Decimalization and market liquidity

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On January 29, 2001, the New York Stock Exchange (NYSE) implemented decimalization. Beginning on that Monday, stocks began to be priced in dollars and cents, and price changes were allowed to be as small as 1 cent.[1] Prior to this change, NYSE stocks were quoted in fractions of a dollar and traded in increments of 1/16, or 6.25 cents. Decimalization of stock markets is relevant for policymakers because it has the potential to affect market liquidity, and therefore the overall functioning of financial markets.

Advocates of the adoption of decimalization argue that the finer gradation of stock prices will benefit investors. This is because the pricing increment dictates the smallest possible bid–ask spread for a given stock. This spread represents the difference between the lowest price an investor can pay for a stock and the highest price an investor can receive for selling the same stock. Prior to decimalization, actively traded stocks often had a spread equal to the minimum price increment, or tick, of 6.25 cents. For instance, an investor might have faced a bid–ask spread of 50 1/2–50 9/16 for shares of stock in XYZ company on Friday, January 26, 2001. That is, abstracting from any transaction fees levied by brokers, an investor wanting to sell a round lot of 100 shares of XYZ could expect to receive $5,050 and an investor needing to buy 100 shares would have to pay $5,056.25. Following decimalization, however, the two investors might face a spread of 50.51–50.53. Thus, the seller of XYZ would receive an extra penny per share and the buyer of XYZ shares would save 3.25 cents per share.

However, decimalization may affect more than a stock's bid–ask spread. To understand this, consider the set of firms and individuals that stand ready to buy and sell the stock of XYZ company. For example, prior to decimalization, a dealer might have been willing to commit to buy 10,000 shares of XYZ company at 50 1/2 and to sell 10,000 shares at 50 9/16. In practice, these commitments may have been made by the dealer placing a limit buy order for 10,000 at 50 1/2 and a limit sell order for 10,000 shares at 50 9/16. If these are the only outstanding orders for XYZ stock at these prices, then the stock will have a bid–ask spread of 1/16 and a so-called depth of 10,000 (at the bid price) by 10,000 (at the ask price) shares. With decimal pricing, the same dealer may have decided not to post limit orders of the same size at the new prices of 50.51–50.53. This is because the profitability of committing to be willing to both buy and sell a given stock, as measured by the bid–ask spread, has declined. Thus, the dealer might only be willing to offer depth of 1,000 by 1,000. From the perspective of a small investor, for example one wishing to trade only a few hundred shares, this reduction in depth at the bid–ask spread is not a concern. Depth at the best available prices will suffice. However, for large traders, for example those wishing to trade several thousand shares, quoted depth at the best-quoted prices may be insufficient to fill the desired order. For such trades, the effective transaction price lies somewhere outside the posted bid and ask.

In this article, I examine how various measures of stock market liquidity changed following decimalization. A stock's illiquidity measures the cost to a buyer or seller of transacting in shares beyond the true underlying value of the security. These costs arise from a lack of an infinite supply of shares that can be purchased and sold at the same price. That is, if investors could buy or sell any number of shares of XYZ stock at 50.52, then one would say that XYZ shares are perfectly liquid at that price. Bid–ask spreads and limited depth represent two departures from this situation and, thus, bid–ask spreads and depth are two measures of

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liquidity. Lower spreads and higher depth represent more liquidity. Higher spreads and lower depth signal less liquidity.

I document that decimalization did lead to smaller spreads and lower depth, and thus caused a theoretically ambiguous change to market liquidity. Thus, to empirically address whether and/or to what extent market liquidity was affected by decimalization, one must focus on a liquidity measure that is affected by both a finer pricing grid and lower depth. In this article, I examine the revision to a stock's price that follows a trade as a direct measure of a stock's liquidity. This is known as the price impact of a trade. By definition, perfect liquidity implies that a given trade should not affect the price.[2] With imperfect liquidity, the size of the price revision following a trade is likely positively related to tick size, since any adjustment to prices must be at least as large as the minimum tick. Likewise, the price impact should be negatively related to market depth, since lower depth implies that a given (large) trade may have to travel through more prices in order to be filled.

In this study, I examine the stocks of 1,339 companies that began decimal trading on the NYSE on January 29, 2001. I document what previous studies have found regarding the relationship between tick size, bid–ask spreads, and depth. I then estimate the price impact of a trade, distinguishing trades undertaken before decimalization from those after and further distinguishing large trades from small trades. I find that for both large and small trades, decimalization typically led to an improvement in liquidity as measured by a decline in the price impact of a trade for actively traded stocks. For less actively traded stocks, decimalization led to improved liquidity more often than it led to reduced liquidity. However, the most common empirical finding for infrequently traded stocks was that there was not a statistically significant change in liquidity following decimalization.

Selective literature review

I mention only a few contributions to the extensive literature on the effects of reducing tick sizes on various measures of market performance, including liquidity. In Seppi's (1997) theoretical framework, reduction in tick sizes leads to a reduction in the willingness of both small and large traders to supply liquidity through limit orders (depth). However, because retail investors require less depth to conduct trading, optimal tick size depends positively on typical trade size. That is, institutions that typically trade in large amounts prefer large tick sizes, whereas small investors prefer small tick sizes.

Harris (1994), using data from a time when the minimum tick was 1/8, fits a regression model estimating the frequency at which spreads are at the minimum. Using this relationship, Harris estimates that the impact of reducing the minimum tick size to 1/16 would be accompanied by both lower bid–ask spreads and lower quoted depth. His results are therefore also consistent with the notion that optimal tick size is related to the size of a trade. They indicate that small traders would almost certainly benefit from smaller tick sizes, but that large traders might be hurt if the depth of the market were to fall sufficiently.

Goldstein and Kavajecz (2000) analyze the NYSE's reduction in tick size from 1/8 to 1/16 and address the relationship between minimum tick size, bid–ask spreads, and market liquidity. What is unique about this study is that these authors not only look at the depth reported at the best bid and ask prices, they also collect data on liquidity available at some distance away from the best bid and ask prices. This complete collection of prices and available depth is called the limit order book. They find that not only did depth at the best bid and ask decline, but cumulative depth similarly declined throughout the limit order book following the NYSE's previous reduction in minimum tick size. They found such declines in depth as far as 50 cents from the midpoint of the bid–ask spread. Using implied average price of a trade of a given size derived from the limit order book, these authors find that large traders were not made better off by the smaller tick sizes and were made worse off for infrequently traded stocks.

More recent work has examined changes in market liquidity for NYSE-listed stocks since decimalization. Chakravarty et al. (2001) study a small set of stocks that began trading in decimals as part of an NYSE pilot program in 2000. These authors find that decimalization has led to significantly lower spreads and also lower quoted depth. Bacidore et al. (2001) also study stocks in the decimalization pilot. These authors focus on whether decimalization leads to significant changes in order submission strategies. They find that there is no noticeable change in the use of limit versus market orders, but the size of limit orders has fallen and the frequency of limit order cancellation has increased since decimalization. Smaller limit orders and higher cancellation rates explain how lower depth materialized.

Bessembinder (2003) studies a larger sample of NYSE and Nasdaq (National Association of Securities Dealers Automated Quotation) stocks and documents that following decimalization, bid–ask spreads fell noticeably, with the largest declines seen for the most actively traded stocks. Bessembinder also reports an increase in the frequency of price improvement on the NYSE following decimalization. Price improvement

occurs when a trade is conducted at a price inside the bid–ask spread. Higher rates of price improvement are consistent with the fact that decimalization makes it easier for traders to step in front of the current best bid or ask to take the other side of a market order.

Data, sample selection, and summary statistics

For this study, I extracted stock market trade and quote data from the NYSE TAQ (Trades and Quotes) database, covering the 24 trading days beginning Tuesday, January 16, 2001, and ending on February 16, 2001.[3] Following Hasbrouck (1991), I also impose a minimum price requirement on each company's stock. I require each stock to be trading for at least $5, on average, during the five-week sample period. I similarly impose a maximum price of $200. Also following Hasbrouck (1991), I require a minimum level of trading activity. I limit my sample to stocks that traded, on average, at least every ten minutes over these five weeks. Finally, I eliminate those stocks that were part of the NYSE pilot program and, therefore, traded in decimals prior to January 29, 2001. My final sample consists of 1,339 stocks.

The data are then adjusted according to procedures common in the microstructure literature. Following Hasbrouck (1991), I keep only New York quotes and consider multiple trades on a regional exchange for the same stock at the same price and time to be one trade. Then, I sort the trade data (for each company and day) by time, with the prevailing quote at transaction t defined to be the last quote that was posted at least five seconds before the transaction (Lee and Ready, 1991).

I group the 1,339 stocks into six categories according to their average trade frequency, with Category 1 stocks being the least traded and Category 6 stocks being the most frequently traded. The number of stocks in each category is shown in table 1. I first calculate the narrowest bid–ask spread witnessed by each stock and for each day. I then average these minimums across stocks within the same trading category. These average minimum values are plotted in figure 1. As is apparent from figure 1, minimum tick size strongly influences the extent to which bid–ask spreads can narrow within a day. Every stock in the four most actively traded categories experienced a bid–ask spread equal to the minimum tick size at least once on every day of the sample period. For stocks in Category 2, that is, those trading every one to five minutes, minimum spreads were always within 1/10 of a cent of the minimum tick

Category	Average time between trades	Number of stocks
1	5–10 minutes	191
2	1 minute–4 minutes, 59 seconds	722
3	30–59 seconds	237
4	15–29 seconds	108
5	5–14 seconds	70
6	Less than 5 seconds	11

TABLE 1

Average trading activity of sample stocks

Source: New York Stock Exchange, 2001, Trades and Quotes (TAQ) database, January 16–February 16.

size, suggesting that nearly all of the 722 stocks in that category experience minimum tick-sized spreads during each day. Even for those stocks trading only every five to ten minutes, average minimum spreads hover around 6.5 cents when the minimum tick size was 6.25 and fall to around 2 cents after decimalization.

Figure 2 plots the mean spread within a day averaged across stocks in a given trading category. As expected, more frequently traded stocks have lower spreads. For stocks in all categories, decimalization has led to a decline in average bid–ask spreads. This decline in mean spreads is most pronounced for the more actively traded stocks. For example, mean bid–ask spreads for stocks in Category 1 averaged 13.6 cents, about a penny over two ticks, in the two weeks prior to decimalization. Following decimalization, the average mean spread of these stocks fell to 10.5 cents. For the most actively traded stocks, average mean spreads were 11.3 cents before decimalization and fell to 7.0 cents after.
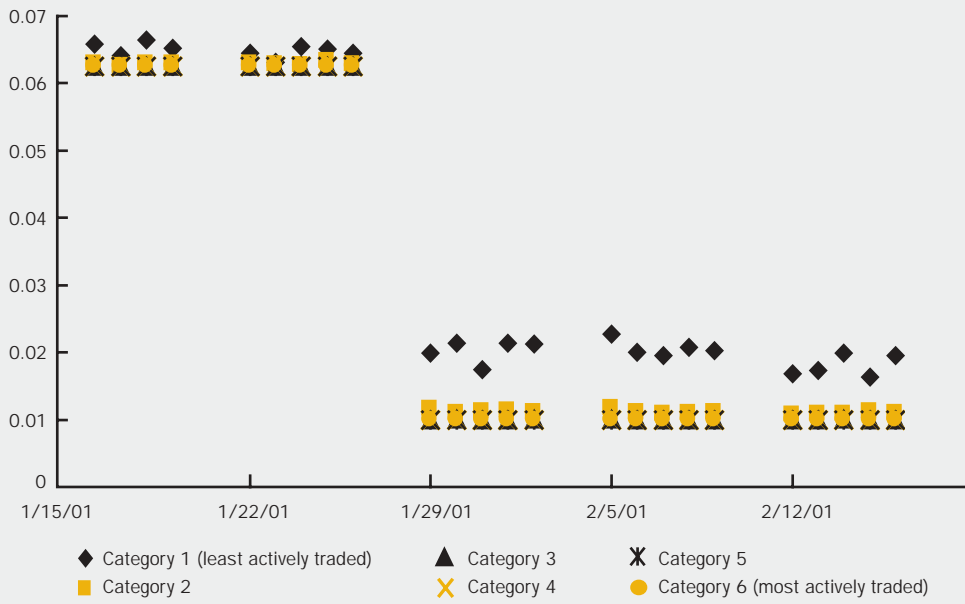
The narrowing of bid–ask spreads following decimalization illustrated in figures 1 and 2 has been accompanied by a decline in average depth at the posted prices. Figure 3 reports the mean of the bid and ask depth posted throughout a day, averaged across stocks in each category. The post-decimalization decline in posted depth was significant, especially for the most actively traded stocks that had previously had a very large number of shares committed to trade at the posted spread. For the least actively traded stocks, posted depth fell by half, from just under 6,600 shares to 3,300 shares on average. The most actively traded stocks experienced depth declines of more than two-thirds, from an average of 18,700 shares to slightly more than 6,000 shares.

Price impact of trading

The statistics reported in the previous section confirm that decimalization has led to both a decline
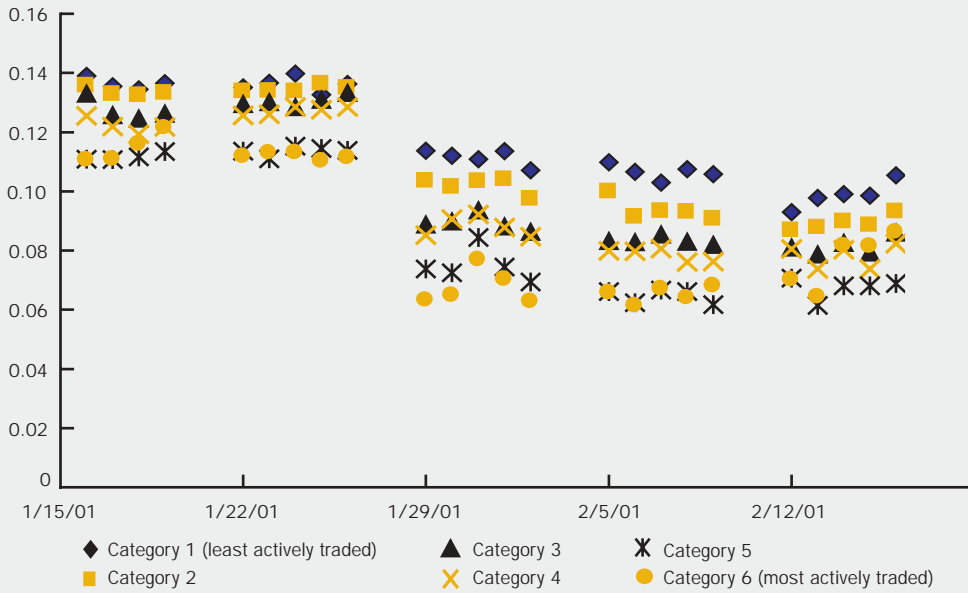
FIGURE 1

Average minimum daily spread

Category 1 (least actively traded) — Category 3 — Category 5
Category 2 — Category 4 — Category 6 (most actively traded)

Source: NYSE TAQ database from January 16–February 16, 2001.

FIGURE 2

Average mean daily spread

Category 1 (least actively traded) — Category 3 — Category 5
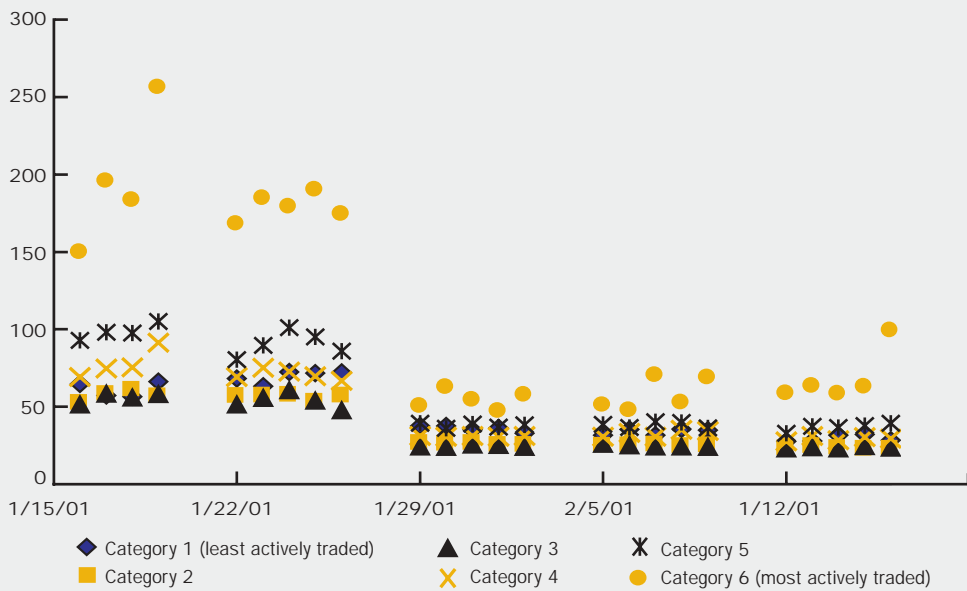Category 2 — Category 4 — Category 6 (most actively traded)

Source: NYSE TAQ database from January 16–February 16, 2001.

FIGURE 3

Average daily quoted depth (in number of round lots)

Category 1 (least actively traded) ◆ Category 3 ▲ Category 5 ✳
Category 2 ■ Category 4 ✕ Category 6 (most actively traded) ●

Source; NYSE TAQ database from January 16–February 16, 2001.

in spreads and a decline in depth. Thus, an investor making a relatively small trade generally faces improved liquidity, since the trade can be executed at a narrower spread. For institutional investors making large trades, however, the lower depth may imply that a large trade must travel through several prices before being ful-filled, and thus decimalization may not necessarily have led to better execution prices. To try to combine the effects of spread and depth in one framework, I examine a liquidity measure called the price impact of a trade, which was first motivated and estimated by Hasbrouck (1991). This is a measure of how much the price of a stock changes following a given trade as estimated in an autoregression framework. While other measures of liquidity are conceivable, price impact has the advantage of being influenced by both smaller price increments and lower depth. In particular, decimalization may cause the price impact to decline since prices can ad-just by smaller increments, but it may also cause the price impact to rise since more prices must be exhaust-ed because depth at any given price is lower.

In the price impact framework, the dependent vari-able of interest is the trade-to-trade return on a given stock. I denote this return r_t and define it formally as the change in the natural logarithm of the midquote of a given stock that follows the trade at time t.[4] That is,

$$1) \quad r_t = 100 \left(\ln\left(\frac{bid_{t+1} + ask_{t+1}}{2} \right) - \ln\left(\frac{bid_t + ask_t}{2} \right) \right).$$

The use of midquotes eliminates price changes caused by the bid–ask bounce, that is, the alternating arrival of buys and sells transacting at the ask and bid price, respectively. Following Hasbrouck (1991), I de-fine the variable x_t as an indicator of the direction of the trade occurring at time t. If the trade is initiated by the buyer, the variable $x_t = 1$. If the trade is initiated by the seller, then the variable $x_t = -1$. I assume trades at a transaction price greater than the midquote were buyer-initiated and trades below the midquote were seller-initiated. For trades at the midquote, x_t is as-signed to equal zero. Defining D_t as an indicator that equals 1 if trade t occurs during the first 30 minutes of the trading day and dec_t as an indicator that equals 1 if trade t occurs during the decimal period after January 29, 2001,[5] I estimate the regression

$$2) \quad r_t = \alpha D_t x_t + \sum_{i=1}^{5} \left[\beta_i + \delta_i dec_{t-i} \right] r_{t-i}$$

$$+ \sum_{i=0}^{5} \left[\gamma_i + \lambda_i dec_{t-i} \right] x_{t-i} + \varepsilon_t$$

for each stock in my sample.[6] The price impact of a trade in this framework is equal to the sum of the γ_i coefficients during the pre-decimalization period and equal to the sum of the $\gamma_i + \lambda_i$ coefficients after decimalization. Because purchases should put upward pressure on prices, I expect that γ_i should be positive for some or all of the trade lags i. This prediction follows from traditional microstructure theory. In Glosten and Milgrom (1985), for example, market makers set a positive bid–ask spread as compensation for trades made with counterparties with superior information. As a sequence of sell orders arrives, market makers lower bid prices, incorporating the probability that the order flow implies that better-informed investors believe the previous price was too high. The reverse occurs when a sequence of buy orders arrives. This type of dynamic quote adjustment leads to the prediction of a positive value of the γ_i coefficients. The λ_i coefficients may be either positive or negative depending on whether the stock has become less or more liquid (higher or lower price impact of a trade) since decimalization.

Table 2 summarizes the results from these 1,339 regressions. Each row of table 2 corresponds to stocks in different trade activity categories. The numbers reported in the first column represent the average value of the sum of the γ_i coefficients across all stocks in the given category. These coefficients measure the price impact of a trade in the two weeks prior to decimalization. For instance, the first entry in the first column reports that the average price impact of a trade during this time is 9.2 basis points for stocks in the least actively traded category. Put another way, 11 trades in the same direction move an infrequently traded stock's price by 1 percent. As the numbers in the first column indicate, liquidity as measured by price impact

increases with trading activity, since trades of more actively traded stocks move prices less. For example, a trade of a stock of a very actively traded security moves the stock's price by just over 1 basis point. The numbers in the second and third columns summarize the statistical significance of the price impact results. The second and third columns report the fraction of stocks in the given category whose price impact estimate was positive and statistically significant (at the 5 percent level) and negative and statistically significant, respectively. As the numbers in columns two and three indicate, none of the stocks in the sample had a negative and significant price impact of a trade, whereas virtually all of the sample stocks had significantly positive price impacts.

The last three columns summarize the results for the decimalization period. A comparison of the fourth column with the first indicates that for stocks in all categories, the average price impact of a trade declined following decimalization. That is, stocks became more liquid on average. However, the numbers reported in the final two columns suggest that this result is not as uniform as the positive price impact result reported for the pre-decimalization period. For stocks in the least actively traded category, only one-quarter saw a statistically significant decrease in price impact following decimalization. Around two-thirds of the stocks in category two had statistically significant increases in liquidity. For the more actively traded stocks, that is, those that on average trade at least once per minute, more than 95 percent witnessed an increase in liquidity (decrease in price impact) following decimalization. The magnitude of the increased liquidity is fairly large, with the typical decline in price impact following decimalization being close to 40 percent.

TABLE 2						
Average price impact of a trade: Before and after decimalization						
	Before decimalization			After decimalization		
Trade category	Average price impact (sum of γ_i)	Share of stocks with positive and sig. γ_i	Share of stocks with negative and sig. γ_i	Average price impact (sum of $\gamma_i + \lambda_i$)	Share of stocks with positive and sig. λ_i	Share of stocks with negative and sig. λ_i
1	0.092	0.974	0.000	0.074	0.016	0.251
2	0.070	0.999	0.000	0.045	0.007	0.652
3	0.043	1.000	0.000	0.025	0.008	0.945
4	0.032	1.000	0.000	0.019	0.000	0.954
5	0.023	1.000	0.000	0.014	0.014	0.957
6	0.011	1.000	0.000	0.006	0.000	1.000

Based on the regression equation $r_t = \alpha D_t x_t + \sum_{i=1}^{5} [\beta_i + \delta_i dec_{t-i}] r_{t-i} + \sum_{i=0}^{5} [\gamma_i + \lambda_i dec_{t-i}] x_{t-i} + \varepsilon_t$.
Note: Sig. indicates significant.

The preceding results suggest that decimalization led to increased liquidity for virtually all stocks that trade at least once per minute. Among less frequently traded stocks, the results were more mixed, with a significant fraction of stocks experiencing no statistically significant change in price impact following the move to decimal pricing. My previous discussion of microstructure theory, however, suggests that decreases in tick size and depth may have different implications for trades of different sizes. In particular, small trades may benefit from tighter spreads and correspondingly smaller price increments because they can normally be executed within posted depth. Large trades, however, may have become less liquid following decimalization due to the significant decline in depth. I extend my empirical framework to test for this possibility. I define the variable Big_t as an indicator that equals 1 when trade t is among the largest 10 percent of trades for the given stock and then estimate an extended regression model described by equation 3.

$$3) \quad r_t = \alpha D_t x_t + \sum_{i=1}^{5} \left[\beta_i + \delta_i dec_{t-i} \right] r_{t-i}$$
$$+ \sum_{i=0}^{5} \left[\gamma_i + \lambda_i dec_{t-i} + \mu_i Big_{t-i} + \theta_i dec_{t-i} Big_{t-i} \right] x_{t-i}$$
$$+ \varepsilon_t .$$

In equation 3, I have extended the previous regression equation by allowing the price impact of a trade, both before and after decimalization, to differ depending on whether the trade is large. Since large trades have been generally found to be less liquid (see Hasbrouck, 1991), one might expect the μ_i coefficients to be positive. That is, larger trades will move prices more than smaller trades. The ϕ_i coefficients allow a direct test of the hypothesis that the liquidity of large trades has been adversely affected by the move to decimal pricing.

Table 3 summarizes the results from estimating equation 3 for all 1,339 stocks in the sample. Table 3 follows a similar format as table 2, only expanded to account for the fact that I now distinguish between large trades (those in the top 10 percent of size within the given stock) and regular trades (all others). The first three columns of panel A in table 3 report statistics for regular trades prior to decimalization. These results are qualitatively similar to those reported in the first three columns in table 2. In particular, I find positive and statistically significant price impacts for virtually all stocks in the sample for regular sized trades. The size of the price impact is lower than that reported for all trades in table 2. This can be explained by

the larger impacts found for large trades reported in columns four to six of table 3. For example, a regular trade of a stock in category 6 (most actively traded) moved the stock's price by roughly 0.9 basis points. Large trades of such a stock moved the price by 3.0 basis points. Since I define large trades to be the top 10 percent of the size distribution, one might expect the average price impact of an actively traded stock to be 90% × 0.9 + 10% × 3.0 = 1.11 basis points, which is the result reported in table 2.

The results in columns four to six of table 3 also indicate that large trades are not necessarily less liquid for relatively infrequently traded stocks. In particular, I find that larger trades have a larger price impact for only 29 percent of stocks trading every five to ten minutes and for only 50 percent of stocks trading every one to five minutes. Large trades of stocks trading at least every 30 seconds, however, do typically move prices more than other trades. For these more actively traded stocks, large trades move prices between two and three times more than regular trades.

Panel B in table 3 summarizes the regression results related to the period following decimalization. Average price impacts of regular trades fell following decimalization for virtually all stocks trading at least once each minute. For example, the price impact of a regular trade of a very actively traded stock (category 6) fell from 0.9 basis points to 0.5 basis points after decimalization. For stocks trading every 30–60 seconds (category 3), the average price impact of regular trades fell from 3.9 basis points to 2.3 basis points. For stocks trading only every five to ten minutes, decimalization did not generally lead to lower price impacts of regular trades. I find a statistically significant decline in price impact (increase in liquidity) for only 17.8 percent of such stocks.

The final three columns of panel B report my findings regarding the liquidity of large trades after decimalization relative to before. On average, large trades are more liquid in the post-decimalization period. For example, a large trade of a stock in the most actively traded category moved the stock's price by an average of 3.0 basis points before decimalization, but by only 1.9 basis points after decimalization. For all 11 of these stocks, the decline in price impact (increase in liquidity) of large trades was statistically significant. Across stocks in the entire sample, the decline in price impact for large trades was less common than that found for regular trades. For example, I find that the price impact of a regular trade declined post-decimalization for 92.0 percent of stocks that were traded every 30–60 seconds (Category 3). However, the price impact of a large trade fell in only 37.1 percent of these stocks

following decimalization. Most stocks trading less frequently did not witness an increase in liquidity for large trades following decimalization. For example, among stocks trading only every five to ten minutes, only 8.4 percent of the stocks saw a decline in price impact for large trades following decimalization. In fact, 2.6 percent of such stocks actually saw an increase in price impact. Higher price impacts following decimalization, however, were virtually nonexistent for stocks trading at least once every five minutes.

As a robustness check, I reestimate equation 3 after changing the definition of a large trade. The previous definition of large was an absolute one, namely any trade that was among the largest 10 percent of all trades of a given stock during the sample period. To consider more explicitly that the liquidity of a trade is not only related to size, but also to depth, I repeat the analysis defining the variable *Big* to be equal to 1 when the given trade is executed for more shares than posted depth. That is, a buy transaction for more shares than posted ask depth or a sell transaction for more shares than posted bid depth would be defined as a large trade. Whereas 10 percent of trades were previously defined as large, this alternative definition

identifies roughly 19 percent of all trades. However, only approximately 60 percent of trades previously identified as large satisfy this new definition. This implies that much of the time, large trades occur when depth is also high.

Table 4 reports results analogous to those in table 3 for this alternative definition of a large trade. The most substantial difference from the earlier results is that trades that satisfy the new definition of big seem more highly correlated with lower levels of liquidity. Whereas less than half of stocks trading less than once per minute (Categories 1 and 2) had higher price impacts for trades in the top 10 percent of the size distribution (table 3), well over half of these stocks experience a greater price impact for trades greater than posted depth (table 4). The magnitude of the price impact for these large trades is now larger under this definition. Whereas the largest 10 percent of trades of the most frequently traded stocks moved price by 3.0 basis points, trades greater than posted depth moved the price of these same stocks by 3.9 basis points before decimalization.

With this new definition of large trades, decimalization is still generally correlated with increased

TABLE 4

Average price impact of a trade: Before and after decimalization, by trade size
(alternative definition of a large trade)

A. Before decimalization

	Regular trades			Trades with size > posted depth		
Trade category	Average price impact (sum of γ_i)	Share of stocks with positive and sig. γ_i	Share of stocks with negative and sig. γ_i	Average price impact (sum of $\gamma_i + \mu_i$)	Share of stocks with positive and sig. μ_i	Share of stocks with negative and sig. μ_i
1	0.074	0.942	0.000	0.188	0.476	0.000
2	0.058	0.988	0.000	0.143	0.731	0.003
3	0.035	1.000	0.000	0.091	0.987	0.000
4	0.026	1.000	0.000	0.070	1.000	0.000
5	0.017	1.000	0.000	0.057	1.000	0.000
6	0.008	1.000	0.000	0.039	1.000	0.000

B. After decimalization

	Regular trades			Trades with size > posted depth		
Trade category	Average price impact (sum of $\gamma_i + \lambda_i$)	Share of stocks with positive and sig. λ_i	Share of stocks with negative and sig. λ_i	Average price impact (sum of $\gamma_i + \lambda_i + \mu_i + \theta_i$)	Share of stocks with positive and sig. θ_i	Share of stocks with negative and sig. θ_i
1	0.062	0.010	0.168	0.140	0.010	0.173
2	0.040	0.011	0.553	0.106	0.010	0.325
3	0.020	0.008	0.895	0.062	0.000	0.679
4	0.015	0.000	0.926	0.044	0.000	0.935
5	0.010	0.014	0.957	0.033	0.000	0.957
6	0.004	0.000	1.000	0.019	0.000	1.000

Based on the regression equation $r_t = \alpha D_t x_t + \sum_{i=1}^{5}[\beta_i + \delta_i dec_{t-i}]r_{t-i} + \sum_{i=0}^{5}[\gamma_i + \lambda_i dec_{t-i} + \mu_i Big_{t-i} + \theta_i dec_{t-i} Big_{t-i}]x_{t-i} + \varepsilon_t$.

Note: Sig. indicates significant.

liquidity (lower price impact) of actively traded stocks. Further, more stocks have a statistically significant decline in price impact for large trades under the new definition. With large trades defined as those with size greater than posted depth, virtually all stocks trading at least every 30 seconds and two-thirds of those trading every 30–60 seconds witnessed an increase in liquidity of large trades following decimalization. Thus, according to these two measures of large trade size, decimalization seems to have led to increased liquidity for most actively traded stocks, and in virtually no cases did decimalization lead to less liquidity, even for large trades.

Conclusion

This article has examined the impact of decimalization on the liquidity of NYSE stocks. Analyzing transaction data for a sample of 1,339 stocks listed on the NYSE over a five-week period surrounding the January 29, 2001, implementation of decimalization, I presented evidence of the following: Minimum price increments do seem to have an impact on bid–ask

spreads. In particular, for nearly all but the least-traded stocks, bid–ask spreads were equal to the minimum price increment at least once each day during the sample period. Decimalization also led to a narrowing of average bid–ask spreads. The largest declines in spreads were found for the most actively traded stocks, where the average decline in spreads was over 35 percent. I also documented that the observed compression of bid–ask spreads was accompanied by a decline in posted depth. The decline in depth was also most pronounced for the most actively traded stocks.

Because these findings suggest that decimalization had an ambiguous impact on market liquidity using spreads and depth as proxies for liquidity, I then estimated a different measure of liquidity that would be affected by changes in both spreads and depth. Specifically, I estimate the price impact of a trade for each stock in my sample. The price impact measures the percentage change in a stock's price that follows a trade. Larger price impacts, therefore, reflect lower liquidity. Intuitively, one would expect lower price increments to imply lower price impacts but lower depth

to imply higher price impacts. Thus, calculating price impacts before and after decimalization is one measure of stock market liquidity that encompasses changes in both spreads and depth.

Estimating price impact regressions, I find that actively traded stocks generally experienced an increase in liquidity (decrease in price impact) following decimalization. For less frequently traded stocks, the results were mixed. In particular, most stocks in the sample traded once every one to five minutes, and of these, only two in three experienced a statistically significant decline in average price impact following decimalization.

I then expanded my empirical framework to consider explicitly the fact that declines in posted depth may be more important for large trades, defined as those among the largest 10 percent of trades for a given stock. These large trades may be more likely to be executed at prices other than the best bid and ask price. I confirm that price impacts of these larger trades are greater, reflecting their lower liquidity. Even though these large trades have higher price impacts than other trades, I still find that decimalization generally improved the liquidity of large trades for actively traded stocks. However, I find no statistically significant improvement in liquidity of large trades for a wider set of stocks in my sample. For my set of stocks trading every one to five minutes, for example, only one in seven experienced a statistically significant increase in liquidity of large trades

following decimalization. The liquidity of large trades of most stocks after decimalization was statistically indistinguishable from their liquidity before. My findings were similar when I defined large trades as those whose size was greater than posted depth.

The findings in this study suggest that decimalization on the NYSE was a positive step because policymakers prefer more liquid markets. Virtually all actively traded stocks had improved levels of liquidity following decimalization using price impact as the liquidity measure, even if this improved liquidity was not realized by those making large trades. Thus, with respect to market liquidity, the lower willingness of market participants to post limit orders seems to be more than offset by the availability of a wider array of prices at which to trade.

In the two years since decimalization, spreads and depth have continued to fall. Actively traded stocks typically have average spreads of around 3 cents, whereas relatively infrequently traded stocks have spreads of around 6 cents. Thus, market developments suggest that it may not be long before one may ask whether minimum price increments of 1 cent should be abandoned. Even before decimalization, prices were not always equal to multiples of a penny, and thus, in principle, prices could be as finely divided as desired by traders. Perhaps, therefore, the optimal tick size is less than a penny.

NOTES

[1]A few months later, the National Association of Securities Dealers did the same for stocks trading on Nasdaq.

[2]Trades can affect prices for reasons of asymmetric information. This will be discussed later in the article.

[3]Monday, January 15, 2001, was a holiday.

[4]I eliminate observations spanning more than one business day.

[5]For the regressions, I do not include the middle week of my sample (that is, the week of January 29, 2001) to control for the possibility that market participants require a period of adjustment to a new quoting system.

[6]I choose five lags following Hasbrouck (1991). The results are robust to adjustments in lag length.

REFERENCES

Bacidore, Jeffrey M., Robert H. Battalio, and Robert H. Jennings, 2001, "Order submission strategies, liquidity supply, and trading in pennies on the New York Stock Exchange," Indiana University, mimeo.

Bessembinder, Hendrik, 2003, "Trade execution costs and market quality after decimalization," *Journal of Financial and Quantitative Analysis*, forthcoming.

Chakravarty, Sugato, Stephen P. Harris, and Robert A. Wood, 2001, "Decimal trading and market impact," Purdue University, working paper.

Glosten, Lawrence R., and Paul R. Milgrom, 1985, "Bid, ask, and transaction prices in a specialist market with heterogeneously informed traders," *Journal of Financial Economics*, Vol. 14, pp. 71–100.

Goldstein, Michael A., and Kenneth A. Kavajecz, 2000, "Eighths, sixteenths, and market depth: Changes in tick size and liquidity provision on the NYSE," *Journal of Financial Economics*, Vol. 56, pp. 125–149.

Harris, Lawrence E., 1994, "Minimum price variations, discrete bid-ask spreads, and quotation sizes," *Review of Financial Studies*, Vol. 7, No. 1, pp. 149–178.

Hasbrouck, Joel, 1991, "Measuring the information content of stock trades," *Journal of Finance*, Vol. 46, No. 1, pp. 179–207.

Lee, Charles M. C., and Mark J. Ready, 1991, "Inferring trade direction from intraday data," *Journal of Finance*, Vol. 46, No. 2, pp. 733–746.

Seppi, Duane J., 1997, "Liquidity provision with limit orders and a strategic specialist," *Review of Financial Studies*, Vol. 10, No. 1, pp. 103–150.