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 predominantly 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 in the futures market (ii) the maturity of the futures contract and (iii) the market trading system. Specifically, bootstrap results from the efficiency measure suggests that the open outcry method is superior for shorter maturities when volatility is high, and indistinguishable from electronic trading when volatility is low or when maturity is long. These results suggest that electronic trading should not supersede open outcry, but rather that there may be benefits to their coexistence.

Keywords: Market efficiency, commodity futures contracts, open outcry, electronic trading, crude palm oil.
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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 (Martinez et al., 2011), 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 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 Ning and Tse [2009], 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 examine under which trading regime the futures price best predicts the future price at maturity.

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 much of the extant literature often focuses solely on shorter terms to maturity.

Our findings indicate that the CPO futures market is long-run efficient for 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], joining with more recent work such as Boyd and Kurov [2012][2], by suggesting there is still a clear role for open outcry in modern futures markets. In the context of the CPO market, this clearly has implications for the price discovery and optimal 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.

[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]Boyd and Kurov [2012] find that when run side-by-side, traders are more likely to survive using both open outcry and electronic trading 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 4$^{\text{th}}$ place, contrasting with staple crops commonly traded on futures exchanges such as soybean (60$^{\text{th}}$), corn (94$^{\text{th}}$), and wheat (124$^{\text{th}}$). 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 up to 24 months ahead.[6] Up until December 2001, futures contracts were traded using

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

[6] The contract specifications have changed little over the span of our sample. Again, see www.bursamalaysia.com for further details.

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

Long-run market efficiency is linked to the spot and futures markets via the notion of unbiasedness. 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 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 (Kellard et al., 1999):

[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.

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

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.

To test CPO market efficiency, we adjust the outlined approach. 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.[9] This is achieved using variants of Equations (3) and (4), accounting for the fact that we use the futures price at delivery in place of the spot rate:

$$f_t = \beta_0 + \beta_1 f_{t-\tau} + \epsilon_t \quad (5)$$

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

Note for long-run efficiency the interpretation for Equation (5) is the same as Equation (3). As with Equation (4) short-run inefficiency is indicated if Equation (6) yields statistically significant lags of the dependent variable.

3.2 Testing CPO efficiency

To utilize the unbiasedness framework in the previous section, we need to construct the appropriate variables. CPO futures mature each month and therefore a time series of 12 monthly maturity prices can be sampled each year. The log of this data is our f_t. To construct the variable $f_{t-\tau}$ note that we follow Kellard et al., 1999 by defining that τ represents a fraction of the unit of observation. In this manner, $f_{t-\tau}$ is the log of the matched futures price selected by working backwards τ (i.e., a fraction of a month) from the maturity date t. Of course, it is also possible to express a monthly fraction in days, and we construct 6 further series where τ is equivalent to 7, 14, 21, 28, 56 and 84 days.

The resulting dataset spans from 15 June 1995 to 15 July 2008 and therefore contains 158 monthly observations.[10] For completeness, Table 1 presents summary measures for

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

[10] The data employed to test unbiasedness are closing futures prices from Reuters (code: FCPO). In

each maturity and it can be observed that both the sample mean and standard deviation tend to increase as τ reduces.

[Insert Table 1 about here]

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:

$$\Delta X_t = \eta_0 + \Pi X_{t-k} + \sum_{i=1}^{k-1} \eta_i \Delta X_{t-i} + v_t \tag{7}$$

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 $\beta_1 = 1$ in Equation (5) - 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

addition to the closing futures price, in later analysis (see Section 4.4.), the daily high and low prices are used as a proxy for volatility. The choice of sample period permits two sub-samples of equal size as discussed in Section 4.2. Values of τ are calendar not business days and therefore when constructing each price series, 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.

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 presents the test of short-run efficiency using Equation (6). 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 and therefore suggestive of some predictability which may be useful to traders.

[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 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 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.[11] 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). One possible explanation cited by Tse and Zabotina [2001] for the poor performance of electronic trading could be that, given an arrival of a high amount of new market-sensitive information (proxied by price volatility), the pre-programmed algorithms behind the electronic trading mechanisms may withdraw from trading. By contrast, humans in the pit may still be willing to trade and therefore impound the new information into the open-outcry price. This clearly supports the findings of Aitken et al. [2004]. In addition to the slower adjustment to information in the electronic market, Tse and Zabotina [2001] also find a negative relationship between trades and lagged quote revisions for electronic trading, but not for open outcry. The authors attribute this last finding to a different inventory approach between these two methods of trading.[12]

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. Even more recent work, such Martinez et al. [2011], show that both systems contribute significantly to price discovery whilst Boyd and Kurov [2012] find that when run side-by-side, traders are more likely to survive using both open outcry and electronic trading systems, rather than one alone.

[11] 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.

[12] The notion here is that pit traders tend to control their inventory levels more easily than electronic traders. See Tse and Zabotina [2001] for more details.

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 discovery. These measures assume semi-strong market efficiency and decompose the futures price into a random walk and a transitory 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.[13]

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.

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

[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:

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

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:

$$\phi_c^\tau = \frac{(n-k-1)^{-1}\sum_{t=1}^{n}\hat{\epsilon}_t^2}{(n-1)^{-1}\sum_{t=1}^{n}[(f_t - f_{t-\tau}) - (\overline{f_t - f_{t-\tau}})]^2} \tag{9}$$

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.[14] 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.,

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

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):

$$f_t - f_{t-\tau} = \begin{cases} \theta_{H,0} + \sum_{i=1}^{k} \theta_{H,i}(f_{t-i} - f_{t-\tau-i}) + \epsilon_{H,t} \text{ if } \sigma_t^2(f) > q(\kappa) \\ \\ \theta_{L,0} + \sum_{i=1}^{k} \theta_{L,i}(f_{t-i} - f_{t-\tau-i}) + \epsilon_{L,t} \text{ if } \sigma_t^2(f) \leq q(\kappa) \end{cases} \tag{10}$$

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 (9) 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 higher or lower regime from Equation (10). 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.[15]

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

[15] 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 (10), 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.

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 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], suggesting that there are potential advantages to using open outcry in modern futures markets.[16]

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

[16]We thank an anonymous referee for noting that when sub-samples are not contemporaneous, one needs to be careful about acknowledging the possibility of other causal factors. This we do. However, given our context (i.e., the imposition of a known structural break representing a complete switch from open outcry to electronic trading), we think there are plausible reasons to suggest that the pre-eminent rationale for any differences between efficiency in the two samples is the type of auction. These include (a) we examine predictive efficiency in 4 different states. Given a change in the regulatory environment or general market conditions between our two sub-samples, we might expect efficiency all 4 states to be affected in the same direction. However, only one 1 state is affected (i.e., short-maturity contracts in high volatility conditions) and (b) the finding that efficiency falls after the structural break (i.e., after the introduction of electronic trading) in the short-maturity contract and high volatility state is consistent with some prior theory and literature (see Martens, 1998; Tse and Zabotina, 2001; Aitken et al., 2004; Ning and Tse, 2009) that open outcry may be better able to impound information into the price during periods of higher volatility than electronic trading.

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. These 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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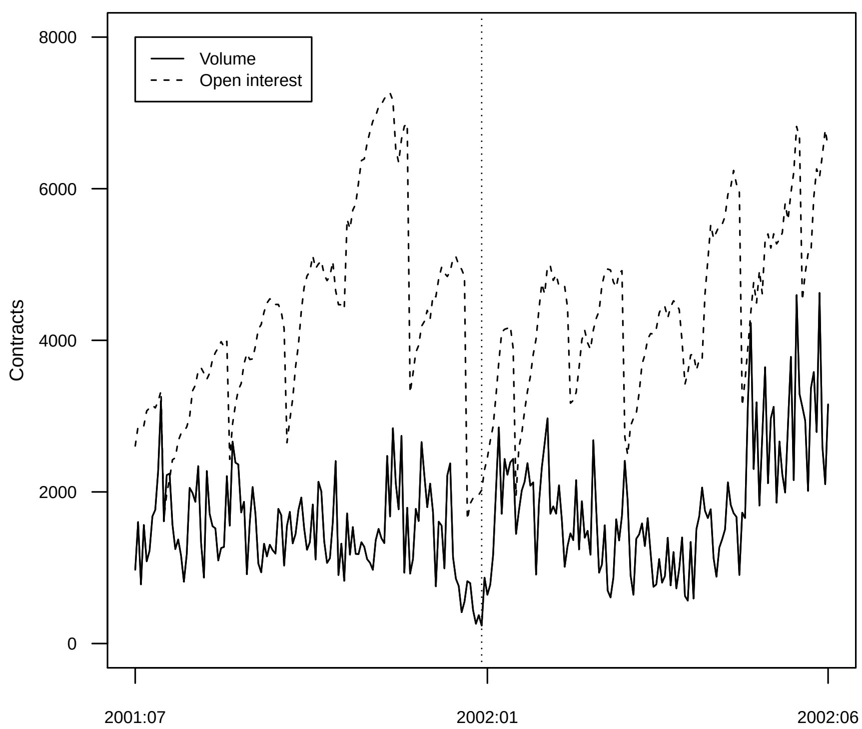
Appendix A

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 denotes the switch over from open outcry to electronic trading. Source: Reuters.

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

	Exogenous specification			
	Constant		Constant and linear trend	
Test	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_0	0.0017	0.0023	0.0017	0.0029	0.0046	0.0047
	(0.0030)	(0.0046)	(0.0055)	(0.0060)	(0.0083)	(0.0086)
θ_1		0.0577	0.1083	0.1044	0.5931	0.8268
		(0.0702)	(0.0778)	(0.0757)	(0.1144)***	(0.0863)***
θ_2		-0.0525	-0.0659	-0.0704	-0.3994	-0.2812
		(0.0853)	(0.0937)	(0.1040)	(0.1494)***	(0.1086)**
θ_3		0.0024	0.0525	0.0513	0.2553	-0.0650
		(0.0869)	(0.1038)	(0.0774)	(0.1307)*	(0.1182)
θ_4		0.2796	0.2736	0.3279	0.1620	0.4417
		(0.0889)***	(0.0813)***	(0.0891)***	(0.0969)*	(0.1527)***
θ_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_0	-0.0023	-0.0024	-0.0038	-0.0018	-0.0030	-0.0082
	(0.0046)	(0.0080)	(0.0106)	(0.0111)	(0.0147)	(0.0132)
θ_1			0.1117	0.0685	0.5511	0.8789
			(0.1110)	(0.1110)	(0.1655)***	(0.1146)***
θ_2			-0.1131	-0.1016	-0.4134	-0.3262
			(0.1099)	(0.1256)	(0.1953)**	(0.1425)**
θ_3			0.0559	0.0728	0.2749	-0.0379
			(0.1440)	(0.1108)	(0.1976)	(0.1492)
θ_4			0.3643	0.4606	0.2183	0.5669
			(0.1044)***	(0.0993)***	(0.1419)	(0.2304)**
θ_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_0	0.0037	0.0065	0.0065	0.0085	0.0174	0.0171
	(0.0028)	(0.0045)	(0.0046)	(0.0062)	(0.0085)**	(0.0101)*
θ_1	-0.0333		0.1521	0.1956	0.6489	0.8020
	(0.1189)		(0.1391)	(0.0836)**	(0.0913)***	(0.1388)***
θ_2	-0.1435		-0.1279	-0.1519	-0.4208	-0.3602
	(0.1060)		(0.1068)	(0.1075)	(0.1111)***	(0.1859)*
θ_3	0.3909		0.2308	0.1727	0.2335	0.0541
	(0.1340)***		(0.1045)**	(0.0752)**	(0.0888)**	(0.1407)
θ_4	0.0864		0.0415	0.0963		0.1709
	(0.0859)		(0.0965)	(0.0888)		(0.0938)*
θ_5	0.2883		0.0668	0.1138		
	(0.0893)***		(0.0843)	(0.1005)		
θ_6			0.3795	0.2476		
			(0.0995)***	(0.1238)*		
θ_7			-0.1373	-0.1199		
			(0.1140)	(0.1312)		
θ_8			-0.0435	-0.0895		
			(0.1427)	(0.1577)		
θ_9			-0.1546	-0.1072		
			(0.1227)	(0.0877)		
P(F)	0.0000***	NA	0.0015***	0.0069***	0.0000***	0.0000***

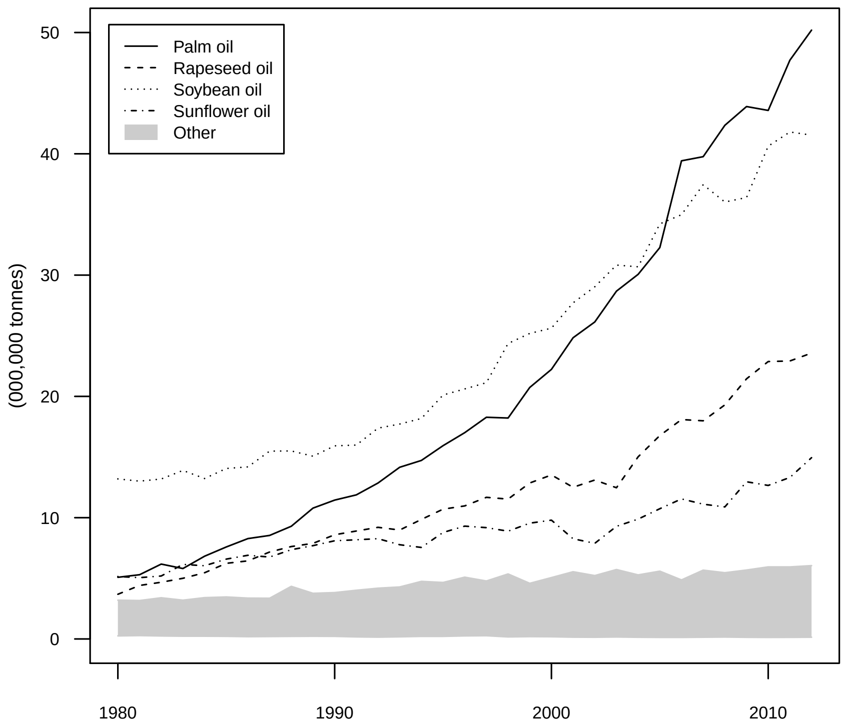
Notes: The table shows the results for the short-run model, Equation (6), with lags selected using AIC.(): HAC standard errors. *, **, *** represents a rejection of the null hypothesis at the 10%, 5%, and 1% significance levels respectively. P(F) denotes the p-value from the joint test of zero restrictions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

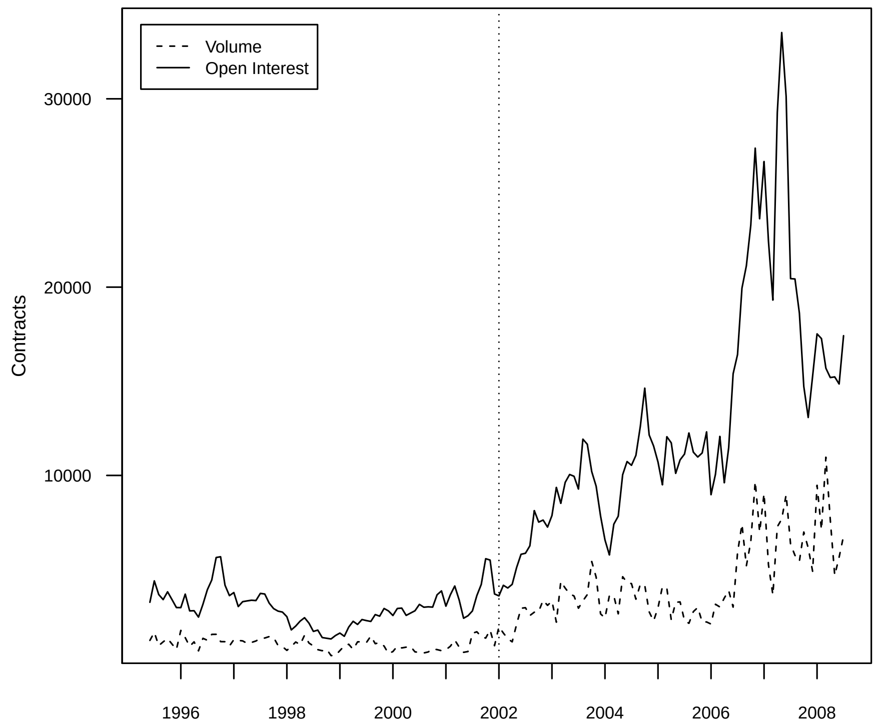
Notes: The table shows the results of the Kellard et al. (1999) short-run efficiency measure. Open outcry sample period: 15 June 1995 - 15 December 2001. Electronic trading sample period: 15 January 2002 - 15 July 2008.

Figure 1: Edible Oil Production



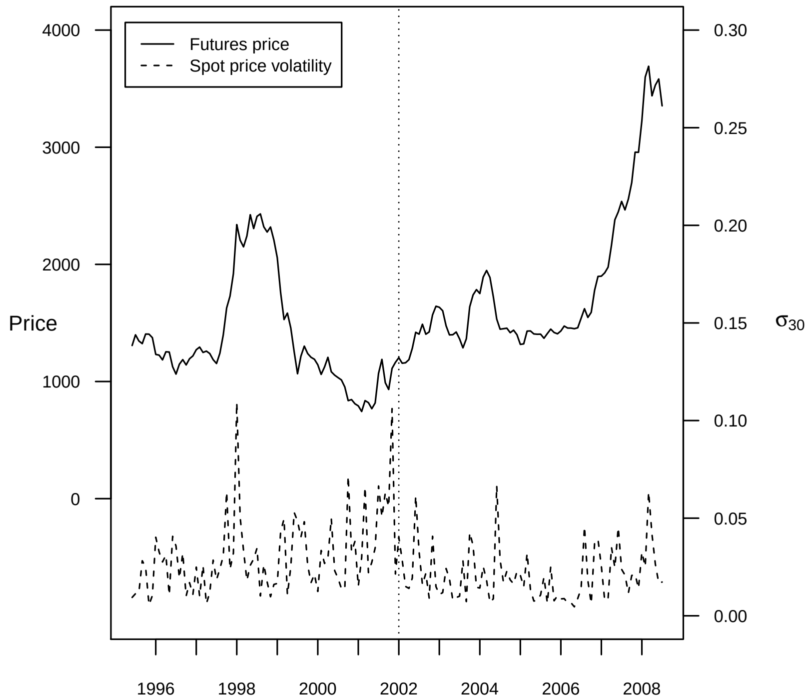
Notes: The graph shows the annual production ('000,000 tonnes) for the most produced edible oils. For ease of interpretation the remaining edible oils are presented by the shaded area and comprise: Coconut oil, cottonseed oil, groundnut oil, linseed oil, maize oil, virgin olive oil, palm oil kernel,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

Figure 2: Average daily volume and open interest for 3-month CPO futures contracts



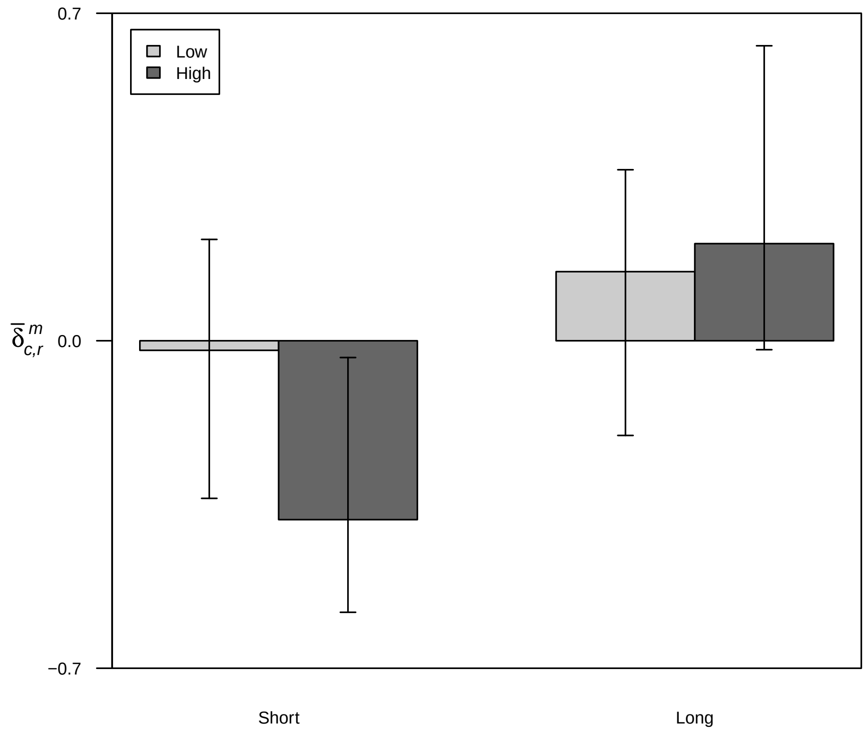
Notes: The graph shows the daily average (per month) volume and open interest for the 3-month futures contract. The vertical dashed line denotes the switch over from open outcry to electronic trading. Source: Reuters.

Figure 3: CPO futures price and 30-day historical spot price volatility



Notes: The figure shows the average (per month) 3-months CPO futures price and the 30-day historical spot price volatility (σ_{30}, standard deviation). The vertical dashed line denotes the switch over from open outcry to electronic trading. Source: Reuters.

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 between electronic trading and open outcry ($\bar{\delta}^m_{c,r}$) as an average across short (m = s: τ = 7 and 14 days) and long (m = l: τ = 56 and 84 days) maturities and across high (r = H, κ = 0.6) and low (r = L, κ = 0.4) volatility environments. See equations (9) and (10). Positive (negative) values denote a higher value for electronic trading (open outcry). The bands denote 10% bootstrapped confidence intervals calculated using 5000 replications.