Trading platform, market volatility and pricing efficiency in the floor-traded and E-mini index futures markets

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ABSTRACT

This study examines the pricing efficiency of E-mini and floor-traded index futures under electronic versus open-outcry trading platforms. By using OLS and quantile regressions to control for changes in market characteristics, we find that pricing errors are smaller in the E-mini markets than the floor-traded markets, thereby confirming that electronic trading has special attractions for arbitrageurs and informed traders. However, during periods of higher volatility, the advantages of speedier execution, anonymity and information efficiency may be offset by arbitrage risks; as a result, larger pricing errors are observed in the E-mini markets. We provide new evidence confirming the important roles in pricing efficiency played by both traditional open-outcry systems and electronic trading systems.

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1. Introduction

With electronic trading having become a mainstream mechanism in global financial markets, many futures exchanges have now made the move from open-outcry to electronic trading systems.[1] Although such movement seems all but inevitable, the majority of futures trading in the US remains floor-based; indeed, despite the potential loss of their scale economy advantage, as opposed to making the complete transition from open-outcry to electronic trading, some of the futures exchanges clearly prefer to offer parallel trading platforms.[2]

This therefore raises quite an intriguing question as to whether an open-outcry system is an indispensable form of trading in derivatives. This study aims to clarify the argument by examining the pricing efficiency of index futures markets featuring E-mini (electronically-traded) and traditional (floor-traded) contracts. Although several analyses have been undertaken on price

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  [1] Including the Marche a Terme International de France (MATIF), the Sydney Futures Exchange (SFE) and the London International Financial Futures Exchange (LIFFE).
  [2] Over recent years, some exchanges have gradually begun offering a choice between trading derivatives products on an electronic trading platform, an open-outcry market, or a combination of both; for example, the Chicago Board of Trade (CBOT), the Chicago Mercantile Exchange (CME), the New York Mercantile Exchange (NYMEX) and the Singapore Exchange (SGX) have all made such shifts, with trading beginning with S&P 500, Nasdaq-100 and DJIA index futures, and Russell 1000, Russell 2000, S&P MidCap 400, S&P MidCap 600 and Euro FX products having subsequently been introduced.

discovery and price clustering under coexisting electronic and open-outcry futures markets,[3] pricing efficiency relating to both trading platforms has yet to be examined in this field.[4]

In the index futures markets of the US, both electronic and open-outcry trading systems have been retained, operating simultaneously during regular trading hours. This unique market mechanism offers a natural experimental environment in which to directly compare the differences in pricing efficiency between electronic and open-outcry trading systems.[5] We therefore examine pricing errors in active trading on the Dow Jones Industrial Average (DJIA) and Nasdaq-100 indices, where both E-mini and floor-traded futures are simultaneously traded, and where their trade prices are generally found to have a high degree of correlation. The transactions in these contracts are, nevertheless, dealt with under different trading systems; this uncommon contrast, in terms of the trading systems used, provides us with a unique opportunity to examine the real effects on pricing errors based upon the trading system used, whilst removing the influences of any changes in market conditions. Such comparisons between E-mini and floor-traded futures should prove to be particularly informative, and may well contribute to our understanding of causes of differences in pricing efficiency between the electronic trading and the open-outcry platforms with consideration of market volatility.

We provide several contributions to the extant literature in the present study. Firstly, the differences in pricing efficiency between coexisting E-mini and floor-traded index futures markets are analyzed from the perspective of arbitrage trading. This is an area which has received relatively little attention in the prior studies.[6] With both floor-traded and E-mini contracts increasingly being offered by futures exchanges around the world, they have largely become accepted over time. Nevertheless, no examination has yet been undertaken on the differences in pricing efficiency attributable to the variations in the two trading platforms.[7]

Our second contribution is our test of the influence of market volatility on pricing efficiency for electronically-traded versus floor-traded index futures at different quantile levels. By controlling for the influence of market characteristics on pricing efficiency, the quantile regressions can reveal the entire distribution of the differences in the magnitude of mispricing between E-mini and floor-traded index futures.[8] With additional dummy variables representing high market volatility, we can observe the specific effects of high market volatility on mispricing differences between E-mini and floor-traded index futures across various quantile levels.

Our third contribution is the alternative explanation supporting the existence of open-outcry markets. The liberty of trading in parallel electronic trading and open-outcry platform in the US futures markets provides us with an opportunity to test the limit-to-arbitrage argument, and thereby, to propose a reasonable explanation for the phenomenon that efficiency of the electronic trading relative to the open-outcry system deteriorates during periods of high volatility.

The empirical results of our study indicate that the average pricing efficiency found in the E-mini markets is superior to that found in floor-traded markets, a result which may be explained by the characteristics of E-mini futures contracts; that is, by reducing pricing errors and pushing the market prices towards equilibrium, the speedier execution which is characteristic of electronic trading systems may help arbitrageurs to contend with the latent risk when executing their arbitrage trades. However, our results also show that with high volatility, more serious attacks occur on the pricing efficiency of an electronic trading system than that of an open-outcry trading system, a finding which indicates that the impact on an electronic trading system arising from noise trader risk is higher during periods of high volatility than during normal periods. Periods of high volatility will induce more noise traders to trade in the markets because they believe that profits are more easily made from such market timing. Both systems admittedly fulfill an important role in pricing efficiency; it is, however, also clear that, despite the electronic trading system having some special attractions for arbitrageurs and informed traders, in terms of enhancing pricing efficiency, these important advantages are offset by the influences of arbitrage risks (noise trader risk in particular) during periods characterized by higher market volatility.

The remainder of this paper is organized as follows. A review of the related literature is presented in Section 2, along with the development of our empirical hypotheses. Section 3 presents the data and methodology, including a description of the data sources and the research methodology adopted for this study. Section 4 reports the empirical results, followed in Section 5 by our presentation of the conclusions drawn from this study.

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[3] Examples include Kurov and Lasser (2004), Ates and Wang (2005) and Chung and Chiang (2006). Ates and Wang (2005) find that operational efficiency and relative liquidity jointly determine the rate of price discovery in electronic trading versus open-outcry trading systems, whilst Chung and Chiang (2006) also point to the increased occurrence of price clustering in open-outcry markets due to the higher levels of human participation.

[4] Although research has been undertaken comparing the market characteristics of E-mini and floor-traded index futures markets–including Pirrong (1996), Kofman and Moser (1997), Frino, McInish, and Toner (1998) and Franke and Hess (2000)–such analyses have tended to be confined to comparisons between the various markets in different countries, such as the DTB and the LIFFE.

[5] Trading in E-mini index futures on the DJIA by the Chicago Board of Trade (CBOT) began on 4 April 2002; thereafter, the three most actively traded contracts (DJIA, S&P500 and Nasdaq-100 index futures) could be traded in both the E-mini and floor-traded futures markets.

[6] There are only a few isolated examples of examinations of the trade characteristics of electronic E-mini and corresponding floor-traded futures indices over recent years; these are, essentially, Hasbrouck (2003), Ates and Wang (2005), Chung and Chiang (2006) and Kurov (2008).

[7] Although Cheng, Fung, and Tse. (2005) examine the effects of a switch to electronic trading on relative pricing efficiency, their event focuses on a "before and after" analysis of a single market over different time periods. Similar studies are provided by Tse and Zabotina (2001) and Gilbert and Rijken (2006).

[8] We follow the method of Chen, Chou, and Chung (2009) in which an investigation is undertaken into the impact of decimalization on overall pricing efficiency using quantile regressions.

2. Literature review and hypothesis development

2.1. Pricing efficiency in electronic and open-outcry systems

The comparison between electronic and open-outcry systems has attracted considerable research attention, with the prior studies having summarized the advantages to demonstrate that an electronic trading system is more operationally and informationally efficient than an open-outcry system. Proponents of electronic trading systems argue that the benefits of such trading include greater speed and accuracy of processing transactions, timely and accurate reporting of fills, improved pricing transparency, higher liquidity and anonymity.[9] Conversely, the speed of execution in open-outcry markets is limited by the mechanics of pit trading, with the process of order submission, execution and relaying the trade information to the customer potentially taking several minutes, particularly during periods of high activity.

The argument that an electronic trading system appears to play a more important role in the price discovery process than the open-outcry system has been generally accepted; furthermore, advocates of the screen-based system also contend that this enhances price discovery. By examining the intraday transaction data of the coexisting E-mini and traditional index futures markets, the empirical evidence discussed in Kurov and Lasser (2004) and Ates and Wang (2005) provides support for the argument that an electronic trading system plays a more important role in the price discovery process than an open-outcry system.

Our first hypothesis is motivated by the results from the extant market microstructure literature. In the present study, we enlarge upon the prior price discovery studies to conduct a parallel test of our hypothesis in the E-mini and floor-traded futures markets. If the operational advantages of an electronic trading system encourage arbitrageurs to execute their transactions in the markets, then E-mini index futures may well have lower pricing errors than floor-traded index futures. Accordingly, the first hypothesis proposed in this study is as follows:

Hypothesis 1. E-mini index futures have lower pricing errors than floor-traded index futures.

2.2. The effects of noise trading on pricing efficiency

The execution speed of a floor-traded system is essentially limited by the relative mechanics of pit trading, since it can take several minutes to process order submission, execution and information conveyance, which can clearly cause delays in transactions, particularly during periods of high activity in the exchanges (Kurov & Lasser, 2004; Ates & Wang, 2005). An alternative viewpoint, however, is that an open-outcry system will be more efficient in a rapidly moving market due to the way in which prices are released; Martens (1998) demonstrates the importance of competing market markers in an open-outcry market, indicating that the disadvantage of the electronic order book lies in its slackness in changing prices, particularly in rapidly moving markets.[10]

Clearly, the shift in the futures markets from open-outcry to electronic trading is justified in the vast majority of the market microstructure literature; nevertheless, the recent behavioral literature prompts us to rethink the rationality of the coexistence of electronic trading and floor-traded platforms from an arbitrage standpoint. The limit-to-arbitrage literature features noise traders who either deal on the basis of mistaken information on fundamentals, or trade on rules in the spirit of technical analysis (such as examining historical security prices).[11] Whilst the motives of these noise traders are still indefinite, the momentum trading behavior or contrarian trading strategy of such traders may affect the willingness of arbitrageurs to compete with/against them, thereby impeding the recovery of price divergence.[12]

Noise traders act as if they have valuable fundamental information when they do not, with such overconfident characteristics inspiring them to increase their transactions during periods of higher market volatility on the basis of their belief that profits can be more easily made from such market timing. Consistent with such assumptions, in their recent investigation of the laboratory market, Bloomfield, O'Hara, and Saar (2009) find that the addition of noise traders into the markets actually leads to a dramatic increase in trading volume, particularly when the fundamental value of the security is far from its prior expected value.

Those trading under an electronic system may suffer higher noise risk than those trading in an open-outcry market; indeed, Chelley-Steeley (2005) concludes that the introduction of an electronic trading mechanism leads to an increase in noise risk. In addition, as noted by Kurov and Lasser (2004), whereas large institutional traders may still actively trade in the traditional contracts, trading in the E-mini market is dominated by small retail traders who simply do not have sufficient capital to trade full-size contracts.[13] This characterization is consistent with the argument of Black (1986), who indicated that noise traders prefer low-priced stocks to high-priced ones. Furthermore, Tu and Wang (2007) also empirically demonstrate that the small size of futures contracts attracts relatively ignorant noise traders, leading to greater price fluctuations caused by noise trading.

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[9] See for example, Pirrong (1996), Frino et al. (1998), Franke and Hess (2000), Kurov and Zabotina (2005) and Fung, Lien, Tse, and Tse (2005).

[10] Franke and Hess (2000) also suggest that the contribution made by electronic trading systems to information sharing is relatively greater during quiet periods than during highly volatile periods.

[11] Examples include De Long, Shleifer, Summers, and Waldman (1990), Shleifer and Summers (1990), Shleifer and Vishny (1997), Shleifer (2000) and Barberis and Thaler (2003).

[12] Barber, Odean, and Zhu (2009) document informed trader faces some risks (such as information risk, fundamental risk and noise trader risk) when they execute their arbitrage strategy and thereby create losses for the investor whose trading horizon is short or whose cost of carrying a short position is high.

[13] Kurov and Lasser (2004) argue that E-mini trading has higher transaction costs for larger traders. As a result, they expect to find trading in the E-mini market being dominated by small retail traders who simply have insufficient capital to trade in the full-size contracts, whereas large institutional traders may still actively trade in the lower cost floor-traded contracts.

Table 1
Contract specifications for floor-traded and E-mini index futures[*].

Futures indices	Specifications	Floor-traded index futures	E-mini index futures
Dow Jones	Date of first trade	6 October 1997	4 April 2002
	Contract size	10[*] Dow Jones futures value	5[*] E-mini Dow Jones futures value
	Minimum tick size and price fluctuation	1 futures index point, US$10	1 futures index point, US$5
	Trading hours	7:20 a.m. to 3:15 p.m.	Virtually 24 h
Nasdaq-100	Date of first trade	10 April 1996	21 June 1999
	Contract size	100[*] Nasdaq-100 futures value	20[*] E-mini Nasdaq-100 futures value
	Min. tick size and price fluctuation	0.5 futures index point, US$50	0.5 futures index point, US$10
	Trading hours	8:30 a.m. to 3:15 p.m.	Virtually 24 h

Note: [*]The sample period runs from 1 May 2002 to 30 April 2005, with trading being examined in Chicago time.

The formulation of our second hypothesis, that during periods of high market volatility, E-mini index futures suffer greater deterioration in pricing efficiency than floor-traded index futures, is based upon the foregoing analysis. This hypothesis extends the prior research into the relative damage to pricing efficiency caused by electronic trading platforms in rapidly moving markets, a phenomenon which De Long et al. (1990) attributed to the impact of noise traders in the market.[14] We note that one of the advantages of electronic trading systems is that they attract greater execution of transactions by arbitrageurs in the E-mini markets, thereby accelerating the recovery in price divergence; however, in periods of high market volatility, the potential for even greater disturbance caused by noise trader behavior may severely dampen any desire to engage in arbitrage trading, thereby impeding the recovery in price divergence. Accordingly, the second hypothesis proposed in this study is as follows:

Hypothesis 2. E-mini index futures suffer greater deterioration in pricing efficiency than floor-traded index futures during periods of high market volatility.

3. Data and research methodology

3.1. Data and sample

The sample data used in this study comprises of all floor-traded index futures and E-mini index futures traded on the DJIA and Nasdaq-100 indices.[15] The contract specifications of our dataset are provided in Table 1, which shows that the Dow Jones E-mini and floor-traded index futures are all traded at a minimum tick size of 1.0 futures index point. Similarly, the tick size of the floor-traded index futures and E-mini index futures in the Nasdaq-100 are also equally scaled, at 0.5 futures index point. We can therefore examine the real effects of the trading systems on pricing efficiency by focusing our research on the sample of index futures traded on both the electronic and open-outcry markets under the same tick rules.[16]

Our sample period runs from 1 May 2002 to 30 April 2005, covering the three-year period after the CBOT initiated the trading of E-mini futures on the DJIA index; only the nearby futures contracts are selected for our analysis. We employ the tick-by-tick transaction data on E-mini and floor-traded index futures to examine and compare the pricing efficiency of the electronically-traded and open-outcry index futures markets, obtaining the index futures prices and trading volume from the intraday database of Tick Data Inc., with the risk-free rate being substituted by the three-month T-Bill rates.[17] All other variables, such as the dividend rates on the DJIA and Nasdaq-100 indices, are obtained from the OptionMetrics database.

We adopt certain data processing principles in this study in order to ensure the accuracy of our sample data; all trades that are out of time sequence from 8:30 a.m. to 3:00 p.m. (Chicago time) are deleted,[18] as are those where the trade prices are equal to, or less than, zero. Following Huang and Stoll (1996), we further minimize data errors by eliminating trades meeting the following additional criteria: (i) all trades which took place either before the market opened or after it closed; and (ii) all trade prices with consecutive absolute relative changes (absolute returns) of more than 10%.

In order to explore both the magnitude and the sustained effects of the pricing errors in the two markets, we match the prices of each reported spot index and the respective futures contract (E-mini index futures and floor-traded index futures) with the

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[14] De Long et al. (1990) demonstrate that the risk associated with the unpredictability of the opinions of unsophisticated investors significantly reduces the attractiveness of arbitrage, such that noise trading can lead to considerable divergence between market prices and fundamental value.

[15] In the index futures markets of the US, both electronic trading and floor-traded index futures contracts are traded side by side during regular trading hours. This uncommon contrast, in terms of the trading systems used, provides us with a unique opportunity to examine the real effects on pricing errors stemming from a particular trading system, whilst removing the influences of any changes in market conditions.

[16] The three most actively traded futures in the US equity index futures markets are Dow Jones, Nasdaq-100 and S&P 500 futures. The E-mini and floor-traded index futures traded on the Dow Jones and Nasdaq-100 are all equally scaled, at 1.0 and 0.5 futures index points, respectively; however, the tick size of the floor-traded index futures and electronically-traded index futures in the S&P 500 are traded at minimum tick sizes of 0.1 and 0.25 futures index points each; this sample is therefore excluded from the present study.

[17] The data on T-Bill rates is available from website: www.federalreserve.gov/releases/h15/data.htm.

[18] In order to ensure the accuracy of our sample data, we only analyze the tick-by-tick transaction data from 8:30 a.m. to 3:00 p.m. (Chicago time) each trading day within the sample period.

most recent (trading time) futures trade prices in order to form trading pairs.[19] Given that the information on floor-traded and E-mini index futures is provided for various time horizons (Table 1), pricing efficiency is considered only for those cases where both the futures and the underlying assets can be analyzed simultaneously, that is, from 8:30 a.m. to 3:00 p.m. (Chicago time). Although the price series are not uniformly spaced over time, it is clear that relative pricing efficiency should be compared over a standardized time interval; we therefore adopt 5-minute data which is formed by the tick data within the 5-minute interval. The calculations of the data on each 5-minute interval (for the dependent and independent variables in our regression analysis in Table 5) use all tick data within the same time interval.[20]

3.2. Methodology

We begin by using the cost-of-carry model to calculate the fair value (F_t^*) of an index futures contract at time t:

$$F_t^* = Idx_t e^{(r-q)(T-t)},\tag{1}$$

where Idx_t is the value of the index at time t; r is the risk-free interest rate; q is the dividend yield on the stock index portfolio;[21] and T is the expiration day of the index futures contract.

The pricing error, or mispricing, Z_t, is defined as the deviation in the actual futures price (F_t) from its theoretical value (F_t^*) at time t.[22]

$$Z_t = |F_t - F_t^*|,\tag{2}$$

The magnitude of the pricing error may reflect the pricing efficiency of the index futures; if the futures market is efficient, the market price of a futures contract (F_t) will be equal to its theoretical value (F_t^*) and will therefore push the pricing error closer to zero. However, within the open-outcry and electronic trading markets, differences exist between certain factors such as transaction costs, price discreteness, exchange price rules and arbitrage risks (noise trader risk in particular) which make the price less efficient; these differences have further distinct effects on the formation of pricing errors within the two markets.

It has been argued in several of the prior studies that the existence of transaction costs and other types of market friction allows the futures prices to fluctuate within the no-arbitrage boundary:

$$\left[Idx_t e^{(r-q)(T-t)}\right](1-C) < F_t < \left[Idx_t e^{(r-q)(T-t)}\right](1+C)\tag{3}$$

where C represents the total transaction costs involved in executing arbitrage; and F_t is the market price of the index futures at time t.

Once the futures price goes beyond the no-arbitrage boundary depicted in Eq. (3), it may trigger the simultaneous trading of spot and futures by arbitrageurs in pursuit of profits, with the actions of these arbitrageurs ultimately leading to a recovery from the earlier price divergence. In order to determine which trading mechanism may lead to a recovery from the earlier price divergence, we adopt an approach similar to that used in the prior studies, measuring the no-arbitrage violation at different levels of transaction costs.[23] The one-way transaction cost levels used in our analysis are set at 0.2% to 0.4% of the theoretical futures price, at 0.05% increments. Given that no-arbitrage boundary violations tend to occur in clusters, we use the method suggested by Chu and Hsieh (2002) to compute the occurrence of ex-post no-arbitrage violations, and further compare the pricing efficiency of the coexisting open-outcry and electronic trading futures markets.[24]

We also compute the average maximum signal size within an occurrence by calculating the average of the maximum deviation in all no-arbitrage violations, and then observe the degree of boundary violation deviation attributable to the behavior of traders

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[19] The futures prices and their spot index are synchronized using the MINSPAN procedure suggested by Harris, McInish, Shoesmith, and Wood (1995). Every reported index is matched with the trading price of an E-mini future so as to form trading pairs; if a futures trade occurs at exactly the same time in the reported index, then a pair is formed, whereas if no futures trades occur at exactly the same time in the reported index, the futures trades within the prior and subsequent 7-second periods 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. Our empirical results, presented in Tables 3 and 4, are calculated using pair data synchronized under the MINSPAN procedure.

[20] The qualitatively similar empirical results are obtained from an examination using variables defined over 10 min and 30 min intervals.

[21] The continuous dividend yield data is obtained from the OptionMetrics database.

[22] We follow the prior studies on pricing efficiency, including Draper and Fung (2002) and Cheng et al. (2005), disregarding the signs of the magnitude (absolute value) of the errors.

[23] See Chung (1991), Yadav and Pope (1994) and Chu and Hsieh (2002).

[24] In Chu and Hsieh (2002) the potential overestimation of actual opportunities for arbitrage is avoided by integrating all mispricing occurring within a 20-minute period as a single occurrence of a boundary violation.

within the markets.[25] We provide an additional measure of the speed of recovery from price divergence through a measurement of the average time span of a no-arbitrage violation occurrence in order to compare the speed of execution of trades by arbitrageurs. Although the pricing efficiency of floor-traded and E-mini index futures markets is depicted in Eq. (3), the existence of time lags in program trading renders ex-post analysis insufficient. We therefore follow Chu and Hsieh (2002) to compute the realized arbitrage profits by imposing 10 s time lags for program trading.[26] Eqs. (4) and (5) measure the respective ex-ante profits for long and short arbitrage:

$$AP_L = F_{t^+} - \left[Idx_{t^+} e^{(r-q)(T-t^+)} \right](1 + C) \tag{4}$$

$$AP_S = \left[Idx_{t^+} e^{(r-q)(T-t^+)} \right](1-C) - F_{t^+} \tag{5}$$

where t^+ represents the time of the first trade price of the index futures after the perceived ex-post mispricing signal; F_t^+ is the price of the index futures at time t^+; and Idx_t^+ is the value of the spot index at time t^+. We further analyze the arbitrage outcomes by dividing them into profitable and unprofitable arbitrage transactions, so as to better identify the sources of arbitrage profits and losses.

Since the changes in pricing efficiency are potentially influenced by factors other than the trading mechanism itself, we accordingly add certain other variables into the regression to control for the changes in market transitions. These variables include the bid–ask spread and time to expiration of the futures contracts, the volatility of the index and the number of trades in the futures contract. We therefore explore the possible effects of trading systems on pricing errors with a regression model based upon the following equation:

$$\left(Z_t^F - Z_t^E\right) = \beta_0 + \beta_1 D_t^{\text{open}} + \beta_2 D_t^{\text{close}} + \beta_3 \left(SP_t^F - SP_t^E\right) + \beta_4 \text{Vol}_t + \beta_5 D_t^{\sigma 95\%}$$
$$+ \beta_6 D_t^{\sigma 5\%} + \beta_7 ET_t + \beta_8 \left(NT_t^F - NT_t^E\right) + \sum_{i=1}^{12} \varphi_i \left(Z_{t-i}^F - Z_{t-i}^E\right) + \varepsilon_t \tag{6}$$

The dependent variable within the regression model, $Z_t^F - Z_t^E$, represents the absolute pricing errors of floor-traded index futures minus those of E-mini index futures. We use this variable to examine whether there are any conspicuous differences in pricing efficiency between electronic trading and open-outcry index futures. If the difference in the pricing errors is positive ($Z_t^F - Z_t^E > 0$), pricing efficiency is deemed to be better under an electronic trading market; otherwise, pricing efficiency is deemed to be better in an open-outcry market. The independent variables, D_t^{open} and D_t^{close}, are the dummy variables for the 5-minute market opening and closing intervals. These two variables are included in the regression model to control for the market open and close effects on mispricing.

The independent variable, $SP_t^F - SP_t^E$, represents the bid–ask spread of the floor-traded index futures minus the bid–ask spread of E-mini index futures at time t. As noted in Roll, Schwartz, and Subrahmanyam (2007), the deviations from the no-arbitrage position should be related to market liquidity; hence, we use the variable relating to the difference between the bid–ask spread in the two futures markets to control for the possible influence on mispricing.

The method used to estimate the bid–ask spread is identical to that proposed in Wang, Michalski, Jordan, and Moriarty (1994). The estimator, which is also used by the Commodity Futures Trading Commission (CFTC), is calculated as the average absolute price change in price reversal. We also compute the average bid–ask spread of the index futures during 5 min intervals, and use the difference between the two futures markets to control for the influences on the differences in mispricing.[27]

The independent variable Vol_t is the Parkinson (1980) extreme value estimator which we use as a proxy for the volatility of the index. The extreme value estimate is calculated as follows:

$$\sigma_t = \sqrt{\frac{1}{4\log 2} \left(\log \frac{H_t}{L_t} \right)} \tag{7}$$

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[25] The term "maximum signal size within an occurrence" refers to the maximum observed mispricing signal within a boundary violation occurrence. We define the "occurrence" of a boundary violation as a series of same-side violations so that any two adjacent violations in the same occurrence occur within a 20-minute interval. In other words, a new boundary violation occurrence is recognized only when the direction of mispricing changes, or when a mispricing occurs 20 minutes apart from the previous one. By integrating persistent mispricing into a single occurrence of a boundary violation, we avoid the problem of overestimating actual arbitrage opportunities. We use maximum signal size within an occurrence to observe the extent of the deviation in boundary violations attributable to the behavior of traders in the markets. If the value of a "maximum signal size within an occurrence" is large, a limit-to-arbitrage situation is more likely to occur in the market; that is, the unpredictable trading behavior of market participants appears to frustrate the willingness of arbitrageurs to compete with/against them, particularly when these traders become active during periods of higher market volatility, thereby extending the deviation in the boundary violations.

[26] Since the results are virtually the same when we use 30 s and 1 min transaction lags, only the results of the 10 s execution lag are provided here.

[27] We use the mean of the estimated realized bid–ask spreads during specific time intervals to compute the bid–ask spread following the method of Wang et al. (1994); they computed the realized bid–ask spread based upon the following steps: (i) create an empirical joint price distribution of ΔP_t and ΔP_{t-1} during a time interval; (ii) discard the subset of price changes which exhibit price continuity (i.e., a positive change followed by another positive change); (iii) take the absolute values of the price changes that refer to price reversals; and (iv) compute the mean of the absolute values obtained under step (iii). Wang et al. (1994) document this process as "calculating the average absolute price change in the opposite direction". Overall, this spread measure is calculated as the average absolute price change in the opposite direction. Price changes in the same direction as the preceding price change are discarded so as to reduce the impact of changes in the underlying futures price unrelated to the bid–ask bounce. This measure proxies for the average magnitude of the bid–ask spread.

where H_t (L_t) denote the highest (lowest) prices within the time interval t. This method, referred to as the "extreme value method" has been extensively used by researchers as the means of estimating variance in the rate of return. This variable is selected on the basis of the research undertaken by Brailsford and Hodgson (1997). From their examination of the stock index futures pricing in Australia, they found that the mispricing series had a positive correlation with contemporaneous volatility in the futures market.

Following the study of Ates and Wang (2005), we use the dummy variables $D_t^{\sigma\ 95\%}$ and $D_t^{\sigma\ 5\%}$ to classify the sample period into time intervals of high volatility (if their volatility is equal to or greater than the 95th percentile of the empirical distribution of 5 min volatility) and time intervals of low volatility (if their volatility is equal to or less than the 5th percentile of the empirical distribution of 5 min volatility).[28] We add the two dummy variables into the regression model in order to examine the differences in pricing efficiency between the electronic trading and the open-outcry trading systems under the extreme market volatility.

We also include the annualized time to expiration of the index futures (ET_t) within the regression model. In the study by Fung and Fung (1997), the arbitrage profits of the futures contracts were found to have positive correlations with the time to maturity; we therefore include this variable so as to control for the potential influences on mispricing.

According to the line of reasoning adopted in Jones, Kaul, and Lipson (1994), the number of futures trades acts as a proxy for the arrival of information; we therefore hypothesize that a negative relationship will be found to exist between pricing errors and the overall number of trades. We also control for the possible effect of this variable on mispricing by using the variable, $NT_t^F - NT_t^E$; that is, the differences between the logarithms of the number of trades in an open-outcry market and the logarithms of the number of trades in an electronic trading market.

Following Kurov and Lasser (2002) and Chen et al. (2009), we take the difference between occurrences of mispricing in the two futures markets, $Z_{t-i}^F - Z_{t-i}^E$, with twelve lag periods, in order to reduce the influence on the regression model arising from autocorrelation of the error terms. In addition to using the ordinary least squares (OLS) method in Eq. (6), we further estimate this equation using the linear quantile regression method proposed by Koenker and Bassett (1978). This approach permits the estimation of various quantile functions of a conditional distribution; amongst these, the median (0.5th quantile) function is a special case.[29]

This approach is also referred to as the "least absolute deviations" (LAD) regression, the use of which was advocated by Connolly (1989) as an alternative means of solving for the low power problem of the OLS regression attributable to greater sample sizes.[30] The results from the different quantile regressions are therefore regarded as providing a more complete and robust description of the differences in mispricing.

4. Empirical results

4.1. Summary statistics

The descriptive statistics of the DJIA and Nasdaq-100 indices are reported in Table 2, along with their futures prices, showing the mean and standard deviation of certain variables depicting the market characteristics of the two futures markets. As expected, higher levels of pricing error are found for each of the indices during the market opening and closing periods. There are, however, obvious differences between the numbers of trades in the open-outcry and electronic trading futures markets, clearly indicating the frequent trading characteristic of the electronic trading market; in particular, the execution speed advantage within the electronic trading markets is found to result in higher liquidity.

Furthermore, the positive relationship between volatility and the number of trades appears to reflect some particular trading characteristics of the participants in both markets; for example, noise traders and informed traders may be more active during periods of higher volatility. The results presented in Table 2 also demonstrate that for both the DJIA and Nasdaq-100 indices, the average mispricing appears to be higher for floor-traded index futures than for E-mini index futures.

4.2. Ex-post pricing efficiency of floor-traded and E-mini futures

Details of the ex-post no-arbitrage boundary violations for floor-traded and E-mini futures are provided in Table 3, for both the DJIA and Nasdaq-100 indices, with the table indicating the apparent existence of more violations in the electronic trading markets than in the open-outcry markets; however, there are no obvious differences between boundary violation occurrences in the two markets.

These results suggest that the total number of violations may result in overestimation of the actual index arbitrage opportunities, essentially because such boundary violations tend to occur in clusters. The differences are particularly obvious in

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[28] Ates and Wang (2005) define the high and low volatility periods as the 90th and 10th percentile of the volatility distribution. Given that the sample size in the regression model in our study is extremely large (52,164 for the DJIA and 48,851 for the Nasdaq-100), we use both the 95th and 99th percentiles of the volatility distribution as the dummy variables for the differential degrees of high volatility periods. Since the results remain significant, even when we use the 99th and 1st percentiles, only the results of the 95th and 5th percentiles are provided here.

[29] Each quantile regression characterizes a particular (center or tail) point of a conditional distribution; by combining different quantile regressions, this provides a more complete description of the underlying conditional distribution. This analysis is particularly useful when the conditional distribution does not have a "standard" shape, such as an asymmetric, fat-tailed or truncated distribution.

[30] Extensive research has established that in such cases, estimation by the LAD method provides superior performance; for example, Bassett and Koenker (1978) demonstrate that for any independent and identically distributed errors and distribution functions in linear models (for which the sample median is a more efficient estimator of location than the sample mean) the LAD estimator has strictly smaller asymptotic confidence ellipsoids than the OLS estimator. A detailed explanation of the estimation procedure is provided in Koenker (2005).

Table 2
Summary statistic of DJIA and Nasdaq-100 futures and the underlying indices. The table illustrates the market characteristics of the two futures markets, reporting the summary statistics of the index and futures price variables for 30 min time intervals on the DJIA and Nasdaq-100 indices. The pricing error is calculated as $|F - F^*|$, where F (F^*) is the futures market price (theoretical price). The bid–ask spread is calculated following the method proposed by Wang et al. (1994), and the underlying index volatility is calculated using the extreme value estimator of Parkinson (1980).

Time	Floor-traded futures						E-mini futures						Underlying volatility	
	Average pricing error		Average bid–ask spread		Average no. of trades		Average pricing error		Average bid–ask spread		Average no. of trades			
	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.	Mean	S.D.
Panel A: DJIA index														
08:30–09:00	7.6928	11.0514	3.4097	1.0867	141	53.31	6.7837	8.3531	1.6230	0.8628	1747	1213.70	0.2253	0.1562
09:00–09:30	5.4635	4.2546	3.3969	1.0922	143	56.66	5.1439	4.0140	1.6353	0.8949	1741	1265.06	0.1598	0.1018
09:30–10:00	5.2446	4.1731	3.3181	1.0518	109	47.43	5.0156	3.9590	1.5613	0.8069	1433	1060.27	0.1272	0.0833
10:00–10:30	5.0586	3.9348	3.2751	0.9896	87	43.80	4.9663	3.8873	1.5286	0.7662	1156	890.72	0.1091	0.0718
10:30–11:00	5.0319	3.9578	3.2315	0.9591	72	41.37	4.9335	3.8454	1.5110	0.7582	924	687.25	0.0946	0.0630
11:00–11:30	5.2702	4.9971	3.2186	0.9423	67	42.19	4.9420	4.0812	1.4837	0.7211	836	661.82	0.0914	0.0610
11:30–12:00	5.0381	3.8792	3.1464	0.9407	59	37.51	4.8940	3.8471	1.5041	0.7588	703	536.24	0.0856	0.0590
12:00–12:30	5.0323	3.8994	3.1268	0.9502	57	34.55	4.8727	3.8252	1.5123	0.7805	747	626.09	0.0881	0.0594
12:30–13:00	5.0415	3.9093	3.1334	0.9568	64	39.16	4.8616	3.7945	1.4926	0.7557	863	671.80	0.0944	0.0697
13:00–13:30	5.1537	4.1306	3.2520	0.9718	80	44.72	4.9104	3.8927	1.5037	0.7471	1230	999.32	0.1122	0.0673
13:30–14:00	5.1363	3.9731	3.2689	0.9599	85	48.39	4.9183	3.8444	1.4952	0.7426	1310	1037.26	0.1167	0.0792
14:00–14:30	5.2379	4.1383	3.2427	0.9749	89	46.06	4.9435	3.9060	1.5281	0.8111	1363	1062.51	0.1219	0.0868
14:30–15:00	5.2558	4.0901	3.1655	0.9719	94	43.51	4.9857	3.8964	1.5511	0.8298	1327	994.28	0.1203	0.0787
Panel B: Nasdaq-100 index														
08:30–09:00	0.7994	0.6488	0.7181	0.1950	134	35.65	0.7535	0.6325	0.5108	0.0233	5618	1973.73	0.2628	0.1481
09:00–09:30	0.7700	0.6237	0.7108	0.2025	120	37.80	0.7347	0.6219	0.5120	0.0365	5269	2071.85	0.2663	0.1489
09:30–10:00	0.7371	0.5832	0.7021	0.1875	96	32.36	0.7034	0.5870	0.5096	0.0461	4185	1864.10	0.2102	0.1239
10:00–10:30	0.7356	0.5843	0.7033	0.1939	75	31.78	0.6838	0.5772	0.5081	0.0543	3320	1738.73	0.1724	0.1084
10:30–11:00	0.7524	0.5908	0.7123	0.1886	58	26.31	0.6823	0.5683	0.5055	0.0175	2621	1417.51	0.1499	0.0940
11:00–11:30	0.7648	0.6057	0.7322	0.1969	48	24.56	0.6833	0.5764	0.5060	0.0165	2216	1384.71	0.1384	0.0903
11:30–12:00	0.7738	0.6135	0.7563	0.1993	38	18.68	0.6769	0.5671	0.5053	0.0119	1839	1083.66	0.1292	0.0913
12:00–12:30	0.7789	0.6192	0.7594	0.2037	39	20.63	0.6762	0.5752	0.5055	0.0156	1884	1207.08	0.1344	0.0897
12:30–13:00	0.7730	0.6136	0.7527	0.2003	42	22.30	0.6779	0.5820	0.5048	0.0126	2150	1257.94	0.1416	0.0972
13:00–13:30	0.7681	0.6195	0.7509	0.1992	53	27.78	0.6900	0.5895	0.5053	0.0168	3045	1772.70	0.1682	0.1053
13:30–14:00	0.7631	0.6074	0.7427	0.2022	59	33.09	0.6928	0.5802	0.5054	0.0216	3406	1916.63	0.1754	0.1163
14:00–14:30	0.7603	0.6036	0.7587	0.1961	53	24.05	0.6965	0.5826	0.5054	0.0209	3566	1885.45	0.1787	0.1169
14:30–15:00	0.7782	0.6085	0.7089	0.1799	66	26.34	0.7057	0.5804	0.5056	0.0149	3839	1848.15	0.1817	0.1176

the E-mini index futures markets, where the results imply that traders reveal relatively piecemeal influences on price changes, as compared to traders in open-outcry index futures markets; furthermore, such phenomenon of permanent violations could be inferred as the prevalent noise in the E-mini futures market.[31] This particular phenomenon provides support for our argument that traders in the E-mini markets reveal relatively clear noise trader characteristics.[32]

In almost all cases, the average time span of an occurrence is shorter in the E-mini futures markets than in the open-outcry markets; however, a reverse pattern is discernible in the maximum signal size within an occurrence. Of these two phenomena, the former indicates the speed advantage of trading in E-mini futures markets, whilst the latter indicates that limit-to-arbitrage situations are more likely to occur in the E-mini index futures markets. More specifically, the noise trader behavior existing in the market participants appears to frustrate the willingness of arbitrageurs to compete with/against them, particularly when these traders become more active during periods of higher market volatility, thereby extending the deviations in the boundary violations.

4.3. Ex-ante no-arbitrage violations of floor-traded and E-mini futures

The ex-ante arbitrage profits, assuming a 10-second transaction lag for a trading index portfolio, are summarized in Table 4, for both the DJIA and Nasdaq-100 indices; these results provide further observations on the differences in pricing efficiency between open-outcry and electronic trading markets. The frequency of ex-ante arbitrage opportunities is slightly lower than the number of violations reported in Table 3, essentially because some violations are likely to have occurred near to the closing period, which would have left insufficient time for traders to initiate their arbitrage activities. As shown in Panel A of Table 4, the ex-ante mean profits for all arbitrage are roughly higher for DJIA floor-traded futures than for DJIA E-mini futures, which suggests that pricing

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[31] Chung (1991) suggest that persistent violations can be taken as proxy of varied phenomenon, such as underestimated transaction cost, the lack of arbitrage capital, or noise.

[32] The clientele factor hypothesis (Tu and Wang, 2007) also supports the contention that E-mini index futures may suffer far more serious noise trader risk than traditional index futures.

Table 3

Ex-post violations of DJIA and Nasdaq-100 indices futures price boundaries. The ex-post tests refer to the frequency and persistence of boundary violations. No-arbitrage boundaries are constructed using the index and index futures prices, which are defined as:

$$\left[Idx_t e^{(r-q)(T-t)}\right](1-C)<F_t<\left[Idx_t e^{(r-q)(T-t)}\right](1+C)$$

where Idx_t represents the values of the index at time t; F_t is the market prices of the index futures at time t; q refers to the dividend yield of the index at time t; and C are the transaction costs, which are measured as the percentage of the theoretical futures value under the cost-of-carry model. A boundary violation occurrence is defined as a series of same-side boundary violations where any two adjacent violations are separated by less than 5, 10 or 20 min; the average maximum signal size refers to the average maximum observed mispricing signal within a boundary violation occurrence; and the average time span measures the duration of a boundary violation occurrence.

Transaction costs (%)	Floor-traded futures		Boundary Violation			E-mini futures		Boundary violation		
	Total no. of matches	Total no. of violations	Boundary violation occurrences	Average maximum signal size	Average time span (min:sec)	Total no. of matches	Total no. of violations	Boundary violation occurrences	Average maximum signal size	Average time span (min:sec)
Panel A: DJIA index										
0.20	828,847	12,784	1119	14.80	09:07	4,783,304	36,096	1066	16.97	08:10
0.25		6218	614	21.23	04:34		16,344	646	22.54	03:52
0.30		4098	433	24.84	02:28		10,874	465	26.05	02:20
0.35		2996	325	27.92	01:37		7733	382	26.73	01:45
0.40		2396	272	28.45	01:19		5782	309	28.10	01:23
Panel B: Nasdaq-100 index										
0.20	465,708	8448	2058	0.64	10:51	1,078,317	8267	1955	0.73	08:43
0.25		2643	934	0.65	06:36		2726	899	0.80	05:26
0.30		889	397	0.75	04:10		1008	422	0.97	02:43
0.35		354	180	0.88	03:03		432	214	1.19	01:35
0.40		166	96	0.98	02:12		226	125	1.37	01:25

efficiency is superior in the electronic trading markets. In order to better identify the sources of arbitrage profits and losses, we further analyze the arbitrage outcomes by dividing them into profitable and unprofitable arbitrage transactions.

The profitable and unprofitable arbitrage for the DJIA and Nasdaq-100 indices reported in Panel A of Table 4 reveal that arbitrage in the electronic markets is slightly more profitable than in the floor-traded markets; in particular, the proportion of profitable ex-ante arbitrage is greater in the E-mini futures markets than in the floor-traded futures markets. These results are consistent with the argument of Black (1986), who noted that although noise creates the opportunity to trade profitably, at the

Table 4

Ex-ante arbitrage for DJIA and Nasdaq-100 index futures, by arbitrage profitability level, for 10 s execution lag. The ex-ante tests impose a 10-second execution lag for trading in DJIA index futures. Long and short arbitrage profits are measured as:

$$AP_L = F_{t^+} - \left[Idx_{t^+} e^{(r-q)(T-t^+)}\right](1+C) \text{ or } AP_S = \left[Idx_{t^+} e^{(r-q)(T-t^+)}\right](1-C)-F_{t^+}.$$

The ex-ante mean profit measure is the profit/loss after considering the 10-second execution lag. Signal size refers to the ex-post profit.

Transaction costs (%)	Floor-traded futures							E-mini futures						
	All arbitrage			Profitable arbitrage		Unprofitable arbitrage		All arbitrage			Profitable arbitrage		Unprofitable arbitrage	
	Frequency	Average signal size	Ex-ante mean profit	Ex-ante mean profit	%	Ex-ante mean profit	%	Frequency	Average signal size	Ex-ante mean profit	Ex-ante mean profit	%	Ex-ante mean profit	%
Panel A: DJIA index														
0.20	12,770	12.03	7.20	16.47	57.06	⁻5.13	42.94	36,070	10.31	7.55	11.87	71.50	⁻3.29	28.50
0.25	6216	18.57	12.65	21.75	67.71	⁻6.45	32.29	16,341	16.17	12.14	17.03	77.47	⁻4.68	22.53
0.30	4098	22.87	16.15	25.19	72.06	⁻7.16	27.94	10,873	18.81	14.09	19.25	78.90	⁻5.21	21.10
0.35	2996	26.25	18.85	27.69	75.07	⁻7.75	24.93	7732	21.14	15.70	21.67	78.09	⁻5.59	21.91
0.40	2396	28.01	20.08	29.53	75.04	⁻8.34	24.96	5782	23.16	17.15	23.61	78.29	⁻6.12	21.71
Panel B: Nasdaq-100 index														
0.20	8417	0.45	⁻0.78	0.75	20.53	⁻1.17	79.47	8246	0.50	⁻0.43	0.72	31.57	⁻0.95	68.43
0.25	2633	0.50	⁻0.98	0.86	19.94	⁻1.44	80.06	2718	0.59	⁻0.57	0.80	32.45	⁻1.22	67.55
0.30	887	0.61	⁻1.10	0.97	20.97	⁻1.65	79.03	1007	0.74	⁻0.69	0.99	29.99	⁻1.41	70.01
0.35	354	0.71	⁻1.36	1.10	19.49	⁻1.96	80.51	432	0.96	⁻0.87	1.32	28.24	⁻1.73	71.76
0.40	166	0.78	⁻1.63	1.22	17.47	⁻2.23	82.53	226	1.13	⁻1.10	1.51	27.88	⁻2.11	72.12

Table 5

Analysis of mispricing differences in the relationship between floor-traded and E-mini futures using OLS and quantile regressions. The change in the average mispricing difference between open-outcry and E-mini futures is tested by an autoregressive model with twelve lags defined in the following equation:

$$\left(Z_t^F - Z_t^E\right) = \beta_0 + \beta_1 D_t^{open} + \beta_2 D_t^{close} + \beta_3\left(SP_t^F - SP_t^E\right) + \beta_4 Vol_t + \beta_5 D_t^{\sigma 95\%} + \beta_6 D_t^{\sigma 5\%} + \beta_7 ET_t + \beta_8\left(NT_t^F - NT_t^E\right) + \sum_{i=1}^{12} \varphi_i\left(Z_{t-i}^F - Z_{t-i}^E\right) + \varepsilon_t$$

where t denotes one of the 5-minute time periods; Z_t^F and Z_t^E are the respective average absolute pricing errors of floor-traded and E-mini futures during time period t; and D_t^{open} and D_t^{close} are dummy variables respectively controlling for the open and close interval effects; $D_t^{\sigma 95\%}$ and $D_t^{\sigma 5\%}$ are dummy variables representing high volatility periods (95th percentile) and low volatility periods (5th percentile), SP_t^F and SP_t^E are the average bid–ask spreads of floor-traded and E-mini futures during time period t; Vol_t is the Parkinson (1980) extreme value estimator which is used as a proxy for volatility in the underlying index; NT_t^F and NT_t^E are the respective logarithms of the number of floor-traded and E-mini futures trades during time period t; and ET_t is the time to expiration of the futures contract during time period t. Twelve lags are employed in the dependent variable in the regression model to eliminate autocorrelation in the regression residuals. The OLS method and the quantile regression model are used to estimate the equation. We further apply the Bayesian sample size-adjusted critical t-value suggested by Connolly (1989). Based upon the sample sizes in the DJIA and Nasdaq-100 indices, the sample size-adjusted critical values are 3.30 for the DJIA and 3.29 for the Nasdaq-100. Figures in parentheses are p-values; "****" indicates significance of the traditional t-test at the 1% level; "***" indicates significance at the 5% level; and "**" indicates significance at the 10% level; "†" in the OLS column indicates that the t-value reaches its sample size-adjusted critical value.

Variable	OLS	Quantile regression (θ)						
		0.5 (LAD)	0.4	0.3	0.2	0.1	0.05	0.01
Panel A: DJIA index								
Constant	0.118***	0.187***	0.016	−0.194***	−0.446***	−0.823***	−1.171***	−1.908***
	(<0.001)†	(<0.001)	(0.326)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
D_t^{open}	0.250***	0.026	−0.169***	−0.363***	−0.598***	−1.163***	−1.602***	−3.074***
	(<0.001)†	(0.404)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
D_t^{close}	0.030	0.027	0.042	0.081**	0.130***	0.098**	0.139*	0.192
	(0.375)	(0.356)	(0.190)	(0.020)	(0.004)	(0.034)	(0.057)	(0.230)
$SP_t^F - SP_t^E$	0.083***	0.099***	0.081***	0.058***	0.030***	0.005	−0.016	−0.050*
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.371)	(0.106)	(0.085)
Vol_t	0.156**	−0.275***	−0.420***	−0.469***	−0.620***	−0.888***	−1.089***	−2.171***
	(0.026)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$D_t^{\sigma 95\%}$	−0.022	−0.012	−0.020	−0.062**	−0.110***	−0.119***	−0.159***	−0.210*
	(0.381)	(0.588)	(0.410)	(0.017)	(0.001)	(0.001)	(0.006)	(0.078)
$D_t^{\sigma 5\%}$	0.014	0.009	−0.013	−0.018	−0.065**	−0.123***	−0.151***	−0.335***
	(0.437)	(0.580)	(0.471)	(0.364)	(0.010)	(<0.001)	(<0.001)	(<0.001)
ET_t	−0.584***	−0.588***	−0.701***	−0.807***	−0.966***	−1.197***	−1.431***	−1.977***
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$NT_t^F - NT_t^E$	0.033***	0.050***	0.027***	−0.002	−0.043***	−0.094***	−0.141***	−0.242***
	(<0.001)†	(<0.001)	(<0.001)	(0.535)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$Z_{t-1}^F - Z_{t-1}^E$	0.110***	0.112***	0.114***	0.121***	0.118***	0.116***	0.121***	0.113***
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.009)
$Z_{t-2}^F - Z_{t-2}^E$	0.055***	0.058***	0.063***	0.064***	0.067***	0.068***	0.070***	0.093***
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.004)
$Z_{t-3}^F - Z_{t-3}^E$	0.044***	0.041***	0.047***	0.049***	0.057***	0.057***	0.069***	0.070***
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.002)
$Z_{t-4}^F - Z_{t-4}^E$	0.019***	0.025***	0.029***	0.036***	0.040***	0.037***	0.031***	0.001
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.005)	(0.970)
$Z_{t-5}^F - Z_{t-5}^E$	0.021***	0.024***	0.031***	0.032***	0.035***	0.038***	0.054***	0.065***
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.009)
$Z_{t-6}^F - Z_{t-6}^E$	0.026***	0.028***	0.030***	0.035***	0.038***	0.035***	0.036***	0.067***
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.003)
$Z_{t-7}^F - Z_{t-7}^E$	0.033***	0.023***	0.026***	0.029***	0.039***	0.048***	0.056***	0.072***
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.004)
$Z_{t-8}^F - Z_{t-8}^E$	0.030***	0.024***	0.029***	0.031***	0.035***	0.041***	0.057***	0.051*
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.080)
$Z_{t-9}^F - Z_{t-9}^E$	0.024***	0.024***	0.031***	0.035***	0.038***	0.049***	0.032***	0.014
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.003)	(0.526)
$Z_{t-10}^F - Z_{t-10}^E$	0.030***	0.028***	0.032***	0.035***	0.034***	0.039***	0.044***	0.053**
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.027)
$Z_{t-11}^F - Z_{t-11}^E$	0.020***	0.017***	0.021***	0.030***	0.033***	0.034***	0.025**	0.054**
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.018)	(0.022)
$Z_{t-12}^F - Z_{t-12}^E$	0.029***	0.035***	0.033***	0.034***	0.033***	0.034***	0.032***	0.028
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.002)	(0.267)
R^2	0.0727	0.0559	0.0521	0.0502	0.0516	0.0635	0.0837	0.1509
Panel B: Nasdaq-100 index								
Constant	0.106***	0.117***	0.093***	0.068***	0.040***	0.002	−0.030*	−0.114**
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.852)	(0.072)	(0.015)
D_t^{open}	−0.019***	−0.015**	−0.016**	−0.018**	−0.013	−0.015	−0.011	−0.044
	(0.004)	(0.037)	(0.038)	(0.013)	(0.147)	(0.159)	(0.414)	(0.203)
D_t^{close}	0.029***	0.034***	0.031***	0.032***	0.028***	0.032***	0.043***	0.060*
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(0.002)	(0.003)	(0.003)	(0.066)

(continued on next page)

Table 5 (continued)

Variable	OLS	Quantile regression (θ)						
		0.5 (LAD)	0.4	0.3	0.2	0.1	0.05	0.01
$SP_t^F - SP_t^E$	0.118***	0.131***	0.113***	0.086***	0.061***	0.016***	−0.015*	−0.055**
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.005)	(0.061)	(0.014)
Vol_t	−0.069***	−0.061***	−0.043***	−0.024**	−0.028*	0.001	0.009	0.071
	(<0.001)†	(<0.001)	(<0.001)	(0.034)	(0.051)	(0.938)	(0.717)	(0.300)
$D_t^{\sigma 95\%}$	−0.018***	−0.017***	−0.021***	−0.034***	−0.036***	−0.058***	−0.077***	−0.148***
	(<0.001)†	(0.003)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$D_t^{\sigma 5\%}$	0.000	0.003	−0.004	−0.015***	−0.028***	−0.044***	−0.057***	−0.082***
	(0.982)	(0.440)	(0.311)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
ET_t	−0.234***	−0.225***	−0.292***	−0.347***	−0.436***	−0.565***	−0.692***	−0.978***
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)
$NT_t^F - NT_t^E$	0.013***	0.017***	0.018***	0.019***	0.020***	0.022***	0.023***	0.025**
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.015)
$Z_{t-1}^F - Z_{t-1}^E$	0.123***	0.110***	0.110***	0.106***	0.107***	0.106***	0.110***	0.123***
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.001)
$Z_{t-2}^F - Z_{t-2}^E$	0.067***	0.055***	0.060***	0.061***	0.063***	0.071***	0.061***	0.070*
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.057)
$Z_{t-3}^F - Z_{t-3}^E$	0.052***	0.047***	0.044***	0.048***	0.047***	0.042***	0.044***	0.057*
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.055)
$Z_{t-4}^F - Z_{t-4}^E$	0.041***	0.034***	0.039***	0.038***	0.038***	0.032***	0.033***	0.053
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.003)	(0.121)
$Z_{t-5}^F - Z_{t-5}^E$	0.035***	0.029***	0.027***	0.029***	0.027***	0.026***	0.025**	0.032
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.024)	(0.345)
$Z_{t-6}^F - Z_{t-6}^E$	0.027***	0.023***	0.020***	0.019***	0.026***	0.031***	0.030***	0.025
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.008)	(0.399)
$Z_{t-7}^F - Z_{t-7}^E$	0.028***	0.030***	0.028***	0.026***	0.023***	0.021***	0.017	0.025
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.008)	(0.111)	(0.375)
$Z_{t-8}^F - Z_{t-8}^E$	0.024***	0.020***	0.026***	0.029***	0.026***	0.029***	0.029***	0.030
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.008)	(0.308)
$Z_{t-9}^F - Z_{t-9}^E$	0.023***	0.017***	0.019***	0.020***	0.024***	0.021***	0.019*	−0.008
	(<0.001)†	(0.001)	(<0.001)	(<0.001)	(<0.001)	(0.006)	(0.083)	(0.784)
$Z_{t-10}^F - Z_{t-10}^E$	0.015***	0.015***	0.011**	0.013**	0.012*	0.014*	0.013	0.030
	(0.001)†	(0.003)	(0.034)	(0.013)	(0.066)	(0.070)	(0.232)	(0.292)
$Z_{t-11}^F - Z_{t-11}^E$	0.016***	0.015***	0.021***	0.025***	0.024***	0.025***	0.016	−0.018
	(<0.001)†	(0.004)	(<0.001)	(<0.001)	(<0.001)	(0.001)	(0.131)	(0.544)
$Z_{t-12}^F - Z_{t-12}^E$	0.026***	0.025***	0.026***	0.023***	0.025***	0.030***	0.039***	0.019
	(<0.001)†	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.457)
R^2	0.1357	0.0733	0.0720	0.0727	0.0759	0.0871	0.0970	0.1183

same time, it makes profitable trading more difficult. Furthermore, as shown in the results for the Nasdaq-100 index in Panel B of Table 4, the ex-ante average profits of floor-traded and E-mini futures at each transaction cost level are all negative, thereby indicating that the market is relatively ex-ante efficient.

The empirical results in Table 4 also indicate that pricing efficiency appears to be superior in the DJIA E-mini index futures markets than in the DJIA floor-traded index futures markets as a result of the lower signal size arising from arbitrage transactions. However, no similar phenomenon is discernible in Panel B of Table 4 with regard to the Nasdaq-100 futures market; therefore, pricing efficiency in both trading systems is clearly affected by market participants. The inconsistency of the ex-ante results may arise from the lack of consideration of market characteristics, such as bid–ask spread or market volatility. Thus, in order to analyze the effects of trading systems on pricing errors, and to examine our second hypothesis, we construct an additional empirical model featuring appropriate controls for these factors.

4.4. Regression analysis of futures mispricing

The regression analysis results on mispricing in the DJIA and Nasdaq-100 indices are presented in Table 5. Since inferences on the differences in the cash/futures pricing efficiency under the various trading mechanisms may well be affected by changes in market conditions over the sample period, we employ a number of control variables, including an open dummy, a close dummy, spread, volatility, high volatility dummy, low volatility dummy, time to expiration, number of futures trades and lagged differences in pricing errors.

We begin by estimating Eq. (6) using the OLS method to examine the differences in the degree of average mispricing. Since our sample size is large, in order to avoid the impact of such large sample sizes on the classical hypothesis testing procedures of the OLS method, we also apply the Bayesian sample size-adjusted critical t-value, t^*, as suggested by Connolly (1989):

$$t^* = \left[(T-k)\left(T^{1/T}-1\right) \right]^{0.5} \tag{7}$$

where k is the number of parameters to be estimated and T is the sample size. Based upon the number of parameters estimated in the regressions, as well as the sample sizes for the DJIA and Nasdaq-100 indices, the actual sample size-adjusted critical values are 3.30 for the DJIA index and 3.29 for the Nasdaq-100 index.

As demonstrated by the OLS method in Table 5, the positively significant constant terms for the DJIA and Nasdaq-100 indices indicate that when taking market conditions into consideration, the electronic trading markets contain fewer pricing errors than the floor-traded markets. Similar results are also revealed for both the DJIA and Nasdaq-100 indices under the LAD regression ($\theta = 0.5$). These results highlight the differences in pricing efficiency between floor-traded and E-mini index futures, and reveal that pricing efficiency is generally superior in electronic trading markets to that in the open-outcry markets. This finding is consistent with the supposition that the introduction of E-mini commodities into futures markets has facilitated arbitrage trading; indeed, consistent with the findings of Cheng et al. (2005), the evidence presented here provides additional support for the hypothesis that parity between actual and synthetic futures prices is strengthened under an electronic trading system.

As regards the second hypothesis in this study, the quantile regressions provide support for the finding in our regression model. In the first place, the coefficient of the volatility variable for the DJIA index is not significant if it is adjusted for the sample size under the OLS method; however, the coefficients are clear negative and significant for the two indices under the LAD method. In the second place, the coefficients of the high volatility dummy are found to be negative under the LAD method for both the DJIA and Nasdaq-100 indices.[33] This result indicates that the differences in mispricing between E-mini index futures and floor-traded index futures are reduced during periods of high market volatility. Furthermore, the coefficients of the high volatility dummy become increasingly large and very significant for lower quantiles, further inducing negatively significant constant terms for the DJIA and Nasdaq-100 indices, and thereby indicating that pricing efficiency of electronic trading relative to the open-outcry system deteriorates given high volatility. This result provides support for our argument that arbitrage risk (noise trader risks in particular) has a significant influence on futures prices during periods of higher market volatility.

Overall, the analysis in this study reveals that after controlling for the effects of market conditions, pricing efficiency within the electronic trading markets is superior to that of floor-traded markets, essentially as a result of the small average pricing errors in the E-mini index futures markets. This result generalizes the fact that the characteristics of electronic trading systems, such as speedier execution, anonymity and information efficiency, may provide benefits for arbitrageurs in terms of assisting them to offset the latent risk (such as noise trader risk) when executing their arbitrage trades, thereby reducing the pricing errors and pushing the market prices further towards equilibrium.

We also reveal that under an electronic trading system, the impact of arbitrage risks (noise trader risk in particular) is higher during periods of high volatility than during periods of normal volatility. Although the electronic trading system clearly has some special attractions for arbitrageurs and informed traders, through the enhanced pricing efficiency, the important advantages of electronic trading systems will tend to be offset by the influences of greater arbitrage risks for those periods that are characterized by higher market volatility. In summary, we provide some clear evidence in support of the two hypotheses proposed in this study.

5. Conclusions

We set out in this study to investigate the effects of market volatility on pricing efficiency under the existing open-outcry and electronic trading platforms in the DJIA and Nasdaq-100 index futures markets by examining two specific hypotheses; firstly, we argue that E-mini index futures will have lower pricing errors than floor-traded index futures, and secondly, we suggest that during periods of high market volatility, E-mini index futures will suffer greater deterioration in pricing efficiency than floor-traded index futures. The evidences presented in this study provide some clear support for both of these hypotheses. Our analysis complements the prior studies in this area in which assessment is undertaken of the benefits to be obtained by the exchanges resulting from a switch to electronic trading; however, to the best of our knowledge, none of the prior studies have undertaken any examination of this issue in those futures markets with parallel trading platforms. Our study provides empirical validation of the relationships that exist between trading systems and pricing efficiency, pointing out that an electronic trading system has some special attractions for arbitrageurs and informed traders, such as speedier execution, anonymity and informational efficiency, all of which enhance pricing efficiency.

We also reveal that as compared to normal periods, during periods of high volatility, the impacts of arbitrage risks (such as noise trader risk) are higher under an electronic trading system; given such a scenario, the advantages of an electronic trading system will be largely offset by the greater arbitrage risks, which will thereby further frustrate the execution of transactions in the market by arbitrageurs. Namely, periods of high volatility will tend to induce more noise traders to trade in the markets as a result of their belief that profits can be more easily accrued from such market timing. This finding complements the studies provided by Martens (1998) and Ates and Wang (2005), relying upon the concept of noise trading risk raised in many of the prior studies.[34]

Taken together, the results also provide support for the viewpoint that both electronic and floor-traded systems fulfill important roles in pricing efficiency; however, it must also be noted that as a result of the limitations of our research data, we have

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[33] The coefficients on the volatility variables (95th and 99th percentiles of volatility distribution) are both significantly negative under the quantile regression model. For space considerations, only the empirical results for the 95th percentile of volatility distribution are reported here.

[34] Examples include, amongst many others, Black (1986), De Long et al. (1990) Shleifer and Summers (1990), Shleifer and Vishny (1997) and Bloomfield et al. (2009).

been unable to further discriminate between the arbitrage risks that may be attributable to different market participants. This clearly provides a topic for further research based upon the availability of more detailed data.

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