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Order Imbalance in the FTSE Index Futures Market: Electronic versus Open Outcry Trading

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Abstract: This study examines trading activities before and after the transfer of the FTSE 100 index futures contract from open outcry to electronic trading. Daily order imbalance exhibits strong serial persistence in the electronic limit order market, but not in open-outcry trading. Both excess buying and selling reduce liquidity. In the electronic venue, prior market movements barely affect investors' buying or selling decisions. Excess buy orders do not generate any price impact, but sell orders do. Positive imbalances are more strongly autocorrelated than negative imbalances. No trading elements, such as order imbalance, volume, or open interest, are associated with volatility. Moreover, excess buying decreases volatility. Such evidence suggests that the development and growth of electronic trading has changed the dynamics of trading activities in many important ways.

Keywords: order imbalance, index futures, open outcry, electronic market

1. INTRODUCTION

Volume has traditionally been a proxied trading activity. However, different combinations of buy and sell orders have very different implications even with the same volume of transactions. In two comprehensive studies of the New York Stock Exchange (NYSE) specialist market, Chordia, Roll and Subrahmanyam (2002 and 2005) explore one intriguing aspect of trading activity, daily market order imbalance, which is the net order flow resulting from aggregated daily purchase orders less sell orders. Chordia et al. (2002) (hereafter, CRS) document that daily order imbalance for the S&P 500 index is highly predictable from lagged values and past returns. Generally, excess buy or sell orders both reduce liquidity and increase volatility. In addition, contemporaneous and lagged order imbalances strongly impact returns.

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There has been tremendous growth in electronic trading in the past decade (Jain, 2005). Electronic markets, characterized by anonymity, fast execution, reduced transaction costs, and greater time and space flexibility, are taking away a large volume from the traditional floor trading. Increasingly sophisticated technology and modeling have enabled the execution of huge orders in much less time than was possible prior to automation. We do not fully understand how the development of electronic trading and increased investor sophistication affect the dynamics of financial markets overall. This motivated a comparative study on how order imbalance is associated with return, liquidity, and volatility in futures markets before and after automation.

On May 10, 1999, the London International Financial Futures and Options Exchange (LIFFE) moved its Financial Times Stock Exchange (FTSE) 100 index futures contract from open outcry to electronic trading. The index futures contract is traded on LIFFE CONNECT®, the world's leading electronic trading platform.[1] This change creates an excellent opportunity for research. We examine the six-year periods before and after the shift: January 1993 through April 1999 for open outcry trading, and June 1999 through December 2005 for electronic trading. Our comparison of the trading process in the two periods focuses on an enhanced measure of trading activities—order imbalance.

Most empirical studies on order imbalance are confined to equity markets, mainly the NYSE. Few studies have examined order imbalance in futures markets. Huang and Chou (2007) investigate the behavior of order imbalance on the two Taiwan stock index futures markets, the electronic Taiwan market, and the floor-traded Singapore market. They found that order imbalance had a significant impact on market liquidity and volatility. Moreover, the impact was larger for the Singapore market.

A crucial distinction between electronic and open outcry trading is that the former operates under a transparent limit order book. Quotes on open outcry markets are valid only if the 'breath is warm.' In an electronic marketplace, quotes are retained within the system in the form of limit orders. Trades are matched based on either price/time or pro-rata basis. The transparency of the electronic order book and the abundance of limit orders increase competitiveness.

The underlying asset of an index futures is a basket of stocks, a diversification effect that reduces the impact of both private and firm-specific information (Suhrahmanyam, 1991; and Gordon and Pennacchi, 1993). Recent studies by Berkman, Brailsford and Frino (2005), Frino and Oetomo (2005) and Tse, Bandyopadhyay and Shen (2006) reveal that buying and selling in stock index futures is primarily driven by liquidity. This suggests that order imbalance in futures markets may reveal aspects of trading that are different from those on the NYSE, especially when we consider the evolution of a technology-based environment. Our findings support such a hypothesis.

First, we find that daily order imbalances for the FTSE 100 index futures contract are positively autocorrelated for lags of many days in the electronic trading period, indicating that excess buys (sells) tend to be followed by further days of buys (sells). This can be attributed to the characteristics of an electronic limit order book. The arrival of a sizable market order, either purchase or sale, is split against multiple quotes existing

1 LIFFE was acquired by Euronext in December 2001 to become Euronext.liffe. In April 2007, NYSE completed a merger with Euronext, which became NYSE Euronext, creating the first global exchange.

on the book (Chng, 2004; and Gilbert and Rijken, 2006). Alternatively, if computer algorithms are exercised to automatically split a large market order into smaller pieces, these trades could either hit a comparably sized standing limit order or many smaller sized orders. Either way, trades tend to be clustered together, resulting in a sequence of transactions on one side of the market. We also note that positive order imbalance (with daily aggregate buy orders being greater than sell orders) displays stronger serial correlation than negative imbalance (with daily aggregate sell orders being greater than buy orders).

Lagged order imbalances have strong predictive power for the current day's order imbalance, but the relation between lagged returns and order imbalance is insignificant, indicating that past market movements do not affect investors' buying or selling decisions. Such findings are in contrast to those by CRS, who show that investors are basically contrarians on the NYSE.

In the earlier open-outcry period, there is no autocorrelation in order imbalance, implying that serial persistence in order imbalance is completely eliminated within one day. This phenomenon is mainly due to the extremely short-term speculative behavior of futures floor traders. Silber (1984) and Manaster and Mann (1996) document that floor traders in the Chicago Mercantile Exchange aggressively managed the inventories during trading hours. These traders generally had a strong aversion for carrying overnight positions because it involved inventory risk. They always closed out their positions before trading ceased. Thus, the daily net inventory changes were approximately zero.

Second, in the open-outcry period, daily returns are strongly affected by contemporaneous order imbalances; excess buy orders move prices up and excess sell orders force them down. However, the relation disappears within one day. Surprisingly, on the electronic platform, neither contemporaneous nor lagged positive order imbalance has any impact on the current day's returns. Yet, negative imbalances reduce returns, which then rebound on the subsequent day. The unusual behavior of the buyers may be a consequence of the evolution of on-line order submission strategies.

Third, in both trading periods, excess buy or sell orders diminish liquidity. In the electronic market, liquidity increases following market upturns. Moreover, the change in the number of trades has a large and positive impact on concurrent liquidity, which is then reversed on the subsequent day. In the floor trading period, a change in liquidity is closely linked to prior market conditions, which diminish following market declines and increase following market rises. This evidence is generally consistent with the inventory paradigm (Stoll, 1978).

Finally, we partition order imbalance, volume, and open interest into expected and unexpected (both positive and negative) components. In the case of floor trading, nearly all of the variables impact volatility. Surprisingly, in the electronic venue, none of these components affects volatility (with the exception of negative unexpected volume). Our finding of a lower volume-volatility relation in the electronic market is broadly consistent with the studies of Pirrong (1996) and Gilbert and Rijken (2006) that compare electronic and floor trading in the futures market. They find that the more liquid electronic trading dampens volatility.

An important insight we have gained from the above analysis is that buying and selling is asymmetric in the computerized trading environment. We noted that some unusual patterns mainly arise from the buying side. Corcoran (2007) observes that buy-side traders create sophisticated algorithms which go beyond the initial intention of hiding large trades.

Given the nature of futures markets, particularly following the switch from floor to electronic trading, the inventory control-adverse selection framework on the NYSE is not completely applicable to the context of our study, in terms of the trading dynamics. The order imbalance measure provides many more insights.

2. FLOOR TRADING VERSUS ELECTRONIC TRADING

Exchange floors on futures markets are the epitome of competition, where all bids and offers are announced openly. Trading pits are dominated by a particular group of traders known as scalpers, who trade actively out of their own accounts. Scalpers act as voluntary market makers and supply liquidity by constantly quoting bids and offers against which market orders can be executed.

Scalpers are able to observe first-hand information about order flow because they are physically present in the trading pit and thus, make the adjustments necessary to balance their inventories. More scalpers show up in the pit at times of high volatility in order to absorb high trading volumes. Silber (1984) notes that scalpers only maintain an inventory level that is adequate to accommodate markets orders. They typically hold the positions open for only a few minutes. Scalpers trade frantically in only a couple of contracts per trade. Thus, their inventories do not deviate from zero for any considerable length of time.

Manaster and Mann (1996) present evidence that floor traders with long positions are the most active sellers, while traders with short positions are the most active buyers. The speed of inventory adjustment in the futures market is much faster than that in the equity market. A trader can reduce the inventory imbalance by half in one trade in the case of S&P 500 index futures. Yet, it may take an NYSE specialist a few weeks to attain the same goal, although they could adjust the inventory much faster if they wished. Futures positions are rarely held overnight and are closed out at the end of the trading day. Tse (1999) observed that trading volume on FTSE 100 index futures surges while spreads decline significantly in the late afternoon, as traders rush to liquidate their inventory before the market closes. Inventory risks are negligible in open outcry markets.

The FTSE 100 index futures contract is traded on LIFFE CONNECT®, which is available in the world's major financial centers. The electronic system offers considerable execution speed, with the capacity for huge order flows. A wide variety of complex strategies can be exercised at the best possible price. LIFFE CONNECT® Trading Host is at the heart of the electronic market. The central limit order book holds all of the submitted orders. Market orders are executed immediately against limit orders, while limit orders remain on the system until they are either executed or cancelled. Every trading agent is engaged in de facto market making in the absence of designated market makers, mainly via the placement of limit orders ('How the Euronext.liffe Markets Work,' 2006).

A computerized system provides anonymity, therefore, any person entering a bid or an offer cannot be identified, and neither can the direction of any order (Pirrong, 1996). Some market depth insight is provided by the electronic limit order book but it is not easy to immediately recognize order imbalance. Tse and Zabotina (2001) demonstrate that the inventory costs in futures markets are much lower than those on the NYSE. However, inventory costs increase via an electronic venue compared to an open outcry setting.

The difference in trading mechanisms affects the severity of asymmetric information. For open-outcry trading, adverse selection cost seems trivial, as informed traders are easily identified in the trading pits. Individually isolated computerized traders, however, have little information on the identity of counterparts. Huang (2002) and Barclay, Hendershott and McCormick (2003) show that trades on electronic communication networks convey more information content than trades in settings with market makers for Nasdaq stocks.

Trading strategies based on algorithms is the fastest growing area in the futures market in recent years.[2] According to Euronext.liffe in a private communication, algorithmic trading is now far more popular and has been facilitated by the growth of electronic order routing networks and the resilience of exchange electronic trading platforms.[3] Algorithmic traders are attracted to products, such as the FTSE index futures, that have a high level of liquidity and a long history of data available for analysis.

3. DATA AND METHODOLOGY

(i) Data

We obtained transaction data for the FTSE 100 index futures contract, which consists of trades, quotes, and volume. The data covers the period from 1993 through 2005. We used the most liquid nearby contracts for the entire study period.

The FTSE 100 index futures contract migrated from the open outcry market to the electronic market on May 10, 1999. We investigated the same product traded in two different ways in two subperiods: January 1993–April 1999 and June 1999–December 2005, excluding the transition month of May 1999. We call the open outcry trading period Period 1 and the electronic trading period Period 2.

Figures 1 and 2 depict the intraday patterns of trading volume for both periods during the regular trading hours: from 8:35 to 16:10 GMT for Period 1 and 8:00 to 16:30 GMT for Period 2.[4] For Period 2, there is a one-hour settlement period between 16:30 and 17:30, after which the market closes.

Both Figure 1 and Figure 2 show a U-shaped curve with a spike at the time of US macroeconomic news announcements (13:30 GMT, or 8:30 a.m. New York time). In Period 1, scalpers frequently trade at the open, mainly because they consider inventory control risks at the open to be trivial and they can easily close out their positions over the rest of the day. Near the close, scalpers trade aggressively to avoid holding overnight inventory. In Period 2, a significant proportion of the total daily volume is transacted

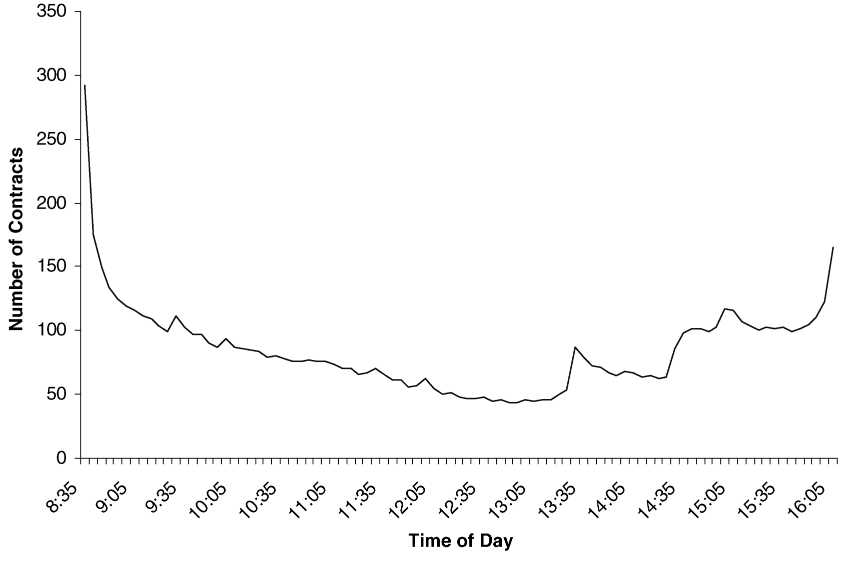
2 In Euronext.liffe, the biggest traders in the Euribor and the three-month interest-rate futures contract are computers. Algorithmic trading, the order submission strategy that relies on software to automatically execute trades, has become the hot property of large institutional investors and banks ('Small Traders Face Losing Calculus,' 2007).

3 Euronext.liffe migrated its trading engines to a fully Linux on HP architecture in late summer 2006. The upgrade adds more processing power and capacity to handle greater levels of algorithmic trading.

4 In mid-July 1997, the trading hours were extended from 16:10 to 16:30. It was not until mid-September 1999 that the morning hours were extended from 8:35 to 8:00, several months after the full automation.

Figure 1

Intraday Patterns of Volume for Open Outcry Trading



Notes:
Volume is calculated by the number of contracts. Each trading day is partitioned into 91 five-minute intervals for floor trading from 8:35 to 16:10. The vertical axis represents the average volume at each interval. The data used are FTSE 100 index futures for the open outcry period (January 1993–April 1999).

in the opening and closing auctions. Notably, trading is even more active at the close than at the opening.[5]

Overall, the patterns for both periods appear to be consistent with the model of Brock and Kleidon (1992), which asserts that much of the trading at the beginning and the end of the trading day stems from the inability to trade when the market is closed, as investors are shifting the risk of holding a position while the market is closed.

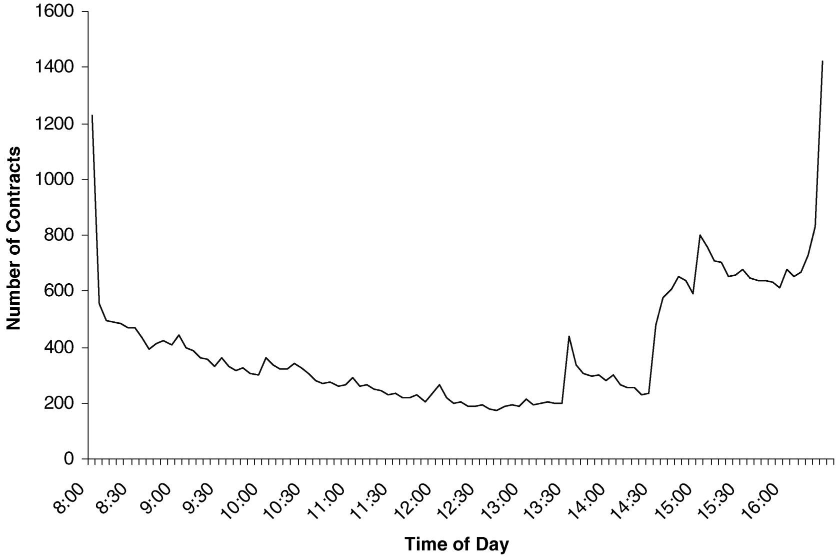
(ii) Descriptive Statistics

A particular trade is signed as buyer- or seller-initiated by applying the widely used Lee and Ready (1991) trade classification algorithm. If the transaction price is at the bid, the trade is classified as a sale. If the price is at the ask, the trade is classified as a buy. If trade price is equal to the mid-quote price, a tick rule is used to identify the trade direction. For each trading day, the daily estimated order imbalance is calculated as the total number of buys minus the total number of sells divided by total number of trades. Order imbalance (denoted by OIM) is bounded by -1 and $+1$, with more positive values corresponding to greater buying and more negative values to greater selling.

5 Although the U-shaped pattern of intraday trading volume has been documented extensively in the literature, Lee, Fok and Liu (2001) find a J-shaped pattern for the 30 most actively traded stocks in the electronic Taiwan Stock Exchange. The low trading volume at the open implies that traders tend to place orders strategically and conservatively at the beginning of the day.

Figure 2

Intraday Patterns of Volume for Electronic Trading



Notes:
Volume is calculated by the number of contracts. Each trading day is partitioned into 103 five-minute intervals for floor trading from 8:00 to 16:30. The vertical axis represents the average volume at each interval. The data used are FTSE 100 index futures for the electronic trading period (June 1999–December 2005).

We use the number of trades to measure the order imbalance for three reasons. First, the number of trades and volume are highly correlated. The correlation coefficients are 0.84 for the open outcry trading period and 0.93 for the electronic trading period (see Table 1). Second, we follow closely the study of Chordia, Roll and Subrahmanyam (2002). Although they report all the results using the number of trades, they show that using either the number of trades or the volume for the order imbalance measure yields qualitatively similar results. Third, Jones, Kaul and Lipson (1994) state that the number of trades per se contains nearly all the information in the trading behavior of market participants during a particular time frame. The volume virtually provides no additional information once they control for the number of trades.

Panel A of Table 1 presents descriptive statistics for daily order imbalance, average daily quoted spread (proxy for liquidity), volume, and number of transactions. Percentage spread is defined as 100×(ask-bid)/midquote, where midquote is the average of the ask and bid prices. The mean, median, and standard deviation are of similar magnitude for order imbalance in the two subperiods (slightly negative). The average quoted spread drops significantly after trading switches to the electronic system, from 0.032% to 0.022%. In the meantime, the daily average number of transactions increases dramatically by more than ten times, from 1,242 to 14,305. Also, the daily average volume increases more than fivefold, from 9,152 to 51,754. This implies that trades occur more frequently, but in smaller sizes. Such results are similar to the findings of Gwilym and Alibo (2003) and Gilbert and Rijken (2006). Also, returns are generally positive for Period 1 and slightly negative for Period 2. Figure 3 clearly shows that, over

Table 1
Summary Statistics and Correlations

Panel A: Summary Statistics

	Open Outcry (January 1993–April 1999)			*Electronic Trading (June 1999–December 2005)*		
Variable	*Mean*	*Median*	*Std Dev*	*Mean*	*Median*	*Std Dev*
OIM	−0.004	−0.006	0.057	−0.008	−0.009	0.050
NTRAN	1,242	1,167	439	14,305	14,001	9,011
VOL	9,152	6,978	6,668	51,714	48,431	35,114
RET	0.041	0.033	1.022	−0.014	0.010	1.273
PSPD	0.032	0.032	0.005	0.022	0.022	0.009

Panel B: Correlations

	Open Outcry (January 1993–April 1999)					*Electronic Trading (June 1999–December 2005)*				
	NTRAN	*VOL*	*RET*	*OIM*	*PSPD*	*NTRAN*	*VOL*	*RET*	*OIM*	*PSPD*
NTRAN	1.00					1.00				
VOL	0.84	1.00				0.93	1.00			
RET	−0.13	−0.08	1.00			−0.01	−0.01	1.00		
OIM	−0.07	−0.05	0.61	1.00		0.29	0.31	0.17	1.00	
PSPD	−0.04	−0.05	−0.08	−0.07	1.00	−0.51	−0.56	−0.03	−0.28	1.00

Notes:
Descriptive statistics are given for average daily order imbalance measures for the FTSE 100 index futures in the open outcry period (January 1993–April 1999, with 1,594 trading days) and the electronic trading period (June 1999–December 2005, with 1,647 trading days). Trades are identified using the Lee and Ready (1991) algorithm. OIM measures buyer-initiated trades less seller-initiated trades, divided by the total number of transactions. NTRAN, VOL and PSPD are the total number of transactions, volume and the average daily quoted spread. RET is the daily return on the FTSE 100 index futures.

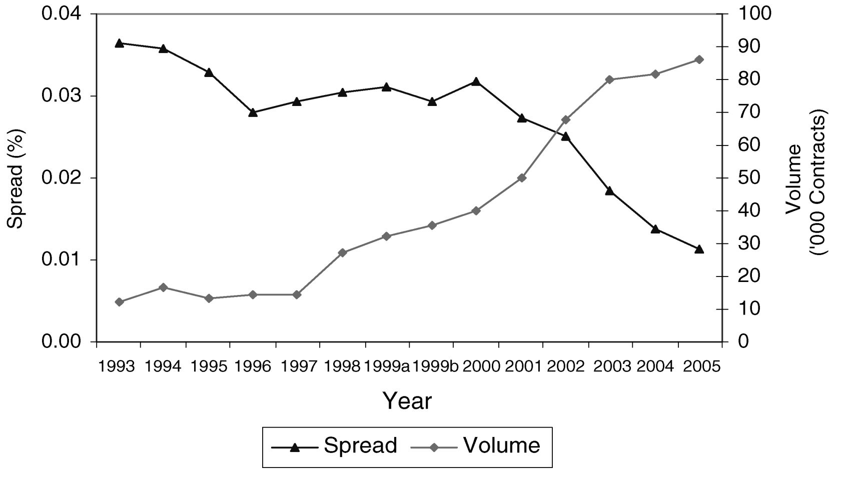
our entire study period from 1993–2005, volume rises and spreads narrow. Starting in early 1998, there has been a steady increase of trading volume while spreads have fallen progressively since 2000.[6]

Panel B displays correlations among the total number of trades, volume, daily return, order imbalance, and percentage of quoted spread. The total number of trades and volume are strongly positively correlated, with 0.84 in Period 1 versus 0.93 in Period 2. Returns are negatively associated with trades in Period 1, but not in Period 2. Order imbalance and return have a strong positive relation in Period 1, which indicates that buying and selling activity and returns are closely related through imbalances. The relation becomes much weaker in Period 2.

Clearly the variables are more closely interlinked in the automated trading period. Order imbalance is strongly positively related to the total number of trades and volume, but strongly negatively related to the percentage of quoted spread. Quoted bid-ask spreads are strongly and negatively associated with the number of trades and volume.

6 The tick size was reduced from £12.5 to £5 for the front contract from March 23, 1998. Gwilym and Alibo (2003) observed that the trading volume in the second quarter of 1998 more than doubled compared to its previous quarter, which subsequently stabilized in two quarters.

Figure 3
Daily Average Quoted Spread and Volume



Notes:
Quoted spread is calculated as (Ask – Bid)/(Ask + Bid)/2. The vertical axis represents the average time-weighted proportional spread at each interval. Volume is calculated by the number of contracts. The data used are FTSE 100 index futures for the open outcry period (January 1993–April 1999) and the electronic trading period (June 1999–December 2005).

4. ORDER IMBLANCE, RETURN, AND LIQUIDITY

(i) Autocorrelations of Order Imbalance in the Electronic Market

Table 2 reports autocorrelations of order imbalance and returns for both trading periods. For the FTSE 100 index futures, order imbalances are strongly autocorrelated within the electronic trading period (although five daily lags are reported here), implying that investors continue buying or selling for many days. There is no such pattern in open-outcry trading. Index returns are not autocorrelated in Period 1, but are slightly negatively autocorrelated in Period 2.

In the open-outcry mechanism of futures markets, scalpers correct an inventory imbalance effectively by making simultaneous countervailing trades (trades that move in the opposite direction from the initial order imbalances). Although order imbalance may exist within any given trading day, it should not persist over one day's horizon as traders typically liquidate their positions before market ceases (Silber, 1984; and Manaster and Mann, 1996), eliminating any serial correlations in order imbalance.

Large financial institutions or sophisticated market making firms trade actively on electronic platforms. Small local traders are relatively unimportant (Pirrong, 1996). Frino and Oetomo (2005) examine SPI 200 index futures on the electronic Sydney futures exchange. The average order was generally split into approximately 10 smaller trades for both buy and sell orders. The average time taken to execute a trade package is around two days. These findings are similar to the results for US equity markets documented by Chan and Lakonishok (1995) and Keim and Madhavan (1997) that the typical institutional trades were always divided into smaller sizes and executed over a period of several days because they were so large.

Table 2
Autocorrelations of Order Imbalances and Returns

	Open Outcry (January 1993–April 1999)	
	OIM	*RET*
Lag (days)	*Correlation*	*Correlation*
1	0.012	l0.010
2	0.019	−0.045
3	0.013	−0.058
4	0.015	−0.019
5	0.057	−0.051*
	Electronic Trading (June 1999–December 2005)	
	OIM	*RET*
Lag (days)	*Correlation*	*Correlation*
1	0.291*	−0.093*
2	0.223*	−0.027*
3	0.234*	−0.088*
4	0.240*	0.053*
5	0.224*	−0.044*

Notes:
Autocorrelations of daily order imbalances and returns are given for the FTSE 100 index futures for the open outcry period (January 1993–April 1999, with 1,594 trading days) and the electronic trading period (June 1999–December 2005, with 1,647 trading days). OIM measures buyer-initiated trades less seller-initiated trades, divided by the total number of transactions. RET is the daily return on the FTSE 100 index futures. The Ljung-Box *Q*-test is for the null hypothesis that there is no autocorrelation up to order 5, which follows the chi-square distribution.
*denotes statistical significance level at 5%.

Berkman et al. (2005) reveal the dominance of small trades for the electronic FTSE 100 index futures. An overwhelming majority of purchases (86%) fall into the smallest trade size (5 contracts per trade) versus 87% for sales. Traders may spread trades across time to minimize price impact (Kyle, 1985) and execution costs (Chan and Lakonishok, 1993 and 1995).

The electronic system facilitates a greater amount of order splitting, which is manifested by the reduction of trade sizes and higher frequency of submitted orders (see our finding in the previous section). Gwilym and Alibo (2003) show that the average trade size for FTSE 100 index futures fell by half in the days immediately following the shift to electronic trading. Gilbert and Rijken (2006) report that the number of contracts per trade after automation is only one-third of its open outcry level. Moreover, Chng (2004) finds that screen trades are serially correlated while floor trades are not.

It is important to recognize the significance of an electronic limit order book, which retains a long list of quotes in the form of limit orders. Essentially, a trader can choose to place a limit order at a predetermined price. Conversely, the trader can act as a counterparty to hit an existing limit order via a market order. A trading agent who demands immediacy could submit the market order(s) against the electronic limit order book in two ways. First, a large market order, either purchase or sale, is executed against a series of existing quotes (Chng, 2004; and Gilbert and Rijken, 2006). Alternatively, strategic traders could exercise computer algorithms to automatically split a large market order into many smaller pieces, which either hit an existing limit order of comparable size or multiple smaller size orders. In both situations, trades tend to occur in succession, resulting in continued presence on one side of the market.[7]

There are other possible explanations for the serial correlation of order imbalance in the electronic market. Tse and Zabotina (2001) estimate a vector autoregression (VAR) model, showing that trade direction is more persistent on an electronic venue at short horizons. They suggest that trades adjust more slowly to information and that the market price probably departs from the efficient price for a longer period of time in the electronic market.

Traders could be herding when they observe the trades of others or they may react to the same events (Biais, Hillion and Spatt, 1995). Inventory imbalances are not easily accommodated on a fully automated execution venue. Price pressure caused by inventory imbalances on a given day could persist if there is not enough countervailing force, such as scalpers, to remove it. Lee et al. (2004) obtain data from the Taiwan Stock Exchange. They show that herding is the predominant cause of imbalance persistence at both large and small domestic institutions and that order-splitting is an important cause of imbalance persistence for small foreign institutions.

To go one step further, we separate the order imbalance in Period 2 into positive and negative parts in Table 3. We find that positive order imbalance is much more strongly serially correlated than negative order imbalance. Such a trend lasts up to seven days. This evidence is consistent with the observation that buying trades occur

Table 3

Autocorrelations of Positive and Negative Order Imbalances in Electronic Trading Period

Lag (days)	*Autocorrelation for Positive OIM*	*Autocorrelation for Negative OIM*
1	0.323*	0.209*
2	0.254*	0.152*
3	0.264*	0.167*
4	0.263*	0.161*
5	0.235*	0.164*
6	0.202*	0.148*
7	0.233*	0.138*
8	0.168*	0.167*
9	0.155*	0.162*
10	0.156*	0.110*

Notes:
Autocorrelations of positive and negative parts of daily order imbalances are given for the FTSE 100 index futures for the electronic trading period (June 1999–December 2005, with 1,647 trading days). OIM measures the buyer-initiated trades less the seller-initiated trades, divided by the total number of transactions. The Ljung-Box Q-test is for the null hypothesis that there is no autocorrelation up to order 10, which follows the chi-square distribution.
*denotes statistical significance level at 5%.

7 A popular order-splitting strategy is called Time Weighted Average Price, through which a large market order is split up into smaller slices. These small trades are sent at regularly timed intervals with an aim to minimize spread and price impact costs ('A Buy-side Handbook: Algorithmic Trading,' 2005).

more frequently. Our findings of stronger trade persistence for buy orders could be reasonably attributed to larger trade sizes from contract buyers, most of which may be submitted by financial services firms that need to frequently trade in large sizes.

(ii) Order Imbalance and Market Movements

With the intent to better understand the motives behind index futures trading, we examine whether market participants follow strategies that are based upon past returns. We regress the daily order imbalance on weekday dummies and return variables designed to capture past up and down market movements and lagged order imbalance. The results of these time series regressions are reported in Table 4.[8]

Table 4

Determinants of Order Imbalances

	Open Outcry (January 1993–April 1999)	*Electronic Trading (June 1999–December 2005)*
Dependent Variable	*OIM*	*OIM*
Explanatory Variable	*Coefficient*	*Coefficient*
Intercept	−0.005	0.002
Monday	0.009*	0.000
Tuesday	0.001	−0.004
Wednesday	−0.001	−0.007*
Thursday	−0.001	−0.002
$-\text{RET}_{t-1}$	0.000	−0.002*
$-\text{RET}_{t-2}$	−0.006**	−0.003**
$-\text{RET}_{t-3}$	0.002	0.000
$-\text{RET}_{t-4}$	−0.003	0.000
$-\text{RET}_{t-5}$	−0.002	0.002
$+\text{RET}_{t-1}$	0.000	−0.002*
$+\text{RET}_{t-2}$	0.003	0.000
$+\text{RET}_{t-3}$	−0.002	0.000
$+\text{RET}_{t-4}$	−0.003	−0.002
$+\text{RET}_{t-5}$	−0.003	−0.004***
OIM_{t-1}	0.012	0.196***
OIM_{t-2}	0.029	0.095***
OIM_{t-3}	0.014	0.104***
OIM_{t-4}	0.047	0.114***
OIM_{t-5}	0.078**	0.102***
Adj R-Sq	0.003	0.153

Notes:
Dependent variables are the daily order imbalances (OIM_t), which are the buyer-initiated trades less the seller-initiated trades divided by the total number of transactions for the FTSE 100 Index futures over the open outcry period (January 1993–April 1999, with 1,594 trading days) and the electronic trading period (June 1999–December 2005, with 1,647 trading days). RET_t denotes the FTSE 100 index return on day t. OIMt are regressed on day-of-the-week dummies and past positive and negative parts of daily index returns. The estimates are corrected for heteroskedasticity using White's (1980) procedure.
***, ** and * denote significance levels of 1%, 5% and 10%, respectively.

8 The ARCH (autoregressive conditional heteroskedasticity) Lagrange Multiplier tests detect the presence of ARCH effects in the regression residuals. Thus, for all regressions, the t statistics are adjusted by the White procedure to account for various forms of heteroskedasticity.

In Period 1, almost none of the estimated parameters are significant. Yet in Period 2, order imbalances are highly predictable by their lagged values, particularly the one-day lagged value. This is not surprising, given that order imbalances are strongly autocorrelated. The forecasting model has some explanatory power with an adjusted R^2 of 0.15.

We can see that the order imbalance in Period 2 is barely affected by the lagged returns. Evidence reveals some signs of contrarian trading two days after market upturns and one day after downturns. There appears to be some sort of excess selling on Wednesday. These coefficients are very small and have low t-statistics. This indicates that prior aggregate market returns exert little influence on market participants' buying or selling decisions. This finding is in sharp contrast to what CRS found on the NYSE. They show strong evidence of a contrarian trading pattern among investors.

Some literature suggests that order imbalance may be driven by herding (e.g., Lee et al., 2004). Traders who herd typically buy following up markets and sell following down markets. Welch (2000) finds that herding is significantly stronger in up markets than in down markets when the consensus is optimistic. If herding triggers order imbalances, we would expect to observe excess buying following positive market returns, but this is not the case.

Market participants in futures markets, either for risk hedging or speculative purposes, are more concerned about future prices movements (Kleiman, 2005). Moreover, liquidity effects dominate information effects in the trading decision (Frino and Oetomo, 2005; and Berkman et al., 2005). Thus, in an index futures market, prior market conditions are relatively unimportant in terms of buying and selling decisions.

(iii) Order Imbalance and Returns

We divide the order imbalance into positive and negative parts and include them as control variables to differentiate the impact of excess buy and sell orders. Separate regressions are run on contemporaneous and lagged order imbalances and lagged returns. RET+ and RET− denote positive and negative returns, respectively. The results are presented in Table 5.

The first column of Table 5 shows that, in Period 1, contemporaneous order imbalances exert a strong impact on market returns in the anticipated direction: excess buy (sell) orders are related to increased (reduced) share prices. This relation dissipates quickly, as the predictive relation between imbalances and returns is eliminated within a single day. Typical floor traders in futures trading pits almost always close out their positions at the end of the day and then re-establish their positions at the beginning of a new trading day (Manaster and Mann, 1996). This highlights the distinction between the futures market and the NYSE specialists market, as CRS find that a lagged order imbalance has predictive power for the next day's returns.

On the electronic trading platform, excess sell orders impact returns, yet excess buy orders do not. Moreover, a contemporaneous negative order imbalance brings down share prices. The selling price pressure seems to continue over the course of one day, as negative imbalances are not accommodated effectively. The previous day's negative imbalance is reversed and, hence, has a negative effect on the contemporaneous return. This implies that the current day returns go up following a day with excess sell orders. The reversals following selling activity are consistent with the inventory models of Grossman and Miller (1988).

Table 5
Returns and Order Imbalances

Open Outcry (January 1993–April 1999)				
	Dependent Variable: RET_t			
	(1)	*(2)*	*(3)*	*(4)*
Intercept	0.070	0.067	0.021	0.043
$+OIM_t$	11.681***	11.678***		
$-OIM_t$	10.453***	10.460***		
$+OIM_{t-1}$	−0.563	−0.845	0.313	
$-OIM_{t-1}$	0.180	−0.041	−0.785	
$+RET_{t-1}$		0.026	0.009	0.007
$-RET_{t-1}$		0.019	0.028	0.014
Adj R-Sq	0.372	0.372	−0.002	−0.001
Electronic Trading (June 1999–December 2005)				
	Dependent Variable: RET_t			
Intercept	0.119**	0.102	−0.093	−0.047
$+OIM_t$	−0.667	−0.593		
$-OIM_t$	8.974***	8.702***		
$+OIM_{t-1}$	1.392	1.449	2.060**	
$-OIM_{t-1}$	−2.737***	−2.051**	−0.415	
$+RET_{t-1}$		−0.053	−0.051	−0.056
$-RET_{t-1}$		−0.106	−0.134*	−0.127*
Adj R-Sq	0.044	0.049	0.009	0.008

Notes:
Dependent variable is the daily return on the FTSE 100 index futures, denoted RET. Explanatory variables include contemporaneous and lagged positive and negative daily order imbalances and lagged positive and negative index returns. The data are for the open outcry period (January 1993–April 1999) and the electronic trading period (June 1999–December 2005). The estimates are corrected for heteroskedasticity using White's (1980) procedure.
***, ** and * denote significance levels of 1%, 5% and 10%, respectively.

Intuitively, prices should be affected by order imbalances with a prevalence of either buy or sell orders. Yet, in this context, neither a contemporaneous nor lagged positive imbalance moves stock prices. Such a result is inconsistent with the findings of Berkman et al. (2005) and Frino and Oetomo (2005), who show that the price reaction between purchases and sales is symmetric for the electronic futures contract. They attribute their results to the ease with which new short or long positions can be created in the futures market. Given the fact that the price impact for trades in the index futures markets is smaller than that for trades on the equity markets, these authors claim that the information content of trades in index futures is low. Execution costs in index futures markets are mainly related to temporary liquidity effects. However, they admit that their sample only spans two contract cycles in 2000, which may limit the applicability of their data.

It is plausible that the unusual market behavior of buying activity may reflect the evolution of order submission strategies from the contract buyers. The implementation of such strategies is greatly facilitated by the emergence of more complex computer algorithms and the fast speed of software execution. Through the estimation of a VAR, Tse and Zabotina (2001) show that trades have a smaller effect on prices in electronic trading.

Our results are consistent with the behavior of large institutions documented by Lee et al. (2004), who find that a lagged selling imbalance, but not a buying imbalance, for large domestic institutions is related to the present day's return. Large institutions devote substantial resources to analyzing and developing trading strategies, and hence reasonably gain more advantages in terms of trading tools.[9] Keim and Madhavan (1997) and Frino and Oetomo (2005) suggest that the money manager behind the trade plays the most significant role in market impact costs. These traders are heterogeneous in terms of trading immediacy, order submission strategies, and investment styles.

Columns two to four of Table 5 present the relation between lagged returns and concurrent returns by either controlling for or not controlling for order imbalance. The results from the second regression are basically the same as those from the first regression. The last two models have minimal explanatory power and almost none of these variables are significant.

(iv) Order Imbalance and Liquidity

In an open outcry trading floor, scalpers supply liquidity by constantly quoting bids and offers to meet the demands for immediacy. In an electronic limit-order market, where there are no exogenous liquidity suppliers, liquidity is generated endogenously (Bloomfield, O'Hara and Saar, 2005).[10]

We investigate the association between changes in the absolute level of order imbalance and liquidity. Liquidity is proxied by the daily quoted spread averaged over all daily transactions. Following CRS, we regress the daily percentage change in the quoted spread on the contemporaneous daily change in the absolute order imbalance, the simultaneous daily percentage change in the number of transactions, returns, and volatility (measured by the absolute return). The independent variables are used to control for aggregate trading activity and market movements. As suggested by CRS, order imbalance is transformed by the Box-Cox procedure, in which a variable X is transformed to $(X^{\lambda} - 1)/\lambda$. In our case, the absolute value of order imbalance measure is transformed into $(|\mathrm{OIM}_t|^{\lambda} - |\mathrm{OIM}_{t-1}|^{\lambda})/\lambda$. Such a transformation is used to search for the functional form of the relation between liquidity and order imbalance. The same variables are used here to predict the next day's percentage change in the quoted spread.

The results are presented in Table 6. The first column shows that either excess buy or sell orders reduce liquidity (spreads are wider) in both periods, and there is a strong returns effect. The other columns show that, in Period 2, even though order imbalance provides no predictive power, positive returns can predict future changes in liquidity. For electronic trading, an increase in transactions is associated with a sharp narrowing in the spread on the same day, which is then reversed on the next day. Liquidity increases following market upturns, but it is unaffected by poor market conditions.

9 Chan and Lakonishok (1995) and Keim and Madhavan (1995) find a greater price impact for institutional buys than for sells. Barclay and Warner (1993) conduct a study on a group of tender offer firms and present strong evidence that stock price movements are mainly driven by informed trading. Thus, our finding that buy orders do not move prices is not likely to be driven by informed trading.

10 In Euronext.liffe, locals (scalpers) are important because they are more willing to take the opposite side of trades and keep trading liquid ('Small Traders Face Losing Calculus,' 2007).

Table 6
Changes in Liquidity and Order Imbalance

	Open Outcry (January 1993–April 1999)		
Explanatory Variable	*(1) % Change in PSPD (contemporaneous)*	*(2) % Change in PSPD (next day)*	*(3) % Change in PSPD (next day)*
Intercept	−0.011**	0.000	−0.005
$(\lvert OIM_t\rvert^{\lambda} - \lvert OIM_{t-1}\rvert^{\lambda})/\lambda$	0.066*	−0.009	−0.011
% Change in # of trades	−0.012	0.008	0.009
RET	−0.020***	−0.011***	
|RET|	0.007	0.001	
RET+			−0.010**
RET−			−0.026***
Lagged % change in PSPD		−0.400***	−0.358***
Adj *R*-Sq	0.061	0.152	0.182
	Electronic Trading (June 1999–December 2005)		
Explanatory Variable	*% Change in PSPD (contemporaneous)*	*% Change in PSPD (next day)*	*% Change in PSPD (next day)*
Intercept	−0.004	−0.002	0.002
$(\lvert OIM_t\rvert^{\lambda} - \lvert OIM_{t-1}\rvert^{\lambda})/\lambda$	0.049**	−0.012	0.000
% Change in # of trades	−0.082***	0.017*	0.022***
RET	−0.015***	−0.007***	
|RET|	−0.001	0.002	
RET+			−0.014***
RET−			−0.007
Lagged % change in PSPD		−0.298***	−0.026***
Adj *R*-Sq	0.132	0.104	0.116

Notes:
Dependent variables are the contemporaneous and following day's daily percentage change in the quoted spread for the FTSE 100 index futures. Explanatory variables include the daily first difference in a Box/Cox transformation of the absolute value of the value-weighted order imbalance for FTSE 100 index futures measured in number of buyer-initiated trades less the seller-initiated trades divided by the total number of trades (OIM_t), the daily percentage change in the number of trades, the FTSE 100 index futures return if it is positive, and zero otherwise (RET+), and the FTSE 100 index futures return if it is negative, and zero otherwise (RET−). The data are for the open outcry period (January 1993–April 1999) and the electronic trading period (June 1999–December 2005). The estimates are corrected for heteroskedasticity using White's (1980) procedure.
***, ** and * denote significance levels of 1%, 5% and 10%, respectively.

In Period 1, liquidity consistently follows previous market trends. Liquidity drops following market declines and rises following market advancements. These results are generally consistent with inventory models of the spread (see Stoll, 1978).

The overall results are similar to those obtained by the NYSE research. The findings suggest that electronic markets are preferable in generating liquidity, even without reliance on dealers or specialists.[11] The role of liquidity demander or supplier in

11 However, some literatures suggest that a pure limit order system may perform poorly for the thinly traded securities. Using data of the less liquid FTSE Mid-250 stocks from London Stock Exchange, Lai (2007) shows

electronic trading is a strategic choice that can be quickly reversed (Hasbrouck, 2007).

5. ORDER IMBALANCE, VOLUME, OPEN INTEREST, AND VOLATITY

(i) Partitioning Trading Activities into Expected and Unexpected Components

Stock return volatility is essential to a better understanding of the dynamics of trading. Following Schwert and Seguin (1990) and Bessembinder and Seguin (1993), we calculate unbiased estimates of the conditional daily return volatility while controlling for lagged returns, the persistence of volatility, and the day of the week. Equation (1) estimates the conditional return and equation (2) estimates conditional volatility. Equation (3) transforms the lagged volatility:

$$R_t = a + \sum_{j=1}^{n} \gamma_j R_{t-j} + \sum_{i=1}^{4} \rho_i d_i + \sum_{j=1}^{n} \pi_j \hat{\sigma}_{t-j} + U_t \tag{1}$$

$$\hat{\sigma}_t = \delta + \sum_{j=1}^{n} w_j \hat{U}_{t-j} + \sum_{i=1}^{4} \eta_i d_i + \sum_{j=1}^{n} \upsilon_j X_{t-j} + \sum_{j=1}^{n} \beta_j \hat{\sigma}_{t-j} + e_t \tag{2}$$

$$\hat{\sigma}_{\mathrm{t}} = |\hat{U}_t| \sqrt{\pi/2}0 \tag{3}$$

where R_t is the return on the FTSE 100 index futures contracts; d_i represents the four dummy variables, Monday through Thursday; $\hat{\sigma}_t$ is the volatility; and X_k are the trading activity variables of (differenced) order imbalance, (differenced) volume, and (differenced) open interest. The residual U_t represents unexpected returns. See also Martinez and Tse (2008).

Open interest, the number of outstanding contracts is an important indicator of trading activity that is unique to futures markets. Open interest has been used as a proxy for market depth (Bessembinder and Seguin, 1993). In a study of the NYSE and NASDAQ, Chan and Fong (2000) find that the volatility-volume relation becomes much weaker after controlling for the impacts of order imbalance, indicating that order imbalance is an important trading variable.

First, using equation (1), the series of daily returns on FTSE 100 index futures is regressed on lagged returns and the day-of-the-week dummy. We then pull out the residuals and transform them into volatility using equation (3).

Second, we decompose the trading activity variables X_k, the (differenced) order imbalance, (differenced) volume, and (differenced) open interest, into the expected and unexpected components.[12] We choose a long set of autoregressive coefficients by

that even a hybrid market with a limit order book and voluntary market makers generates less liquidity than a dealership market with obligatory market makers.

12 The augmented Dickey-Fuller tests are performed to identify the presence of unit roots in these series. The existence of a unit root is found in all three trading variable series in Period 1. The series in Period 1 becomes stationary after first differencing. In Period 2, open interest is sensitive to the testing method. A Dickey-Fuller test shows that the series is stationary, but a Philips-Perron test reveals that the series is not stationary. In order to be consistent, we follow the Dickey-Fuller test result. As a robustness check, we use level volume and order imbalance, and differentiated open interest in both periods. The results are qualitatively the same.

setting the lag limits to 10. We then obtain the one-step ahead forecast error for the three trading activity variables from an AR(10) for a stationary series or an ARIMA(10, 1, 0) for a non-stationary series. This step yields six series of forecast errors, $\hat{\varepsilon}_t$.

Third, such errors are regressed against lagged total volatilities used to control for the persistence in volatility, order imbalance, volume (VOL), open interest (OPIN), and trading days to contract maturity (DTE), as shown in equation (4):

$$\hat{\varepsilon}_t = \Psi + \sum_{k=1}^{10} \rho_k \hat{\sigma}_{t-k} + \sum_{i=1}^{4} \lambda_i d_i + \sum_{k=1}^{10} \chi_k \mathrm{OIM}_{t-k} + \sum_{k=1}^{10} \lambda_k \mathrm{VOL}_{t-k} + \sum_{k=1}^{10} \mu_k \mathrm{OPIN}_{t-k} + \phi \mathrm{DTE} + \nu_t. \quad (4)$$

The unexpected component is the residual from equation (4), ν_t, while the expected component is obtained by subtracting the unexpected component from the actual series, $X_k - \nu_t$. Thus, the expected component of the order imbalance, volume and open interest series is conditioned on its own lagged values, volatility and stage of the contract life cycle.

Finally, we use the transformed values of volatility from equation (3) and the expected and unexpected components of three trading activity variables to estimate equation (2). The predicted volatility values from equation (2) are used as explanatory variables to re-estimate equation (1). We then re-estimate equation (2) with residuals from the consistent estimation obtained from the second round of equation (1).

(ii) Empirical Results

Table 7 reports estimates for the conditional volatility in equation (2), including expected and unexpected components of the three trading variables. In Period 1, both expected and unexpected volume shocks increase volatility, with the unexpected volume component having a larger impact. The evidence is consistent with the empirical findings for futures markets reported by Bessembinder and Seguin (1993), Pirrong (1996) and Daigler and Wiley (1999). In Period 2, only unexpected volume shocks drive up volatility. In both periods, the volatility series exhibit significant persistence. The sum of estimated coefficients on a lagged unexpected return is negative and highly significant, indicating that negative shocks have a greater effect on subsequent volatilities.

Bessembinder and Seguin (1993) show that unexpected shocks may be divided into positive and negative parts, and that positive unexpected shocks have a larger impact on volatility than negative unanticipated shocks. Table 8 reports results obtained when we allow for asymmetries in the unexpected components of trading variables. Interaction terms are defined as zero for a negative shock and one for a positive shock. We create a product of the interaction term and the unexpected series. The coefficient associated with the unexpected value represents the marginal impact of a negative shock on volatility. The marginal effect of a positive shock can be obtained by adding the coefficients related to the unexpected series and the product of the series and the interaction term.

Table 7

Regressions of Volatility on Expected and Unexpected Trading Activity

	Open Outcry (January 1993–April 1999)	*Electronic Trading (June 1999–December 2005)*
Intercept	0.425***	0.338**
Expected Volume	0.431**	0.003
Unexpected Volume	0.896***	0.105***
Expected Open Interest	−0.229	−0.001
Unexpected Open Interest	0.096	−0.019
Expected Order Imbalance	0.036	−0.860
Unexpected Order Imbalance	0.335	0.080
Sum of Lagged Total Volatilities	0.676***	0.699***
Sum of Lagged Unexpected Returns	−0.243***	−0.453***
Adj R-Sq	0.247	0.279

Notes:
Dependent variable is the absolute value of the unexpected return for the FTSE 100 index futures. Volumes are in units of 10,000 contracts. Expected and unexpected series are fitted values and residuals from multivariate forecasting models fitted to the original series. Test statistics for individual coefficients are t-statistics. Test statistics for lagged coefficients are F-statistics for the hypothesis that the sum of the 10 coefficients is zero. The estimates are corrected for heteroskedasticity using White's (1980) procedure.
***, ** and * denote significance levels of 1%, 5% and 10%, respectively.

Once the unexpected shocks are partitioned into positive and negative components, the relation between volatility and nearly all components of trading variables in Period 1 becomes significant. More specifically, all of the positive shocks are associated with higher levels of volatility. While negative volume shocks reduce volatility, an unanticipated reduction in order imbalance and open interest increases volatility. Chan and Fong (2000) show that daily order imbalance explains a substantial portion of the daily price volatility in the volume-volatility relationship. Our results support their findings.

In Period 2, once again, the separation of unexpected shocks into positive and negative components does not change the insignificant relation of order imbalance and open interest with volatility. Only negative unexpected shocks on volume influence volatility.

Our finding that the partitioned components of order imbalance do not affect volatility is new in the literature. Despite consecutive days of buy or sell orders, we see that price volatility barely moves on the electronic futures market. Such results are in stark contrast to the findings of CRS from the floor traded NYSE setting, where both excess buying and selling strongly influence volatility.

Our finding of a lesser volume-volatility relation in Period 2 is especially relevant to the study of Pirrong (1996), which compares simultaneous trading of the German Bund futures contract via open outcry on the LIFFE and via computerized trading system on the Deutsche Terminborse by using 15-minute frequency data. For the electronic contract, Pirrong finds that negative unexpected volume increases volatility, but the positive unexpected volume and expected volume decrease volatility (in our case, these

Table 8

Regressions of Volatility on Trading Activity, Allowing for Asymmetries

	Open Outcry (January 1993–April 1999)	*Electronic Trading (June 1999–December 2005)*
Intercept	0.080	0.313*
Expected Volume	0.357*	0.006
Unexpected Volume	0.269**	0.136***
Positive*Unexpected Volume	0.945***	−0.052
Expected Open Interest	0.489	−0.002
Unexpected Open Interest	−0.168*	−0.034
Positive*Unexpected Open Interest	0.868***	0.080
Expected OIM	−0.050	−1.190
Unexpected OIM	−4.630***	−0.550
Positive*Unexpected OIM	9.970***	1.312
Sum of Lagged Total Volatilities	0.608***	0.695***
Sum of Lagged Unexpected Returns	−0.249***	−0.436***
Adj R-Sq	0.317	0.279

Notes:
Dependent variable is the absolute value of the unexpected return for the FTSE 100 index futures. Volumes are in units of 10,000 contracts. Expected and unexpected series are fitted values and residuals from multivariate forecasting models fitted to the original series. Positive is equal to 1 if unexpected values of volume, open interest and order imbalance are positive, and zero otherwise. Test statistics for individual coefficients are t-statistics. Test statistics for lagged coefficients are F-statistics for the hypothesis that the sum of the 10 coefficients is zero. The estimates are corrected for heteroskedasticity using White's (1980) procedure.
***, ** and * denote significance levels of 1%, 5% and 10%, respectively.

coefficients are insignificant). For the pit-traded contract, there is a stylized positive volume-volatility relation for all three partitioned volume components.

The overall evidence suggests that electronic trading dampens volatility. Pirrong (1996) argues that the electronic market is substantially deeper than the open outcry market. Gilbert and Rijken (2006) present evidence that the volume-volatility terms are strongly negative in screen trading. They claim that a crucial aspect of screen trading is the decline in high frequency price volatility, which perhaps results from a highly transparent electronic order book. They argue that the impact of high volatility is attenuated in periods of high liquidity, which is characterized by a large volume. Increased volume implies a lower spread or superior market depth.

Given the apparent distinction between positive and negative order imbalance documented in previous sections, we examine the relation between volatility and signed order imbalance. The results are shown in Table 9. In Period 1, both excess buying and selling increase volatility. On the next day, however, the relation becomes insignificant. In both periods, volume and the lagged quoted spread are significant explanatory variables. In Period 2, excess buying reduces volatility, although excess selling does not affect volatility. Such a result confirms our previous finding that some buyers behave differently from sellers, as the former may pursue more complex order placement strategies.

Table 9
Volatility and Positive and Negative Order Imbalances

	Open Outcry (January 1993–April 1999)		*Electronic Trading (June 1999–December 2005)*	
	Dependent Variable		*Dependent Variable*	
	$\vert R_t\vert$	$\vert R_{t+1}\vert$	$\vert R_t\vert$	$\vert R_{t+1}\vert$
Intercept	−0.619***	−0.154	−0.907***	−0.719***
maxOIM	6.802***	0.317	−1.211**	−0.712
minOIM	−4.055***	−0.871	0.814	0.751
Volume	0.406***	0.236***	0.098***	0.075***
PSPD	23.176***	19.897***	60.014***	55.730***
Lagged Return	0.033	0.045	0.005	0.024
Adj R-Sq	0.266	0.087	0.233	0.204

Notes:
Dependent variable is the absolute value of the daily return on the FTSE 100 index futures, denoted $|R_t|$. Explanatory variables include contemporaneous and lagged positive and negative daily order imbalances measured in number of trades, volume (scaled by 10,000), and quoted spreads. Order imbalances, volume, and spreads are value-weighted averages for FTSE 100 index futures. The estimates are corrected for heteroskedasticity using White's (1980) procedure.
***, ** and * denote significance levels of 1%, 5% and 10%, respectively.

6. CONCLUSION

Focusing on an enhanced measure of trading activity-daily order imbalance, we investigate the interaction of order imbalances with returns, liquidity, and volatility in the transition of the FTSE 100 index futures contract from open outcry to electronic trading. Such minute examination of trades reveals new and essential aspects of trading in a futures market, particularly in an electronic venue. Two themes emerge: the change of market behavior on an electronic limit order book and an increase in investor sophistication.

Order imbalances are strongly autocorrelated over lags of many days in the electronic setting, but are not serially correlated in open outcry trading. Investors' buy or sell decisions are rarely affected by prior market conditions. That is, they are neither consistent contrarians nor trend followers, supporting the concept that buying and selling is more liquidity-driven in an index futures market. Moreover, despite consecutive days of buying or selling, price volatility barely moves on LIFFE CONNECT®, supporting the idea of a deeper and inherently more liquid market in a highly transparent computerized platform.

On the electronic market, buying and selling is not always symmetric. We notice that buy orders are more strongly serially correlated than sell orders. Excess buy orders have no impact on returns, yet excess sell orders do. Moreover, excess buying reduces volatility. These behaviors need to be traced back to the originators of submitted orders. This leads one to conclude that some investors may pursue more complex order placement strategies via an anonymous electronic execution venue.

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