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Electronic trading system and returns volatility in the oil futures market ☆

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A B S T R A C T

This paper uses daily Brent crude prices to investigate the employment of electronic trading on the returns conditional volatility in the oil futures market. After a suitable GARCH model is established, the conditional volatility series are found. The Bai and Perron model is then used to find two significant structural breaks for these conditional volatility series around two implementation dates of electronic trading. This result indicates that the change in the trading system has significant impacts on the returns volatility since our estimated second break date is very close to the all-electronic trade implementation date. Moreover, the conditional volatility in the all-electronic trading period is found to be more dominated by the temporal persistence rather than the volatility clustering effect. All these evidence can shed some light for explaining the high relationship between more volatile world oil price and the more popular electronic trade.

1. Introduction

The record high crude oil price and its high volatility attract lots of attention in the whole world. Most experts are eager to reveal the reasons behind. These authors wonder that the more pervasive electronic trade may also play an important role for enlarging the crude oil price volatility. The Intercontinental Exchange (ICE) employed partial electronic trading on November 1, 2004. It further shut down its open

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Table 1
Comparison between open outcry system and electronic trading system

	Open outcry system	Electronic trading system
Number of employees	More	Less
Employee training	Costly	Cheaper
Hardware equipment	Cheaper	Costly
Information transition	More	Less
Trading process	Complicated	Simple
Trading area limits	Yes	No
Trading period limits	Yes	No
Change of orders	Simple	Complicated
Order matching process	Human decision	Computer operation
Errors	Human mistakes	Computer failure
Access to trade	Difficult	Easy
Commodity specification	Rough	Well-defined

outcry trading floor and shifted its benchmark ICE Brent crude to an all-electronic format on April 7, 2005[1]. More recent news has pointed out that the NYMEX also plans to give up its traditional open outcry trading system and transit to all-electronic trading. These events show that electronic trading is more popular and may be more suitable for the rapid changing world.

Electronic trading systems are more pervasive today ever since the Commodity Exchange Act was implemented in 1974. Except the all-electronic trading market (Appendix Table 1), most of the financial markets use hybrid system by blending the open outcry and electronic trading system currently such as NYSE and NYMEX. The trading system is adjusted much smoothly due to the controvertible arguments of trade efficiency and larger volatility in the all-electronic trade system. Evans (1998) investigated the effects of an electronic trading system on an open outcry commodity exchange. He contended that the electronic trading system would dominate the market trading in commodities since computers have become more involved with our daily lives. Tsang (1999) tried to compare the open outcry and electronic trading in futures exchanges. He concluded that the electronic trading system is superior in many aspects, although there are still some supporters for the open outcry system. Concerning the support of an open outcry system, Coval and Shumway (2001) argued that this system brings pit traders more market information since various hand signals combined with shouts and body movements could deliver more buy/sell eagerness. Stoll (2006) wrote an excellent survey paper on electronic trading and pinpointed its efficient trade characteristics. Those fully electronic markets (i.e. Electronic Communications Networks, ECNs), have several advantages in the trading process. ECNs are automatic, anonymous, fast, have a lower cost, and can be programmed to offer complex orders. Once an order is submitted using the fully automated trading system, the order routing, execution, and confirmation can be done in seconds without human intervention. We summarize all these studies in the literature and list the comparisons between open outcry and electronic trading systems as shown in Table 1.

The above distinctions between an open outcry system and an electronic trading system bring different impacts for an economy. Generally speaking, efficiency and price volatility are two main issues when comparing this trade system transition. Most of the items in Table 1 are related to the issue of operational and information efficiency. Massib and Phelps (1994) found that the electronic trading system enhances the operational efficiency. Freund et al. (1997) and Freund and Pagano (2000) paid more attention on the information efficiency and found electronic trading system has less support for enhancing the information efficiency. The market volatility is also investigated since the implementation of electronic trade may result in more volatile price due to the larger involvement of uninformed small traders. Battalio et al. (1997) examined the market volatility of the Small Order Execution System (SOES). They found that large SOES trades lead to greater volatility within a one-minute interval, but cause lower volatility in two to five min, suggesting that the existence of SOES concentrates the price discovery process. Daiglar and Wiley (1999) had similar findings for claiming that uninformed traders increase volatility due to less capability at

[1] IPE (International Petroleum Exchange) merged with ICE in June 2001.

differentiating liquidity demand from fundamental value changes. Except the volatility issue, as our knowledge, Maghyereh (2005) and Assaf (2006) should be the only two papers also examining the impacts on mean returns. Maghyereh found the transition from open outcry to the all-electronic trade not only have significant impacts on mean returns but also increase the price volatility, while Assaf found inconsistent impacts on mean returns (i.e. one has significant but negative impact, two have significant and positive impacts, while the other one has insignificant result among the four research target stock index). Since little evidence supports the existence of mean returns for trade system transition, this paper would only focus on the volatility issue.

Volatility is a hot issue in recent years not only for its stylized characteristics, but also for the consideration of value at risk (VaR). There is an abundant amount of literature dealing with volatility issues. Most studies in the literature investigate typical financial issues (Hong, 2000; Tatom, 2001), while few mention the issue of oil price volatility. Plourde and Watkins (1998) used two volatility measurements, monthly rate of price change and absolute values of the monthly rate of price change, and they found less crude price volatility than for other commodities. Fleming and Ostdiek (1999) initiated the rolling estimation approach and applied the stochastic volatility model, showing less apparent evidence for the relationship between crude oil prices and the introduction of energy related derivatives. Weiner (2002) took the "Sheep in wolves clothing" method to illustrate the relationship between speculators and price volatility in petroleum futures. He doubted that speculators might be the losers, rather than the manipulators, in the oil futures market. More recent literature focuses on the estimation of VaR (Cabedo and Moya, 2003; Giot and Laurent, 2003; Sadorsky, 2006). These three papers used time-series models to estimate the returns volatility in the oil futures market and brought some interesting intuitions to manage business risk.

Unlike the above oil price literature, this paper pays more attention to examine how the implementation of an electronic trading system affects returns' conditional volatility in the oil futures market. Instead of simple volatility, conditional volatility is investigated here due to its superiority in revealing more information as we will show in the final part of this paper. Section 2 introduces the related analyzed models. The data and empirical results are illustrated in Section 3 and Section 4, respectively. Conclusions are in Section 5.

2. Methodology

Rather than just selecting the electronic trade employing date as the break point and then comparing the price volatility before and after this break date, this paper would consider a more robust empirical analysis process[2]. This is because we believe the traders' investment behavior may not exactly react to information right at the announcing date of an event. Some traders tend to react early, while others may wait and see for a while in the trading market. Therefore, an impact period may be more suitable for us to implement our analysis as with the event windows applied in the literature of event analysis (MacKinlay, 1997; Deans and Seaton, 1999; Wirl and Kujundzic, 2004). Usually, the event window is decided by an interval around the occurring date of an event. Unfortunately, our analyzed period combines two important event dates: a partial implementation date (November 1, 2004) and a full implementation date (April 7, 2005). It is difficult to decide upon a convincing event window period. In order to choose a suitable impact period, these authors allow the data to choose the best period by applying the statistical model (Bai and Perron, 1998; 2003). Based on these considerations, we use more steps to tackle our issue.

First of all, the daily returns of the oil futures market are calculated. We choose daily returns as our measurements since they are widely used. The daily returns are calculated by the log-difference of the closing price[3]. However, these authors also use the direct returns (i.e. $y_t=(p_t-p_{t-1})/p_{t-1}$) without log form for analyzing our issue since the smoothness characteristics of log form may not deliver enough information of possible break points. We believe more evidence will be provided for the existence of break times in the oil market dynamics by considering the case of direct returns. Therefore, we use "LOG Returns" and "Direct Returns" to implement our analysis. Secondly, by applying the GARCH model (Bollerslev, 1986), we use the calculated daily returns to estimate the conditional volatility. Sadorsky (2006) found that the

[2] Although time dummy or threshold-GARCH can be used to categorize data groups and do more analysis, these two methods also need to define exact break points, which is not suitable for our observed data set (unclear break dates).

[3] The return on day t is calculated as $y_t=(\log p_t-\log p_{t-1})$, where p_t is the closing price.

GARCH model is more suitable to forecast oil price volatility. Thirdly, the model developed by Bai and Perron (1998, 2003) is taken to estimate both the number and location of structural breaks for our data series and then examine whether there are any significant volatility changes during the period of electronic trading.

It should be notified that the impacts of trade transition from open outcry to all electronic on the price volatility may not be a spontaneous but a smoothly process. Consequently, we might have trouble to find an exact cutting dates for larger volatility change as ICE employs its all-electronic trading system. Fortunately, the literature supports the more volatile results for this trade transition. Except the insignificant results found by Eldor et al. (2006), more articles (e.g. Colley-Steeley, 2005; Maghyereh, 2005; Assaf, 2006) find significant volatile results after implementing the electronic trade. These outcomes indicate that it is more likely for us to date a break for our oil price volatility data series.

2.1. Generalized autoregressive conditional heteroscedasticity, GARCH

The conditional mean and variance equations for the GARCH(p, q) process can be expressed as follows:

$$y_t = \mu + \varepsilon_t \quad \varepsilon_t | \Omega_{t-1} \sim N(0, \sigma_t^2) \tag{1}$$

$$\sigma_t^2 = \omega + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2 + \sum_{j=1}^{q} \alpha_j \varepsilon_{t-j}^2 \tag{2}$$

where y_t represents the dependent variable over period t; μ is a constant mean; ε_t denotes a stochastic process; Ω_{t-1} denotes the information set of all information through time $t-1$; σ_t^2 represents the conditional variance of the process changing over time t; ω denotes a constant mean; α and β are vectors of coefficients to be estimated; p and q refer to the order of the autoregressive and moving average part, respectively. We get the GARCH(1,1) model by setting p and q equal to one.

Eq. (2) indicates that the GARCH model is a more general form of the ARCH model, where the conditional variance consists not only of the previous periods' error square terms, but also the lagged periods' conditional variance. Apparently, the GARCH process can better capture the movement of an error term. In empirical works, an integrated conditional process implies that shocks to the conditional variance process tend to have permanent effects. Using the LM test, we can decide the values of p and q. The GARCH (p, q) process is simplified to an ARCH(q) process if p=0, while ε_t is a white noise if p=q=0. We use the GARCH(1,1) model to estimate the conditional return volatility of BRENT crude oil in our empirical study.

2.2. Structural breaks examination

This paper attempts to find returns' volatility breaks by applying the structural change testing method of Bai and Perron (1998, 2003), which is developed to solve the problem of locating and identifying significant changes by estimating both the number and location of structural breaks of volatility in the global oil futures market[4]. To examine the existence of a structural change, traditional models first choose a break based on personal judgment and then test its significance. The traditional approach has been criticized for being less flexible in the current dramatically changing world with its greater fluctuations. Obviously, it is easy to identify a break for a smooth path where there is a jump, but it is difficult to verify the break in a path characterized by many fluctuations. The BP model, however, uses statistical inference to date a break by taking advantage of the computer's superior processing ability.

We formulate the model following Bai and Perron (1998, 2003) as below:

$$\mathrm{PV}_t = \theta_j + e_t \quad t = T_{j-1} + 1, \ldots, T_j,\ j = 1, \ldots, m+1 \tag{3}$$

where PV_t are the conditional volatility of daily returns, θ_j is average conditional volatility over period, and e_t present the error terms.

[4] More recent papers apply the similar methods to find multiple breaks in different time paths like Perron and Qu (2006, 2007), Hung and Cheng (2005) and Liao and Suen (2006).

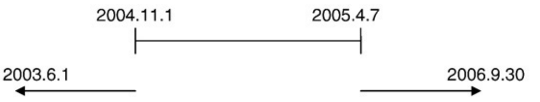

Fig. 1. The sample size period.

Bai and Perron (1998) addressed three test statistics — the SupF test, the Double maximum test, and the Sequential test — to determine the significant multiple structural changes. Following that, Bai and Perron (2003) recognized that all of the above tests have their advantages and disadvantages, and they suggested the best way of combining these three tests. First, an investigation of the existence of structural change requires that one first check whether the SupF test and the Double max test are significant or not. Next, it is essential to use a sequential test to determine the numbers of structural change. This suggestion helps us date the right structural breaks much more easily. More detailed model and test settings can be seen in Bai and Perron (1998, 2003).

3. Data sources and characteristics

This paper collects all the daily futures prices for Brent crude from Datastream. The data begin from June 1, 2003 and end on September 30, 2006. This observed period is selected, because of several reasons. First of all, the influential event (i.e. the U.S.—Iraq war in the early period of 2003) is precluded to prevent unnecessary interference on our volatility analysis. Second, the event window concept is applied. Due to the consideration of two important implementation dates (November 1, 2004; April 17, 2005), we choose the dates from November 1, 2004 to April 17, 2005 as our middle sample period and extend it to both sides around almost equal dates as illustrated in Fig. 1 below.

There is a total of 870 samples. Table 2 describes the data characteristics. The mean of oil prices and its daily return are 48.191 and 0.010, respectively, while oil prices range from 25.32 to 78.3 US dollar per barrel and daily returns range from −7.291 to 7.294. The related numbers of skewness and kurtosis indicate our price data series is skewed to the left and fatter than a normal distribution. All these characteristics are consistent with the findings by Sadorsky (2006).

4. Empirical results

4.1. Model selection and GARACH(1,1) results

The AIC and SIC criteria are used to select a best GARCH model. The results are shown in Table 3. The GARCH(1,1) model is selected due to its minimum value of AIC and SIC.

Table 4 lists the GARCH(1,1) results for both daily return data series. The α_1 and β_1 of the GARCH results indicate that the conditional volatility of oil returns is affected both by the volatility clustering effect (α_1) and the temporal persistence (β_1). The significant and larger β_1 represents that the conditional volatility is more dominated by temporal persistence rather than the volatility clustering effect. Moreover, the large $\alpha_1+\beta_1$

Table 2
Basic statistics

Variables	Price	Return (%)
Mean	48.191	0.010
Median	48.030	0.071
S.D.	15.141	1.951
Maximum	78.300	7.294
Minimum	25.320	−7.291
Skewness	0.125	0.067
Kurtosis	1.697	3.727
Jarque-Bera	63.73	19.799
Probability	0.000	0.000
Observations	870	869

Note: Price denotes the daily closing price. Return is the difference of the natural logarithm of the daily closing price.

Table 3
Model selection for GARCH(p,q)

	GARCH(1,1)[a]	GARCH(1,2)	GARCH(2,1)	GARCH(2,2)
Panel A. LOG returns: y_t=(logp_t−log p_{t-1})				
AIC	−5.044	−5.015	−5.043	−5.042
BIC	−5.022	−5.014	−5.015	−5.009
Log likelihood	2195.515	2195.631	2196.04	2196.537
Panel B. Direct returns: y_t=(p_t−p_{t-1})/p_{t-1}				
AIC	−5.040	−5.038	−5.039	−5.038
BIC	−5.018	−5.010	−5.011	−5.005
Log likelihood	2193.77	2193.88	2194.30	2194.82

[a] The preferred model.

represents that the volatility will persist longer for our data. It should be notified that the data characteristic of longer volatility persistency may imply the difficulty in identifying an exact cutting break dates such as the trading changing date. This is because some part of the observed higher volatility of a date may be resulted from another early impact. Fortunately, this phenomenon has little effect on our dating breaks process since our observed volatility is decaying over time. BP model still can find out the relating breaks form our observed volatility data as the much larger volatility created by the nearest impact will dominate the past decaying volatility.

4.2. The number and location of structural breaks

Based on the above GARCH results, we can calculate the conditional volatility data series from the GARCH models as shown in Eq. (2). We then find the number and location of structural breaks for these conditional volatility data series by following the model developed by Bai and Perron (1998, 2003) as illustrated in Section 2.2. It is found that the shapes of the conditional volatility data series are quite similar for both the LOG Returns and Direct Returns cases. And, the dates of structural breaks estimated by both cases are also quite similar as shown in Table 5. Both breaks (May 25, 2004; March 24, 2005) of LOG Returns case are only 1 days behind the two breaks (May 24, 2004; March 23, 2005) of Direct Returns case. Such an outcome indicates that the smoothness characteristics of log form have little effect on our break points selection. Since the break dates for both LOG Returns and Direct Returns cases are almost the same, here we only draw the related curves for the case of LOG Returns, and use the break dates for LOG Returns for more detailed illustration in this subsection. The price, Log Returns and its conditional volatility trends calculated from the GARCH model are shown in Fig. 2. The dashed lines in this figure represent the estimated break points from Table 5. Fig. 2 shows that there are two structural breaks for the data series of the LOG Returns, and the conditional volatility in the first period is in the middle, much larger in the second period, but smaller and mild in the third period.

Generally speaking, the dates (May 25, 2004; March 24, 2005) of two structural breaks estimated by BP model are not far from our two trading systems' changing dates (November 1, 2004; April 17, 2005). The second structural break (March 24, 2005) is especially very close to the all-electronic implementation date (April 17, 2005), which locates in the period for both the 90% confident interval and 95% confident interval as shown in Table 5. Such an outcome provides us with strong evidence to show the significant impact on the return conditional volatility brought upon by the trading system change. The much earlier date for the first break (May 25, 2004 vs. November 1, 2004) may be due to the early announcing impact, since many market traders tend to react much earlier before the occurrence of an event once they hear some news.

Table 4
GARCH(1,1) results

	LOG returns	Direct returns
μ	0.0001 (0.0001)	0.001 (0.0007)
ω	0.032 (0.098)	0.027 (0.064)
α_1	0.012 (0.014)	0.015 (0.012)
β_1	0.979 (0.039)***	0.978 (0.027)***

Note: *** denotes significant at the 1% level. The standard deviations of the estimations are in parentheses.

Table 5
Dates of structural breaks

Form	Break points	95% Interval	90% Interval
LOG returns	2004/05/25	2004/05/19–2004/05/26	2004/05/19–2004/05/26
	2005/03/24	2005/03/22–2005/03/30	2005/03/22–2005/03/29
Direct returns	2004/05/24	2004/05/18–2004/05/25	2004/05/18–2004/05/25
	2005/03/23	2005/03/21–2005/03/29	2005/03/21–2005/03/28

4.3. Volatility comparison among different periods

In order to find more policy implications, we also do some volatility comparisons for different periods. Since our estimated second structural break point is very close to the all-electronic trading implementation dates, a comparison between the second and third periods should bring us more meaningful policy implications. The GARCH model of LOG Returns and Direct Returns cases are run again for different periods. Separated by our estimated structural breaks, the original oil returns data series is separated into three series. For the LOG Returns (Direct Returns) case, the first series begins from June 1, 2003 and ends on May 24 (May 23), 2004. The second begins from May 25 (May 24), 2004 and ends on March 23 (March 22), 2005. The final series begins from March 24 (March 23), 2005 and ends on September 30, 2006. Again, we run the GARCH(1,1) of LOG Returns and Direct Returns cases for these three data series respectively and expect to get three GARCH(1,1) results of LOG Returns and Direct Returns cases.

The GARCH results shows that α_1 turns out to be smaller and insignificant, while β_1 becomes larger from the first, to the second, and to the third periods. Since β_1 represents the temporal persistence effect, our empirical results imply that people tend to use more complete information when trading in electronic system. Such a behavior is quite reasonable, because people find it is easier to check information with the help of a computer. Current electronic trade floors always provide many analytical tools and lots of historical information. Apparently, market traders find it difficult to enjoy these kinds of services in the open outcry trade (Table 6).

5. Conclusions

High oil price and its volatility attract a lot of attention all over the world. People are very eager to know the background for creating high prices and significant volatility. Except for the fundamental cause of oil

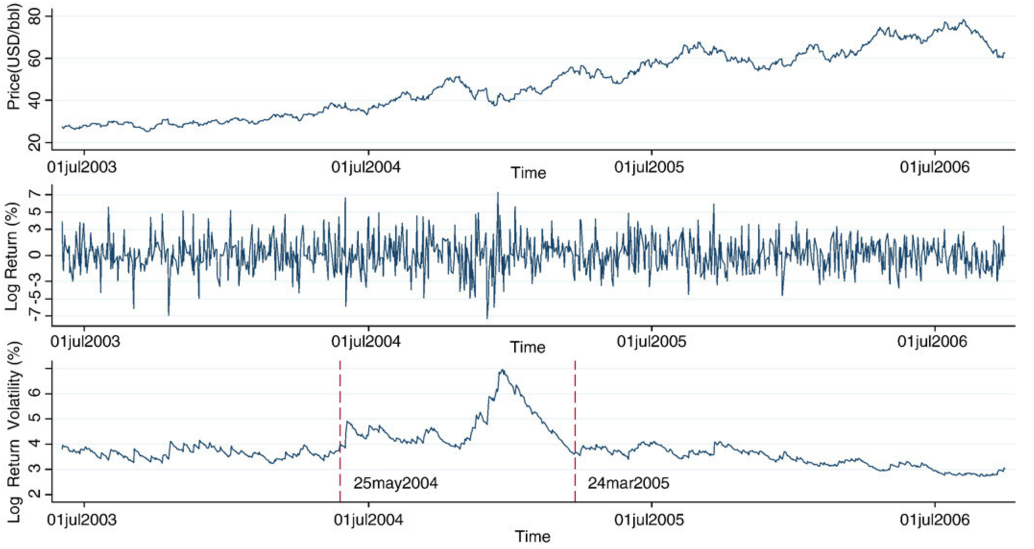

Fig. 2. BRENT crude oil futures' price daily pattern, log form return and return volatility.

Table 6
GARCH(1,1) results in different periods

	Period I	Period II	Period III
Panel A. LOG returns: $y_t = (\log p_t - \log p_{t-1})$			
μ	0.003 (0.002)**	0.003 (0.002)*	0.001 (0.001)
ω	0.239 (0.177)	0.000 (0.000)	0.000 (0.000)
α_1	0.080 (0.036)**	0.058 (0.038)	0.004 (0.029)
β_1	0.875 (0.044)***	0.884 (0.078)***	0.903 (0.119)***
Panel B. Direct returns: $y_t = (p_t - p_{t-1})/p_{t-1}$			
μ	0.001 (1.066)	0.003 (0.001)**	0.001 (0.001)
ω	0.668 (0.553)	0.000 (0.000)	0.000 (0.000)
α_1	0.023 (0.026)	0.070 (0.047)	0.006 (0.029)
β_1	0.851 (0.136)***	0.892 (0.054)***	0.904 (0.112)***

Note: ***, **, and * denote significant at 1%, 5%, and 10% levels, respectively. The standard deviations of the estimations are in parentheses.

demand and supply, many experts doubt that the increasing trade volume and many uninformed traders induced by the electronic trading system may play important roles ever since ICE employed partial electronic trading on November 1, 2004 and shifted its benchmark ICE Brent crude to an all-electronic format on April 7, 2005. These authors believe that a price data comparison before and after the implementation of electronic trading should bring us some interesting findings.

This paper therefore uses daily Brent crude prices to investigate the effects of a trading system change on return volatility in the oil futures market. By building up a suitable GARCH model, we have derived two conditional returns volatility series. We then applied the structural breaks model developed by Bai and Perron and found two significant structural breaks for our return conditional volatility series around the implementation date of electronic trading. Since there are no other significant events around this period, we believe that these two structural breaks are strongly related to the implementation of electronic trading especially for the second break, which is very close to the all-electronic trade implementation date. Moreover, our empirical results also show that the conditional volatility in the all-electronic trade period is dominated more by temporal persistence rather than the volatility clustering effect. Such an outcome indicates that people tend to use more complete information when trading under an electronic system. This finding is quite reasonable since people can easily check information with the help of a computer.

In sum, as those findings of electronic trades' positive impacts on price volatility in the financial articles, this paper also found the more pervasive electronic trade brings more volatile world oil price. Since electronic trade is more and more popular today, people should learn to accept the more volatile price as very few of us would like to use the old outcry trade system. In fact, although we may pay for the higher trade cost due to the volatile price, we actually earn much more advantages due to the implementation of electronic trade as we mentioned in Section 1.

Appendix A

Table A1
Current major all-electronic trading exchange

Exchange	Year
Toronto Stock Exchange (TSE)	1997
London Stock Exchange (LSE)	1997
European Exchange (EUREX)	1998
London International Financial Futures Exchange (LIFFE)	2000
Intercontinental Exchange (ICE)	2005
Singapore Exchange (SGX)	2006

Notes:

1. There are some other small local all-electronic trading system markets, such as Amman Stock Exchange (ASE), Tel Aviv Stock Exchange (TASE), Taiwan Stock Exchange (TSEC).
2. In LSE, only FTSE100 stocks and some companies from the FTSE250 index are traded in a fully electronic trading system.

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