DECIMALIZATION, ETFS AND FUTURES PRICING EFFICIENCY

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This study investigates the impact of decimalization (penny pricing) on the arbitrage relationship between index exchange-traded funds and E-mini index futures. The empirical results reveal that subsequent to penny pricing, there is a significant fall in the mean ex ante arbitrage profit, especially in the cases with higher transaction costs. Using the ordinary least squares and quantile regressions to control for the influences of changes in other market characteristics, it is found that the overall pricing efficiency has deteriorated in the post-decimalization period. These results are consistent with the hypothesis that, due to the lowered market depth and increased execution risks, the introduction of decimalization has in general resulted in weakening the ability and the willingness of arbitrageurs to initiate arbitrage trades, which subsequently leads to a reduction in the general

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INTRODUCTION

Tick size is the minimum price variation allowed for quoting and trading in financial assets. For some considerable time, stocks on the New York Stock Exchange (NYSE) had been quoted in eighths of a dollar; however, on June 24, 1997, the NYSE reduced the tick size from one-eighth to one-sixteenth. Starting from January 29, 2001, all stocks traded on the NYSE and on the American Stock Exchange (AMEX) were subsequently quoted in decimals (i.e., penny pricing or decimalization).[1] The decimalization of the stock markets represents an important issue for market participants because it had potentially significant influences on market efficiency and market liquidity and, therefore, the overall functioning of the financial markets.

In this study, the authors analyze market pricing efficiency in the pre- and post-decimalization periods by examining the pricing efficiency and arbitrage relationship between exchange-traded funds (ETFs) and index futures. Although many studies have been undertaken on the influence of tick reductions on the equity markets, only a few studies have examined pricing efficiency across related markets following tick reductions (see, for example, Chou & Chung, 2006; Henker & Martens, 2005). This is, however, an important topic, since a structural change within one market may have significant impacts on another.

The decimalization of the U.S. stock markets has attracted considerable research attention. Proponents of penny pricing argue that the reduction in tick size would improve market quality and liquidity. They suggest that a smaller tick size would benefit liquidity demanders as competition between liquidity providers increases, which would induce a reduction in overall bid–ask spreads (Bollen & Whaley, 1998; Henker & Martens, 2005; Ronen & Weaver, 2001).

Opponents of penny pricing nevertheless argue that although such a change may have benefited certain liquidity demanders, this is to the detriment of liquidity providers (Chakravarty, Wood, & Van Ness, 2004; Graham, Michaely, & Roberts, 2003). The increase in the costs of providing liquidity would lead to a decline in their willingness to provide liquidity (Bollen & Busse, 2006; Goldstein & Kavajecz, 2000; Harris, 1994; Jones & Lipson, 2001).

[1]The NYSE lowered the tick size to a penny for 7 securities on August 28, 2000, for a further 57 securities on September 25, 2000, and an additional 94 securities on December 5, 2000. All remaining securities began trading in decimals on January 29, 2001. NASDAQ began converting to decimal pricing on March 12, 2001, and completed the process on April 9, 2001.

Regarding the efficiency of the cash/futures pricing system, proponents of decimalization also argue that the lower transaction costs should result in a general reduction in index futures mispricing errors (which provide the trigger for arbitrage trading), because the finer increments of stock prices benefit investors as the pricing increment dictates the smallest possible bid–ask spread for a given stock. However, this particular viewpoint ignores the importance of possible reductions in liquidity due to penny pricing. As noted by Kumar and Seppi (1994), arbitrage activities may be affected by liquidity. Roll, Schwartz, and Subrahmanyam (2007) empirically demonstrated that market liquidity enhances the efficiency of the futures/cash pricing system.

In their study of the impact of decimalization on institutional traders, Chakravarty, Panchapagesan, and Wood (2005) found that decimalization appears to have benefited those institutions with greater patience, whereas it may have hurt those seeking quick execution of trades. Since arbitrageurs require quick execution of their submitted orders, and since they must also be well capitalized, this implies that arbitrageurs are more likely to be institutional investors that demand quick execution of their trades.[2] Further, in order to cover transaction costs and make sufficient profits, arbitrageurs tend to take on large positions, which require a deep market. It is therefore argued that after decimalization, the benefits obtained by the arbitrageurs, due to the reduction in the bid–ask spread, may have been more than offset by their losses stemming from the reduction in market depth, which may ultimately affect the ability and the willingness of arbitrageurs to initiate arbitrage trades.

There are three possible explanations from the literature as to why arbitrageurs' profits may have suffered as a result of decimalization. First, arbitrageurs require a deep market when engaging in arbitrage activities. They would be affected by the fall in liquidity if liquidity providers are less willing to provide it due to lowered profitability of supplying liquidity following the move to penny pricing (Anshuman & Kalay, 1998).

Second, the execution risk would likely rise due to the reductions in average execution speed. A successful arbitrage trade carries almost no risk except for execution risks. Harris (1991) noted that a smaller tick size leads to an increase in the number of possible prices at which traders can trade, thereby complicating the negotiation process, and reducing the average speed of execution, which results in increased execution risk for arbitrageurs.

Third, a reduction in tick size may weaken the priority rules in the limit order book (Angel, 1997; Harris, 1994, 1996; Seppi, 1997). It lowers the cost of jumping ahead of existing orders in the book and gaining priority. It is likely that this activity, referred to as "front-running," would discourage investors

[2]Attari, Mello, and Ruckes (2005) noted that if arbitrageurs were not well capitalized, capital constraints would make their trades predictable.

from placing limit orders.[3] Front-running tends to reduce the profits of informed traders.[4] Harris (2003) argued that the long-run effect of front-running is to make prices less informative.[5]

Liquidity is composed of many factors, including market depth, trading volume, and the bid–ask spread. In this study, the focus is on the effect of changes in market depth after decimalization. Decimalization is an exogenous event. There have been extensive studies showing that market depth has been significantly lowered after decimalization. It is thus argued that less market depth after decimalization makes arbitrage activity less profitable, which in turn makes arbitrageurs less willing to engage in such activities and that eventually causes the pricing efficiency to deteriorate.

ETFs are used as the index proxies, which include both the S&P 500 Depositary Receipts (SPDRs) and the NASDAQ 100 Index Tracking Stocks (QQQs).[6] The sample index futures include the E-mini versions of the S&P 500 and NASDAQ 100 index futures.

This study differs from the extant literature in the following ways. First of all, the influences of penny pricing on pricing efficiency across closely related markets are analyzed, from the perspective of arbitrage opportunities; this is an area that has received relatively little attention in the literature. Chou and Chung (2006) found that ETFs began to lead index futures in the price discovery process after decimalization. However, they provided no evidence on the ways in which decimalization may have affected pricing efficiency.

Second, this study differs from Henker and Martens (2005), who studied the spot–futures arbitrage during the pre- and post-introduction of sixteenths on the NYSE. Their focus was on the examination of the size of the theoretical mispricing signals (i.e., the ex post arbitrage trading profits) with no consideration of either the transaction costs or the time lag involved in initiating arbitrage trades.

[3]Investors wary of front-runners would be more likely to conceal their true trading interest (depth) in a market with a lower minimum price variation. Harris (1996) argued that the minimum price increment should be economically significant in order to protect liquidity providers from quote matchers.

[4]Harris (2003) defined informed traders as value traders, news traders, information-oriented technical traders, and arbitrageurs.

[5]In December 2004, the Securities and Exchange Commission proposed Regulation National Market System (Reg NMS) to overhaul the structure of the nation markets. The sub-penny pricing rule of Reg NMS would prohibit market participants from displaying quotes in stocks that are priced in increments of less than a penny. The rule aims to prevent active traders from gaining execution priority by improving the price of another limit order by an economically insignificant amount. Thus, the sub-penny pricing rule of Reg NMS is consistent with the arguments on the effect of decimalization on front-running.

[6]On November 9, 2004, NASDAQ and the AMEX announced that the NASDAQ 100 Index Tracking Stock (listed under the symbol "QQQ") would be transferred from the AMEX to NASDAQ effective from December 1, 2004, where it would trade under the new symbol "QQQQ." In this study, the old symbol "QQQ" is used because the sample period covers the time when the old symbol was in effect.

Finally, the average pricing efficiency is analyzed by the ordinary least squares (OLS) regression, as well as the pricing efficiency of the entire distribution of mispricing sizes by the quantile regression. By controlling for the influence of the market characteristics on pricing efficiency, the OLS method would show the change in degree of mispricing on average; however, the quantile regression method could show the change in mispricing under various quantiles.

The remainder of this article is organized as follows. The second section describes the data and discusses the research methodology. The third section presents the empirical results on the efficiency of the cash/futures pricing system. The last section concludes the article.

DATA AND METHODOLOGY

Data

The sample ETFs include SPDRs and QQQs, and the sample E-mini futures include S&P 500 and NASDAQ 100 E-mini futures. The ETFs prices are usually scaled down in order to make them comparable to stock prices. The prices of SPDRs are $\frac{1}{10}$th of the S&P 500 index level and the prices of QQQs are $\frac{1}{40}$th of the NASDAQ 100 index level.[7] The respective contract sizes of S&P 500 and NASDAQ 100 E-mini futures are \$50 multiplied by the S&P 500 index level and \$20 multiplied by the NASDAQ 100 index level.

The sample covers the period July 27, 2000–July 30, 2001, a period which spans six months prior to, and six months after, the date of decimalization.[8] The data on ETFs, which include the tick-by-tick quote and trade prices, trading volume, and quoted depth, are obtained from the NYSE Trade and Quote database. Only regular AMEX quote and trade prices are used for ETFs. The corresponding data on E-mini futures, which include trade prices and number of trades, are obtained from the intraday database of Tick Data Inc.[9] The ETF dividend data are obtained from the University of Chicago's Center for Research in Security Prices database. The three-month T-Bill rates on the secondary market, obtained from the web-based Federal Reserve Board database, are used as the risk-free rate (as a proxy for the opportunity costs of arbitrage trades).[10]

[7]On February 14, 2000, NASDAQ announced that the Board of Directors of NASDAQ Investment Product Services, Inc. (the sponsors of QQQs) had approved a two-for-one stock split. The payment date for the stock split was March 17, 2000, payable to all stockholders held on record as at February 28, 2000. Therefore, the prices of QQQs became $\frac{1}{40}$th of the index level from $\frac{1}{20}$th at this date of split.

[8]On July 31, 2001, the NYSE began trading the DIAs, QQQs, and SPDRs listed on the AMEX on the unlisted trading privileges (UTP) basis. Boehmer and Boehmer (2003) showed that the introduction of UTP leads to an improvement in liquidity. In order to avoid any confounding effect, the authors confine their sample period up to this date.

[9]The quote data for index futures are unavailable, as is the case in most futures studies.

[10]The T-Bill rate data are obtained from web site: www.federalreserve.gov/releases/h15/data.htm.

For the intraday analyses, the daily T-Bill rates are transformed into continuous compounded rates, assuming constant rates within a day.

In order to ensure the accuracy of the sample data, all trades and quotes that are out of time sequence are deleted. The quotes that meet the following three conditions are also omitted: (i) either the bid or the ask price is equal to, or less than, zero; (ii) either the bid or the ask depth is equal to, or less than, zero; and (iii) either the price or the volume is equal to, or less than, zero. Data errors are further minimized by eliminating trades and quotes meeting those criteria in Huang and Stoll (1996).

The futures prices and ETF quotes are synchronized using the MINSPAN procedure suggested by Harris, McInish, Shoesmith, and Wood (1995). Every reported quote for an ETF is matched with the trading price of an E-mini future so as to form trading pairs. If there is a futures trade at the exact time of the reported ETF quote, then a pair is formed; if there is no futures trade at the exact time of the reported ETF quote, the futures trades within the previous and the subsequent seven seconds are then considered. When only one futures trade meets this criterion, a pair is formed. If both leading and lagging futures trades are obtained, the closer of the two trades is used to form the pair with the other trade being discarded.[11]

To address the potential non-synchronicity problem in matching trading pairs, all of the analyses are repeated using the data formed with the trading pairs matched with zero time gaps (i.e., 70% of the trading pairs that have exact time matches) to control for the potential non-synchronicity problem. It is found that the results are qualitatively similar to those based on the original samples. Thus, the non-synchronicity problem in matching trading pairs should have a minimal effect on the empirical results.

Although, on each trading day, futures contracts continue to trade until 4:15 P.M. Eastern Standard Time, the trading pairs are only formed until 4:00 P.M. The number of matches equals the minimum of the total number of index futures trades and the total number of ETF quotes. For SPDRs and S&P 500 E-mini futures, there are 301,018 observations in the pre-decimalization period and 322,524 in the post-decimalization period. For QQQs and NASDAQ 100 E-mini futures, there are 387,404 observations in the pre-decimalization period and 463,823 in the post-decimalization period.

Methodology

Using the cost-of-carry model, the ex ante no-arbitrage conditions are established between ETFs and E-mini futures as follows:

[11]The percentage of trading pairs matched with zero time gaps is about 70% and that of trading pairs matched with time gaps less than three seconds is close to 99%.

$$F(t) = [S(t) - Div(t)]e^{r(T-t)} \tag{1}$$

where $F(t)$ is the theoretical futures price at time t for a contract expiring at time T; $S(t)$ is the spot price of the underlying index at time t; r is the risk-free interest rate; and $Div(t)$ is the present value of the dividend for holding the underlying index from time t to time T. In a perfect market, if prices deviate from Equation (1), then arbitrageurs will simultaneously sell the overpriced instrument and buy the underpriced one.

The impact of transaction costs is to permit futures prices to fluctuate within a band around the theoretical price in Equation (1) without triggering profitable arbitrage opportunities, with the width of the band being dependent upon both the amount of the round-trip commission of trading spot and futures and the size of the market impact of arbitrage trades. The market impact costs can be measured by the bid–ask spread and the market depth. Taking transaction costs into consideration, the following equation describes the no-arbitrage band for the futures prices:

$$\begin{aligned}\{[S(t) - Div(t)]e^{r(T-t)}\}(1 - C_c - C_m) < F(t) \\ < \{[S(t) - Div(t)]e^{r(T-t)}\}(1 + C_c + C_m)\end{aligned} \tag{2}$$

where C_c and C_m represent commissions and market impact costs, respectively. If the futures price penetrates the upper bound, a long arbitrage trade will simultaneously buy the spot and short the futures and vice versa for a short arbitrage.

ETFs are used as the cash proxy and E-mini futures as the sample futures contract, assuming that an arbitrage trade is placed at time t and lifted at the futures expiration date T.[12] With commissions and spread costs (proxy for the market impact costs), the no-arbitrage bands between SPDRs and S&P 500 E-mini futures (ES) are as shown in the following equations:

$$\{10 \times [SPDR(t)_{bid} - SDiv(t)]e^{r(T-t)}\}(1 - C_c) < ES(t)_{ask} \tag{3}$$

$$\{10 \times [SPDR(t)_{ask} - SDiv(t)]e^{r(T-t)}\}(1 + C_c) > ES(t)_{bid} \tag{4}$$

and the no-arbitrage band between QQQs and NASDAQ 100 E-mini futures (NQ) is as shown in the following equations:

$$\{40 \times [QQQ(t)_{bid} - QDiv(t)]e^{r(T-t)}\}(1 - C_c) < NQ(t)_{ask} \tag{5}$$

$$\{40 \times [QQQ(t)_{ask} - QDiv(t)]e^{r(T-t)}\}(1 + C_c) > NQ(t)_{bid} \tag{6}$$

[12]As argued by previous studies (Chu & Hsieh, 2002; Kurov & Lasser, 2002), the introduction of ETFs has provided index futures arbitrageurs with an easy way of taking advantage of arbitrage opportunities and, hence, has also improved price efficiency.

where $SPDR(t)_{bid}$ is the SPDR bid price and $SPDR(t)_{ask}$ is the SPDR ask price at time t. $QQQ(t)_{bid}$ is the QQQ bid price and $QQQ(t)_{ask}$ is the QQQ ask price at time t.

The bid and ask prices are used to gauge the market impact costs, assuming that when trading in ETFs and E-mini futures, arbitrageurs can buy at the ask prices and sell at the bid prices. However, the bid and ask quotes for E-mini futures are unavailable. Kurov and Zabotina (2005) demonstrated that the minimum E-mini futures bid–ask spread is binding. Thus, the authors use the futures trade prices minus and plus one minimum tick size to proxy for the bid and ask prices of E-mini futures, respectively.[13]

Thus, $ES(t)_{bid}$ is the S&P 500 E-mini bid price and $ES(t)_{ask}$ is the S&P 500 E-mini ask price at time t. $NQ(t)_{bid}$ is the NASDAQ 100 E-mini bid price and $NQ(t)_{ask}$ is the NASDAQ 100 E-mini ask price at time t. $SDiv(t)$ and $QDiv(t)$ are the respective present values of the dividends of SPDRs and QQQs from time t to time T. As previously explained, since ETF prices are usually scaled down to make them comparable to those of stocks, adjusting factors of 10 and 40 are added.

The transaction costs, C_c, in Equations (3)–(6) are composed of trading commissions. An approach similar to that of Chung (1991) and Chu and Hsieh (2002) is adopted, in which several levels of commission are assumed when measuring the arbitrage profits. The levels of one-way transaction costs are set as from 0.05 to 0.5% of the theoretical futures price with 0.05% increments.[14]

It is further assumed that arbitrageurs can trade at the next available ETF quote and futures trade prices immediately after observing a mispricing signal, which would yield more reasonable estimates of the profits that arbitrageurs are expected to make ex ante. The respective ex ante profits of long ($ESAP_L$) and short ($ESAP_S$) arbitrage trades, between SPDRs and S&P 500 E-mini futures, are measured by Equations (7) and (8). Similarly, Equations (9) and (10) measure the respective ex ante profits of long ($NQAP_L$) and short ($NQAP_S$) arbitrage between QQQs and NASDAQ 100 E-mini futures:

$$ESAP_L = ES(t^+)_{bid} - \{10 \times [SPDR(t^+)_{ask} - SDiv(t)]e^{r(T-t^+)}\}(1 + C_c) \quad (7)$$

$$ESAP_S = \{10 \times [SPDR(t^+)_{bid} - SDiv(t)]e^{r(T-t^+)}\}(1 - C_c) - ES(t^+)_{ask} \quad (8)$$

[13]The E-mini futures trades and ETF quotes are synchronized using the MINSPAN procedure suggested by Harris et al. (1995). However, there are still possible spread pricing errors and one tick variations may be too narrow for estimating the bid–ask spread of the E-mini futures. In order to check the robustness of the results, various measures for the E-mini quotes and trade prices are used and additional empirical analyses are performed as follows: (i) two minimum tick sizes are adjusted to the E-mini trade prices; (ii) ETF trades are matched with E-mini trades, both adjusted for two minimum tick sizes; (iii) two minimum tick sizes are adjusted to the E-mini trade prices and the sample estimated effective spreads are adjusted to the ETF trade prices. The results are qualitatively similar and do not change the inferences.

[14]Following Chu and Hsieh (2002) and Kurov and Lasser (2002), the specification covers most ranges of transaction costs proposed in the literature.

$$NQAP_L = NQ(t^+)_{bid} - \{40 \times [QQQ(t^+)_{ask} - QDiv(t)]e^{r(T-t^+)}\}(1 + C_c) \quad (9)$$

$$NQAP_S = \{40 \times [QQQ(t^+)_{bid} - QDiv(t)]e^{r(T-t^+)}\}(1 - C_c) - NQ(t^+)_{ask} \quad (10)$$

where t^+ indicates the time of the first quote (trade) price of ETFs (E-mini futures) immediately after the mispricing signal is observed and all other variables are defined similarly as those in Equations (3)–(6).

The empirical methodologies up to now focus on the ex ante mispricing errors. However, the changes in pricing efficiency can be affected by the changes in market factors other than decimalization. Thus Chung (1991) and Kurov and Lasser (2002) are followed to control for other factors.

The change in average futures mispricing is considered after the introduction of decimalization by using an autoregressive regression model as defined in the following equation:

$$|x_t| = \beta_0 + \beta_1 D_t^{decimal} + \beta_2 D_t^{open} + \beta_3 D_t^{close} + \beta_4 Vol_t + \beta_5 NT_t + \beta_6 ET_t + \beta_7 TE_t + \sum_{i=1}^{\tau} \varphi_i |x_{t-i}| + \varepsilon_t \quad (11)$$

where t denotes the five-minute time interval.[15] $|x_t|$ is the average absolute pricing error during time period t, defined similar to that in Kurov and Lasser (2002):

$$x_t = \frac{F_t - F_t^*}{ETF \times f} \quad (12)$$

where F_t is the actual futures price, F_t^* is the theoretical value from the cost-of-carry model, and f is the adjusting factor for ETF prices. $D_t^{decimal}$ is a dummy variable that equals 0 for the pre-decimalization period and 1 thereafter; D_t^{open} and D_t^{close} are dummy variables indicating the market opening and the market closing five-minute intervals.

Vol_t is the Parkinson (1980) extreme value estimator to proxy for ETF volatility. NT_t is the number of ETFs trades during time period t, ET_t is the annualized time to expiration of the futures contract during time period t, and TE_t is the previous day's absolute tracking error of ETFs, calculated as the absolute difference in return of the net asset value of ETFs and the benchmark index. The dummy variable, $D_t^{decimal}$, is included in the regression to test for the structural shift in mispricing after decimalization. A positive (negative) and significant coefficient of the dummy variable will indicate an increase (decrease) in average absolute mispricing. The dummy variables D_t^{open} and D_t^{close} are included in the regression to control the market open and close effects. The number of

[15]Tests are also performed with variables defined over the three-minute intervals and the results are qualitatively similar.

lagged error terms, τ, is equal to six and eight periods for SPDRs and QQQs, respectively.[16]

A significant positive relation is expected between volatility and pricing errors (Chan & Chung, 1993; Yadav & Pope, 1994). It is conjectured that there is a significant negative relation between number of trades and average mispricing, as number of trades is a proxy for information arrivals (Jones, Kaul, & Lipson, 1994). The possible effect of tracking error by ETFs on the arbitrage opportunity is also controlled.

To analyze the entire distribution of mispricing, Equation (11) is further estimated by a linear quantile regression model proposed by Koenker and Bassett (1978). This approach permits estimating various quantile functions of a conditional distribution. Among them, the median (0.5th quantile) function is a special case, which is also referred to as the least absolute deviations (LAD) regression.[17] Connolly (1989) advocated the use of the LAD regression as an alternative to solve for the low-power problem of the OLS regression due to large sample sizes. Furthermore, the results from different quantile regressions provide a more complete description of the underlying conditional distribution of pricing errors.

EMPIRICAL RESULTS

Summary Statistics

Table I reports the summary statistics. As expected, after decimalization, there are decreases in bid–ask spreads and quoted depth, and these is an increase in the average daily trading volume for SPDRs and QQQs. This result is consistent with those found in the prior studies (for example, Chou & Chung, 2006; Gibson, Singh, & Yerramilli, 2003). As argued above, a smaller spread size may not necessarily be advantageous to arbitrageurs due to the simultaneously lowered market depth.

Such reduction in market depth of ETFs is likely to harm arbitrageurs, who usually trade large positions in order to realize the arbitrage profits. Even though the average quoted depth for both ETFs seems to be large, the standard deviation of the quoted depth indicates that the quoted depth is quite volatile. Thus, it is very likely that arbitrageurs will experience times when the market depth is low and thus face high execution risk.

From Table I, it is found that there is a decrease (increase) in the average absolute mispricing errors for QQQs (SPDRs) after decimalization. From the

[16]Durbin's alternative statistic is used to test for the serial correlation problem. The test results indicate that there are no first-, second-, and third-order serial correlations presented when the number of lag periods is set to six and eight periods for SPDRs and QQQs, respectively.
[17]A detailed explanation of the estimation procedure is provided in Koenker (2005).

TABLE I
Summary Statistics

	Pre-Decimalization (July 27, 2000–January 28, 2001)	*Post-Decimalization (January 29, 2001–July 30, 2001)*	*Entire Period (July 27, 2000–July 30, 2001)*
Panel A: SPDRs and S&P 500 E-mini			
No. of trading days	127	127	254
No. of obs. (ETF–futures trades pairs)	131,049	205,971	337,020
No. of obs. (ETF–futures quotes pairs)	301,018	322,524	623,542
Average absolute mispricing errors (%)	0.0942 (0.0787)	0.0842 (0.0560)	0.0881 (0.0660)
A1: SPDRs			
Average bid–ask spread	0.1366 (0.0323)	0.1216 (0.0443)	0.1287 (0.0398)
Average quoted depth (100 shares)	3,283 (2,434)	1,526 (2,244)	2,358 (2,495)
Average daily trading volume (100 shares)	54,605 (22,287)	72,454 (26,433)	63,530 (25,987)
Average no. of trades per five minutes	13.74 (7.75)	21.66 (10.54)	17.70 (10.06)
Average daily close price	140.26	123.80	132.03
Annualized std. dev. Of daily return (%)	22.19	22.53	22.28
Market quality index (MQI)	166.80	76.75	119.15
A2: S&P 500 E-mini			
Average days to maturity	54.42 (26.10)	56.60 (27.94)	55.51 (27.01)
Average no. of trades per five minutes	333.35 (168.65)	443.15 (223.66)	388.19 (205.51)
Panel B: QQQs and NASDAQ 100 E-mini			
No. of trading days	127	127	254
No. of obs. (ETF–futures trades pairs)	358,905	408,859	767,764
No. of obs. (ETF–futures quotes pairs)	387,404	463,823	851,227
Average absolute mispricing errors (%)	0.3349 (0.1534)	0.3910 (0.1187)	0.3648 (0.1389)
B1: QQQs			
Average bid–ask spread	0.1151 (0.0697)	0.0615 (0.0417)	0.0853 (0.0619)
Average quoted depth (100 shares)	132 (162)	108 (201)	119 (185)
Average daily trading volume (100 shares)	254,978 (116,058)	344,598 (112,590)	299,788 (122,626)
Average no. of trades per five minutes	39.52 (10.44)	45.65 (12.13)	42.58 (11.72)
Average daily close price	79.07	46.33	62.70
Annualized std. dev. of daily return (%)	63.33	55.98	59.59
Market quality index (MQI)	4.37	4.01	4.18
B2: NASDAQ 100 E-mini			
Average days to maturity	54.41 (26.10)	56.59 (27.95)	55.50 (27.01)
Average no. of trades per five minutes	458.32 (243.01)	630.32 (312.98)	544.26 (293.06)

Note. The table reports summary statistics for ETFs and their corresponding E-mini futures. Quoted depth is calculated as $(Q_{ask}+Q_{bid})$ and bid–ask spread is calculated as $(P_{ask}-P_{bid})$, where P_{ask} is the ask price, P_{bid} is the bid price, Q_{ask} is the depth at ask, and Q_{bid} is the depth at bid. The market quality index (MQI) is calculated as $[(Q_{ask}+Q_{bid})/10{,}000/2]/[(P_{ask}-P_{bid})/[(P_{ask}+P_{bid})/2]\times 100]$ and the absolute mispricing error is calculated as $|F_M-F_T|/(ETF\times f)$, where f is the adjusting factor for ETF prices, F_M is the futures market price, and F_T is the futures theoretical price. Figures in parentheses are standard deviations. SPDR, S&P 500 Depositary Receipts; ETF, exchange-traded fund; NASDAQ, National Association of Securities Dealers Automated Quotation System.

summary statistics of pricing errors, it seems that no definite conclusions can be made regarding the cash/futures pricing efficiency after decimalization, which might be caused by failing to control for changes in other market factors, an issue that will be addressed later by the OLS and quantile regressions. The authors further gauge the overall market quality by adopting a market quality index (MQI) (Bollen & Whaley, 1998). MQI is the ratio between the half-quoted depth of the prevailing bid–ask quotes and the percentage quoted spread. As can be seen from Table I, there is significant deterioration in market quality after decimalization, as measured by the MQI.

Ex Ante Arbitrage Profit Analyses

In this section, the results of the ex ante analyses are reported under the assumption that arbitrageurs can only transact at the next available prices after observing a mispricing signal.[18] Tables II and III present the results for SPDRs and QQQs surrounding decimalization, respectively. As Table II reports, under different levels of transaction costs, there are significant decreases in the number and percentage of profitable trades for SPDRs after decimalization. Table III, on the contrary, reports substantial increases in the number and percentage of profitable trades for QQQs after decimalization.

Nevertheless, from Tables II and III, it is seen that the ex ante mean arbitrage profits decrease for both SPDRs and QQQs, and the correlation of signal and profit is lower after penny pricing. Interestingly, the decreases in mean arbitrage profits are relatively more significant at higher levels of transaction costs, when the required mispricing signals are large. This indicates that pricing efficiency changes are likely to be different for mispricing signals of different sizes.

The decrease in minimum tick size makes the boundary conditions to be tighter and tends to make smaller mispricing signals; thus a decrease in mispricing signals also implies decreased mean arbitrage profits after decimalization and this does not necessarily indicate an improvement in pricing efficiency. However, due to the simultaneous reduction in quoted depth, and the increase in execution risk, it is much more difficult for arbitrageurs to initiate profitable arbitrage trades when they observe small mispricing signals.

The order sizes of arbitrageurs need to be large to cover the transaction costs; thus price concessions may be more prevalent in terms of working through the book. Additional information on profitable trades is provided with sufficient sizes in Tables II and III. As seen from Tables II and III, the ratios of trades with sufficient ETF quote size (trades with ETF quote sizes greater than one or two times the required offsetting positions) to all profitable trades decrease substantially after decimalization. This result is consistent with the hypothesis that decimalization is likely to reduce the feasibility of arbitrage trades due to the reduction in profitable quote sizes.

[18]The assumption of trading at the next available quotes should be reasonable because the average time span between the tick-by-tick trades are about 9.46 and 6.94 seconds for SPDRs and QQQs, respectively, which would be sufficient for arbitrageurs who closely monitor the market.

TABLE II

Ex Ante Arbitrage Analyses for SPDRs and S&P 500 E-Mini Futures

Transaction Costs (%)	*Number of Violations*	*Profitable Trades*	*Profitable Trades as % of All Trades (%)*	*Median of Profitable Trade Sizes (100 shares) (Std. Dev.)*		*Trades With Size >500 Shares as % of Profitable Trades (%)*	*Trades With Sizes >1,000 Shares as % of Profitable Trades (%)*	*Average Signal (Std. Dev.)*		*Average Profit (Std. Dev.)*		*Correlation of Signal and Profit (p-Value)*	
Panel A: Pre-Decimalization (July 27, 2000–January 28, 2001)													
0.05	97,052	85,723	88.33	5,000	(2,356.00)	97.85	83.99	0.8676	(0.7289)	0.8001	(0.8058)	0.8477	(<0.0001)
0.10	51,030	42,690	83.66	5,000	(2,397.32)	97.72	82.90	0.6286	(0.6972)	0.5370	(0.7749)	0.8227	(<0.0001)
0.20	3,250	2,003	61.63	200	(2,463.29)	92.71	68.70	0.6288	(1.8628)	0.3544	(1.9405)	0.8937	(<0.0001)
0.30	207	157	75.85	4,998	(2,115.15)	90.45	85.99	3.9332	(5.5026)	3.2152	(5.9267)	0.8888	(<0.0001)
0.40	111	91	81.98	4,997	(1,890.31)	93.41	92.31	5.6452	(6.0114)	4.6436	(6.8690)	0.8644	(<0.0001)
0.50	78	64	82.05	4,935	(2,120.22)	90.63	89.06	6.3624	(6.0732)	5.2624	(7.1859)	0.8467	(<0.0001)
Panel B: Post-Decimalization (January 29, 2001–July 30, 2001)													
0.05	81,250	64,508	79.39	10	(1,510.77)	88.53	43.32	0.4357	(0.3587)	0.3302	(0.4674)	0.6229	(<0.0001)
0.10	20,182	12,674	62.80	10	(1,137.98)	79.67	36.15	0.2900	(0.3468)	0.0971	(0.4848)	0.5271	(<0.0001)
0.20	191	89	46.60	12	(2,399.30)	79.78	50.56	1.0461	(1.8296)	0.3226	(2.2563)	0.5388	(<0.0001)
0.30	36	23	63.89	4,730	(2,485.85)	86.96	65.22	2.8677	(2.4379)	1.3992	(4.1028)	0.2765	(0.1026)
0.40	25	16	64.00	2,281	(2,529.64)	87.50	56.25	2.7175	(2.1589)	0.3362	(4.6920)	0.3537	(0.0828)
0.50	17	10	58.82	4,845	(2363.19)	90.00	70.00	2.4601	(1.9545)	−0.3359	(5.1468)	0.3478	(0.1713)

Note. The ex ante tests impose an execution lag for trading in SPDRs and S&P 500 E-mini futures, and thus the ex ante mean profits are arbitrage profits after considering the transaction lag. A long arbitrage ($ESAP_L$), triggered by futures overpricing, buys 500 SPDR shares and shorts an S&P 500 E-mini futures contract after observing an upper-boundary violation, whereas a short arbitrage ($ESAP_S$), triggered by futures underpricing, executes the reverse transactions. Profits for long and short arbitrage are measured as

$$ESAP_L = ES(t^+)_{bid} - \{10 \times [SPDR(t^+)_{ask} - SDiv(t^+)]e^{r(T-t^+)}\}(1 + C_c) \text{ and}$$

$$ESAP_S = \{10 \times [SPDR(t^+)_{bid} - SDiv(t^+)]e^{r(T-t^+)}\}(1 - C_c) - ES(t^+)_{ask}$$

where t^+ indicates the time of the first quote (trade) price of ETFs (E-minis) immediately after observation of the mispricing signal; $SPDR(t^+)_{bid}$ is the SPDR bid price and $SPDR(t^+)_{ask}$ is the SPDR ask price at time t^+; $ES(t^+)_{bid}$ is the S&P 500 E-mini futures bid price and $ES(t^+)_{ask}$ is the S&P 500 E-mini futures ask price at time t^+; $SDiv(t^+)$ refers to the present value of the SPDR dividend from time t^+ to time T; and C_c is the trade commission. Since SPDR prices are $\frac{1}{10}$th of the index level, an adjustment factor of 10 is applied. SPDR, S&P 500 Depositary Receipts; ETF, exchange-traded fund.

TABLE III

Ex Ante Arbitrage Analyses for QQQs and NASDAQ 100 E-Mini Futures

Transaction Costs (%)	*Number of Violations*	*Profitable Trades*	*Profitable Trades as % of All Trades (%)*	*Median of Profitable Trade Sizes (100 shares) (Std. Dev.)*	*Trades With Size >800 Shares as % of Profitable Trades (%)*	*Trades With Sizes >1,600 Shares as % of Profitable Trades (%)*	*Average Signal (Std. Dev.)*	*Average Profit (Std. Dev.)*	*Correlation of Signal and Profit (p-Value)*
Panel A: Pre-Decimalization (July 27, 2000–January 28, 2001)									
0.05	353,120	341,812	96.80	19 (149.59)	65.32	51.59	6.4107 (3.5484)	6.2775 (3.7377)	0.8204 (<0.0001)
0.10	324,440	306,998	94.62	18 (148.95)	64.57	50.84	5.2944 (3.3139)	5.0962 (3.5671)	0.8046 (<0.0001)
0.20	223,104	197,362	88.46	15 (154.45)	62.23	48.66	3.7663 (2.7843)	3.3872 (3.2056)	0.7413 (<0.0001)
0.30	116,932	94,684	80.97	13 (148.17)	59.28	46.17	2.7937 (2.4158)	2.1832 (3.0194)	0.6566 (<0.0001)
0.40	44,967	32,573	72.44	10 (143.48)	55.85	43.63	2.3261 (2.3776)	1.4054 (3.1803)	0.5855 (<0.0001)
0.50	14,839	9,875	66.55	10 (157.36)	53.40	41.81	2.1576 (2.7303)	0.9230 (3.6393)	0.5355 (<0.0001)
Panel B: Post-Decimalization (January 29, 2001–July 30, 2001)									
0.05	446,619	440,968	98.73	10 (200.74)	62.55	43.94	4.6321 (1.9583)	4.5937 (2.0357)	0.8076 (<0.0001)
0.10	432,848	423,466	97.83	10 (202.24)	62.41	43.84	3.8367 (1.8439)	3.7794 (1.9445)	0.7943 (<0.0001)
0.20	367,937	345,420	93.88	10 (200.50)	61.39	43.03	2.4794 (1.5547)	2.3574 (1.7246)	0.7432 (<0.0001)
0.30	228,519	195,022	85.34	10 (184.59)	58.00	40.64	1.5732 (1.2649)	1.3277 (1.5373)	0.6441 (<0.0001)
0.40	82,145	59,928	72.95	10 (174.07)	51.92	36.51	1.1202 (1.1585)	0.6655 (1.5792)	0.4905 (<0.0001)
0.50	17,507	10,394	59.37	5 (168.30)	45.57	31.79	0.9901 (1.5165)	0.1695 (2.1472)	0.3546 (<0.0001)

Note. The ex ante tests impose an execution lag for trading QQQs and NASDAQ 100 E-mini futures, and thus the ex ante mean profits are arbitrage profits after considering the transaction lag. A long arbitrage ($NQAP_L$), triggered by futures overpricing, buys 800 QQQ shares and shorts a NASDAQ 100 E-mini futures contract after the observation of an upper-boundary violation, whereas a short arbitrage ($NQAP_S$), triggered by futures underpricing, executes the reverse transactions. Profits for the long and short arbitrage are measured as

$$NQAP_L = NQ(t^+)_{bid} - \{40 \times [QQQ(t^+)_{ask} - QDiv(t^+)]e^{r(T-t^+)}\}(1 + C_c) \text{ and}$$
$$NQAP_S = \{40 \times [QQQ(t^+)_{bid} - QDiv(t^+)]e^{r(T-t^+)}\}(1 - C_c) - NQ(t^+)_{ask}$$

where t^+ indicates the time of the first quote (trade) price of ETFs (E-minis) immediately after observation of the mispricing signal; $QQQ(t^+)_{bid}$ is the QQQ bid price and $QQQ(t^+)_{ask}$ is the QQQ ask price at time t^+; $NQ(t^+)_{bid}$ is the NASDAQ 100 E-mini futures bid price and $NQ(t^+)_{ask}$ is the NASDAQ 100 E-mini futures ask price at time t^+; $QDiv(t^+)$ refers to the present value of the QQQ dividend from time t^+ to time T; and C_c is the trade commission. Since QQQ prices are 1/40th of the index level, an adjustment factor of 40 is applied. NASDAQ, National Association of Securities Dealers Automated Quotation System; ETF, exchange-traded fund.

Therefore, arbitrageurs will only participate in trading when there is sufficient profit to be made, i.e., when the mispricing signal is large enough to cover the increased execution risk. It is argued that the pricing efficiency may be improved only when the mispricing signal is sufficiently large. The overall pricing efficiency might actually deteriorate after decimalization. In order to test this assertion, the attention is now turned to the analyses of the changes in the entire distribution of mispricing signals.

Regression Analyses of Mispricing

Inferences on improvements in the cash/futures pricing efficiency after decimalization could be affected by changes in market conditions over the sample period. The decimal dummy, open dummy, close dummy, volatility, number of ETFs trades, time-to-maturity, and pricing errors are employed as control variables. Let θ denote quantile for which the relation between mispricing and explanatory variables is estimated. The authors estimate coefficients of quantile regression at θ from 0.05 to 0.95 with a 0.05 increment.[19] They also consider two additional extreme percentiles, i.e., $\theta = 0.99$ and 0.01, to observe the changes in pricing efficiency when large arbitrage opportunities are present. The statistical inferences of the quantile regression coefficients are drawn by the bootstrapping method.[20]

The OLS regression is first estimated to examine changes in degree of average mispricing. As demonstrated in Tables IV and V, the positively significant OLS coefficients of decimal dummy indicate higher pricing errors after decimalization and imply that the pricing efficiency of the cash/futures system has become significantly worse on average after decimalization.

The sample size is large. Thus, to avoid the impact of large sample size on classical hypothesis testing procedures in OLS, the authors also apply the Bayesian sample size-adjusted critical t-value, t^*, as suggested by Connolly (1989):

$$t^* = [(T - k)(T^{1/T} - 1)]^{0.5} \tag{13}$$

where k is the number of parameters estimated and T is the sample size. Based on the number of parameters estimated in the regressions and the sample size, the proper sample size-adjusted critical value of t^* is about 3.14. It is illustrated in Tables IV and V that using the Bayesian sample size-adjusted critical t-value does not change the inferences, because the coefficients of the decimal dummy are still significantly positive under the adjusted t-values. Also from Tables IV

[19]Since the inferences based on the results of all quantiles examined are consistent, to save space, the authors only report part of the quantile regression results in the tables.
[20]For details, see Eforn (1982), De Angelis, Hall, and Young (1993), and Andrews and Buchinsky (2000, 2001).

TABLE IV

Mispricing Analyses for the Relationship Between SPDRs and S&P 500 E-Mini Futures Using OLS and Quantile Regressions

		Quantile Regression (θ)						
Variable	*OLS*	*0.99*	*0.95*	*0.9*	*0.85*	*0.8*	*0.75*	*0.7*
$D^{decimal}$	0.025***	−0.033	−0.050***	−0.036***	−0.027***	−0.018***	−0.014***	−0.007*
	(<0.001)#	(0.148)	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.002)	(0.074)
D^{open}	0.114***	0.825	0.622***	0.482***	0.353***	0.313***	0.263***	0.218***
	(<0.001)#	(0.176)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
D^{close}	0.044***	0.057	0.042*	0.032	0.034*	0.039**	0.037**	0.032**
	(0.002)	(0.220)	(0.058)	(0.143)	(0.068)	(0.011)	(0.017)	(0.046)
Vol	0.921***	2.946***	1.440***	1.004***	0.810***	0.665***	0.531***	0.456***
	(<0.001)#	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
NT	−0.063***	−0.179***	−0.082***	−0.063***	−0.053***	−0.044***	−0.036***	−0.029***
	(<0.001)#	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
ET	0.029	0.004	−0.027	0.020	0.039	0.033	0.029	0.021
	(0.201)	(0.969)	(0.530)	(0.508)	(0.148)	(0.209)	(0.213)	(0.341)
TE	−0.001	0.046	0.033***	0.018*	0.008	0.005	0.007	0.007
	(0.883)	(0.128)	(0.004)	(0.063)	(0.358)	(0.393)	(0.241)	(0.188)
$\|x_{t-1}\|$	0.405***	0.598***	0.386***	0.354***	0.344***	0.337***	0.329***	0.323***
	(<0.001)#	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\|x_{t-2}\|$	0.156***	0.174***	0.229***	0.202***	0.201***	0.202***	0.205***	0.206***
	(<0.001)#	(0.002)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\|x_{t-3}\|$	0.108***	0.123***	0.149***	0.148***	0.150***	0.148***	0.150***	0.148***
	(<0.001)#	(0.002)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\|x_{t-4}\|$	0.079***	0.033	0.085***	0.127***	0.123***	0.125***	0.117***	0.116***
	(<0.001)#	(0.436)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\|x_{t-5}\|$	0.094***	0.145***	0.135***	0.123***	0.129***	0.124***	0.113***	0.116***
	(<0.001)#	(0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\|x_{t-6}\|$	0.109***	0.054	0.085***	0.097***	0.092***	0.089***	0.102***	0.100***
	(<0.001)#	(0.291)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Constant	0.088***	0.529***	0.306***	0.234***	0.190***	0.153***	0.123***	0.091***
	(<0.001)#	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
R^2	0.8088	0.6274	0.6552	0.6631	0.6653	0.6659	0.6645	0.6620

$D^{decimal}$	0.001	0.007*	0.014***	0.021***	0.029***	0.042***	0.046***	0.038***
	(0.880)	(0.057)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
D^{open}	0.160***	0.134***	0.105***	0.032	−0.020	−0.154	−0.466***	−0.315***
	(<0.001)	(<0.001)	(<0.001)	(0.276)	(0.595)	(0.194)	(<0.001)	(<0.001)
D^{close}	0.019	0.015	0.011	0.014	0.022**	0.003	−0.003	−0.011
	(0.185)	(0.243)	(0.306)	(0.244)	(0.047)	(0.875)	(0.911)	(0.750)
Vol	0.362***	0.244***	0.154***	0.069*	−0.049	−0.177***	−0.275***	−0.071
	(<0.001)	(<0.001)	(<0.001)	(0.053)	(0.228)	(0.001)	(<0.001)	(0.566)
NT	−0.021***	−0.012***	−0.003	0.003	0.012***	0.024***	0.038***	0.052***
	(<0.001)	(0.001)	(0.402)	(0.313)	(0.003)	(<0.001)	(<0.001)	(<0.001)
ET	0.023	0.013	0.013	0.020	−0.016	−0.044	−0.037	−0.037
	(0.222)	(0.494)	(0.545)	(0.358)	(0.484)	(0.161)	(0.310)	(0.575)
TE	<0.001	−0.004	−0.008	−0.005	−0.002	−0.008	−0.013	−0.001
	(0.964)	(0.473)	(0.133)	(0.325)	(0.716)	(0.244)	(0.256)	(0.926)
$\|x_{t-1}\|$	0.328***	0.331***	0.321***	0.302***	0.311***	0.293***	0.296***	0.267***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\|x_{t-2}\|$	0.189***	0.179***	0.174***	0.180***	0.169***	0.166***	0.150***	0.101***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.007)
$\|x_{t-3}\|$	0.151***	0.149***	0.146***	0.142***	0.126***	0.119***	0.084***	0.029
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.002)	(0.542)
$\|x_{t-4}\|$	0.119***	0.112***	0.111***	0.104***	0.101***	0.097***	0.106***	0.045
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.287)
$\|x_{t-5}\|$	0.111***	0.112***	0.111***	0.115***	0.106***	0.093***	0.075**	0.021
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.018)	(0.630)
$\|x_{t-6}\|$	0.101***	0.101***	0.103***	0.102***	0.104***	0.088***	0.075***	0.064*
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.006)	(0.067)
Constant	0.046***	0.006	−0.035***	−0.073***	−0.109***	−0.146***	−0.181***	−0.165***
	(<0.001)	(0.460)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
R^2	0.6543	0.6397	0.6174	0.5868	0.5446	0.4763	0.4162	0.2962

Note. The change in average futures mispricing after the introduction of decimalization is tested by an autoregressive model with six lags defined in the following equation:

$$|x_t| = \beta_0 + \beta_1 D_t^{decimal} + \beta_2 D_t^{open} + \beta_3 D_t^{close} + \beta_4 Vol_t + \beta_5 NT_t + \beta_6 ET_t + \beta_7 TE_t + \sum_{i=1}^{6} \varphi_i |x_{t-i}| + \epsilon_t$$

where t denotes one of the five-minute time periods; $|x_t|$ is the average absolute mispricing error during time period t; $D_t^{decimal}$ is a dummy variable that equals 0 during the pre-decimalization period and 1 afterward; D_t^{open} and D_t^{close} are dummy variables that, respectively, control for the open and close interval effects; Vol_t is the Parkinson (1980) extreme value estimator, which is used to be a proxy for volatility; NT_t is the number of SPDRs trades during time period t; ET_t is the time to expiration of the S&P 500 E-mini futures contract during time period t; and TE_t is the previous day's absolute tracking error of SPDRs. In addition, six lags of the dependent variable in the regression model are employed to eliminate autocorrelation in the regression residuals. OLS method and a linear quantile regression model proposed by Koenker and Bassett (1978) are adopted to estimate this equation. The total number of time periods is 19,632. Figures in parentheses are p-values. "***," "**," and "*" represent significance levels of 1, 5, and 10%, respectively, for the traditional t-test. The Bayesian sample size-adjusted critical t-value, t^*, suggested by Connolly (1989) is further applied. Based on the sample size, the sample size-adjusted critical value of t^* is 3.14. The "#" sign by the OLS p-value indicates that the t-value reaches the sample size-adjusted critical value of 3.14. SPDR, S&P 500 Depositary Receipts; OLS, ordinary least squares.

TABLE V

Mispricing Analyses for the Relationship Between QQQs and NASDAQ 100 E-Mini Futures Using OLS and Quantile Regressions

		Quantile Regression (θ)						
Variable	*OLS*	*0.99*	*0.95*	*0.9*	*0.85*	*0.8*	*0.75*	*0.7*
$D^{decimal}$	0.107***	−0.076	−0.035**	−0.030**	−0.017**	0.001	0.005	0.013
	(<0.001)#	(0.109)	(0.017)	(0.011)	(0.047)	(0.872)	(0.558)	(0.106)
D^{open}	0.087**	11.653*	0.759	0.047	0.019	−0.099*	−0.084***	−0.088*
	(0.015)	(0.078)	(0.279)	(0.676)	(0.842)	(0.055)	(0.008)	(0.088)
D^{close}	0.073**	0.074	0.184***	0.111**	0.124***	0.103**	0.093***	0.078**
	(0.042)	(0.457)	(<0.001)	(0.018)	(<0.001)	(0.017)	(0.009)	(0.020)
Vol	0.484***	2.364***	1.466***	1.093***	0.909***	0.717***	0.622***	0.500***
	(<0.001)#	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
NT	−0.099***	−0.350***	−0.177***	−0.147***	−0.124***	−0.100***	−0.090***	−0.071***
	(<0.001)#	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
ET	1.272***	0.323	0.589***	0.388***	0.424***	0.433***	0.492***	0.495***
	(<0.001)#	(0.378)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
TE	0.006	0.061	0.011	−0.002	−0.003	<0.001	−0.001	<0.001
	(0.215)	(0.153)	(0.196)	(0.744)	(0.422)	(0.930)	(0.712)	(0.999)
$\lvert x_{t-1}\rvert$	0.369***	0.533***	0.273***	0.242***	0.226***	0.217***	0.203***	0.204***
	(<0.001)#	(0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\lvert x_{t-2}\rvert$	0.017**	0.090	0.134***	0.160***	0.163***	0.165***	0.163***	0.160***
	(0.023)	(0.136)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\lvert x_{t-3}\rvert$	0.094***	0.076	0.122***	0.115***	0.116***	0.119***	0.130***	0.132***
	(<0.001)#	(0.216)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\lvert x_{t-4}\rvert$	0.077***	0.050	0.124***	0.123***	0.116***	0.122***	0.120***	0.117***
	(<0.001)#	(0.240)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\lvert x_{t-5}\rvert$	0.058***	0.045	0.074***	0.085***	0.088***	0.089***	0.090***	0.094***
	(<0.001)#	(0.380)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\lvert x_{t-6}\rvert$	0.091***	0.076	0.097***	0.097***	0.099***	0.095***	0.091***	0.092***
	(<0.001)#	(0.118)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\lvert x_{t-7}\rvert$	0.060***	0.049	0.058***	0.066***	0.080***	0.081***	0.085***	0.082***
	(<0.001)#	(0.302)	(0.003)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\lvert x_{t-8}\rvert$	0.084***	0.068	0.082***	0.081***	0.073***	0.068***	0.069***	0.065***
	(<0.001)#	(0.210)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
Constant	0.526***	1.649***	0.909***	0.769***	0.663***	0.561***	0.506***	0.425***
	(<0.001)#	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
R^2	0.7195	0.5335	0.5684	0.5883	0.5982	0.6046	0.6090	0.6119

$D^{decimal}$	0.031***	0.050***	0.068***	0.086***	0.110***	0.168***	0.242***	0.528***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
D^{open}	−0.134***	−0.210***	−0.249***	−0.323***	−0.380***	−0.398***	−0.399***	−0.375*
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.094)
D^{close}	0.057**	0.057**	0.036	0.024	0.031	0.037	0.084	0.089
	(0.028)	(0.037)	(0.167)	(0.537)	(0.204)	(0.244)	(0.141)	(0.703)
Vol	0.246***	0.038	−0.190***	−0.410***	−0.697***	−0.954***	−1.186***	−1.220***
	(<0.001)	(0.372)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
NT	−0.038***	−0.007	0.014	0.051***	0.074***	0.103***	0.137***	0.199***
	(<0.001)	(0.510)	(0.205)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
ET	0.498***	0.575***	0.644***	0.698***	0.808***	1.201***	1.846***	4.314***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
TE	<0.001	−0.001	0.002	0.001	0.004	−0.002	−0.013	−0.147***
	(0.901)	(0.891)	(0.547)	(0.841)	(0.274)	(0.769)	(0.223)	(<.001)
$\lvert x_{t-1}\rvert$	0.205***	0.189***	0.187***	0.180***	0.199***	0.203***	0.227***	0.190***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$\lvert x_{t-2}\rvert$	0.156***	0.158***	0.150***	0.153***	0.141***	0.140***	0.080**	0.009
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.044)	(0.764)
$\lvert x_{t-3}\rvert$	0.131***	0.138***	0.139***	0.134***	0.114***	0.105***	0.073*	0.060***
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.071)	(0.007)
$\lvert x_{t-4}\rvert$	0.112***	0.114***	0.112***	0.107***	0.112***	0.091***	0.082**	0.014
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.023)	(0.705)
$\lvert x_{t-5}\rvert$	0.099***	0.094***	0.089***	0.087***	0.071***	0.060**	0.067**	0.012
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.003)	(0.036)	(0.046)	(0.663)
$\lvert x_{t-6}\rvert$	0.094***	0.094***	0.096***	0.097***	0.099***	0.108***	0.098***	0.069**
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.003)	(0.011)
$\lvert x_{t-7}\rvert$	0.076***	0.073***	0.070***	0.078***	0.084***	0.070***	0.051	0.022
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.008)	(0.116)	(0.400)
$\lvert x_{t-8}\rvert$	0.065***	0.065***	0.074***	0.069***	0.071***	0.068***	0.085***	0.056
	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.114)
Constant	0.293***	0.169***	0.078**	−0.068	−0.177***	−0.298***	−0.343***	−0.229
	(<0.001)	(<0.001)	(0.034)	(0.107)	(<0.001)	(<0.001)	(<0.001)	(0.281)
R^2	0.6165	0.6180	0.6163	0.6119	0.6024	0.5711	0.5260	0.4175

Note. The change in average futures mispricing after the introduction of decimalization is tested by an autoregressive model with eight lags defined in the following equation:

$$|x_t| = \beta_0 + \beta_1 D_t^{decimal} + \beta_2 D_t^{open} + \beta_3 D_t^{close} + \beta_4 Vol_t + \beta_5 NT_t + \beta_6 ET_t + \beta_7 TE_t + \sum_{i=1}^{8} \varphi_i |x_{t-i}| + \varepsilon_t$$

where t denotes one of the five-minute time periods; $|x_t|$ is the average absolute mispricing error during time period t; $D_t^{decimal}$ is a dummy variable that equals 0 during the pre-decimalization period and 1 afterward; D_t^{open} and D_t^{close} are dummy variables that, respectively, control for the open and close interval effects; Vol_t is the Parkinson (1980) extreme value estimator, which is used to be a proxy for volatility; NT_t is the number of QQQs trades during time period t; ET_t is the time to expiration of the NASDAQ 100 E-mini futures contract during time period t; and TE_t is the previous day's absolute tracking error of QQQs. In addition, eight lags of the dependent variable in the regression model are employed to eliminate autocorrelation in the regression residuals. OLS method and a linear quantile regression model proposed by Koenker and Bassett (1978) are adopted to estimate this equation. The total number of time periods is 19,713. Figures in parentheses are p-values. "***," "**," and "*" represent significance levels of 1, 5, and 10%, respectively, for the traditional t-test. The Bayesian sample size-adjusted critical t-value, t^*, suggested by Connolly (1989) is further applied. Based on the sample size, the sample size-adjusted critical value of t^* is 3.14. The "#" sign by the OLS p-value indicates that the t-value reaches the sample size-adjusted critical value of 3.14. NASDAQ, National Association of Securities Dealers Automated Quotation System; OLS, ordinary least squares.

and V, consistent with the OLS results, for the LAD regression ($\theta = 0.5$), the coefficients of the decimal dummy are again significantly positive, indicating worse pricing efficiency after decimalization.

Quantile methods provide support for the argument that the coefficients on decimal dummy in the pooled quantile regressions become significantly negative for quantiles greater than 70% for SPDRs and 85% for QQQs. These results show that the improvement in the pricing efficiency occurs only when large mispricing signals occur, because larger profits help arbitrageurs against latent risk when executing arbitrage trades. For the other control variables, quantile regression estimates are also quite similar to the OLS estimates in high quantiles and the signs and significances of the OLS coefficient are generally consistent with those in Kurov and Lasser (2002).

Overall, these results show that after penny pricing, the general pricing efficiency of the cash/futures pricing system does not seem to improve. It is shown that arbitrageurs require larger mispricing signals to be engaged in arbitrage trading, as pricing efficiency is found to be improved only at higher quantiles of mispricing signals. In other words, due to increased execution risk after decimalization, such as reduction in market depth and lower average arbitrage profits, arbitrageurs would wait for the occurrences of large mispricing size to be compensated for the increased risk of arbitrage trades.

CONCLUSIONS

The influences of penny pricing on the efficiency of the cash/futures pricing system have been studied. It is shown that penny pricing has lowered the mean arbitrage profits and led to a reduction in the willingness of arbitrageurs to engage in arbitrage trading, which has, in turn, led to lower pricing efficiency on average. The authors have shown that after decimalization, the mispricing analyses by quantile regressions show significant increases in mispricing errors on average for both ETFs. Using the quantile regression method, it has been shown that the improvement in pricing efficiency only occurs when the mispricing size is extremely large.

These findings are consistent with the hypothesis that the pricing efficiency between ETFs and E-mini futures would deteriorate after decimalization, and are also consistent with the results of Chakravarty et al. (2005), who argue that institutional traders seeking quick executions may have been hurt by penny pricing. Decimalization is likely to reduce the viability of arbitrage trades, due to the reduction in profitable market depth, and the increase in execution risks. It seems clear, therefore, that decimalization has reduced the ability and the willingness of arbitrageurs to engage in arbitrage activities unless the mispricing size is enough to cover the execution risk.

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