PRICE CLUSTERING IN E-MINI AND FLOOR-TRADED INDEX FUTURES

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This article sets out to investigate price clustering in both the open-outcry (floor-traded) and electronically traded (E-mini) index futures markets of the DJIA, S&P 500, and NASDAQ-100 indices. The results show that although price clustering is ubiquitous in both the floor-traded and E-mini index futures markets, it nevertheless tends to be higher for open-outcry index futures, with the clustering in floor-traded NASDAQ-100 index futures demonstrating the highest level (97%) at zero digits. A significant increase was also found in price clustering in floor-traded index futures after the introduction of E-mini futures trading. The results tend to suggest that those trading mechanisms that involve higher levels of human participation, such as the open-outcry markets, may well lead to increased incidences of price clustering. © 2006 Wiley Periodicals, Inc. Jrl Fut Mark 26: 269–295, 2006

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INTRODUCTION

Under a constrained minimum tick size, and in the absence of market friction and bias, prices should be uniformly distributed across every likely value; however, it is invariably the case that observed prices are rounded either up or down. The resultant clustering of trade prices, which is the tendency for certain prices to be observed with greater frequency than others, is very common; indeed, it is already well documented in the literature both across and within markets.[1] Clustering can be the result of many factors, such as human bias, uncertainty with regard to an asset's underlying value, or even cultural factors influencing the preference for certain numbers (Brown, Chua, & Mitchell, 2002). There is also the likelihood of collusion between market makers (Christie & Schultz, 1994) or differences between market structures (Grossman et al., 1997).

An important recent development in the futures markets of the world has been the growing shift toward electronic trading systems and the resultant adoption of such systems by many of the world's exchanges.[2] Although there is an abundance of comparative studies on the effects of market structure between open-outcry markets and electronically traded markets,[3] precious few studies have investigated the prevalence of price clustering within both types of markets. One such study by ap Gwilym and Alibo (2003), however, reported a significant decrease in price clustering in the LIFFE following such migration to electronic trading.

In the index futures markets of the United States, both electronic and open-outcry trading systems have been retained, operating simultaneously during regular trading hours. This unique market mechanism provides a natural experimental environment in which to directly compare the extent of price clustering between regular and electronically traded (E-mini) index futures. The prior studies that have engaged in such a comparison have generally focused on price discovery or information transmission between these markets. Hasbrouck (2003) and Kurov and Lasser (2004), for example, both showed that E-mini index futures were highly successful in attracting a retail customer base, demonstrating

[1]Examples of the literature on price clustering include underwritten offerings (Yeoman, 2001), initial public offerings (Kandel, Saring, & Wohl, 2001), foreign-exchange markets (Goodhart & Curcio, 1991; Osler, 2003), the London gold market (Grossman et al., 1997), underlying stock prices on options expiration dates (Ni, Pearson, & Poteshman, 2005), and futures markets (ap Gwilym & Alibo, 2003; Schwartz et al., 2004).
[2]There are a number of examples of exchanges transferring from an open-outcry to an automated trading system in recent years, such as the MATIF, the Sydney Futures Exchange (SFE), the New Zealand Stock Exchange (NZSE), the London International Financial Futures Exchange (LIFFE), and several other exchanges around the world.
[3]See, for example, Naidu and Rozeff (1994), and Blennerhassett and Bowman (1998).

a dominant role in the price discovery process within the markets of index instruments.[4] Nevertheless, despite the successful development of E-mini index futures, to the best of the authors' knowledge, no research has yet documented the differences in clustering behavior between E-mini index futures and open-outcry futures.

Although the study by Schwartz, Van Ness, and Van Ness (2004) did provide evidence on price clustering in the S&P 500, showing that clustering dramatically changed with a move from lead-month contracts to back-month contracts, their analysis was, nevertheless, confined to the study of the open-outcry market in isolation. This article explores price clustering in both floor-traded and E-mini futures on the Dow Jones Industrial Average (DJIA), the Standard and Poor's (S&P) 500 index, and the NASDAQ-100 index. It is expected that such a comparison of both floor-traded and E-mini index futures will be particularly informative, in part because both contracts are traded simultaneously, but also because the prices at which they are traded are almost perfectly correlated. Furthermore, such a comprehensive analysis should also provide a clear opportunity to gain a better understanding of the effects of market structures on price clustering.

The empirical results, based upon intraday analyses, have raised a number of interesting issues; for example, the results have provided clear evidence to show the existence of price clustering in both floor-traded and E-mini index futures, although they also suggest that clustering tends to be higher in open-outcry index futures trading, with the highest level of clustering being demonstrated among floor-traded index futures in the NASDAQ-100. The smallest contract differences were found to be between E-mini and regular-traded futures in the DJIA index, where tick sizes were also equal; by direct comparison, the percentage of clustering in floor-traded futures in the DJIA was more than twice that of its E-mini counterpart. Furthermore, despite there being differences in tick sizes between E-mini index futures and floor-traded index futures in both the S&P 500 and the NASDAQ-100, the results also showed that floor-traded index futures exhibited higher *excess clustering*, which is defined in this study as the actual percentage minus the expected percentage of clustering under null distribution.

In general, the results tend to suggest that those trading mechanisms that involve higher levels of human participation, such as open-outcry

[4]Kurov and Lasser (2004) found that exchange locals used both their vicinity to the order flow into the exchange, and their superior implementation speed of GLOBEX to front-run large trades occurring on the floor, which resulted in the price leadership of E-mini index futures. Their results suggest that the institutional order flow that arrives at the CME floor continues to represent an important source of price discovery.

markets, may well lead to increased incidences of price clustering. The results also indicate that there was an increase in clustering among all three floor-traded index futures following the introduction of their corresponding E-mini index futures. This may be caused by the fact that in order to compete with the electronically traded index futures, rounded quotations are more frequently used by both market makers and traders alike. Because E-mini contracts have been successful in attracting smaller investors, open-outcry trading has largely become recognized as a wholesale market, within which larger increments in price may be more common due to the larger trading sizes.

The remainder of this article is organized as follows. The next section presents the related literature on price clustering followed by a description of the data and the empirical methodology adopted for this study. The penultimate section presents the results of this study, with the final section summarizing the conclusions drawn from the results.

RELATED LITERATURE ON PRICE CLUSTERING

Price clustering within financial markets is a widely recognized phenomenon, with some of the previous studies in this area suggesting that, for certain reasons, prices may cluster at specific numbers. Price clustering may occur, for example, from investors trading at a particular price in order to simplify the overall trading process; in proposing the "haziness and bounded rationality" hypothesis, Loomes (1988) found that most subjects dealt with their "sphere of haziness" by rounding their valuations.

The price-resolution hypothesis proposed by Ball, Torous, and Tschoegl (1985) argued that price clustering may also come about as a result of the achievement of the optimal degree of price resolution, because they found that price clustering within the London gold market increased with both price and volatility. Higher price volatility leads to greater clustering, because investors wish to deal quickly with all trades, which will normally lead to less precise valuations.

Price clustering may also come about as a matter of convenience, in terms of reducing the costs of negotiation, because a reduced set of prices will bring down negotiation costs (Harris, 1991). The inevitable result would be an increase in price clustering with price and volatility, and a decrease with trade frequency and market capitalization. Hameed and Terry (1998) and Ikenberry and Weston (2003) both reported evidence in support of the Harris (1991) negotiation hypothesis.

In practice, some individuals prefer certain numbers to others, a phenomenon that Hornick, Cherianand, and Zakay (1994) referred to as "human bias." In their surveys of self-reported time-based activities, they found that investors displayed a bias for rounding numbers to 0 or 5, whereas Kandel, Saring, and Wohl (2001) also found that investors preferred round numbers in the Israeli IPO auctions. Goodhart and Curcio (1991) and Aitken et al. (1996) argued that some numbers have a basic attraction to investors, with the final digit 0 having greater attraction than 5, which in turn is more popular than others; they referred to this as the "attraction hypothesis," and indeed, consistent with this hypothesis, in their examination of price clustering on the LSE, Grossman et al. (1997) found that quotes ending in 0 and 5 were the most frequently seen.

Having found evidence of an increase in price clustering with the onset of decimalization, Ikenberry and Weston (2003) suggested that psychology may well play an important role in explaining the tendency for stock price clustering within the NYSE. Christie and Schultz (1994) had earlier found evidence of extreme clustering within certain NASDAQ stocks, which suggested that NASDAQ dealers were implicitly colluding to maintain wider bid/ask spreads than those that would prevail under full competition. Following from the Christie and Schultz (1994) empirical findings (although Barclay, 1997; Bessembinder, 1997; Christie, Harris, & Schultz, 1994; Cooney, Van Ness, & Van Ness, 2003, all reported consistent results), in an examination of several competitive markets, Grossman et al. (1997) nevertheless found that differences in the degree of clustering reflected differences in market structures.

Studies of the derivative markets have generally been consistent with the results from the equity markets, because they have also reported significant price clustering. In an examination of the price clustering of both equity index futures and options contracts traded on the LIFFE, ap Gwilym, Clare, and Thomas (1998a) found that there was an increase in the degree of clustering with volatility and trade frequency, whereas there was a decrease in clustering with the size of the trade. Their results support the price-resolution hypothesis and, to a lesser extent, the negotiation hypothesis; however, the positive relationship between price clustering and trade frequency runs contrary to Harris (1991). Support for the attraction hypothesis was provided by ap Gwilym et al. (1998b) in their study of price clustering for four long-term government bond futures on the LIFFE, and ap Gwilym and Alibo (2003) went on to provide evidence of decreased clustering in a subsequent examination of the impact of migration to the electronic trading of FTSE 100 stock index futures traded on the LIFFE; these results also support the Harris (1991) negotiation hypothesis. All of these explanations suggest that price clustering may well vary with uncertainty, market structure, resolution costs, or human preference.

Although the traditional method of trading in the futures markets of the United States continues to take place primarily through open-outcry auctions on the exchange floor, the recent introduction of E-mini futures has nevertheless been very successful in attracting small retail investors (Ates & Wang, 2004; Kurov & Lasser, 2004). Schwartz et al. (2004) found significant price clustering among S&P 500 floor-traded futures, demonstrating that clustering is both a positive function of volatility and a negative function of volume. Extending the research of Schwartz et al. (2004) and ap Gwilym and Alibo (2003), this research aims to examine the extent of price clustering among regular and E-mini index futures for the DJIA, NASDAQ-100, and S&P 500 indices. Because the U.S. futures market facilitates the simultaneous operation of both trading mechanisms, a comparison of the extent of clustering between regular and E-mini contracts should prove useful in providing an understanding of how the various differences in the trading mechanisms affect clustering behavior.

DATA AND METHODOLOGY

Data Description

This analysis of price clustering is based upon intraday tick-by-tick transaction prices obtained from Tickdata Inc. Nearby futures contracts are selected for this analysis because they are the most actively traded futures contracts within their own classification; this therefore minimizes the problem of infrequent trading. The sample period for the analysis of floor-traded futures covers the 1-year periods prior to, and following, the date of the introduction of E-mini index futures trading. E-mini index futures contracts were introduced into the S&P 500 on 9 September 1997 and into the NASDAQ-100 on 21 June 1999 (see Table I). The Chicago Mercantile Exchange (CME) reduced the multiplier for S&P 500 index futures contract from U.S.$500 to U.S.$250 from 31 October 1997 onwards, while also doubling the minimum tick size from 0.05 to 0.1 index points. The Chicago Board of Trade (CBOT) subsequently began trading in E-mini index futures on the DJIA on 4 April 2002. Open-outcry trading in S&P 500 index futures, during the period immediately after the introduction of E-mini trading, is further

TABLE I

Contract Specifications for the Three Floor-Traded and E-Mini Futures Indices

Futures indices	*Specifications*	*Floor-traded index futures*	*E-mini index futures*
DJIA	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, U.S.$10	1 futures index point, U.S.$5
	Trading hours	7:20 a.m. to 3:15 p.m.	Virtually 24 hours
S&P 500	Date of first trade	21 April 1982	9 September 1997
	Contract size	250*S&P 500 futures value	50*E-mini S&P 500 futures value
	Minimum tick size and price fluctuation	Before 1 Nov 1997, 0.05 futures index points, U.S.$50 After 1 Nov 1997, 0.1 futures index points, U.S.$25	0.25 futures index points, U.S.$12.50
	Trading hours	8:30 a.m. to 3:15 p.m.	Virtually 24 hours
NASDAQ-100	Date of first trade	10 April 1996	21 June 1999
	Contract size	100*E-mini NASDAQ-100 futures value	20*E-mini NASDAQ-100 futures value
	Minimum tick size and price fluctuation	0.05 futures index points, U.S.$50.00	0.5 futures index points, U.S.$10.00
	Trading hours	8:30 a.m. to 3:15 p.m.	Virtually 24 hours

Note. Trading time is Chicago time. The minimum tick size for NASDAQ-100 floor-traded index futures is 0.05 futures index points for the period studied; the CME enlarged its minimum tick size from 0.05 to 0.5 futures index points after 2002.

divided into two subperiods (pre- and post-31 October 1997), in order to investigate whether there were any changes in price clustering after the redesign of the S&P 500 contracts.

E-mini index futures transaction data for the 1-year period after the introduction of E-mini trading is also analyzed in order to provide a direct comparison of price clustering. Tick-by-tick data are used to examine whether the frequency distribution of the last digit, or the last two digits, follows uniform distribution for the three index futures. As reported in Table I, there are differences in contract size and trading hours between regular and E-mini index futures, and although the tick sizes are the same for E-mini and floor-traded contracts in the DJIA, in both the NASDAQ-100 and the S&P 500, the tick sizes of floor-traded contracts are smaller than those of E-mini futures. The NASDAQ-100 and the S&P 500 E-mini contracts are just one-fifth the size of their respective open-outcry contracts, whereas the contract size of DJIA E-mini is half of its open-outcry contract. Because traders can liquidate their E-mini positions against their offsetting positions in regular futures trading, arbitrage activities between E-mini and floor-traded contracts ensure that their prices are almost perfectly correlated. Kurov and Lasser (2004) indicated that trading in the E-mini markets is dominated by small retail traders, whereas large institutional traders continue to actively trade in lower-cost regular contracts.

Empirical Models

Tests for Price Clustering

This section presents details of the clustering measures used in this study. First of all, standard chi-square goodness-of-fit statistics are used to explore whether the frequency distribution of the last digit, or the last two digits for the three index futures, follow uniform distribution; that is, the sum of the squared deviations between the observed level of price clustering and the expected level of such clustering under uniform distribution is computed as

$$W = \sum_{i=1}^{k} \frac{(O_i - A_i)^2}{A_i} \tag{1}$$

where O_i is the observed frequency of the last digit, or last two digits, A_i is the expected frequency under uniform distribution, and W is the distributed chi-square with $(k - 1)$ degrees of freedom under standard conditions. A large value of W would signify a significant deviation from uniform distribution.

Following Grossman et al. (1997) and Ikenberry and Weston (2003), the measure of price concentration is estimated with the use of a variation of the Hirshmann-Herfindal index (HHI) to observe the ways in which prices cluster for the three index futures. The HHI is a well-known and widely used measure of concentration calculated by summing the squared values of the market shares of all market participants. Specifically,

$$\text{HHI} = \sum_{i=1}^{k} (f_i)^2 \tag{2}$$

where f_i is the frequency of trades (in percentage terms) that occur at fraction i, $i = 1, 2, \ldots, k$ possible ticks. The HHI is computed based upon the last digit, or the last two digits, of the trade price according to the minimum tick sizes for the three index futures contracts. Under the null hypothesis of no price clustering, HHI should be equal to $1/k$; for example, under null distribution, the HHI should be equal to 0.1 for DJIA floor-traded and E-mini index futures.

The standardized range is also used as an alternative measure of clustering, following Grossman et al. (1997). The numerator of the standardized range is the difference between the highest and lowest quotation frequency. A standardized range can be computed by dividing the range by the expected quotation frequency under null distribution.

Price Clustering of Floor-Traded and E-Mini Index Futures

A multivariate regression approach is further employed to investigate the price-clustering behavior of floor-traded index futures, with hourly data used to examine the impact of various trading characteristic variables on price clustering for the three floor-traded index futures, both prior to and after the introduction of E-mini index futures trading. Any interval between these initial and terminal points that does not contain price observations for a given series is deleted. For ease of interpretation, and in order to ensure an equally comparable base, the work of Ikenberry and Weston (2003) and Schwartz et al. (2004) is used to compute the excess clustering on the last digit, or the last two digits, of the prices that appear the most. Hence, the regression analysis focuses mainly on excess clustering [Clustering $-$ E(Clustering)], that is, the observed percentage of clustering minus the expected percentage of clustering under null distribution. The use of excess clustering could help to mitigate the problem of differences in tick sizes between index futures.

For DJIA index futures, percentage clustering is defined as the percentage of trade prices where the last digit occurs at 0 and 5. For S&P 500 floor-traded index futures, prior to contract adjustment, the last two digits correspond to 00 (integer) and 50 (cent), whereas for the contract redesign period, percentage clustering is defined for the last digit of 0 (integer) and 5 (dime). For E-mini index futures in the S&P 500, percentage clustering is defined as the percentage of trade prices where the last two digits occur at 00. As for the NASDAQ-100 markets, the last digits of clustering are defined as 00 (integer) and 50 (cent) for floor-traded contracts, and 0 (integer) for E-mini index futures contracts.

Motivated by the related theories drawn from the prior studies, the control variables include return, tick volume, volatility, and bid/ask spread. Dummy variables are also added for the open and close intervals to account for the potential periodic effects on price clustering from market opening and closing; ap Gwilym et al. (1998a) reported that the proportion of odd ticks was significantly lower near market opening, and higher near market closing. Hence, the following regression model is specified for the DJIA and NASDAQ-100 regular futures markets:

$$\begin{aligned}\text{Clustering}_t - E(\text{Clustering}_t) = {} & \alpha_0 + \alpha_1 * D1_t + \beta_1 * \text{Open}_t + \beta_2 * \text{Close}_t \\ & + \beta_3 * \text{Ret}_t + \beta_4 * \text{Spr}_t + \beta_5 * \text{Tickvol}_t \\ & + \beta_6 * \sigma_t + \varepsilon_t \end{aligned} \tag{3}$$

where Open and Close are (0,1) dummy variables controlling for the open and close interval effects, respectively; $D1$ is a dummy variable controlling for the effect of the introduction of E-mini futures trading; Ret is the intraday hourly return; and Tickvol is the total number of ticks (price changes) for each hourly interval, reflecting the trading activities of the futures markets. Spr is the bid/ask spread determined by using the estimator suggested in Wang et al. (1994) and Wang, Yau, and Baptiste (1997). This estimator, which is used by the Commodity Futures Trading Commission (CFTC), is calculated as the average absolute price change in the opposite direction. σ is the intraday hourly volatility, calculated with the use of the Parkinson (1980) extreme value estimator; that is,

$$\sigma_t = 0.361 \times [\log(H_t/L_t)]^2$$

where H_t and L_t denote the high and low prices during time period t.[5] The regular trading hours for DJIA index futures are from 7:20 to 15:15, and those for the S&P 500 and NASDAQ-100 futures markets are from 8:30 to 15:15; therefore, the last interval for the DJIA futures market is comprised of 55 minutes, whereas in both the S&P 500 and the NASDAQ-100 futures markets, the last interval is 45 minutes. For ease of interpretation, although also reducing skewness, three of the explanatory variables, that is, spread, volatility, and tick volume, are first log-transformed; these variables, together with the return variable, are then standardized by subtracting the sample mean and dividing the result by the standard deviation.

The regression model for the S&P 500 regular futures market is slightly modified because of its contract adjustment during the sample period:

$$\begin{aligned}\text{Clustering}_t - E(\text{Clustering}_t) = {} & \alpha_0 + \alpha_1 * D1_t + \alpha_2 * D2_t + \beta_1 * \text{Open}_t \\ & + \beta_2 * \text{Close}_t + \beta_3 * \text{Ret}_t + \beta_4 * \text{Spr}_t \\ & + \beta_5 * \text{Tickvol}_t + \beta_6 * \sigma_t + \varepsilon_t \end{aligned} \tag{4}$$

[5] Alizadeh, Brandt, & Diebold (2002) demonstrated that such a range-based estimation of volatility is not only a highly efficient volatility proxy, but that it is also robust to microstructure noise, such as bid/ask bounce.

The above equation includes a new dummy variable, $D2$, designed to capture the effects of the contract redesign for S&P 500 index futures, and the definitions of the remaining variables remain the same as those in Equation (3).

Although bid/ask spread is an important factor in determining the overall degree of clustering, some of the prior empirical studies have shown that price clustering could also influence the bid/ask spread (ap Gwilym et al., 1998a; Hasbrouck, 1999). Hence, both the bid/ask spread and the degree of clustering could be determined simultaneously. The Hausman (1978) specification test is used in order to test for potential endogeneity in the bid/ask spread variable in Equations (3) and (4), with the results indicating that the bid/ask spread is generally endogenous; therefore, the models are estimated by using the generalized method-of-moments (GMM) approach, which uses the lagged bid/ask spread and the previous day's open interest as the instrument variables for bid/ask spread.

Let z_t be the vector of the instrument variables, that is, the dummy variables for the open and close intervals, return, tick volume, volatility, bid/ask spread at period $t - 1$, and open interest at the previous day. The GMM estimator is based mainly on the moment conditions that:

$$E(z_t \varepsilon_t) = 0$$

where ε_t is the error term in Equations (3) and (4).[6]

According to Harris (1991) and Aitken et al. (1996), clustering is expected to increase during periods of high volatility and bid/ask spread; therefore, the volatility and bid/ask spread coefficients are expected to be positive. Tick volume behaves in a fashion similar to that of actual trade volume and, when there is no change in the price, in most cases, the market will be inactive. Similarly, when trade volume is high, the tick volume normally has a correspondingly large value.[7] Therefore, a reduction in clustering is expected during periods of high tick volume, and the coefficient is expected to be negative, as argued by Harris (1991).

A multivariate regression approach is used to explore the impacts of various trading characteristic variables on the price clustering of E-mini index futures. The empirical model is written as follows:

$$\begin{aligned} \text{Clustering}_t - E(\text{Clustering}_t) = \alpha_0 + \beta_1 * \text{Open}_t + \beta_2 * \text{Close}_t + \beta_3 * \text{Ret}_t \\ + \beta_4 * \text{Spr}_t + \beta_5 * \text{Tickvol}_t + \beta_6 * \sigma_t + \varepsilon_t \quad (5) \end{aligned}$$

[6]See Hamilton (1994, chap. 14) for a detailed explanation of the estimation procedure.
[7]Karpoff (1986) suggested that, as a measure of information arrival during any given period, tick volume is superior to actual volume; thus tick volume is a relatively good substitute for trade volume.

Equation (5) is also estimated by GMM, and the definitions of the explanatory variables are the same as those in Equation (3). Although E-mini index futures can be traded for virtually 24 hours, the frequency of price changes (tick volume) is relatively thin during nonregular trading hours. For ease of interpretation and comparison, the analysis focuses on the trading time of E-mini index futures, which coincides with that of floor-traded index futures.[8]

Differences in Price Clustering Between Floor-Traded and E-Mini Index Futures

Because there may well be variations in the differences in price clustering with different market conditions, a multivariate regression analysis is also used to examine the significance of the differences in price clustering after controlling for the trading characteristic variables, such as return, spread, volatility, and tick volume. The control variables are calculated for the trading characteristics of E-mini futures, because these futures are dominant in the price discovery process (Hasbrouck, 2003).

The following regression model is estimated:

$$\text{Clus\_Differ}_t = \alpha_0 + \beta_1 * \text{Ret}_t + \beta_2 * \text{Spr}_t + \beta_3 * \text{Tickvol}_t + \beta_4 * \sigma_t + \varepsilon_0 \quad (6)$$

where Clus_Differ_t represents the excess percentage of clustering of floor-traded index futures, minus that of E-mini index futures, for each 1-hour period.

The explanatory variables are the trading characteristics of E-mini futures; for example, Ret_t is the return of E-mini futures at hour t. All trading characteristics of E-mini index futures are defined and computed as in the previous equations. If the estimated coefficient of α_0 is significantly larger than zero, this would indicate that floor-traded futures have a higher degree of excess clustering than their E-mini counterparts.

EMPIRICAL RESULTS

The Extent and Frequency of Price Clustering

Table II presents the frequency distribution of the last digit, the Hirshmann-Herfindal index (HHI), and the standardized range for futures contracts within the DJIA index. The results reveal that the last

[8]For DJIA E-mini index futures, the trading time is from 7:20 to 15:15; for S&P 500 and NASDAQ-100 E-mini index futures, the trading time is from 8:30 to 15:15. In addition, calculations were made and regressions were run on the full trading data for E-mini index futures, but no material changes are found.

TABLE II
Comparison of Price Clustering in DJIA Floor-Traded and E-Mini Index Futures

Last digit	Floor-Traded index futures: Before E-mini trading (4 Apr 2001–3 Apr 2002) Frequency	(%)	Floor-Traded index futures: After E-mini trading (4 Apr 2002–3 Apr 2003) Frequency	(%)	E-mini index futures (4 Apr 2002–3 Apr 2003) Frequency	(%)
1	12,352	3.46	13,775	3.08	122,130	8.50
2	12,351	3.46	11,467	2.56	137,050	9.54
3	9,696	2.72	8,811	1.97	123,925	8.63
4	10,077	2.83	10,959	2.45	138,385	9.63
5	132,318	37.09	177,725	39.75	183,682	12.79
6	11,458	3.21	11,863	2.65	137,992	9.61
7	10,445	2.93	9,651	2.16	122,879	8.55
8	13,378	3.75	12,119	2.71	138,988	9.67
9	11,434	3.21	12,407	2.78	120,382	8.38
0	133,195	37.34	178,302	39.88	211,215	14.70
No. of obs.	356,704	100.00	447,079	100.00	1,436,628	100.00
Goodness of fit (χ^2_9)	660938.91***		994085.34***		56504.79***	
HHI	0.285 (0.1)		0.322 (0.1)		0.104 (0.1)	
Standardized range	3.462		3.791		0.632	

Note. Cell frequencies are determined based on the last digit with goodness-of-fit statistics being constructed as the sum of the squared deviations of the cell frequencies from the expected frequency under the null hypothesis of uniform distribution (i.e., one-tenth). Hirshmann-Herfindal index (HHI) and standardized range method are also used to test for price concentration. Numbers in the parentheses of the row labeled HHI are the expected HHI values under the null distribution of no price clustering.

***Indicates significance at the 1% level.

digit 0 occurred most frequently prior to the introduction of E-mini trading, appearing in about 37.34% of all trades. The last digit 5 was the next most likely to occur, appearing in about 37.09% of all trades. Of all other possible last digits, none occurs with a frequency of more than about 4%.

Following the introduction of E-mini index futures trading, there was a rise in the frequency of occurrences of last digits 0 and 5, appearing in about 39.88% and 39.75%, respectively, of all trades, whereas the frequency of the remaining numbers was reduced. Although price clustering was relatively more uniform in E-mini trading than in floor-traded index futures, the respective frequency of the last digits 0 and 5 occurring in E-mini trading was still higher than expected, at about 14.70 and 12.79%, of all trades. Thus, the frequency of other possible numbers as the last digit was of course higher than in floor-traded index futures, with occurrences varying between 8.3 and 9.7%, approximately.

Table III presents the results of the analysis of S&P 500 index futures, covering three subperiods; the first period is comprised of the 1-year period prior to the introduction of E-mini trading, and the E-mini postintroduction period is divided into two subperiods because of the redesign of the S&P contract during that 1-year period. The results reveal that the largest percentages of clustering in all periods are demonstrated where the last two digits are 00; for the period before the introduction of E-mini trading the figure was 9.10%, whereas for the two periods after the introduction of E-mini trading, the respective figures were 14.88 and 15.64%. The next most likely two-digit combinations before the introduction of E-mini trading in floor-traded index futures trading were 50, followed by the last two-digit ending in the units of 0.10, with each of these combinations appearing with similar frequency of approximately 7.00–7.41%, respectively.

In the period after the introduction of E-mini index futures trading, but before 31 October 1997, after the last two digits of 00, the next most likely to occur were 50, 25, and 75, appearing in about 13.76, 9.95, and 8.30% of all trades, respectively. The frequency of the remaining numbers (i.e., 5, 10, 15, 20, 30, 35, 40, 45, 55, 60, 65, 70, 80, 85, 90, and 95 cents) appearing in this period was less than before.

After the redesign of the S&P 500 futures contracts, price clustering was still not uniform across all categories, with the highest and the second highest numbers ending in the last digit of 0 and 5; these last digits together accounted for 30.84% of all reported trading prices, as opposed to the expected 20%. It is also found that an increase in the frequency of 0 and 5 was observed following the adjustment of the S&P 500 index futures contracts; this result is consistent with the findings of Bollen, Smith, and Whaley (2003). E-mini index futures in the S&P 500 had a relatively higher tick size, and it seems that E-mini futures traders in the S&P 500 still prefer the last two digits of 00 (integer), which appeared in about 29.36% of all trades.

For NASDAQ-100 floor-traded index futures, prior to the introduction of E-mini futures trading, there was an 80.93% occurrence of clustering, where the last two digits were 00 (integer); the occurrence of these two digits was 97.08% after the introduction of E-mini futures trading. Furthermore, over 99% of the last two digits of all trading prices were concentrated on 00 and 50 after the introduction of E-mini trading.

For trading in E-mini index futures, investors tend to prefer the last digit 0 (a full index point) to the last digit 5 (a half index point), with the respective occurrence of these digits being 64.17 and 35.83%. The results of the goodness-of-fit statistics show that the futures markets do

TABLE III

Comparison of Price Clustering for S&P 500 Floor-Traded and E-Mini Index Futures

Floor-traded index futures

Last two digits	*Before E-mini trading (10 Sep 1996–9 Sep 1997)*		*After E-mini trading (10 Sep 1997–31 Oct 1997)*	
	Frequency	*(%)*	*Frequency*	*(%)*
05	19,611	1.81	500	0.33
10	79,362	7.31	10,402	6.82
15	22,051	2.03	580	0.38
20	77,872	7.17	9,148	6.00
25	56,259	5.18	15,173	9.95
30	77,413	7.13	9,535	6.25
35	21,482	1.98	402	0.26
40	76,013	7.00	8,992	5.90
45	18,374	1.69	364	0.24
50	97,634	8.99	20,987	13.76
55	20,486	1.89	463	0.30
60	76,753	7.07	9,322	6.11
65	19,624	1.81	479	0.31
70	80,029	7.37	9,670	6.34
75	46,819	4.31	12,665	8.30
80	80,489	7.41	10,373	6.80
85	19,824	1.83	408	0.27
90	77,461	7.13	9,956	6.53
95	19,403	1.79	394	0.24
00 (integer)	98,782	9.10	22,688	14.88
No. of obs.	1,085,741	100.00	152,501	100.00
Goodness of fit (χ^2_{19})	328942.84***		122678.46***	
HHI	0.065 (0.05)		0.090 (0.05)	
Standardized range	1.482		2.928	

E-mini index futures

Last digit	*After E-mini trading and contract adjustment (1 Nov 1997–31 Oct 1998)*		*Last two digits*	*(10 Sep 1997–31 Oct 1998)*	
	Frequency	*(%)*		*Frequency*	*(%)*
1	78,536	7.82	25	441,457	22.26
2	100,198	9.98			
3	96,301	9.59			
4	73,888	7.36	50	517,305	26.08
5	152,657	15.20			
6	74,924	7.46	75	442,233	22.30
7	96,003	9.56			
8	100,762	10.03			
9	74,014	7.37	00 (integer)	582,399	29.36
0 (integer)	157,076	15.64			
No. of obs.	1,004,359	100.00	No. of obs.	1,983,394	100.00
χ^2_9	84685.11***		χ^2_3	27799.68***	
HHI	0.108 (0.1)		HHI	0.253 (0.25)	
Standardized range	0.828		Standardized range	0.284	

Note. Cell frequencies are determined by the last digit, or last two-digits, with goodness-of-fit statistics being constructed as the sum of the squared deviations of the cell frequencies from the expected frequency under the null hypothesis of uniform distribution (i.e., 1/20th and 1/10th before and after the CME redesigned contract; 1/4th for E-mini index futures). Hirshmann-Herfindal index (HHI) and standardized range method are also used to test for price concentration. Numbers in the parentheses of the row labeled HHI are the expected HHI values under the null distribution of no price clustering.

***Indicates significance at the 1% level.

not follow any uniform distribution (all of the χ^2 values are significant at the 1% level).

There are differences in tick sizes between floor-traded and E-mini index futures for both the S&P 500 and NASDAQ-100 indices, although the tick sizes in these two contracts are the same as for the DJIA index. Thus, the DJIA futures market provides us with a good sample for direct comparison of whether the differences in price clustering are driven by the differences in trading mechanisms. Even if different minimum tick sizes do lead to variations in price clustering, the extent of price clustering can still be compared by using the standardized range to analyze whether there was greater price clustering in the S&P 500 and NASDAQ-100 futures markets following the introduction of E-mini trading.

Related Results

The Hirshmann-Herfindal index (HHI) of clustering is also reported in Tables II–IV. Although the expected HHI under null distribution is 0.1, the HHI for DJIA floor-traded index futures before the introduction of E-mini futures trading was 0.285, whereas the HHI for the period after the introduction of E-mini trading was 0.322. The HHI for E-mini index futures in the DJIA was only 0.104.

For E-mini contract trading in the S&P 500, the estimated HHI was 0.253, slightly higher than its expected value of 0.25 under null distribution, whereas the HHI for floor-traded index futures in the S&P 500, prior to the introduction of E-mini trading, was 0.065. As a result of the change in tick size, the sample period for the analysis of clustering in floor-traded contracts in the S&P 500, after the introduction of E-mini trading, was divided into two subperiods. The HHI estimations for floor-traded contracts, for the two subperiods after the introduction of E-mini trading, were 0.090 and 0.108, respectively, whereas their expected values under null distribution were 0.05 and 0.1. The HHI estimations for NASDAQ-100 floor-traded index futures, for the periods both before and after the introduction of E-mini trading, were 0.676 and 0.943, respectively, whereas the HHI for E-mini index futures was 0.540. Because the expected HHI values for floor-traded contracts and E-mini futures, under no price clustering, were 0.05 and 0.50, respectively, the floor-traded index futures demonstrated a higher degree of price concentration. The analysis also suggests that the trading prices for the three regular index futures became more centralized after the introduction of E-mini index futures trading, but higher than the trading prices of the E-mini futures themselves.

TABLE IV
Comparison of Price Clustering for NASDAQ-100 Floor-Traded and E-Mini Index Futures

	Floor-traded index futures				*E-mini index futures*		
	Before E-mini trading (21 Jun 1998–20 Jun 1999)		*After E-mini trading (21 Jun 1999–20 Jun 2000)*			*(21 Jun 1999–20 Jun 2000)*	
Last two digits	*Frequency*	*(%)*	*Frequency*	*(%)*	*Last digit*	*Frequency*	*(%)*
05	326	0.13	149	0.03			
10	655	0.25	443	0.10			
15	31	0.01	15	0.00			
20	234	0.09	116	0.03			
25	5,322	2.07	973	0.22			
30	144	0.06	84	0.02	5	1,023,580	35.83
35	17	0.01	42	0.01			
40	219	0.09	58	0.01			
45	69	0.03	22	0.01			
50	36,939	14.34	9,721	2.22			
55	111	0.04	38	0.01			
60	198	0.08	55	0.01			
65	12	0.00	16	0.00			
70	119	0.05	59	0.01			
75	3,486	1.35	363	0.08			
80	213	0.08	71	0.02	0 (integer)	1,833,485	64.17
85	30	0.01	10	0.00			
90	662	0.26	408	0.09			
95	334	0.13	153	0.03			
00 (integer)	208,469	80.93	425,448	97.08			
No. of obs. 100.00	257,590	100.00	438,244	100.00	No. of obs.	2,857,065	
Goodness of fit (χ^2_{19})	3225900.53***		7826650.67***		χ^2_1	229587.39***	
HHI	0.676 (0.05)		0.943 (0.05)		0.540 (0.5)		
Standardized range	16.186		19.416			0.567	

Note. Cell frequencies are determined based on the last digit, with goodness-of-fit statistics being constructed as the sum of the squared deviations of the cell frequencies from the expected frequency under the null hypothesis of uniform distribution (i.e., 1/20th and 1/2 for floor-traded futures and E-mini futures). Hirshmann-Herfindal index (HHI) and standardized range method are also used to test for price concentration. Numbers in the parentheses of the row labeled HHI are the expected HHI values under the null distribution of no price clustering.

***Indicates significance at the 1% level.

Very similar results are obtained from the standardized ranges. Those for DJIA regular futures, before and after E-mini index futures trading, were 3.462 and 3.791, respectively, whereas the figure for E-mini futures was 0.632.

The standardized range for S&P 500 regular futures for the three periods (before E-mini introduction, and the postintroduction periods 1 and 2) were 1.482, 2.928, and 0.828, respectively. The figure for E-mini index futures in the S&P 500 was 0.284. Although the HHI value was almost equal to the corresponding value for S&P 500 floor-traded index futures, under no clustering, following the contract redesign (tick size increase) of regular futures, the standardized range for the former was higher than that for the latter; that is, price clustering was still greater for floor-traded futures in the S&P 500 than for E-mini futures, even after the CME doubled the minimum tick size.

The standardized range for NASDAQ-100 index futures, before and after the introduction of E-mini index futures trading, was 16.186 and 19.416, respectively; the figure for E-mini index futures was 0.567.

For all three indices, the introduction of E-mini futures led to an increase in the occurrence of price clustering in the floor-traded markets; however, all three tables show that price clustering was less severe in E-mini futures than in floor-traded index futures. This result is consistent with the findings of ap Gwilym and Alibo (2003), who found that price clustering decreased significantly in the FTSE 100 futures market after the switch to an electronically traded system. Nevertheless, the lower severity in E-mini futures trading may also be due to the fact that investors can easily change their bid or ask prices through the increasing use of nonzero final digits, so as to get their orders placed into the order book at better time and execution priorities in an electronic trading system. Moreover, the electronic trading system allows traders to refine their price resolution more easily. The market competition between floor-traded and E-mini futures markets may be another reason for the lower severity of price clustering in E-mini futures trading, along with the relatively lower level of human intervention in the electronic trading system. In short, the observed behavior is consistent with the Ball et al. (1985) price resolution hypothesis. Another factor contributing to the higher extent of clustering in open-outcry futures trading in the DJIA, the S&P 500 and the NASDAQ-100 indices may be that the relatively larger contract size has led to their emergence as the *de facto* wholesale markets for futures trading.

GMM Estimation Results on the Price Clustering of Floor-Traded and E-Mini Index Futures

Table V presents the results of the Hausman test carried out on Equations (3)–(5) by the addition of one extra explanatory variable, that is, the residuals from the regression of the bid/ask spreads on the set of

TABLE V
The Results of the Hausman Specification Test

	Estimated coefficient of $\hat{\nu}$ in the clustering equation		
	DJIA	*S&P 500*	*NASDAQ-100*
Floor-traded futures	0.0695***	0.0997***	0.0182***
	(43.47)	(24.88)	(10.66)
E-mini futures	0.0146***	0.0137***	0.0048***
	(3.59)	(7.44)	(3.01)

Note. The Hausman test is conducted to determine the endogeneity of the bid/ask spread (Spr) in Equations (3)–(5). The variable $\hat{\nu}$ denotes the residuals from the regression of bid/ask spreads on the set of predetermined variables in the equation. The price clustering equations are estimated after including $\hat{\nu}$ as an extra explanatory variable. The null hypothesis of no endogeneity corresponds to the coefficient of $\hat{\nu}$ being equal to 0. Numbers in parentheses are *t* statistics.

****Indicates significance at the 1% level.

predetermined variables within the equation. The null hypothesis corresponds to the coefficient on the residual term (denoted as $\hat{\nu}$) being equal to 0. As reported in Table V, the estimated coefficients of the residual terms are all significant at the 1% level. Hence, the test results generally reject the hypothesis that bid/ask spread is exogenous, indicating that the bid/ask spread could also be affected by the degree of clustering.

Panel A of Table VI presents the GMM estimation results of Equation (3) on the excess clustering of floor-traded index futures, both before and after the introduction of E-mini index futures trading. The total numbers of observations on DJIA, S&P 500, and NASDAQ-100 contracts were 3982, 3775, and 3530, respectively. The results show that price clustering during the open and close intervals appears to be lower for NASDAQ-100 index futures; however, although the occurrence of price clustering is significantly lower for both the DJIA and S&P 500 indices during the close interval, it is, nevertheless, higher near the open interval. Because negotiation costs are lower during periods of high volume, observations of lower price clustering during the open and close intervals (periods of high volume) are consistent with the negotiation hypothesis and, to a lesser extent, the results of ap Gwilym et al. (1998a).

The return variable has a significantly positive effect on price clustering for DJIA index futures, with the impact on price clustering from bid/ask spread being positive for all three floor-traded index futures. This result is consistent with the findings of Aitken et al. (1996) and Ikenberry and Weston (2003), each of which found that clustering increased with bid/ask spread. As to the tick volume, the impact on price

TABLE VI
GMM Estimation Results on Price Clustering for Floor-Traded and E-Mini Index Futures

Variables	*DJIA*	*S&P 500*	*NASDAQ-100*
Panel A: Floor-traded index futures			
α_0(Constant)	0.5380*	0.0874*	0.8620*
	(194.75)	(20.00)	(433.29)
α_1($D1$)	0.0220*	0.11361*	0.0133*
	(5.86)	(14.14)	(5.12)
α_2($D2$)		−0.0719	
		(−8.49)	
β_1(Open)	0.0332*	0.0260*	−0.0067*
	(3.76)	(7.38)	(−4.77)
β_2(Close)	−0.0096*	−0.0442*	−0.0026***
	(−5.44)	(−10.77)	(−1.90)
β_3(Ret)	0.0088*	−0.0021	0.00003
	(5.79)	(−1.19)	(0.05)
β_4(Spr)	0.0506*	0.1123*	0.0139*
	(7.89)	(25.27)	(9.94)
β_5(Tickvol)	0.0234*	−0.0457*	0.0156*
	(6.48)	(−12.81)	(10.71)
$\beta_6(\sigma)$	0.0073*	0.0314*	−0.0037*
	(3.88)	(8.42)	(−3.16)
No. of obs	3,982	3,775	3,530
R^2	65.60%	84.57%	48.23%
Panel B: E-mini index futures			
α_0(Constant)	0.0555*	0.0362*	0.1422*
	(15.88)	(34.73)	(55.48)
β_1(Open)	−0.0801*	0.0080*	0.0019
	(−10.72)	(3.07)	(0.50)
β_2(Close)	−0.0054***	−0.0089*	−0.0015
	(−1.96)	(−3.10)	(−0.50)
β_3(Ret)	−0.0002	−0.0001	0.0004
	(−0.14)	(−0.19)	(0.41)
β_4(Spr)	0.0198*	0.0190*	0.0104*
	(4.38)	(11.35)	(2.68)
β_5(Tickvol)	−0.0585*	−0.0013	0.0041
	(−11.93)	(−0.76)	(1.34)
$\beta_6(\sigma)$	0.0061**	0.0032***	−0.0038
	(2.02)	(1.82)	(−1.08)
No. of obs	2,004	1,996	1,771
R^2	51.45%	22.97%	6.19%

Note. The overall sample period for floor-traded index futures covers the 1-year periods both before and after the introduction of E-mini trading. For E-mini futures, the sample period is the 1-year period after the introduction of E-mini trading. The explained variable is the excess percentage of clustering. Open and Close are (0,1) dummy variables controlling for the open and close interval effects, respectively. $D1$ and $D2$ are dummy variables controlling for the effects of the introduction of E-mini trading and the effects of the redesign of S&P500 floor-traded contracts. Ret is the intraday hourly return and Tickvol is the total number of ticks (price changes) for each hourly interval, reflecting the trading activities of futures markets. Spr is the bid/ask spread obtained by using the estimator suggested by the CFTC method. σ is the intraday hourly volatility, calculated with the use of the Parkinson (1980) extreme value estimator. Numbers in parentheses are t statistics.

*Indicates significance at the 1% level.

**Indicates significance at the 5% level.

***Indicates significance at the 10% level.

clustering was negative for S&P 500 futures markets, a result that is consistent with the Harris (1991) negotiation hypothesis. However, in contrast to Harris (1991), the impact was positive for both DJIA and NASDAQ-100 floor-traded index futures; this is, nevertheless, consistent with Alexander and Peterson (2004) who suggested that a trade is more likely to be a rounded quotation when the number of trades is relatively large. Volatility appears to have mixed effects on price clustering, because it is positive for both DJIA and S&P 500 floor-traded index futures—consistent with the Harris (1991) negotiation hypothesis—whereas its effect on clustering in the NASDAQ-100 is negative.

The estimated *D*1 coefficients are significantly positive at the 1% level for all three regular index futures, demonstrating that there was an increase in price clustering after the introduction of E-mini futures trading. This result appears to support the view that dealers and market makers in the open-outcry index futures markets will round up their quotations more often so as to compete with the electronically traded index futures. Because E-mini contracts have succeeded in attracting smaller investors, the open-outcry market is more like a wholesale market, where larger price increments appear to be quoted more often. There may also be migration of smaller trades to the E-mini markets, as Ates and Wang (2004) showed that there was a fall in the number of single unit trades in the open-outcry markets after the introduction of E-mini futures.

A significant fall in price clustering was found in the S&P 500 futures markets following the redesign of the S&P 500 contracts, with the estimated coefficient of the dummy variable *D*2 being negative. This result is consistent with those shown in Table III (the HHI and standardized range), that price clustering was less severe after the redesign of the futures contracts. The empirical evidence on the redesign of the contracts reveals that a wider tick size does not necessarily lead to stricter clustering.

For most floor-traded index futures, increases are observed in price clustering with the open-interval, return, bid/ask spread, tick volume, and volatility, but a decrease was seen with the close interval. The estimated constant term—after controlling for the effects of the open and close interval, return, tick volume, bid/ask spread, and volatility—are all significantly greater than zero. The estimated intercept terms are around 0.54 for the DJIA, 0.09 for the S&P 500, and 0.86 for the NASDAQ-100; hence, in the absence of any variations in the explanatory variables, price clustering may well exist naturally. Thus, as argued by Grossman et al. (1997), the degree of price clustering appears to be driven by some other factor, such as differences in market structure.

Panel B of Table VI presents the regression results of excess clustering for the E-mini futures contracts of the three indices. The sample period covers the 1-year period after the introduction of E-mini futures trading, with the dependent variable being the excess clustering of E-mini index futures at period *t*. The total number of observations was 2004 for DJIA contracts, 1996 for S&P 500 contracts, and 1771 for NASDAQ-100 contracts. The results show that price clustering appeared to be lower for DJIA E-mini index futures during the open and close interval. Although the occurrence of price clustering was higher near the open interval for S&P 500 E-mini index futures, it was significantly lower during the close interval. The results were insignificant for NASDAQ-100 E-mini index futures. The return variable had no significant impact on price clustering for all three E-mini index futures.

Consistent with Aitken, Brown, Buckland, Izan, and Walter (1996) and Ikenberry and Weston (2003), the impacts on price clustering from bid/ask spread are significantly positive for all three E-mini futures markets. The bid/ask spread appears to have significant and consistent effects on both floor-traded and E-mini futures for all three indices, and as to the tick volume, the impact on price clustering is significantly negative for DJIA E-mini index futures, a result that is consistent with the Harris (1991) negotiation hypothesis. The effects of tick volume are insignificant for both S&P 500 and NASDAQ-100 E-mini futures. Volatility has positive effects on price clustering for E-mini index futures in both the DJIA and S&P 500, which is consistent with the Harris (1991) negotiation hypothesis.

Although the influence of trading characteristics may explain some of the variation in price clustering for the three E-mini index futures markets, the estimated constant terms for the DJIA, S&P 500, and NASDAQ-100 E-mini are all significantly larger than zero, with the percentage of the last digit or the last two digits being, respectively, about 0.06, 0.03, and 0.14 higher than expected; that is, in the absence of any variations in the independent variables, price clustering may again exist naturally.

In short, for most E-mini index futures, there is an increase in price clustering with the open-interval, bid/ask spread, and volatility, but a decrease with the close-interval, return, and tick volume. Table VI also demonstrates that only the volatility and bid/ask spread variables have consistent effects on price clustering in floor-traded and E-mini index futures. Furthermore, the coefficients of the constant terms for the three floor-traded index futures are higher than their counterpart E-mini index futures. These results again show that the degree of price clustering appears to be driven by the difference in market structure, as argued by Grossman et al. (1997).

GMM Estimation Results on the Differences in Price Clustering

A multivariate regression model is further explored in order to determine whether, after accounting for the trading characteristics of E-mini index futures, the differences in price clustering still exist between regular and E-mini contracts. Table VII presents the GMM estimation results for the differences in price clustering, which are apparently larger when tick volume is higher, and which therefore indicate that the relatively higher clustering in the open-outcry futures markets may be due to an increase in the flow of information into the market. Although the effects of bid/ask spread and volatility are not conclusive on the differences in clustering for various contracts, the intercept terms are all positively significant at the 1% level. Based on the estimated parameter values of the intercept terms, the results thus indicate that the excess clustering of regular contracts over E-mini contracts in the DJIA was 53% higher,

TABLE VII
GMM Estimation Results of the Difference in Price Clustering Between Floor-Traded and E-Mini Index Futures

Variables	*DJIA*	*S&P 500*	*NASDAQ-100*
α_0(Constant)	0.5331***	0.0915***	0.7481***
	(88.26)	(15.33)	(306.01)
β_1 (Ret)	−0.0017	−0.0027	0.0001
	(−0.64)	(−0.87)	(0.12)
β_2 (Spr)	0.0455***	0.1325***	−0.0066***
	(7.06)	(15.19)	(−2.82)
β_3 (Tickvol)	0.0958***	0.0644***	0.0047
	(13.76)	(8.17)	(1.55)
β_4 (σ)	0.0121***	−0.0139	0.0001
	(2.69)	(−1.62)	(0.04)
No. of obs.	2001	1995	1770
R^2	38.59%	64.85%	4.99%

Note. The explained variable is the excess percentage of clustering of regular futures minus that of E-mini futures; the explanatory variables are the trading characteristics of E-mini futures. The sample period is the 1-year period after the introduction of E-mini trading. Ret is the intraday hourly return; Tickvol is the total number of ticks (price changes) for each hourly interval, reflecting the trading activities of futures markets; Spr is the bid/ask spread estimated with the use of the estimator suggested by the CFTC method; and σ is the intraday hourly volatility, calculated with the use of the Parkinson (1980) extreme value estimator. Numbers in parentheses are *t* statistics.

***Indicates significance at the 1% level.

whereas that for the S&P 500 was 9% higher, and that for the NASDAQ-100 was 75% higher.

To summarize, the results indicate the existence of significant differences in price clustering between E-mini and regular contracts, with electronic trading offering traders much easier usage of the full range of prices. Furthermore, open-outcry trading involves greater human involvement within the trading process than is the case for automated trading systems. As noted by Schwartz, Van Ness, and Van Ness (2004), it seems highly unlikely that there will be any collusion in the open-outcry markets of the futures exchange, because there are hundreds of brokers and locals competing for trading in the pit. Therefore, the differences in price clustering between open-outcry and electronic trading systems may result from certain motives relating to the behavior of individual human beings. Nevertheless, the results reveal that when trading face-to-face, as opposed to trading anonymously, traders in the open-outcry markets will use larger price increments. Although automated trading systems can arrange trades more rapidly than floor-based systems, when traders want to negotiate large orders, the open-outcry market is extremely well suited to the purpose.

CONCLUSIONS

This article has explored the occurrence of price clustering in open-outcry and E-mini futures trading in the DJIA, S&P 500, and NASDAQ-100. This analysis has attempted to examine the ways in which differences in market structure can affect price clustering. In line with many of the earlier studies, the results reveal that price clustering is ubiquitous within the index futures markets; however, significant clustering differences are exhibited between floor-traded and E-mini index futures. It appears that clustering and bid/ask spread are jointly determined, indicating that a trader's price quotation may also be affected by price grid preference, whereas clustering also appears to be higher within the open-outcry index futures markets.

The results indicate that there was an increase in clustering in all three floor-traded index futures markets after the introduction of the corresponding E-mini index futures. A potential reason for this may be the more frequent use of rounded quotations by market makers and traders in order to compete with electronically traded index futures. As E-mini contracts have become a suitable trading vehicle for retail and smaller investors, it may be that the relatively larger contract sizes and trading mechanisms of the open-outcry markets have led to their emergence as the *de facto* wholesale markets for futures trading, which might also help to explain the increased occurrence of clustering in the open-outcry markets.

The tick sizes for both E-mini index futures and regular futures are exactly the same within the DJIA index, and by direct comparison, the percentage of clustering in floor-traded futures on the DJIA is more than twice that of its E-mini counterpart. For the S&P 500 and NASDAQ-100 indices, despite the tick sizes of floor-traded contracts being smaller than those of E-mini contracts, a higher percentage of excess clustering is apparent among floor-traded index futures than E-mini futures. As the open-outcry trading mechanism involves more human participation within the trading process, the results thus demonstrate the ways in which the differences in trading mechanisms can lead to differences in price clustering. Such findings may be due to the fact that, within an electronic trading system, investors have the flexibility to submit their bids in all possible price ranges and to use nonzero final digits in order to get their orders placed into the order book at better time and execution priorities.

BIBLIOGRAPHY

Aitken, M., Brown, P., Buckland, C., Izan, H. Y., & Walter, T. (1996). Price clustering on the Australian Stock Exchange. Pacific-Basin Finance Journal, 4, 297–314.

Alexander, G. J., & Peterson, M. A. (2004). An exploratory analysis of trade-size clustering on the NYSE. Seminar paper at the Office of Economic Analysis/SEC and UCLA.

Alizadeh, S., Brandt, M., & Diebold, F. X. (2002). Range-based estimation of stochastic volatility models. Journal of Finance, 57, 1047–1092.

ap Gwilym, O., & Alibo, E. (2003). Decreased price clustering in FTSE 100 futures contracts following the transfer from floor to electronic trading. Journal of Futures Markets, 23, 647–659.

ap Gwilym, O., Clare, A., & Thomas, S. (1998a). Extreme price clustering in the London Equity index futures and options markets. Journal of Banking and Finance, 22, 1193–1206.

ap Gwilym, O., Clare, A., & Thomas, S. (1998b). Price clustering and bid–ask spreads in international bond futures. Journal of International Financial Markets, Institutes and Money, 8, 377–391.

Ates, A., & Wang, G. H. K. (2004, June/July). When size matters: The case of equity index futures. Paper presented at the annual meeting of the European Financial Management Association, Basel, Switzerland.

Ball, C. A., Torous, W. A., & Tschoegl, A. E. (1985). The degree of price resolution: The case of the gold market. Journal of Futures Markets, 5, 29–43.

Barclay, M. (1997). Bid–ask spreads and the avoidance of odd-eighth quotes on the NASDAQ: An examination of exchange listing. Journal of Financial Economics, 45, 35–60.

Bessembinder, H. (1997). The degree of price resolution and equity trading costs. Journal of Financial Economics, 45, 9–34.
Blennerhassett, M., & Bowman, R. G. (1998). A change in market microstructure: The switch to electronic screen trading on the New Zealand Stock Exchange. Journal of International Financial Markets, Institutions and Money, 8, 261–276.
Bollen, N. P. B., Smith, T., & Whaley, R. E. (2003). Optimal contract design: For whom? Journal of Futures Markets, 23, 719–750.
Brown, P., Chua, A., & Mitchell, J. (2002). The influence of cultural factors on price clustering: Evidence from Asia-Pacific stock markets. Pacific-Basin Finance Journal, 10, 307–322.
Christie, W. G., Harris, J., & Schultz, P. H. (1994). Why did NASDAQ market makers stop odd-eighth quotes?. Journal of Finance, 49, 1841–1860.
Christie, W. G., & Schultz, P. H. (1994). Why do NASDAQ market makers avoid odd-eighth quotes?. Journal of Finance, 49, 1813–1840.
Cooney, J., Van Ness, B. F., & Van Ness, R. A. (2003). Do investors prefer even-eighth prices? Evidence from NYSE limit orders. Journal of Banking and Finance, 27, 719–748.
Goodhart, C., & Curcio, R. (1991). The clustering of bid–ask prices and spread in the foreign exchange markets (Discussion Paper No. 110). London: London School of Economics, Financial Markets Group.
Grossman, S. J., Miller, M. H., Cone, K. R., Fischel, D. R., & Ross, D. J. (1997). Clustering and competition in asset markets. Journal of Law and Economics, 40, 23–60.
Hameed, A., & Terry, E. (1998). The effect of tick size on price clustering and trading volume. Journal of Business Finance and Accounting, 25, 849–867.
Hamilton, J. D. (1994). Time series analysis. Princeton, NJ: Princeton University Press.
Harris, L. (1991). Stock price clustering and discreteness. Review of Financial Studies, 4, 389–415.
Hasbrouck, J. (1999). Security bid–ask dynamics with discreteness and clustering: Simple strategies for modeling and estimation. Journal of Financial Markets, 2, 1–28.
Hasbrouck, J. (2003). Intraday price formation in US equity index markets. Journal of Finance, 58, 2375–2399.
Hausman, J. A. (1978). Specification tests in econometrics. Econometrica, 46, 1251–1271.
Hornick, J., Cherianand, J., & Zakay, D. (1994). The influence of prototypic values on the validity of studies using time estimates. Journal of Market Research Society, 36, 145–147.
Ikenberry, D., & Weston, J. P. (2003). Clustering in US stock prices after decimalization (working paper). Urbana-Champaign and Houston: University of Illinois at Urbana-Champaign and Rice University.
Kandel, S., Saring, O., & Wohl, A. (2001). Do investors prefer round stock prices? Evidence from Israeli IPO auctions. Journal of Banking and Finance, 25, 1543–1551.
Karpoff, J. M. (1986). A theory of trading volume. Journal of Finance, 41, 1069–1087.

Kurov, A., & Lasser, D. (2004). Price dynamics in the regular and E-mini futures markets. Journal of Financial and Quantitative Analysis, 39, 365–384.

Loomes, G. (1988). Different experimental procedures for obtaining valuations of risky actions: Implications for utility theory. Theory and Decision, 25, 1–23.

Naidu, G. N., & Rozeff, M. S. (1994). Volume, volatility, liquidity and the efficiency of the Singapore Stock Exchange before and after automation. Pacific-Basin Finance Journal, 2, 23–42.

Ni, S. X., Pearson, N. D., & Poteshman, A. M. (2005). Stock price clustering on option expiration dates. Journal of Financial Economics, 78(1), 49–87.

Osler, C. L. (2003). Currency orders and exchange rate dynamics: An explanation for the predictive success of technical analysis. Journal of Finance, 58, 1791–1820.

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. Journal of Business, 53, 61–65.

Schwartz, A., Van Ness, B. F., & Van Ness, R. A. (2004). Clustering in the futures markets: Evidence from S&P 500 futures contracts. Journal of Futures Markets, 24, 413–428.

Wang, G. H. K., Michalski, R. J., Jordan, J. V., & Moriarty, E. J. (1994). An intraday analysis of bid–ask spreads and price volatility in the S&P 500 index futures market. Journal of Futures Markets, 14, 837–859.

Wang, G. H. K., Yau, J., & Baptiste, T. (1997). Trading volume and transaction costs in futures markets. Journal of Futures Markets, 17, 757–780.

Yeoman, J. C. (2001). The optimal spread and offering price for underwritten securities. Journal of Financial Economics, 62, 169–198.