quoted spread model and the estimated coefficient for DEPTH in the quoted depth model are not statistically significant, indicating that stocks with larger quoted spreads and depths before decimal pricing do not exhibit greater reduction in quoted spreads and depths after decimal pricing. We find however that the estimated coefficient for SPREAD in the effective spread model is positive and statistically significant, indicating that stocks with larger effective spreads before decimal pricing experienced smaller reductions in effective spreads after decimal pricing.

4.3. Sensitivity analysis: Alternative measures of front running and price competition

Although our empirical proxy (PODD) for front running and price competition has an expected effect on both quoted and effective spreads, PODD is likely to be an imperfect proxy for the extent of front running and price competition. To assess

[11] Because we include the pre-decimalization spread in the regression models, the proportion of odd-sixteenths is not likely to serve as a proxy for the pre-decimalization spread.

[12] This result differs from the finding of Bessembinder (2000) for NASDAQ stocks that a smaller tick size led to the largest spread reductions for stocks whose market makers avoided odd-eighth quotes.

[13] We acknowledge that there are other possible explanations for the reduced depth, e.g. the interaction of penny pricing and the treatment of limit orders on the NYSE wherein the crowd can participate with a limit order after the first trade against that limit order. With the $1/8 tick, participation was important because prices moved relatively slowly. Although limit orders had limited protection depending upon the dynamics of the crowd, there was at least some protection afforded by the large tick size. With penny pricing we have seen price changes of well over 100 per minute for actively traded stocks. So the lower displayed depths result in part to this interaction, as well as to the natural result that follows from the shape of the supply/demand curves. Thus, with much smaller tick sizes, we can move closer to the intersection of the supply and demand curves where, by the shape of the curves, smaller quantities are offered/demanded. We thank the referee for pointing out this point.

the sensitivity of our results to different empirical proxies, we employ alternative measures of front running and price competition. Harris and Panchapagesan (1999) and Ronen and Weaver (2001) suggest that active stocks and higher-price stocks are expected to experience larger decreases in spreads following the tick size reduction, especially if the level of price competition among traders is inversely related to the tick size. To test this conjecture with our data, we replicate Table 5 with the pre-decimal share price (PRICE) and number of trades (NT) in the regression models and show the results in Table 6. In regression model (1), we employ PRICE as our empirical proxy for front running and price competition. Regression model (2) employs PRICE and NT, while regression model (3) employs all three variables (PRICE, NT, and PODD) as empirical proxies for front running and price competition.

Table 6 shows that changes in quoted spreads are negatively related to PRICE, NT, and PODD, although the coefficient for PRICE becomes insignificant when the other two variables are also included in the regression. Hence, stocks with higher activity and/or coarser price grids before decimal pricing experienced larger reductions in quoted spreads after decimalization. These results are in line with the idea that decimal pricing exerted a greater impact on price competition and front running for stocks with more active trading and coarser price grids before decimalization. Similarly, we find that changes in effective spreads are negatively and significantly related to PRICE, NT, and PODD. Finally, the results show that decimal pricing led to larger reductions in quoted depths for more active stocks. Overall, these results support the view that the effect of the tick size reduction on front running and price competition is greater for stocks where the competition between specialists and limit order traders is more intense.

4.4. Intraday variation in spread and depth reductions

In so far as the proportion of one-tick spreads varies across different times of the day, the spread and depth changes that resulted from decimal pricing are also likely to vary over time. Thus we anticipate larger reductions in the spread and depth when the proportion of one-tick spreads was higher before decimal pricing. We partition each trading day into thirteen 30 minute intervals and calculate the proportion of one-tick spreads for each stock based on both the quoted and effective spreads during each time interval. Similarly, we calculate percentage changes in the spread and depth during each interval. We then compute the mean values of these variables across stocks during each 30 minute interval.

Our results show that proportions of one-tick quoted and effective spreads are smallest during the first 30 minutes and then increase steadily throughout the trading day. [14] Similarly, we find that percentage declines in the spread and depth are smallest during the first interval, increase steadily until midday, and then level off

[14] For space consideration, we do not report these results here. The detailed results are available from the authors upon request.

Table 6
Regression results with alternative measures of front running and price competition

Independent variable	Change in quoted spread			Change in effective spread			Change in depth		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	−0.0708	−0.0758	−0.0145	−0.0702	−0.0811	−0.0218	0.0220	0.0142	0.0400
	(−8.97)**	(−9.67)**	(−0.89)	(−6.93)**	(−8.14)**	(−1.27)	(1.53)	(0.98)	(1.24)
Pilot 1 dummy	−0.0885	−0.0881	−0.0836	−0.0758	−0.0755	−0.0688	0.1149	0.1152	0.1175
	(−1.69)	(−1.70)	(−1.62)	(−1.33)	(−1.35)	(−1.24)	(1.03)	(1.04)	(1.06)
Pilot 2 dummy	0.0762	0.0676	0.0639	0.0938	0.0830	0.0797	0.0035	−0.0071	−0.0086
	(3.70)**	(3.31)**	(3.13)**	(4.20)**	(3.79)**	(3.65)**	(0.08)	(−0.16)	(−0.20)
Pilot 3 dummy	0.0271	0.0253	0.0221	0.0329	0.0311	0.0277	−0.0204	−0.0234	−0.0250
	(1.68)	(1.58)	(1.39)	(1.88)	(1.82)	(1.62)	(−0.60)	(−0.69)	(−0.73)
ΔLog(share price)	−0.3256	−0.3423	−0.3423	−0.2404	−0.2637	−0.2649	0.2318	0.2113	0.2103
	(−13.18)**	(−13.94)**	(−13.99)**	(−8.98)**	(−10.03)**	(−10.11)**	(4.46)**	(4.06)**	(4.04)**
ΔLog(number of trades)	−0.1700	−0.1694	−0.1667	−0.1676	−0.1676	−0.1662	0.0586	0.0611	0.0630
	(−17.36)**	(−17.47)**	(−17.21)**	(−15.72)**	(−16.06)**	(−15.97)**	(2.92)**	(3.05)**	(3.13)**
ΔLog(trade size)	−0.0358	−0.0339	−0.0364	−0.0148	−0.0132	−0.0147	0.3190	0.3209	0.3197
	(−4.04)**	(−3.86)**	(−4.15)**	(−1.54)	(−1.40)	(−1.56)	(17.02)**	(17.17)**	(17.06)**
ΔLog(return volatility)	0.1208	0.1215	0.1200	0.1114	0.1122	0.1110	−0.0466	−0.0457	−0.0468
	(19.02)**	(19.32)**	(19.12)**	(16.17)**	(16.62)**	(16.49)**	(−3.45)**	(−3.39)*	(−3.45)**
ΔLog(market value of equity)	−0.0290	−0.0287	−0.0290	−0.0618	−0.0609	−0.0614	−0.0493	−0.0491	−0.0493
	(−2.72)**	(−2.72)**	(−2.76)**	(−5.34)**	(−5.38)**	(−5.44)**	(−2.18)*	(−2.18)*	(−2.19)*
Proportion of one-tick spreads (PQMIN)	−0.4404	−0.4019	−0.3532	−0.5577	−0.5082	−0.4350	−0.9441	−0.9028	−0.8794
	(−29.92)**	(−26.00)**	(−18.48)**	(−32.84)**	(−29.42)**	(−17.93)**	(−28.61)**	(−26.16)**	(−20.33)**
SPREAD or DEPTH	−0.1156	−0.2327	−0.3461	0.6036	0.2862	0.1212	0.0000	0.0000	0.0000
	(−0.63)	(−1.27)	(−1.88)	(2.02)*	(0.97)	(0.41)	(−0.89)	(−0.53)	(−0.64)
Share price (PRICE)	−0.0006	−0.0002	−0.0002	−0.0009	−0.0004	−0.0004	−0.0009	−0.0005	−0.0005
	(−4.70)**	(−1.78)	(−1.71)	(−6.98)**	(−3.12)**	(−2.91)**	(−3.69)**	(−1.91)	(−1.83)
Number of trades (NT)	–	−0.0001	−0.0001	–	−0.0001	−0.0001	–	−0.0001	−0.0001
		(−7.44)**	(−7.16)**		(−10.60)**	(−10.15)**		(−3.99)**	(−3.89)**
Proportion of odd sixteenths (PODD)	–	–	−0.1833	–	–	−0.2207	–	–	−0.0816
			(−4.30)**			(−4.28)**			(−0.90)

Table 6 (*continued*)

Independent variable	Change in quoted spread			Change in effective spread			Change in depth		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
F-statistic	196.83**	188.83**	176.91**	197.20**	197.92**	185.32**	150.98**	140.52**	126.76**
Adjusted R^2	0.4529	0.4642	0.4678	0.4534	0.4759	0.4794	0.3880	0.3915	0.3915

To examine how the observed changes in spreads and depths can be explained by the binding constraint together with these other factors, we estimate the following regression models:

$$\Delta\text{SPREAD}_i = \alpha_0 + \sum_{k=1}^{3}\alpha_k D_k + \sum_{k=4}^{8}\alpha_k\left\{\text{Log}\left(A_{k,i}^{\text{Post}}\right) - \text{Log}\left(A_{k,i}^{\text{Pre}}\right)\right\} + \alpha_9\text{PQMIN}_i + \alpha_{10}\text{SPREAD}_i + \alpha_{11}\text{PRICE}_i + \alpha_{12}\text{NT}_i + \alpha_{13}\text{PODD}_i + \varepsilon_{1i},$$

$$\Delta\text{DEPTH}_i = \beta_0 + \sum_{k=1}^{3}\beta_k D_k + \sum_{k=4}^{8}\beta_k\left\{\text{Log}\left(A_{k,i}^{\text{Post}}\right) - \text{Log}\left(A_{k,i}^{\text{Pre}}\right)\right\} + \beta_9\text{PQMIN}_i + \beta_{10}\text{DEPTH}_i + \beta_{11}\text{PRICE}_i + \beta_{12}\text{NT}_i + \beta_{13}\text{PODD}_i + \varepsilon_{2i},$$

where ΔSPREAD_i and ΔDEPTH_i denote the percentage change in the spread and depth, respectively, between the pre- and post-decimalization periods, (post-value – pre-value)/pre-value; D_k ($k = 1, \ldots, 3$) is the dummy variable for each decimalization pilot; $A_{k,i}$ ($k = 4, \ldots, 8$) represents one of the five stock attributes – share price, the number of trades, trade size, the standard deviation of daily stock returns, and the market value of equity; PQMIN_i, SPREAD_i, DEPTH_i, PRICE, NT, and PODD_i are the pre-decimalization values of the proportion of spreads that are equal to the minimum price variation, the spread, the depth, share price, the number of trades, and the proportion of odd sixteenth quotes, respectively; αs and βs are the regression coefficients; and ε_{1i} and ε_{2i} are the error terms. We calculate ΔSPREAD_i and ΔDEPTH_i using the proportional spread and dollar depth. Numbers in parenthesis are *t*-statistics.
* and ** statistically significant at the 1% and 5% levels, respectively.

thereafter. The smallest spread and depth reductions and the least use of one-tick spreads near the open suggest that the tick size is least likely to be the binding constraint on spread widths during this period and, consequently, the reduced tick size yields a smaller impact on the spread and depth. This result is consistent with the well known empirical regularity reported in previous studies that the spread is widest near the open on the NYSE (see McInish and Wood, 1992; Chung et al., 1999). As time elapses and the spread narrows, the minimum price variation becomes a binding constraint more frequently, and thus the reduced tick size exerts a greater impact on the spread and depth.

5. Is the penny tick size a binding constraint for some stocks?

In light of a recent debate among regulatory authorities and the investment community on whether decimal pricing provides liquidity suppliers with sufficient freedom in the quote-setting process, this section assesses the extent of the binding constraint under the penny-tick environment. In its response to the Securities and Exchange Commission (SEC)'s Concept Release on Sub-penny Trading, Island – an ECN currently operating within the NASDAQ market – casts serious doubt on the adequacy of penny tick increments. [15]

Island accounts for more than one of every five trades on NASDAQ and approximately 40% of the orders submitted and 35% of the executions on Island occur in sub-penny increments. Island currently accepts orders priced out to three decimal places. [16] Island argues that its continued growth casts significant doubt on the claims that sub-penny increments would cause investor confusion and harm transparency. Island holds that sub-penny increments provide an opportunity to lower transaction costs and bring further efficiencies to the market. Island advocates that the SEC should not only continue to permit sub-penny trading but should also move forward expeditiously in requiring quotations of at least three decimal places in the publicly disseminated quotation. In the present section, we shed some light on this debate by examining whether the penny tick size is a binding constraint on spread widths using our sample of NYSE stocks.

To assess whether the penny tick size is a binding constraint after full implementation of decimal pricing, we calculate the proportions of quoted and effective spreads that are equal to one penny (PQMIN_QS and PQMIN_ES) as well as the proportion of trading time during which the quoted spread is one penny (PTMIN_QS). Panel A of Table 7 shows the descriptive statistics of these metrics.

[15] Source: A letter addressed to Jonathan Katz, Secretary, US Securities and Exchange Commissions by Cameron Smith, General Counsel, December 18, 2001.

[16] ECNs have been offering sub-penny trading even before decimalization. Prior to decimalization, ECNs traded in increments of 1/256th or $0.0039. In Singapore, small-priced stocks currently trade in ticks of S$0.005, which is equivalent to US $0.0028. On a 1,000 share order, the third decimal place can be worth anywhere from $1 to $9. Given that investors change on-line brokers to save a few dollars on a trade, it is doubtful that $9 is irrelevant to investors.

Table 7
Determinants of the proportion of one-penny spreads after decimalization

	PQMIN_QS	PTMIN_QS	PQMIN_ES
Panel A: Descriptive statistics			
Mean	0.0698	0.0673	0.1379
Standard deviation	0.0639	0.0649	0.0898
Minimum	0.0000	0.0000	0.0000
1st percentile	0.0000	0.0000	0.0000
5th percentile	0.0000	0.0000	0.0120
10th percentile	0.0052	0.0023	0.0262
25th percentile	0.0209	0.0169	0.0662
50th percentile	0.0588	0.0556	0.1350
75th percentile	0.1021	0.1031	0.1979
90th percentile	0.1472	0.1452	0.2471
95th percentile	0.1729	0.1707	0.2800
99th percentile	0.2553	0.2564	0.3796
Maximum	0.7283	0.7589	0.7961
N	2,603	2,603	2,603
Variable			
Panel B: Logit regression results			
Intercept	−7.0516 (−65.43)**	−8.2559 (−50.80)**	−4.9610 (−61.52)**
Pilot 1 dummy	0.0994 (0.34)	0.0469 (0.11)	0.0869 (0.39)
Pilot 2 dummy	0.4421 (4.13)**	0.4374 (2.71)**	0.1820 (2.28)**
Pilot 3 dummy	0.1169 (1.42)	0.0142 (0.11)	−0.0183 (−0.30)
Log(share price)	−0.7054 (−25.32)**	−0.6758 (−16.09)**	−0.5007 (−24.02)**
Log(number of trades)	0.7973 (33.37)**	0.9909 (27.51)**	0.6475 (36.22)**
Log(trade size)	−0.0050 (−0.15)	−0.0857 (−1.74)	−0.1290 (−5.27)**
Log(return volatility)	−0.6574 (−25.58)**	−0.7518 (−19.40)**	−0.4890 (−25.43)**
Log(market value of equity)	0.0178 (0.87)	0.0114 (0.37)	0.0139 (0.91)
F-statistic	524.36**	352.88**	555.39**
Adjusted R^2	0.6301	0.5339	0.6434

We measure the probability that the minimum price variation is a binding constraint on spread widths by the proportion of quoted spreads that are equal to one cent (PQMIN_QS) during the post-decimalization study period. To assess the sensitivity of our results to different measurement methods, we also calculate the proportion of trading time during which the quoted spread is equal to one cent (PTMIN_QS). In addition, we calculate the proportion of effective spreads that are equal to one tick (PQMIN_ES). Panel A reports the descriptive statistics of the three measures of the binding constraints. Panel B presents the Logit regression results showing how these variables are related to stock attributes (share price, number of trades, trade size, return volatility, and market value of equity). To determine whether the relation between the proportion of one-tick spreads and stock attributes differs across decimalization implementation groups, we include three pilot dummy variables in the regressions. Numbers in parenthesis are *t*-statistics. * and ** statistically significant at the 1% and 5% levels, respectively.

Not surprisingly, the mean values (6.98%, 6.73%, and 13.79%) of these variables are much smaller than the corresponding figures (31.40%, 32.3%, and 44.16%) for the pre-decimalization study period, indicating that the penny tick is much less a binding constraint than the $1/16 tick on spread widths. Nevertheless, the results suggest that the penny tick may still be a binding constraint for a certain group of stocks. Notice that about 10% of our study sample (260 stocks) have PQMIN_QS, PQMIN_ES, and PTMIN_QS values that are greater than 0.14. [17]

To determine which stocks are more likely to find the penny tick size a binding constraint, we regress PQMIN_QS, PTMIN_QS, and PQMIN_ES on a common set of stock attributes and report the results in Panel B of Table 7. As in Table 3 with the pre-decimalization data, we find that these variables are significantly and positively related to the number of trades and trade size, and negatively to share price and return volatility. These results suggest that sub-penny pricing may further reduce the spreads of high-volume, low-risk, or low-price stocks.

Although we find some evidence of a penny-tick binding constraint, it is unclear whether sub-penny pricing would lead to an unambiguous increase in market quality and investor welfare due to its possible adverse effects. For example, sub-penny increments may lead to investor confusion, smaller displayed depths due to front running concerns, higher administrative costs due to multiple executions at multiple prices for a given trade, and technological backlog. [18] The accurate quantification of the costs and benefits of sub-penny pricing is likely to be difficult and well beyond the scope of this paper. Suffice it to say that the results of this study should alert regulators and the investment community that the desirability of a further reduction in tick size deserves careful and full consideration.

6. Summary and concluding remarks

Extant theories put forward several inferences on how decimal pricing may affect market quality and execution costs. Theory predicts that the smaller tick size lowers the likelihood that the tick size is the binding constraint on spread widths and thus reduces the bid–ask spread. The narrower spread in turn leads to a smaller depth because liquidity providers are less willing to commit large depths when trading profits are lower. The market depth may further drop because the increased probability of front running discourages buy-side traders to display their interests. As more traders are likely to step in front of existing orders due to the lower cost of price improvement, the spread may also further decline. In this study, we provide empirical evidence on how much of the observed changes in the spread and depth after decimal pricing can be attributed to these different factors.

We show that stocks with higher proportions of one-tick spreads before decimal pricing experienced larger reductions in the spread and depth. In addition, we find that stocks with higher proportions of odd-sixteenth quotes and greater trading frequency before decimalization exhibited larger reductions in the spread and depth

[17] These stocks are likely to account for a much larger (than 10%) proportion of the total market trading volume because they are (as shown below) typically large-volume stocks.

[18] Some commentators have expressed concerns that sub-penny trading would strain capacity limits of both market participants and market data vendors.

after decimal pricing. We interpret these results as evidence that both the relaxation of the binding constraint and the increased front running and price competition exerted a significant impact on the spread and depth. Our results also indicate that a significant portion of the observed changes in the spread and depth can be attributed to the concurrent changes in stock attributes after decimal pricing.

Some caveats are in order. In this study, we measure the binding-constraint and front-running probabilities by the pre-decimalization proportions of one-tick spreads and odd-sixteenth quotes (and number of trades), respectively. In so far as these are imperfect proxies of respective probabilities, our empirical results are open to alternative interpretations. Our study utilizes trade and quote data during 30 trading days before and after decimal pricing. Hence, the results of our study do not capture any long-term effects of decimal pricing. To the extent that market participants need some adjustment time to fully assimilate themselves to decimal environments, our results may not capture the full impact of decimal pricing. For example, although our results suggest that spreads became narrower as a result of the increased front running, they might become wider in the long term if traders reduce the use of limit orders. Due to limited data availability, our study relied on the quoted depth only at the inside market. Because decimal pricing can affect the entire limit order book, a more accurate account of the effect of decimal pricing on liquidity would require an analysis of how the depth has been affected throughout the limit order book. Further investigations of these issues may be a fruitful area for future research.

Acknowledgements

The authors thank the editor and two anonymous referees for their valuable comments and suggestions. Charoenwong and Ding gratefully acknowledge financial supports from Nanyang Business School Research Grant (No. RCC15/2000) and Centre for Research in Financial Services (CREFS). The usual disclaimer applies.

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