Open outcry versus electronic trading: tests of market efficiency on crude palm oil futures

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Abstract

Given the widespread transfer of trading to electronic platforms it is important to ask whether such trading is more efficient than traditional open outcry. To empirically assess this we examine the Crude Palm Oil market from 1995:06 to 2008:07 - a market where all trading swapped over from open outcry to electronic trading at the end of 2001. Results indicate that both forms of trading are long-run efficient but that short-run inefficiencies do exist. Our main findings, derived from the application of a novel threshold autoregressive relative efficiency measure, is that market efficiency is conditional on (i) the volatility of the underlying asset (ii) the maturity of the futures contract and (iii) the market trading system. Specifically, bootstrap results from the efficiency measure suggest that the open outcry trading method is superior for shorter maturities when volatility is high, and indistinguishable from electronic trading when volatility is low or maturity is long. These results suggest that electronic trading should not supersede open outcry, but rather that there are clear benefits to their coexistence.

Keywords: Market efficiency, commodity futures contracts, open outcry, electronic trading, crude palm oil.
JEL Classification: G13, G14, G15.

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1 Introduction

Futures markets provide a tool for risk management and aid in price discovery. However these functions are only optimal in the presence of market efficiency. As is well known, under the assumptions of rationality and risk neutrality, the futures market is not only efficient but the price is an unbiased estimator of the corresponding future spot price.

Using cointegration techniques futures market efficiency has been extensively investigated for a number of commodities and financial assets across a variety of data spans. On the one hand, there is evidence of efficiency (see, for example: Kellard et al., 1999; Switzer and El-Khoury, 2007; Kawamoto and Hamori, 2011), whilst on the other there is evidence of inefficiency (see, for example: Chowdhury, 1991; Mohan and Love, 2004; Figuerola-Ferretti and Gonzalo, 2010). The outstanding question is therefore how can this contradictory evidence be reconciled?

Applying Occam's razor, the obvious answer may be that some markets may be efficient, whilst others may not be. This then points towards unique market specific factors that may contribute to or hinder efficiency. One such factor may be the way in which, if at all, electronic trading systems are implemented. Many asset and commodity markets have now either abandoned open outcry for electronic trading platforms, or run both systems side-by-side. The evidence for either option is mixed, with some work suggesting that a well-functioning market benefits from the latter (Martens, 1998), whilst others posit a fully electronic approach (Tse et al., 2006). However, there is also emerging evidence that when used independently, electronic trading is not as able as open outcry to impound information into the price when volatility is high (Aitken et al., 2004).

Existing work that focuses on these two methods of trading use intraday data to examine issues such as liquidity, the size of spreads, and price discovery, across a broad range financial and commodity futures. Examples of such work include Aitken et al. (2004), Ates and Wang (2005), Copeland et al. (2004), Theissen (2002), and Tse and Zabotina (2001). However the main focus of our study is distinct from this literature, contributing by being the first, to our knowledge, to address predictive efficiency in futures markets under discrete market trading regimes. In other words, we utilize daily data on futures contracts to examine under which trading regime the futures price best predicts the future spot price.

For this experiment we choose the crude palm oil (CPO) futures market due to its discrete migration from open outcry to electronic trading which obviates the need to address a scenario where both open outcry and electronic trading operate simultaneously. In choosing CPO we also address a gap in the literature as this commodity is under-researched. This is surprising given its wide spread use globally and the increasing prominence of this commodity on the world food market. Strikingly production levels

are greater than any other edible oil.[1]

In implementing this experiment we utilise two sub-samples of data pre- and post-introduction of electronic trading and initially assess long-run and short-run efficiency using standard cointegration techniques and Kellard et al.'s (1999) relative efficiency measure. Unlike other efficiency measures which classify whether a market is either solely efficient or inefficient, this relative measure allows an assessment of the degree to which efficiency is present. We further contribute by being the first to examine how well these two methods of trading impound information as a function of the volatility of the underlying asset, which is achieved by adapting the relative efficiency measure to a threshold autoregressive environment with a bootstrap confidence interval. Finally, we examine market efficiency at several points across the term structure permitting a more comprehensive analysis of the market. It is noteworthy that the much of the extant literature is lacking in this respect, often focusing solely on shorter terms to maturity.

Our findings indicate that the CPO futures market is long-run efficient in the vast majority of maturities tested across both trading platforms. However, across the whole sample and open outcry and electronic trading sub-periods there is evidence of short-run inefficiency. Interestingly, applying the relative efficiency measure of Kellard et al. (1999) indicates that open outcry is more efficent at shorter maturities and electronic trading at longer maturities. However, using the new threshold autoregressive relative efficiency measure, bootstrap results suggest that the open outcry method is superior for shorter maturities when volatility is high, and otherwise is indistinguishable from electronic trading. These results suggest that electronic trading should not supersede open outcry, but rather there are benefits to their coexistence. This updates and extends the thesis of Martens (1998), suggesting there is still a clear role for open outcry in modern futures markets to improve price discovery and related issues of risk management, particularly at shorter maturities.[2] In the context of the CPO market, this clearly has implications for the price discovery and hedging of a commodity that is increasingly prominent on the world food market, and one that also has both developmental and environmental effects.[3]

The remainder of the paper is organised as follows: Section 2 provides a short overview of the CPO market, Section 3 examines CPO futures efficiency across the term structure, Section 4 examines CPO futures efficiency across periods of electronic trading and open outcry, and a final section concludes.

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[1]Based on the latest production data, palm oil presents almost a third of edible oil market (source: Food and Agriculture Organization of the United Nations). See Section 2 for more information on the CPO market.

[2]This role for open outcry has been documented at the trader level by Boyd and Kurov (2012), who find that when run side-by-side with electronic trading, traders are more likely to survive using both systems rather than one alone.

[3]See World Bank and IFC (2011) for a discussion of the developmental and environmental effects.

2 A précis: Crude Palm Oil

CPO currently represents the largest share of the edible oil market, thus the functioning of this market warrants close attention in the current climate of an expanding world population and finite resources. It is derived from the fruit of the oil palm tree and is used for a range of purposes, including cooking oil, baked goods, soaps, washing powder, and as a bio-fuel. The demand for palm oil has increased in recent years, linked to (i) the growth of the Indian and Chinese economies (ii) the use of palm oil as a substitute for trans fatty acids and (iii) the use of palm oil as a bio-fuel. Figure 1 demonstrates the impressive growth of CPO production over the last 30 years becoming the most produced edible oil (by tonnes) in 2006.

[Figure 1 about here]

We also compared the production growth 1980-2012 of over 100 crops listed on the Food and Agriculture Organization's database, and found that palm oil ranks in 4th place, contrasting with staple crops commonly traded on futures exchanges such as soybean (60th), corn (94th), and wheat (124th). Taking each of these commodities as a case in point, the absolute production levels of corn and wheat is higher than that of the oil palm fruit. However the production gap between soybean and the oil palm fruit has been closing over time with 2012's figures showing higher production for the oil palm fruit.

   This study focuses on the Malaysian CPO futures price as it represents the global reference price and is the single largest market for CPO futures globally.[4] Trading traditionally takes place on the Bursa Malaysia Derivatives Berhad where trading volumes have increased in recent years - Figure 2 shows the average daily volume and open interest (per month) of the most traded (3-month) CPO futures contract from 1995:06 to 2008:07.[5] Figure 3 shows the average (per month) futures price and the 30-day historical spot price volatility.

[Figure 2 about here]

[Figure 3 about here]

Contracts are for 25 metric tons and are settled on the 15th day of the month, and are available for the current month, the subsequent 5 months, and thereafter alternately

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[4]See online documentation from Bursa Malaysia (www.bursamalaysia.com) or the CME Group (www.cmegroup.com).

[5]Bursa Malaysia Derivatives Berhad was formally the Malaysia Derivatives Exchange (MDEX). Malaysia is also the leading exporter and second largest producer of CPO.

up to 24 months ahead.[6] Up until December 2001, futures contracts were traded using open outcry and subsequently migrated to an electronic trading system on 28 December 2001.[7] Global access to the CPO futures market was further improved on 17 September 2009 via a partnership with the Chicago Mercantile Exchange (CME).[8]

3 Futures market efficiency across the term structure

3.1 Market efficiency hypothesis

We examine long-run and short-run market efficiency for a number of different maturities across the term structure. This is achieved by testing for cointegration and using the quasi-error correction model (QECM) of Kellard et al. (1999).

Long-run market efficiency is linked to the spot and futures markets via the notion of unbiasedness.[9] Specifically, under the joint assumptions of rational expectations and risk neutrality, the unbiasedness hypothesis can be expressed as:

$$E_{t-\tau}[s_t] = f_{t-\tau} \tag{1}$$

where s_t and f_t are the log of the spot and futures prices and $E[.]$ is the expectations operator, and τ is the interval between opening a position and expiry. Equation (1) states that the futures price set at time $t - \tau$, for delivery at time t should equal the time $t - \tau$ expectation of the spot rate for time t. By varying τ we gain the ability to comment on efficiency across the term structure. Under rational expectations, Equation (1) can be recast as:

$$s_t = f_{t-\tau} + \epsilon_t \tag{2}$$

where ϵ_t is a zero mean, finite variance random variable. Testing this simple relationship for any point on the term structure is complicated by the time-series properties of both the spot and futures price. There is a large body of evidence that points towards both series being non-stationary (e.g. Figuerola-Ferretti and Gonzalo, 2010). Therefore for

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[6]The contract specifications have changed little over the span of our sample. For example the contract size, tick size, final trading day, maturity date, and tender period all remain unchanged. However some changes have occurred, for example prior to 2007 contracts were only available alternatively up to 12 months ahead, the size of allowed for speculative positions were smaller, and price limits were statically managed as opposed to dynamically. See www.bursamalaysia.com for further details on the contract specification.

[7]See Appendix A for a plot of daily volume and open interest in the 6 months pre/post-migration.

[8]The agreement included the distribution of the Bursa Malaysia's products through the Globex electronic trading platform.

[9]As explained in the next section we depart from the standard approach outlined in this section using $\{f_t, f_{t-\tau}\}$ in place of $\{s_t, f_{t-\tau}\}$.

unbiasedness to hold s_t and f_t must be cointegrated:

$$s_t = \alpha_0 + \alpha_1 f_{t-\tau} + \epsilon_t \tag{3}$$

where $\alpha_0 = 0$ and $\alpha_1 = 1$, and ϵ_t is serially uncorrelated. If the restriction that $\alpha_1 = 1$ cannot be rejected, then this points towards a long-run equilibrium relationship between s_t and f_t. Given empirical support for this relationship a handle on short-run efficiency can be garnered by rewriting Equation (3) as a quasi-error correction model:

$$s_t - s_{t-\tau} = \gamma_0 + \gamma_1(f_{t-\tau} - s_{t-\tau}) + \sum_{i=1}^{k} \delta_i(s_{t-i} - s_{t-\tau-i}) + \sum_{i=1}^{k} \zeta_i(f_{t-i} - f_{t-\tau-i}) + \epsilon_t \tag{4}$$

Estimating Model (4), efficiency is indicated by there being no significant coefficients on lagged changes in the spot and futures price. In other words, efficiency requires that no information in addition to the basis is of use in forecasting changes in the spot rate.

3.2 Testing CPO efficiency

Utilising the unbiasedness framework in the previous section we examine CPO market efficiency for a number of maturities: $\tau = 7, 14, 21, 28, 56,$ and 84 days, with data spanning from 15 June 1995 to 15 July 2008.[10] Following the observations of Goss (2000), who notes that emerging markets can lack proper underlying wholesale markets which would support price discovery in the corresponding futures market, and that in the case of CPO that spot and futures market are traded on different exchanges in different locations, we follow Beck (1994) and use the futures price at maturity as the spot price.[11]

Futures prices are matched to the spot price on delivery for each τ, thus generating a new time-series for each maturity. Table 1 present summary measures for each maturity. The sample mean and standard deviaiton tends to increase as τ reduces. In the case of the latter this may be linked to an increase in trading activity as traders seek to close out positions as delivery approaches.

[Insert Table 1 about here]

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[10]Data are closing prices from Reuters (code: FCPO). In addition to the futures price the daily high and low are used in Section 4.4. The choice of sample permits two sub-samples of equals size as discussed in Section 4.2. Values of τ are actual days not business days; following the contract specification, if the delivery date is a non-business day the preceding business day is used. When constructing the price series for each τ if the trade date $t - \tau$ is not a business day the preceding business day is taken. Across all series 93% of observations fall on the exact business day, and 99.3% fall within three calendar days prior.

[11]Malaysia Palm Oil Board manage palm oil physical market and Bursa Malaysia Derivatives Berhad govern the futures market.

As discussed, the order of integration of the time series needs to be examined as a precursor to testing for unbiasedness. Table 2 presents the results of tests under the null of the futures price being both non-stationary (augmented Dickey-Fuller test) and stationary (KPSS test) for each τ. Given the uniform inability (ability) to reject the null of the ADF (KPSS) test across all τ we deem the CPO futures prices to be non-stationary.

[Insert Table 2 about here]

[Insert Table 3 about here]

Table 3 presents the results of tests to examine whether f_t and $f_{t-\tau}$ are cointegrated using the Johansen method, specifying a vector error correction model of the m-variable VAR of order k for time-series vector X_t:

$$\Delta X_t = \eta_0 + \Pi X_{t-k} + \sum_{i=1}^{k-1} \eta_i \Delta X_{t-i} + v_t \tag{5}$$

where k is chosen by the Akaike Information Criterion (AIC). The procedure tests the rank (r) of parameter matrix Π, where v_t will only be I(0) if there exists a stationary linear combination of I(1) variables in X_{t-k}. Specifically ΠX_{t-k} has to be stationary. We define $X_t = (f_t, f_{t-\tau})$ and test this using the Johansen λ-max and trace statistics to test sequentially under the null of the $r = 0$ (no cointegration) and $r = 1$ (cointegration). Given the presence of a long-run relationship it is then straightforward to test the restriction $\alpha_1 = 1$ in Equation (3) - this test for unbiasedness is also presented in Table 3.

The results clearly show a rejection of the null of zero rank and thus of no cointegration for all maturities for both test statistics. Further using both tests we are unable to reject the null that $r = 1$ at the 5% significance level for all maturities, and is thus indicative of there being a long-run relationship between f_t and $f_{t-\tau}$. This also supports the findings of the time-series properties of f_t and $f_{t-\tau}$ from the earlier ADF and KPSS tests. Testing the restrictions on the cointegrating vector yields conclusive support unbiasedness as the restriction under the null is unable to be rejected for all maturities tested. Hence we find that in the long-run the futures price is an unbiased predictor of the future spot price.

The evidence of long-run efficiency in the CPO market, whilst encouraging, does not preclude inefficiency in the short-run. Table 4 examines short-run efficiency. This is achieved using a variant of Equation (4), accounting for the fact that we use the futures price at delivery in place of the spot rate:

$$f_t - f_{t-\tau} = \theta_0 + \sum_{i=1}^{k} \theta_i (f_{t-i} - f_{t-\tau-i}) + \epsilon_t \qquad (6)$$

The interpretation is similar to Equation (4), where statistically significant lags of the dependent variable are indicative of inefficiency. We can see from Table 4 that the longest maturity evidences more inefficiency than shorter maturities as indicated by the larger number of lags included. More specifically, as the maturity decreases the number of significant coefficients is at least equal or fewer, finally yielding short-run efficiency 7 days before settlement. Interestingly when lag 4 is present it is always significant.

[Insert Table 4 about here]

4 Open outcry or electronic trading?

4.1 Literature

There is a wide body of research comparing open outcry and electronic trading using intraday data. This research takes the form of examining markets that have made a transition from the former to the latter, or markets that trade under both systems concurrently. Martinez et al. (2011) provides a useful summary of the two trading systems for agricultural commodity futures markets and Cardella et al. (2014) survey the literature that examines the effects of computerization across a variety of markets. Of particular interest for this current study is understanding how efficiency may differ following the advent of electronic trading.

Aitken et al. (2004) uses intraday data and time-weighted bid-ask spreads to examine the determinants of spreads on index futures on three major exchanges: London International Financial Futures and Options Exchange (LIFFE), Sydney Futures Exchange, and the Hong Kong Futures Exchange. Controlling for changes in price volatility and trading volume they find lower spreads result under electronic trading, adducing evidence that electronic trading can result in higher liquidity and lower transaction costs. Interestingly they note that spreads from electronic trading are more sensitive to price volatility and thus the performance of such systems deteriorates during periods of information arrival. Focusing specifically on how information is impounded in periods of high and low volatility, Martens (1998) examines futures contracts on German long-term government bonds traded simultaneously on the LIFFE (open outcry) and Deutsche Terminborse (electronic trading). Using the Hasbrouck's (1995) measure of information share, Martens finds that in low volatility periods it is electronic trading that contributes more to the price discovery process. Conversely, results suggest that in volatile periods

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it is open outcry that makes the larger contribution. However the findings of Martens (1998) differ from Ates and Wang (2005), who find the opposite relationship between electronic trading and volatility for the S&P 500 and NASDAQ 100 index futures.[12] This mixed picture is further reinforced by Tse et al. (2006), who look at futures contracts for foreign exchange (EUR/USD, JPY/USD) and find open outcry trading contributes least to price discovery (vis-à-vis electronic trading and online trading.)

Tse and Zabotina (2001) examine trading activities before and after the FTSE 100 index futures contracts moved from open outcry to electronic trading. In common with the majority of the recent literature they find lower spreads in electronic market vis-à-vis open outcry. However results using Hasbrouck's (1993) market quality indicate that open outcry has greater pricing efficiency (as measured by the variance of pricing error) and a slower adjustment to information in the electronic market. In addition to this slower adjustment they also find a negative relationship between trades and lagged quote revisions for electronic trading, but no relationship for open outcry. The authors attribute this last finding to a different approach inventory between these two methods of trading.[13] In related work Ning and Tse (2009) also examine the FTSE 100 index futures contracts pre-/post-migration to electronic trading. Under electronic trading they find that daily contract order imbalances are autocorrelated for lags of several days, and attribute this to the characteristics of the limit order book. As the authors comment, the arrival of a large market order is split against multiple existing quotes on the order book generating a sequence of transactions on one side of the market. For open outcry there is no autocorrelation in the order imbalance suggesting persistence is eliminated within the day.

On balance, the extant research tends to favour electronic trading, but there does seem to be some evidence that there is a role for open outcry in the price discovery process, particularly during periods of high volatility. However these results may be market specific and it is of course difficult to draw broader conclusions given the limited number of markets examined by researchers to date.

4.2 Market efficiency: open outcry or electronic trading?

This study is the first to examine predictive efficiency across trading systems, using an important and under researched commodity, CPO. Previous work (see, for example: Tse and Zabotina, 2001; Martens, 1998) typically use short sample periods and Hasbrouck (1993, 1995) type measures of pricing efficiency. These measures assume semi-strong market efficiency and decompose the futures price into a random walk and a transitory

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[12]Ates and Wang (2005) attribute this difference in result to market specific factors. Namely that on the U.S. index futures markets some participants are able to trade both in the pit and electronically.

[13]See Tse and Zabotina (2001) for more details.

component, which thus reflects a pricing error. However for the CPO futures market there now exists sufficient data to test for informational efficiency post-implementation of electronic trading, and so we can employ the testing procedures in section 3 and avoid any such initial assumptions. The futures market for CPO represents an ideal candidate as it has made a discrete transfer from open outcry to electronic trading, rather than running both systems in parallel. This obviates the task of trying to understand the behaviour of one market in the presence of another, thus making inference more tractable. This is achieved by forming two datasets, representing the period where CPO was traded via open outcry (15 June 1995 - 15 December 2001) and the current system of electronic trading (15 January 2002 - 15 July 2008) and examine market efficiency under these two trading methods using the methodology previously applied. We view the choice of data-span as appropriate for three reasons: (i) it yields two equally sized sub-samples avoiding any need to address a scenario where one sub-sample may have better statistical power than another by virtue of its longer span (ii) it avoids the unusual volatility exhibited as a result of recent financial crises and (iii) it focuses solely the period prior to the strategic partnership with the CME group in 2009.

[Insert Table 5 about here]

Table 5 presents the summary statistics for both sub-samples. Interestingly open outcry tends to exhibit a downward trend in the sample mean as settlement approaches whilst for electronic trading it is increasing, yet in both samples there typically exists an inverse relationship between volatility and maturity in accordance with that observed for the full sample. Table 6 examines the time-series properties of $f_{t-\tau}$ and Table 7 the results of the cointegration analysis. Overall, for both sub-samples, Table 6 is indicative of the findings for the whole sample, namely the CPO futures price being a non-stationary process across a range of maturities. The one notable discrepancy between the ADF and KPSS tests is for the f_{t-84} (exogenous specification: constant) for the open outcry sub-sample. Given the contradictory results between these tests we defer to the Johansen cointegration framework as this implicitly provides an additional test of the time-series properties of f_t and $f_{t-\tau}$ in Table 7.

[Insert Table 6 about here]

[Insert Table 7 about here]

In Table 7 we find evidence of cointegration for the majority of maturities across both open outcry and electronic trading sub-samples. The two exceptions are f_{t-28} and f_{t-56} where no cointegration is found. Thus we conclude that the dominant picture is one of a long-run relationship between the futures price at maturity $t - \tau$ and the contract price

at delivery. Additionally the Table indicates that for both sub-samples the unbiasedness restriction in the cointegrating vector cannot be rejected, thus where cointegration is found we conclude that the market is long-run efficient under both open outcry and electronic trading regimes.[14]

Turning now to short-run efficiency, Table 8 indicates that both the open outcry and electronic trading sub-samples exhibit evidence of inefficiency to some degree, although there are three noteworthy instances where support for short-run efficiency is found: open outcry, 7 days and 14 days; electronic trading, 14 days. In the case of inefficiency, for open outcry there are 4 (2) significant lag coefficients for $\tau = 84$ ($\tau = 56$). As the maturity decreases further this drops to 1, then finally zero at the shortest maturities. However these results contrast with the electronic trading sub-sample, where there are almost twice as many significant coefficients across the term structure. We argue that the stronger evidence for short-run inefficiency in the electronic trading sub-sample provides, at the very least, prima facia evidence that this trading mechanism may not always be superior, and indeed may sometimes be less efficient than open outcry.

[Insert Table 8 about here]

4.3   Relative efficiency

The estimates reported in Table 8 indicate that there exists short-run inefficiency at various points across the term structure using both open outcry and electronic trading sub-samples. However this approach is not able to quantify the magnitude of this inefficiency. With this in mind we adopt the measure of relative efficiency of Kellard et al. (1999). As they note, the ability to quantify the level of (in)efficiency is important to hedgers (hedging costs rise as markets become more inefficient - Krehbiel and Adkins, 1993) and wider society alike (the link between inefficiency and the social costs attributed to futures trading - Stein, 1987). For the current application, being able to quantify the measure of efficiency allows a new direct comparison between open outcry and electronic trading systems.

The efficiency measure of Kellard et al. (1999) is formed from two forecast error variances. One is the forecast error variance of Equation (4), representing the extent to which the model was unable to forecast the realised change in the spot price. The second is based on the corresponding forecast error should the market be efficient: $E[(s_t - f_{t-\tau}]$. Under the assumption of rationality this is proxied by the mean corrected measure of $s_t - f_{t-\tau}$. This yields the relative efficiency measure:

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[14]Long-run restrictions are provided for f_{t-28} and f_{t-56} for completeness only.

$$\phi_c^\tau = \frac{(n-2k-2)^{-1}\sum_{i=1}^n \hat{\epsilon}_t^2}{(n-1)^{-1}\sum_{i=1}^n[(s_t - f_{t-\tau}) - \overline{(s_t - f_{t-\tau})}]^2} \tag{7}$$

We adapt this efficiency measure using Equation (6) in place of (4). This requires substituting s_t with f_t and an attendant adjustment to the degrees of freedom:

$$\phi_c^\tau = \frac{(n-k-1)^{-1}\sum_{i=1}^n \hat{\epsilon}_t^2}{(n-1)^{-1}\sum_{i=1}^n[(f_t - f_{t-\tau}) - \overline{(f_t - f_{t-\tau})}]^2} \tag{8}$$

where n constitutes the number of dependent variable observations prior to lags being taken. By construction ϕ_c^τ takes values between 0 and 1, with 0 indicative of complete inefficiency, 1 for a fully efficient market, with interim values representing the degree of (in)efficiency. Table 9 presents the results of the test for relative efficiency for both sub-samples, as well as for the whole sample for comparative purposes.

[Insert Table 9 about here]

For the entire sample, short-run efficiency increases as the settlement date approaches, while for the two sub-samples the average across the term structure is within two percent (78% for electronic trading and 76% for open outcry). As maturity reduces there is a marked increase in ϕ_c^τ for the open outcry sub-sample mirroring the full sample results; however the pattern from the electronic trading sub-sample is not quite so clear. Further, our results suggest that open outcry is at least as efficient as electronic trading at shorter maturities whilst electronic trading performs better at longer maturities.[15] Finding that support for open outcry is garnered at shorter maturities could support the notion that when volatility is high open outcry is superior in impounding information (Aitken et al., 2004) - recall from Table 5 that the standard deviation is highest at the 7-day maturity for both samples. We examine this further in the next section.

4.4 Relative efficiency during periods of high and low volatility

Building on the direct comparison between open outcry and electronic trading systems from the previous section, we redeploy the relative efficiency measure in a threshold autoregressive setting permitting a novel comparison between trading systems in times of high and low volatility. To achieve this the following two regime threshold autoregression (TAR) framework replaces Equation (6):

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[15]For f_{t-7} and f_{t-21} open outcry is more efficient while both are short-run efficient at the 14-day maturity.

$$f_t - f_{t-\tau} = \begin{cases} \theta_{H,0} + \sum_{i=1}^{k} \theta_{H,i}(f_{t-i} - f_{t-\tau-i}) + \epsilon_{H,t} \text{ if } \sigma_t^2(f) > q(\kappa) \\ \\ \theta_{L,0} + \sum_{i=1}^{k} \theta_{L,i}(f_{t-i} - f_{t-\tau-i}) + \epsilon_{L,t} \text{ if } \sigma_t^2(f) \leq q(\kappa) \end{cases} \quad (9)$$

where the subscript H denotes the high volatility regime, L the low volatility regime, $\sigma_t^2(f)$ is the transition variable which is defined as the difference between the daily future's high and low price at the pricing date, $q(\kappa)$ is the chosen threshold, and lags are selected up to a maximum of 6 using a modified form of the AIC (see Tong, 1990).

Thereafter it is straightforward to apply the relative efficiency measure in Equation (8) to the high volatility regime using $\epsilon_{H,t}$ and $\epsilon_{L,t}$ for the low regime. We denote these two new measures as $\phi_{c,h}^{\tau}$ and $\phi_{c,l}^{\tau}$, which are estimated using the quantile $\kappa = 0.4$ and 0.6 where values of κ are calculated based on the full available sample across open outcry and electronic trading. For each κ we calculate the difference in the relative efficiency measure between the electronic (EL) and open outcry (OO) samples, $\delta_{c,r}^{\tau} = \phi_{c,r}^{\tau,EL} - \phi_{c,r}^{\tau,OO}$, where r denotes either the upper or lower regime from Equation (9). Complimenting this relative efficiency TAR framework we examine the effect of maturity by creating a short and long maturity measure by averaging $\delta_{c,r}^{\tau}$ across 7- and 14-day maturities ($\bar{\delta}_{c,r}^{s}$, short), and 56- and 84-day respectively ($\bar{\delta}_{c,r}^{l}$, long). Further, we extend this approach by bootstrapping these short and long maturity measures, adding robustness to our approach.[16]

As the focus is on high and low volatility environments, when $\kappa = 0.4$ we examine $\bar{\delta}_{c,L}^{s}$ and $\bar{\delta}_{c,L}^{l}$ (the lower regime) and when $\kappa = 0.6$ we examine $\bar{\delta}_{c,H}^{s}$ and $\bar{\delta}_{c,H}^{l}$ (the upper regime). Figure 4 reports these results and the attendant bootstrapped confidence intervals, showing the difference in relative efficiency between electronic trading and open outcry for the high/low volatility regimes at short/long maturities.

[Insert Figure 4 about here]

Overall, the results of the bootstrap TAR analysis show novel differences in efficiency under electronic trading and open outcry, finding these differences to be a function of the maturity and the volatility of the underlying asset. Inference aside, these results also suggest that electronic trading in the CPO futures market is most efficient when the delivery date is distant, and therefore support the analysis in Table(9). Conversely, as delivery approaches, it is open outcry that better impounds information into the futures price. However on inspection of the bootstrap results, the standout result is to be found

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[16]Taking the short maturity measure as a case in point, the inputs into the relative efficiency measure ($E[(f_t - f_{t-\tau}]$ from the high and low volatility environments and the corresponding residuals from Equation (9) are re-sampled in tandem for 7- and 14-day maturities to generate $\phi_{c,h}^{\tau}$ and $\phi_{c,l}^{\tau}$ which are then averaged to get $\bar{\delta}_{c,r}^{s}$. This is repeated 5000 times to form an empirical distribution from which a 10% confidence interval is calculated.

for the short maturities high volatility case where open outcry is found to be more efficient than electronic trading. This figure is also striking insofar as the remainder of the bootstrap confidence interval suggests that open outcry is as efficient as electronic trading. Thus the best case we can make in favour of electronic trading is that it is no worse than open outcry. Thus our results support and extend earlier work such as Tse and Zabotina (2001) and Martens (1998); that there are potential advantages to using open outcry in modern futures markets.

5   Conclusions

This study presents the first examination of futures market predictive efficiency under different market trading regimes, as well as providing a timely contribution to an under researched yet important commodity in the world food market - crude palm oil (CPO).

We operationalize our test of market efficiency between trading regimes by deriving two sub-samples of data, pre- and post-introduction of electronic trading at the Bursa Malaysia Derivatives Berhad using a number of different contract maturities. Testing for long-run efficiency across a selection of maturities using contegration analysis indicates that the CPO futures market is predominantly long-run efficient across both trading platforms. However, across both sub-samples there is evidence of short-run inefficiency. Applying the relative efficiency measure of Kellard et al. (1999) indicates that the level of short-run inefficiency is lower for shorter maturities under open outcry and conversely is lower for electronic trading when maturities are longer.

Given the summary statistics on the CPO data, this findings fits with existing studies that have suggested that electronic trading platforms may not perform as well when volatility is high. To examine this issue further, we implement a novel bootstrapped version of the relative efficiency measure conditioning on a daily measure of futures price volatility in a threshold autoregressive environment. The results suggest that the open outcry method is superior for shorter maturities when volatility is high, and is indistinguishable from electronic trading when volatility is low or when the maturity is long. Our results help clarify the mixed picture in the extant literature by providing new evidence that the considered trading systems are complimentary and can be usefully run side-by-side.

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Appendix A

Figure A1: Daily volume and open interest prior to and proceeding migration from open outcry to electronic trading
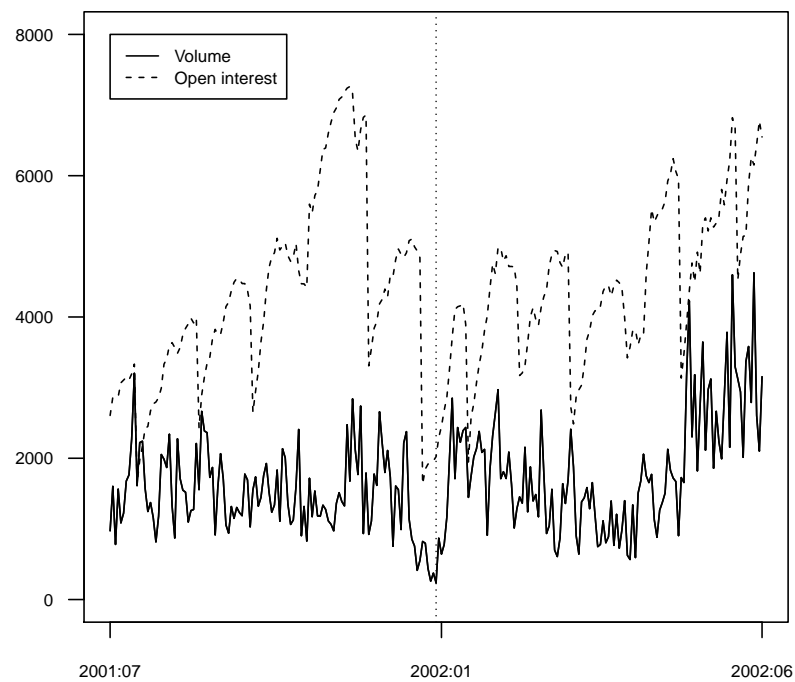
Notes: The figure plots the daily volume and open interest for the 3-month futures contract 6 months prior and 6 months after migration from open outcry to electronic trading on 28 December 2001. The vertical dashed line denoted the the switch over from open outcry to electronic trading. Source: Bursa Malaysia Derivatives

Table 1: CPO summary of statistics, June 1995 - July 2008

	f_t	f_{t-7}	f_{t-14}	f_{t-21}	f_{t-28}	f_{t-56}	f_{t-84}
Mean	7.3102	7.3085	7.3081	7.3084	7.3055	7.2985	7.2917
Standard Deviation	0.3559	0.3501	0.3462	0.3427	0.3438	0.3295	0.3139
Skewness	0.4645	0.4514	0.4729	0.4974	0.4936	0.5048	0.5273
Kurtosis	3.2356	3.1402	3.1955	3.2842	3.2819	3.3515	3.3960

Notes: Observations = 158. f_t is the logged futures price at the settlement date. $f_{t-\tau}$ is the logged futures price τ-days before settlement, where τ = 7, 14, 21, 28, 56, 84.

Table 2: ADF unit root and KPSS stationarity tests, June 1995 - July 2008

| Test | Exogenous specification | | | |
| | Constant | | Constant and linear trend | |
	ADF	KPSS	ADF	KPSS
f_t	-1.4935 (4)	0.4064*	-1.9815 (4)	0.1726**
f_{t-7}	-1.9319 (5)	0.3982*	-2.3701 (5)	0.1706**
f_{t-14}	-1.7103 (5)	0.4064*	-2.1679 (5)	0.1746**
f_{t-21}	-1.4106 (4)	0.3960*	-1.8538 (4)	0.1727**
f_{t-28}	-1.3471 (4)	0.3908*	-1.7896 (4)	0.1693**
f_{t-56}	-1.3472 (4)	0.3830*	-1.8050 (4)	0.1684**
f_{t-84}	-1.4319 (4)	0.3690*	-1.8658 (4)	0.1660**

Notes: The table shows t-statistics for the ADF and KPSS tests. (): number of lags selected by the AIC. *,**,*** represents a rejection of the null hypothesis at the 10%, 5%, and 1% significance levels respectively.

Table 3: CPO cointegration analysis CPO, June 1995 - July 2008

| | λ-max | | | Trace | | $P(\chi^2(\beta))$ |
	H_0: $r = 0$	H_0: $r = 1$		H_0: $r = 0$	H_0: $r = 1$	
f_{t-7}	79.8946***	0.4724		80.3669***	0.4724	0.7943
f_{t-14}	75.8854***	0.3623		76.2477***	0.3623	0.9102
f_{t-21}	90.0689***	0.2693		90.3382***	0.2693	0.5014
f_{t-28}	28.0500***	2.6566		30.7066***	2.6566	0.5704
f_{t-56}	29.6712***	3.1608*		32.8321***	3.1608*	0.8739
f_{t-84}	56.2082***	3.2621*		59.4703***	3.2621*	0.9013

Notes: The table shows the results of the Johansen test (λ-max and Trace) with attendant chi-squared test on the restricted cointegrating vector [1,-1,0]. *, **, ***, represents a rejection of the null hypothesis at the 10%, 5%, and 1% significance levels respectively.

Table 4: Short-run CPO efficiency

	f_{t-7}	f_{t-14}	f_{t-21}	f_{t-28}	f_{t-56}	f_{t-84}
θ_1	0.0017	0.0023	0.0017	0.0029	0.0046	0.0047
	(0.0030)	(0.0046)	(0.0055)	(0.0060)	(0.0083)	(0.0086)
γ_1		0.0577	0.1083	0.1044	0.5931	0.8268
		(0.0702)	(0.0778)	(0.0757)	(0.1144)***	(0.0863)***
γ_2		-0.0525	-0.0659	-0.0704	-0.3994	-0.2812
		(0.0853)	(0.0937)	(0.1040)	(0.1494)***	(0.1086)**
γ_3		0.0024	0.0525	0.0513	0.2553	-0.0650
		(0.0869)	(0.1038)	(0.0774)	(0.1307)*	(0.1182)
γ_4		0.2796	0.2736	0.3279	0.1620	0.4417
		(0.0889)***	(0.0813)***	(0.0891)***	(0.0969)*	(0.1527)***
γ_5						-0.2148
						(0.1178)*
P(F)	NA	0.0066***	0.0005***	0.0001***	0.0000***	0.0000***

Notes: The table shows the results for the short-run model, Equation (6), with lags selected using AIC. (): HAC standard errors. *, **, *** represents a rejection of the null hypothesis at the 10%, 5%, and 1% significance levels respectively. P(F) denotes the p-value from the joint test of zero restrictions on lagged coefficients.

Table 5: Summary of statistics, open outcry and electronic trading

	f_t	f_{t-7}	f_{t-14}	f_{t-21}	f_{t-28}	f_{t-56}	f_{t-84}
Open outcry							
Mean	7.1666	7.1689	7.1690	7.1733	7.1711	7.1739	7.1797
Standard deviation	0.3393	0.3391	0.3302	0.3283	0.3322	0.3219	0.3076
Skewness	0.3690	0.4289	0.4078	0.4035	0.4222	0.4232	0.4450
Kurtosis	2.5832	2.5911	2.5624	2.6258	2.6356	2.5975	2.6444
Electronic trading							
Mean	7.4538	7.4482	7.4473	7.4434	7.4398	7.4231	7.4036
Standard deviation	0.3131	0.3038	0.3049	0.3028	0.3017	0.2889	0.2798
Skewness	1.1498	1.1410	1.1171	1.1790	1.1965	1.2423	1.1643
Kurtosis	3.2525	3.2215	3.2919	3.3856	3.4575	3.7408	3.9076

Notes: f_t is the logged futures price at the settlement date. $f_{t-\tau}$ is the logged futures price τ-days before settlement, where $\tau = 7, 14, 21, 28, 56, 84$. Open outcry sample period: 15 June 1995 - 15 December 2001. Electronic trading sample period: 15 January 2002 - 15 July 2008.

Table 6: ADF unit root and KPSS stationarity tests, open outcry and electronic trading

Panel A: Open outcry

| | Exogenous specification | | | |
| | Constant | | Constant and linear trend | |
Test	ADF	KPSS	ADF	KPSS
f_t	-1.8829 (4)	0.3689*	-2.1086 (4)	0.2079**
f_{t-7}	-1.7223 (4)	0.3655*	-1.9681 (4)	0.2117**
f_{t-14}	-1.5474 (4)	0.3792*	-2.1222 (5)	0.216**
f_{t-21}	-1.8293 (4)	0.3715*	-2.0488 (4)	0.2165***
f_{t-28}	-1.8835 (4)	0.3618*	-2.1609 (4)	0.2184***
f_{t-56}	-1.7283 (4)	0.3509*	-1.9598 (4)	0.2234***
f_{t-84}	-2.0818 (4)	0.3301	-2.2119 (4)	0.2198***

Panel B: Electronic Trading

| | Exogenous specification | | | |
| | Constant | | Constant and linear trend | |
Test	ADF	KPSS	ADF	KPSS
f_t	0.1455 (2)	0.7286**	-0.7159 (2)	0.2265***
f_{t-7}	-0.0735 (2)	0.7312**	-0.9308 (2)	0.2242***
f_{t-14}	-0.2385 (0)	0.7375**	-1.1591 (0)	0.2189***
f_{t-21}	0.0755 (0)	0.7327**	-0.8159 (0)	0.2209***
f_{t-28}	0.2894 (2)	0.7288**	-0.5562 (2)	0.2205***
f_{t-56}	0.4742 (0)	0.7461***	-0.5561 (0)	0.2136**
f_{t-84}	-0.3551 (0)	0.7553***	-1.0637 (0)	0.2019**

Notes: The table shows t-statistics for the ADF and KPSS tests. (): number of lags selected by the AIC. *, **, *** represents a rejection of the null hypothesis at the 10%, 5%, and 1% significance levels respectively. Open outcry sample period: 15 June 1995 - 15 December 2001. Electronic trading sample period: 15 January 2002 - 15 July 2008.

Table 7: CPO cointegration analysis, open outcry and electronic trading

Panel A: Open outcry

	λ-max		Trace		$P(\chi^2(\beta))$
	H_0: $r = 0$	H_0: $r = 1$	H_0: $r = 0$	H_0: $r = 1$	
f_{t-7}	34.3067***	1.7865	36.0932***	1.7865	0.6822
f_{t-14}	29.5163***	1.5155	31.0318***	1.5155	0.9839
f_{t-21}	43.0092***	1.2708	44.2801***	1.2708	0.5210
f_{t-28}	9.4352	3.1375*	12.5727	3.1375*	0.9623
f_{t-56}	11.5456	4.1884**	15.7340**	4.1884**	0.8485
f_{t-84}	28.2994***	3.3478*	31.6472***	3.3478*	0.7139

Panel B: Electronic trading

	λ-max		Trace		$P(\chi^2(\beta))$
	H_0: $r = 0$	H_0: $r = 1$	H_0: $r = 0$	H_0: $r = 1$	
f_{t-7}	18.1087**	0.0272	18.1358**	0.0272	0.5149
f_{t-14}	50.4781***	0.1470	50.6252***	0.1470	0.7266
f_{t-21}	56.6498***	0.1129	56.7627***	0.1129	0.2946
f_{t-28}	48.1009***	0.0450	48.1459***	0.0450	0.2307
f_{t-56}	29.6180***	0.0078	29.6257***	0.0078	0.5319
f_{t-84}	28.2616***	0.6979	28.9595***	0.6979	0.1528

Notes: The table shows the results of the Johansen test (λ-max and Trace) with attendant chi-squared test on the restricted cointegrating vector [1,-1,0]. *, **, ***, represents a rejection of the null hypothesis at the 10%, 5%, and 1% significance levels respectively. Open outcry sample period: 15 June 1995 - 15 December 2001. Electronic trading sample period: 15 January 2002 - 15 July 2008.

Table 8: Short-run CPO efficiency, open outcry and electronic trading

Panel A: Open outcry

	f_{t-7}	f_{t-14}	f_{t-21}	f_{t-28}	f_{t-56}	f_{t-84}
θ_1	-0.0023	-0.0024	-0.0038	-0.0018	-0.0030	-0.0082
	(0.0046)	(0.0080)	(0.0106)	(0.0111)	(0.0147)	(0.0132)
γ_1			0.1117	0.0685	0.5511	0.8789
			(0.1110)	(0.1110)	(0.1655)***	(0.1146)***
γ_2			-0.1131	-0.1016	-0.4134	-0.3262
			(0.1099)	(0.1256)	(0.1953)**	(0.1425)**
γ_3			0.0559	0.0728	0.2749	-0.0379
			(0.1440)	(0.1108)	(0.1976)	(0.1492)
γ_4			0.3643	0.4606	0.2183	0.5669
			(0.1044)***	(0.0993)***	(0.1419)	(0.2304)**
γ_5						-0.4276
						(0.1922)**
P(F)	NA	NA	0.0003***	0.0000***	0.0000***	0.0000***

Panel B: Electronic Trading

|	f_{t-7}	f_{t-14}	f_{t-21}	f_{t-28}	f_{t-56}	f_{t-84}
θ_1	0.0037	0.0065	0.0065	0.0085	0.0174	0.0171
	(0.0028)	(0.0045)	(0.0046)	(0.0062)	(0.0085)**	(0.0101)*
γ_1	-0.0333		0.1521	0.1956	0.6489	0.8020
	(0.1189)		(0.1391)	(0.0836)**	(0.0913)***	(0.1388)***
γ_2	-0.1435		-0.1279	-0.1519	-0.4208	-0.3602
	(0.1060)		(0.1068)	(0.1075)	(0.1111)***	(0.1859)*
γ_3	0.3909		0.2308	0.1727	0.2335	0.0541
	(0.1340)***		(0.1045)**	(0.0752)**	(0.0888)**	(0.1407)
γ_4	0.0864		0.0415	0.0963		0.1709
	(0.0859)		(0.0965)	(0.0888)		(0.0938)*
γ_5	0.2883		0.0668	0.1138		
	(0.0893)***		(0.0843)	(0.1005)		
γ_6			0.3795	0.2476		
			(0.0995)***	(0.1238)*		
γ_7			-0.1373	-0.1199		
			(0.1140)	(0.1312)		
γ_8			-0.0435	-0.0895		
			(0.1427)	(0.1577)		
γ_9			-0.1546	-0.1072		
			(0.1227)	(0.0877)		
P(F)	0.0000***	NA	0.0015***	0.0069***	0.0000***	0.0000***

Notes: The table shows the results for the short-run model, Equation (6), with lags selected using AIC.(): HAC standard errors. *, **, *** represents a rejection of the null hypothesis at the 10%, 5%, and 1% significance levels respectively. P(F) denotes the p-value from the joint test of zero restrictions on lagged coefficients. Open outcry sample period: 15 June 1995 - 15 December 2001. Electronic trading sample period: 15 January 2002 - 15 July 2008.

Table 9: Relative efficiency measure

|	f_{t-7}	f_{t-14}	f_{t-21}	f_{t-28}	f_{t-56}	f_{t-84}
Open outcry	1	1	0.8477	0.7795	0.6156	0.4120
Electronic trading	0.7835	1	0.7403	0.7974	0.6909	0.5411
Whole sample	1	0.9153	0.8994	0.8643	0.6353	0.4648

Notes: The table shows the results of the Kellard et al.'s (1999) short-run efficiency measure. Open outcry sample period: 15 June 1995 - 15 December 2001. Electronic trading sample period: 15 January 2002 - 15 July 2008.

Figure 1: Edible Oil Production
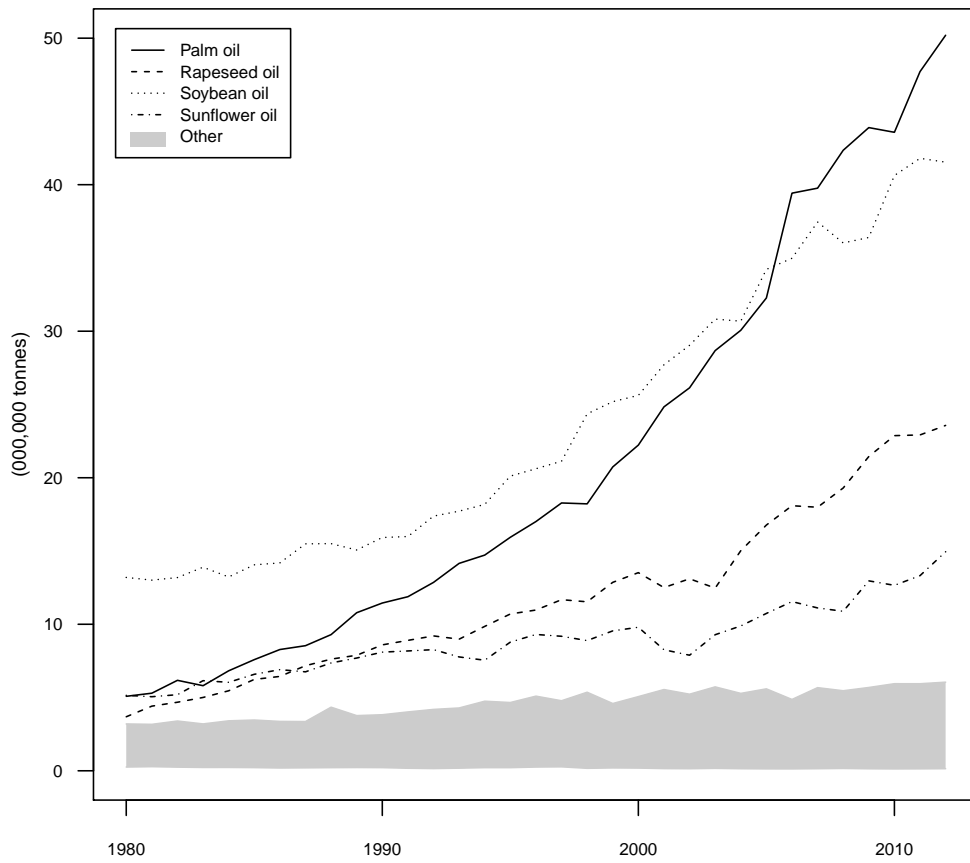
Notes: The graph shows the annual production ('000,000 tonnes) for the most produced edible oils. For ease of interpretation the remaining edible oils are presented by the shaded area and comprise: Coconut oil, cottonseed oil, groundnut oil, linseed oil, maize oil, virgin olive oil, palm oil kernel, safflower oil, and sesame oil. Source: Food and Agriculture Organization of the United Nations.

1

Figure 2: Average daily volume and open interest for 3-month CPO futures contracts
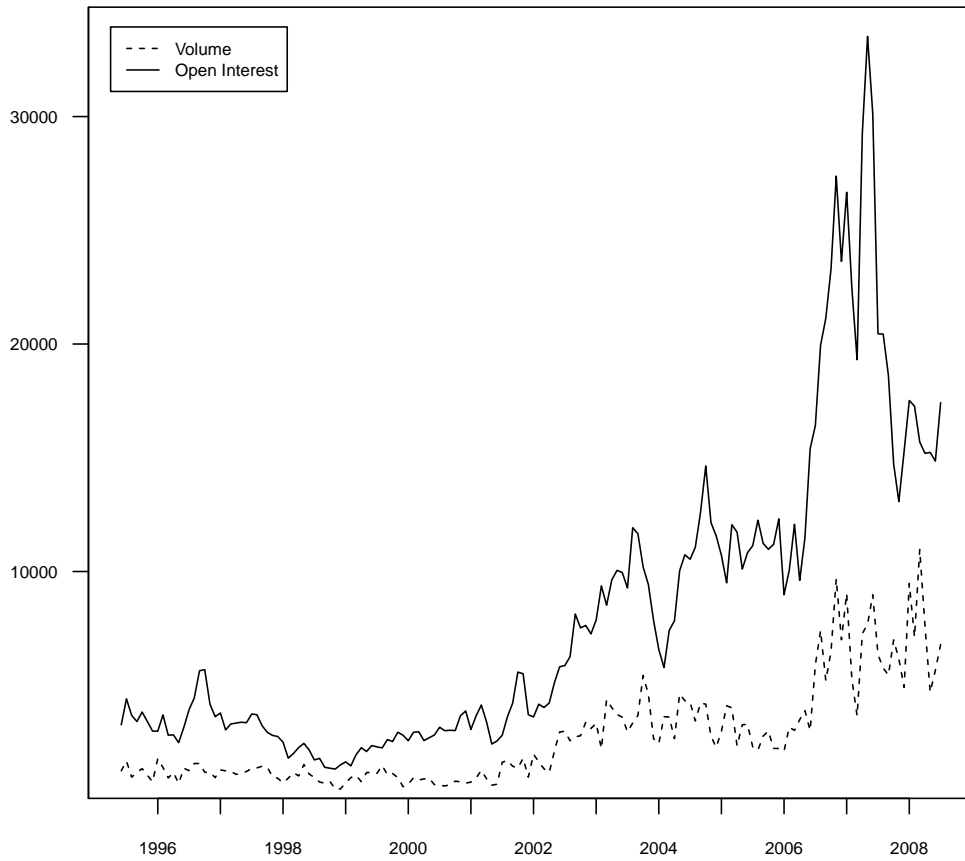
Notes: The graph shows the daily average (per month) volume and open interest for the 3-month futures contract. Source: Bursa Malaysia Derivatives

Figure 3: Price and 30-day historical volatility
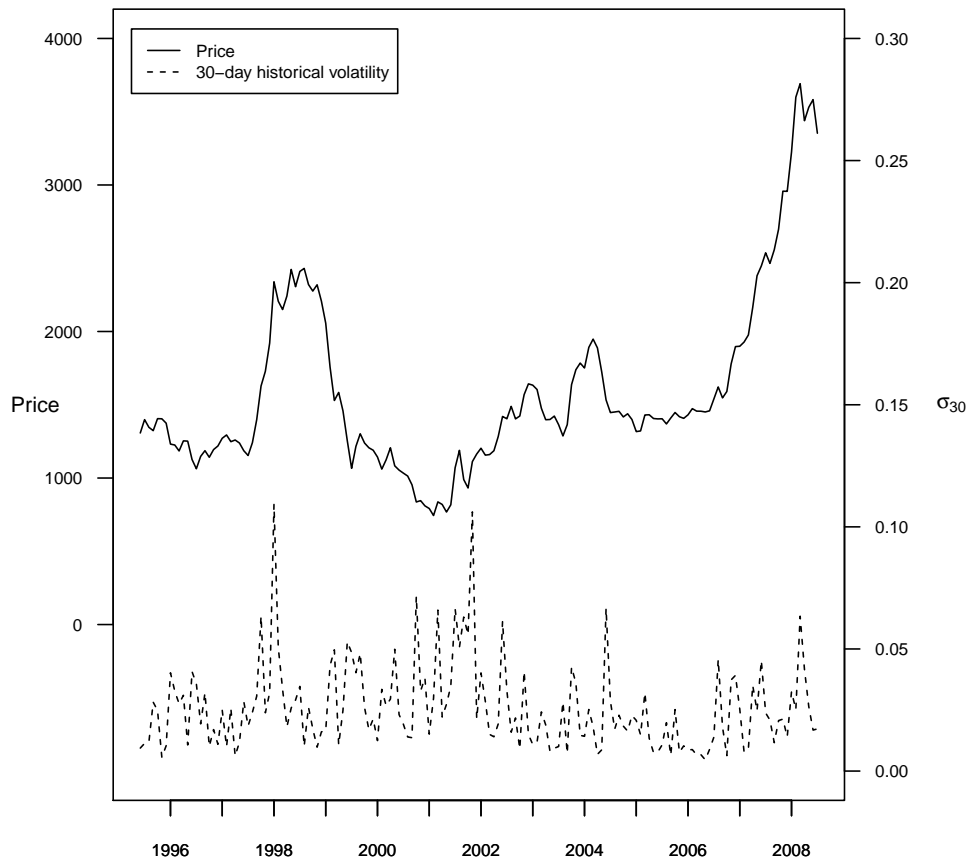
Notes: The figure shows the average (per month) 3-months CPO futures price and the 30-day historical spot price volatility (standard deviation).

3

Figure 4: TAR relative efficiency measure
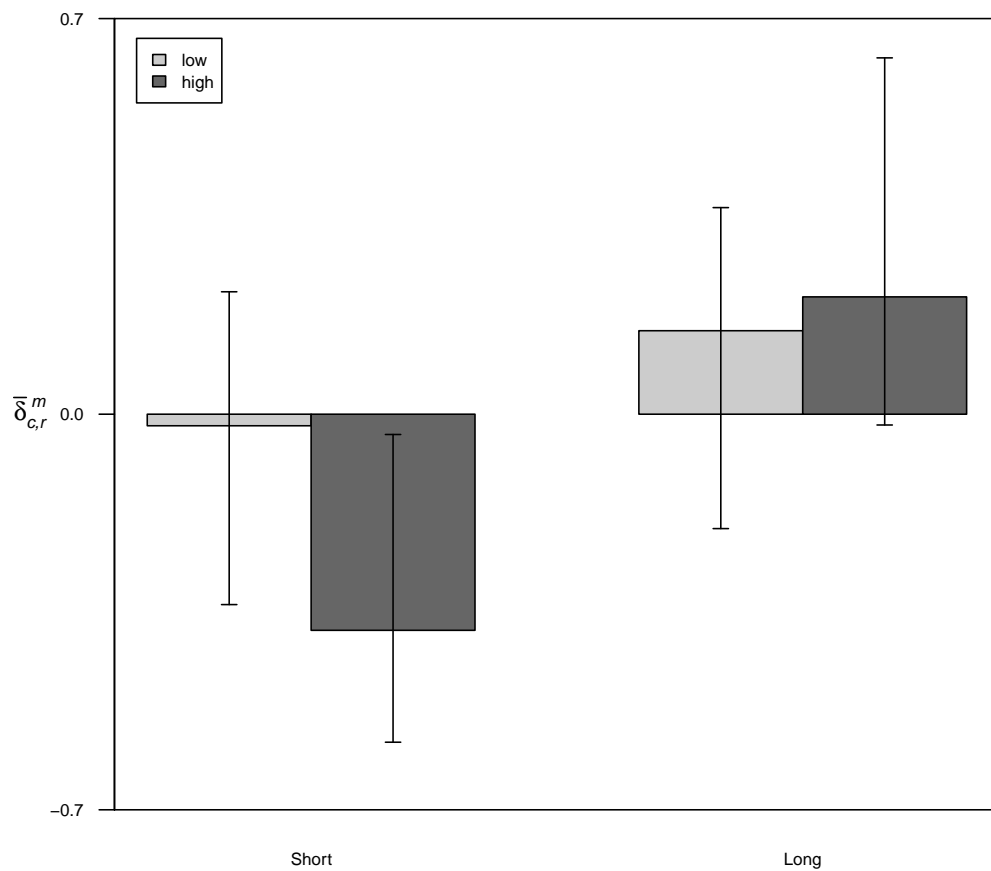
Notes: The figure shows the results of the TAR relative efficiency analysis. The figure shows the difference in relative efficiency ($\bar{\delta}_{c,r}^m$) between electronic trading and open outcry as an average across short ($m = s$: $\tau = 7$ and 14 days) and long ($m = l$: $\tau = 56$ and 84 days) maturities and across high ($r = H$) and low ($r = L$) volatility environments. Positive (negative) values denote a higher value for electronic trading (open outcry). See equations (8) and (9). The bands denote bootstrapped confidence intervals calculated using 5000 replications