Applied Financial Economics, 2007, **17**, 343–350

Execution edge of pit traders and intraday price ranges of soft commodities

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Intraday activity of open outcry pit traders and mechanics of price formation are important for short-term traders, money managers and regulatory bodies. In particular, congestions of stop-loss and limit orders, as well as subsequent highs/lows of the daily prices are among the most important features traders are interested in. We present a comparison of range-based and close-to-open volatility estimators for US-traded soft physical commodities. The comparison indicates that pit traders are able to identify the congestions of pre-placed stop orders, reach them and liquidate on them, or let the prices run. The comparison also suggests a substantial execution edge of soft commodities pit traders compared to currencies traders.

I. Introduction

Intraday dynamics of commodity prices is important for a wide variety of professional traders, money managers, technical analysts, hedge funds operators, regulatory bodies and in risk and money management. There is wide anecdotal evidence that locals in open outcry pit trading are able to identify congestions of pre-placed orders (Schwager, 1993). In particular, the stock market crash of 1987 was partially attributed to the squeeze of money managers by Chicago locals, who detected the pattern of forced liquidation as prices begun to move lower (Taleb, 1997). Overall, common and legitimate tactics of locals is to push the prices until the perceived congestion of stop or limit orders is reached, then liquidate or let prices run into those pre-placed orders from outsiders that seek to be filled. In this way, locals act as conduits of liquidity. Study of this phenomenon is of substantial importance in the assessment of the trading risks, money management, better trades execution and overall understanding of intraday price dynamics of pit-traded physical commodities.

Open outcry pit trading of physical commodities requires a long apprenticeship; by various anecdotal estimates, only 10% of the traders survive financially and emotionally in a very competitive environment of the pits (Schwager, 1993). As a result, in every pit, there is a special 'pit chemistry' of survived players. As was described by Richard Dennis in his interview by Jack Schwager (1993):

> '*Also, the judgments you make looking at prices on the screen aren't as good as those made in the pit watching what is going on. In the pit, there are indicators that you learn subconsciously, like ''these three guys are never right at market turns'', and if they all do the same thing at the same time, a light clicks in*'.

In many cases, pit traders tend to behave coherently, being both competitors and accomplices. We argue that such highly organized behaviour of pit traders should leave its fingerprints on the prices dynamics. In particular, the tendency of the pits to reach for pre-placed orders and liquidate into them is likely to

Applied Financial Economics ISSN 0960–3107 print/ISSN 1466–4305 online © 2007 Taylor & Francis
http://www.tandf.co.uk/journals
DOI: 10.1080/09603100600690093

express itself in the wider intraday high–low range than it would be implied by a random walk model. This is the methodology adopted in the present study. We compare the performance of different volatility estimators on soft physical commodity prices and currencies. The difference between those estimators is in their efficiency and different data needed for the volatility estimations. On the standard lognormal Brownian random walk all those estimators produce the same theoretical volatility. It is well known, however, that real commodity prices are different from lognormal random walk in few respects such as fat tails in the (leptokurtic) distributions of returns. Because various estimators generate the same results for geometric Brownian motion, we expect that the differences in their performance on real prices will highlight the important aspects of price formation mechanisms in the open outcry trading of physical commodities.

Additional importance of the present research is the elucidation of the structural differences between various futures markets. Note that most studies concerned with range estimators of volatilities deal with currencies (see literature review below). Currencies markets are global, with a wide variety of players in their risk profiles, time horizons and capital restrictions. Because of the presence of large dispersed groups of speculators in the currency trading, the intraday price extremes (highs and lows) will likely be distributed more evenly than in the physical commodity markets. This is of interest for regulatory bodies, exchanges, arbitrageurs and brokerage companies, especially in the light of strong resistance of pit traders toward electronic markets (TowerGroup Report, 2000). Comparison of range-based and classic volatility estimators for physical commodities and currencies shows that pit traders of soft commodities enjoy a good execution edge and derive economic benefits from that, whereas execution edge of currency traders is relatively small, being of order of a few ticks.

II. Various Range-based Volatility Estimators

Typical volatility estimators use close-to-close settlement prices. Reasons for that include broad availability of settlement prices, regular time spans between closing prices, and general respectability and integrity of official settlement prices. At the same time, a growing body of literature is devoted to alternative, range-based volatility estimators which strive to utilize additional information available about open, high and low for the intraday prices. Also, many institutional and free charting tools of asset prices show open, high, low and close prices in the form of bar charts, which makes such studies more appealing to the trading community.

It seems that most of the studies about range-based estimators assume that asset prices follow the lognormal Brownian random walk, with constant drift and volatility coefficients. The first article, incorporating additional price information into volatility estimations, was apparently authored by Parkinson (1980). He proposed efficient range estimator of volatility based on high and low intraday prices. Garman and Klass (1980) presented a number of estimators seeking to utilize all the available information about the trading process, including the times when the market is closed, and evaluated the downward bias of range-based estimators. Ball and Tourus (1984) derived a maximum likelihood estimator equivalent to the estimator of Garman and Klass (1980). Rogers and co-workers (1991, 1994, 1998) and Kunitomo (1992) proposed another expression and showed that it provides an unbiased estimate of volatility even in the drift presence. Magdon-Ismail and Atiya (2003) used a maximum-likelihood method and presented efficient explicit formulas for computation of volatility. Yang and Zhang (2000) proposed multiple-period efficient volatility estimators independent on the drift. Alizadeh *et al.* (2002) and Gallant *et al.* (1999) use high/low prices for estimation of stochastic volatility. Lildholdt (2002) incorporated open, high and low prices into GARCH model of volatility. Lin and Rozeff (1994) show that high–low estimators allow one to understand the origin of excess DJIA index returns and contribution of trading volume into the conditional variance.

Note that virtually all of the studies concerned with range estimators of volatilities deal with stocks (Rogers, 1998; Magdon-Ismail and Atiya, 2003), index futures (Kawaller *et al.*, 2001), and currencies (Chaboud and Lebaron, 2001; Brunetti and Lildholdt, 2002; Fiess and MacDonald, 2002; Lildholdt, 2002). It seems that prices of physical commodities have not been studied by the range volatility estimators, and economic implications of such analysis are not available. This is the gap that the present study is seeking to fill.

III. Choice of Commodities

Note that to perform our analysis, it is necessary to carefully restrict the scope of the markets where the

Table 1. Trading times and price limits for soft commodities futures on NYBOT

Softs (NYBOT)	Trading hours	Price limit
Sugar	9:00 am–12:00 pm EST	None
Coffee	9:15 am–12:30 pm EST	None
Cotton	10:30 am–2:15 pm EST	3 cents ($1500 per contract)
Cocoa	8:00 am–11:50 am EST	None
Orange juice	10:00 am–1:30 pm EST	5 cents ($750 per contract)

analysis is performed. The crucial criterion is the structural homogeneity in time of the futures market of interest. In the last 20 years, many of the futures markets in the USA have shifted from open outcry pit trading to simultaneous electronic trading, and to additional night electronic sessions. Examples are S&P500 index futures, energy, metals and agriculture commodities. As a result, microstructure of intraday trading of those commodities has likely changed. Otherwise, only short-time periods might be considered as homogeneous, with a smaller amount of available data and smaller statistical significance. As a result, our attention in the present study will be restricted to 'soft' commodities, and comparison of them with currencies. Soft commodities include sugar, coffee, cotton, cocoa and orange juice that are traded on the New York Board of Trade (NYBOT). All those commodities are pit-traded; the trading is dominated by professionals; character and conditions of their trading have been very consistent over the last twenty years. The information about the commodities is presented in Table 1. The studied set of commodities comprises both liquid markets such as coffee, as well as relatively small markets such as frozen orange juice. These soft commodities are consumable. Some of the markets have daily price limits and some do not.

IV. Data

The comprehensive futures data for the study was obtained from Commodity Futures and Trading Commission. The data consists of daily open, high, low, settlement prices and open interest of individual contracts from 2 January 1985 to 20 February 2004. The prices were carefully and thoroughly cleaned and checked for correctness of decimal points, outliers and missing observations. Obvious outliers were removed and positions of decimal points were corrected. Then, the original price data S_{ij} were log-transformed into $s_{ij} = \mathrm{Log}[S_{ij}]$. Here, the first index i corresponds to the type of the price (open, high, low or close correspond to $i = o, h, l, c$); the second index corresponds to the day when the price was recorded. In the following computations, for each day, only the contracts with the highest open interest were considered, because those contracts may be considered as representative. We used a simple rollover technique to switch from one contract to another which is activated when open interest of one expiring contract becomes smaller than the growing open interest of the next contract.

V. Methodology

We try to emulate the activity of locals in the pit environment. One of the most important features of locals is that, in general, they do not carry overnight, and especially over-weekend positions. The reason for that is frequent overnight jumps in the commodity prices, when the opening price on the next trading day is different from the previous day closing price. One of the primary causes for overnight gaps is new developments and/or information that have been released or revealed during the time that markets have been closed. This is especially so over weekends, including long weekends. Because locals consider their trade execution edge as their major advantage, they do not want to be exposed to the risks of overnight jumps. Therefore, in consideration of locals' activity, it is necessary to consider open, high, low and settlement prices during 1 day, without regard to the previous closing price. In the absence of overnight price jumps, opening price on the next trading day is equal to the settlement price on the previous day.

Note that all of those 'soft' commodities are pit-traded less than 4 hours a day. It might be argued that substantial overnight jumps probably result in some carryover activity and correlated moves during the day because of a relatively short-time span that pit trading takes place for those commodities. The possible impact of overnight jumps to subsequent daily trading was studied by two methods.

First, correlations between overnight jumps $J_j = s_{oj} - s_{c,j-1}$ and subsequent daily moves $D_j = s_{cj} - s_{oj}$ have been computed for all commodities,

Table 2. Comparison of execution edge of pit traders for various soft commodities

Commodities	Number of observations	$\rho(J_i, D_i)$	Average tick size (%)	Average σ_{CO} (%)	Average absolute execution edge (%)
Sugar	4778	0.0081	0.12	2.2	0.86
Coffee	4780	0.003	0.053	2.6	0.81
Cotton	4804	−0.0064	0.016	1.82	0.43
Cocoa	4776	0.0083	0.07	2.23	0.52
Orange juice	4794	−0.015	0.047	1.85	0.36
Japanese Yen	3564	0.041	0.011	1.34	−0.09
Canadian Dollar	3564	−0.1	0.014	0.56	0.039
British Pound	3564	0.04	0.0062	0.95	0.04

The table shows the execution edge of pit traders in comparison with corresponding tick size, and average daily volatility of soft commodities prices.

using the described rollover technique. For all commodities, the correlations turned out to be very small, varying between −0.01 and 0.01. It is important also that soft commodities do not show bias toward upward or downward jumps. The average of the jump sizes turned out to be very small and lying inside 0.95 confidence interval of zero. This shows an important difference between physical commodities with upward and downward jumps, versus equity indices with bias toward downward jumps (Taleb, 1997).

Still, it might be argued that during bull or bear markets there might be a substantial correlation between overnight jumps and daily activity. To elucidate that, the second method of exponentially weighted moving average correlation (EWMA correlation) between overnight jumps J_j and daily moves D_j was applied as follows:

$$\rho_j = \frac{\sum_{j=0}^{k} \lambda^j J_j D_j}{\sqrt{\sum_{j=0}^{k} \lambda^j J_j^2 \sum_{i=0}^{k} \lambda^j D_j^2}}$$

Constant $\lambda \in (0, 1)$ is the decay factor in EWMA correlation, and k is the number of historic observations of the prices, see Table 2. This EWMA correlation approach is well known due to its use in J.P. Morgan RiskMetrics^{TM} software for forecasting variances and covariances. Throughout the text below, we present results for $\lambda = 0.94$ as used in RiskMetrics^{TM} of J.P. Morgan. Simulation results for other λ are similar to the results for $\lambda = 0.94$ and are available upon request. For all studied commodities, time graphics of EWMA correlations show erratic behaviour with near-zero mean, see Figs 1 and 2 for sugar.

We observe in Fig. 1 that during the last 20 years there have been short-time periods when EWMA correlation between overnight jumps J_j and

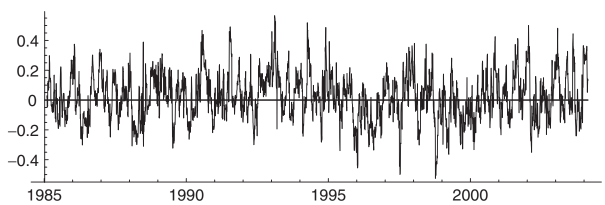

Fig. 1. EWMA correlation for sugar with $\lambda = 0.94$

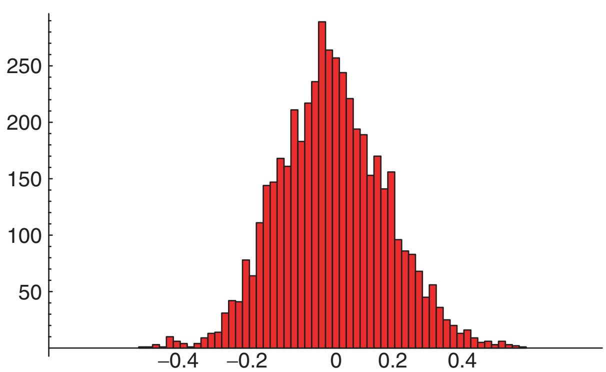

Fig. 2. EWMA correlation histogram for sugar with $\lambda = 0.94$

subsequent daily moves D_j was slightly positive or negative, being on average of order 0.1 by absolute value. Nevertheless, both the small values of EWMA correlation, and the highly symmetric histogram of EWMA correlations in Fig. 2 show an absence of long-term dependencies between overnight jumps and subsequent daily moves. As a result, we conclude that during the trading day, there is no consistent carry-over trading in the same or opposite direction as overnight jumps. This shows that professional physical commodities markets are highly efficient in their trading, and efficiently discount the new information available overnight. Also, this corroborates the hypothesis that locals probably cannot gauge the direction of overnight jumps, dependent on new overnight information, and prefer not to carry overnight positions. Therefore, we can consistently use close-to-open returns in evaluation of conventional intraday volatility instead of close-to-close returns.

VI. Execution Edge of Pit Traders

The detailed dynamics of pit trading has been subject of many papers and extensive microstructure literature (book by O'Hara, 1995, provides an excellent introduction). In particular, Fishman and Longstaff (1992) studied the trade-by-trade data from the soybean pit at CBOT and established that 'dual' brokers that trade for their own accounts as well as accounts of their clients earn more than nondual traders. In the detailed article by Manaster and Mann (1999), the profits of locals at CME have been decomposed into two parts: one is for providing liquidity, which may be thought of as bid-ask spread, and another one due to correct timing of the trades, and corresponding price moves. It turned out that locals have informational advantage, and good timing of their trades. Study of inventory of locals by Manaster and Mann (1996) shows that floor traders actively take directional positions. More than that, individual market makers inventories are rapidly mean reverting. Results of those studies clearly suggest that the locals thrive on mean-reverting prices. Unfortunately, those articles do not provide a quantification of the price capturing by the locals. In other words, it is not clear how many ticks locals are able to make when correctly taking directional position. Also, such type of studies requires highly detailed data with identification of the trader types on each side of the trade. Due to confidentiality reasons, access to such data is quite restricted. And, connection of trading decisions with intraday price dynamics has not been established. In the present work, we choose another path. We study the ranges of intraday prices which use broadly available information, and interpret the excessive degree of mean-reverting as the execution edge of pit traders. This allows one to quantify the execution edge in price terms.

To quantify the execution edge of pit traders, consider in detail the trading activity in the pit. For locals, the necessity to be flat at the end of each trading session imposes the necessity to get out of all positions toward the end of the session. Hence, they have to identify a party willing to trade with them. Trading between locals does not bring profit to the locals as to the group. The way the locals can execute their trading edge is to trade with pit outsiders. If prices do not move, pre-placed orders cannot be executed. As a result, pit traders, 'the ring', make an educated guess as of where the congestion of market and/or limit orders is located. Then, if the ring can push prices in a desirable direction, prices will reach pre-placed orders, the 'ring' will liquidate into those orders and book the profit between initial price and average congestion price, and then press prices in other direction. In all cases, locals are interested in expansion of the trading range and hitting the maximal amount of pre-placed stop and limit orders to increase their profit and to provide the liquidity to outside order flow. The locals benefit the most from the order flow and their ability to make short-term trades in the environment of mean-reverting prices. Therefore, to identify the edge of pit traders and their ability to reach congestion of orders and expand the trading range, it is necessary to compare close-to-open volatility with high–low volatility of intraday prices in time. When high–low volatility is high compared to close–open volatility, this is an evidence of mean-reverting prices, and ability of the locals to benefit from that. Otherwise, it is better 'to follow the trend'.

To quantify the execution edge of pit traders, we use the exponentially weighted moving average (EWMA) scheme to compute both high–low Parkinson daily volatility σ_P and close-to-open daily volatility σ_{CO} (we use constant $\lambda = 0.94$, the same as used in RiskMetrics^{TM} of J.P. Morgan):

$$\sigma^2_{P,i} = \lambda\sigma^2_{P,i-1} + (1-\lambda)(s_{h,i-1} - s_{l,i-1})^2$$
$$\sigma^2_{CO,i} = \lambda\sigma^2_{CO,i} + (1-\lambda)(s_{c,i-1} - s_{o,i-1})^2$$

Note that we use the classic Parkinson (1980) estimator based on high-low prices only. Many other estimators afore described have better efficiency than Parkinson estimators. Our goal, however, is not efficiency improvement but usage of two nonoverlapping sets of data in order to quantify intraday variability of prices. In this respect, use of close-to-open vs. high–low estimators is the most efficient and parsimonious. As was shown by Parkinson (1980), for the lognormal Brownian motion with constant drift and volatility, high–low and close-to-close (close-to-open in the absence of jumps) volatilities relate to each other as

$$\sigma^2_P = 4Ln2\sigma^2_{CO}$$

The execution edge of pit traders and their ability to expand the trading range and liquidate into outside order flow may be defined as an excessive gain of intraday high-low Parkinson volatility σ_P compared to close-to-open volatility σ_{CO} over one trading day:

$$\text{Absolute edge} = \frac{\sigma_P}{\sqrt{4Ln2}} - \sigma_{CO}$$

$$\text{Relative edge} = \frac{\sigma_P}{\sqrt{4Ln2}\sigma_{CO}} - 1$$

Note that σ_P has downward bias (Garman and Klass, 1980). So, the both absolute and relative execution edges of pit traders are somewhat smaller than the actual edge. In the mean-reverting price environment, both absolute and relative edges are positive. That corresponds to the most favourable conditions for locals. Otherwise, if market 'trends', execution edge of floor traders becomes negative, and if they actively make market, they are forced to acquire inventory when prices are moving against them. In such a case, it is better to 'follow the trend'. In the case of Brownian random walk, locals do not have edge, but also do not suffer losses.

Both absolute and relative edges of pit traders were computed for all soft commodities. Relative edges for coffee and cocoa are shown in Figs 3 and 4. Average absolute edges for all considered futures are presented in Table 2. As might be seen from Figs 3 and 4 and Table 2, the execution edge of pit traders for soft commodities is quite substantial in spite of downward bias of σ_P, and consistent in time. On average, the execution edge of soft commodity pit traders is 7–20 times larger than tick size, and is about 20–25% of daily close-to-open volatility. This is in line with a steady rise of NYBOT seat prices from about \$5500 for the Cotton Exchange full membership and about \$13 000 for the Coffee, Sugar and Cocoa Exchange full membership in 1975 to more than \$300 000 for the full membership in NYBOT in 2005. This is also consistent with general resistance of pit traders toward electronic markets (TowerGroup report, 2000). It is clear that pit traders derive economic benefits from their trading activity. The very fact that the execution edge is a few times larger than the tick size, and bid-ask spread, corroborates the conclusion of Manaster and Mann (1996) that a substantial fraction of the locals' profit is derived from the fast intraday directional trades, and not merely due to providing liquidity.

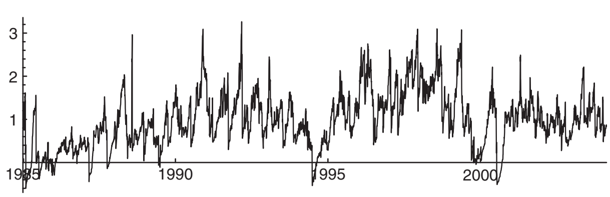

Fig. 3. Relative execution edge of pit traders for coffee

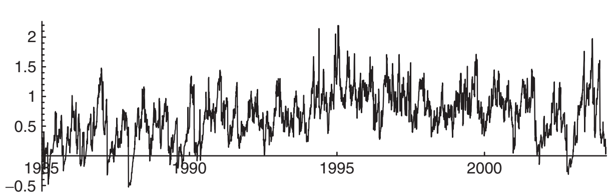

Fig. 4. Relative execution edge of pit traders for cocoa

VII. Comparison with Currencies

To estimate how the results of the execution edge for pit traders depend on the market and its type, consider the same estimators of trading edge for three active currencies with long historical data: Japanese yen, British pound and Canadian dollar. We take currencies prices beginning from 1990 when currency trading was well established at Chicago Mercantile Exchange (CME) and futures prices closely followed the interbank currencies market. Computed relative edges for Japanese yen and British pound are shown in Figs 5 and 6. Average absolute daily execution edges and other statistics for the currencies are shown in Table 2.

As might be seen both from Figs 5, 6 and Table 2, the execution edge of currency traders is relatively small, especially in the last 10 years, and is of order of a few ticks, though correlation of overnight gaps and subsequent daily moves is higher than for commodities. It is likely that the actual execution edge of currency pit traders is somewhat larger that shown in

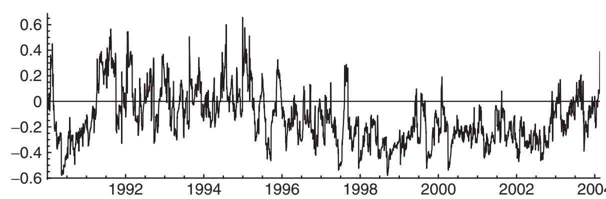

Fig. 5. Relative execution edge of pit traders for Japanese yen

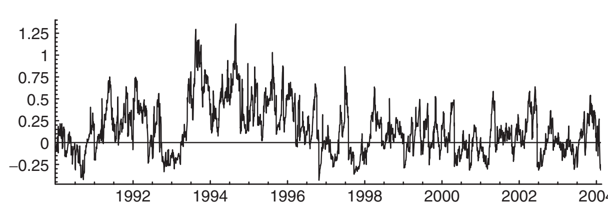

Fig. 6. Relative execution edge of pit traders for British pound

Table 2 because of downward bias of σ_P. Overall, it seems that the major source of the locals' profits in the currency pits is just due to liquidity. The small execution edge of the currency pit traders is a likely manifestation of global nature of currency markets, diversified character of players, strong competition between market makers, and large volumes of trading. As a result, intraday extremes (highs and lows) are not as pronounced as for soft commodities markets. On average, the execution edge of soft commodity pit traders is a few times larger than the edge of currency traders. This is consistent with the fact that the major currency market is the interbank spot market, and futures currency markets just follow the interbank markets. As a result, currency pit traders can not make the markets with a substantial edge. Also, the weakening edge of currency pit traders allows one to understand the fast shift of currency trading from pits to the more efficient GLOBEX electronic platform at CME, where during 1998–2003 years GLOBEX trading became the dominant platform for currency trading, compare with Figs 5 and 6.

VIII. Conclusion

The floor traders benefit the most from, and seek wide intraday ranges of the prices. We associate the execution edge of locals with mean-reverting prices. To quantify the mean reversion, we use widely available information about daily open, high, low and settlement prices. The difference between normalized Parkinson volatility estimator using high-low prices, and conventional estimator using close-open prices, is taken as an execution edge of pit traders. It turned out that in 'soft' commodities markets, the execution edge of locals is quite higher than that in the currencies pits. It seems that the major source of the locals' profits in 'soft' commodity pits is correct timing of their intraday trades. Contrary to that, the main source of the profits for currency pit traders seems to be the providing liquidity to the market. This explains resistance of pit traders in physical commodities toward electronic markets, fast migration of currency trading toward electronic GLOBEX platform and steady rise of NYBOT membership prices.

Acknowledgments

I am deeply grateful to Tim Barry, Kevin Brady, Tim Endres, Daniel Frankel, Jerome Huhman and Carl Zappfe for numerous stimulating discussions of the subject and helpful suggestions. Constructive and insightful comments by the anonymous referee allowed to substantially improve the article.

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