Returns and Volatility in the Kuala Lumpur Crude Palm Oil Futures Market

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This article investigates the determinants of daily returns and volatility in the Kuala Lumpur crude palm oil futures market over the period 1980 to 1994. We find significant evidence of month and open interest effects in returns and also find strong evidence of daily, monthly, yearly, volume and open interest effects in volatility when ARCH/GARCH models are used to estimate volatility. © 1998 John Wiley & Sons, Inc. Jrl Fut Mark 18:985–999, 1998

INTRODUCTION

Economic agents involved in the trading of physical spot commodities are subject to a wide range of risks associated with movements in spot commodity prices. This creates a demand for hedging facilities and is a key factor in the development of and interest in commodity futures markets.

The authors wish to thank David Tan, Kian Why-Ng, Lily Korompis, Robert Faff and Vanitha Ragunathan for their helpful assistance during this project. We also wish to thank two anonymous referees for their helpful comments on earlier versions of this paper.
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The Journal of Futures Markets, Vol. 18, Nol. 8, 985–999 (1998)

CCC 0270-7314/98/080985-15

Given this important hedging role, we are interested in the behavior of commodity futures markets. Techniques used in studying the behavior of commodity futures markets are often based on an analysis of the behavior of returns and volatility. In the present article we analyze a particular commodity futures market, namely the Kuala Lumpur crude palm oil futures market.

The Kuala Lumpur Commodity Exchange (KLCE) is the only market in the world that trades crude palm oil futures. The KLCE was Malaysia's first futures exchange and commenced trading on 14 July 1980. Trading is conducted in a pit on the trading floor using the open outcry system of trading. The crude palm oil futures contract trades on a contract size of 25 tonnes, and prices are quoted in Malaysian Ringgit per tonne.

The spot commodity palm oil is an important part of the world market in vegetable oils and fats. Throughout the 1990s palm oil has accounted for up to 16% of vegetable oil and fat production, and up to 39% of vegetable oil and fat exports. Crude palm oil production in Malaysia has increased greatly from approximately 90,000 tonnes in 1960 to around 8.4 million tonnes in 1996. This constitutes approximately 51% of world palm oil production and about 61% of world palm oil exports. Thus research on the world's only market for palm oil futures is of value to those involved in this important industry.

Research by Milonas (1986, 1991), Gay and Kim (1987), Malick and Ward (1987), Kenyon et al. (1987), and Khoury and Yourougou (1989, 1993) finds significant evidence of seasonality in commodity futures markets. A possible extension of the above research is to make allowance for time varying volatility. Bollerslev, Chou, and Kroner (1992) in a comprehensive survey of research in empirical finance find that models of the ARCH (see Engle (1982)) and GARCH (see Bollerslev (1986)) variety are a popular and parsimonious technique for modeling time varying volatility in high frequency financial data. The use of ARCH techniques to model the behavior of returns and volatility in commodity futures markets has already been conducted by Baillie and Myers (1991) and Yang and Brorsen (1993). Further research by Lamourex and Lastrapes (1990), Bessembinder and Seguin (1993), and Foster (1995) supports a role for volume and open interest in the determination of returns and volatility.

The majority of existing research into the determinants of returns and volatility in commodity futures markets has been conducted on data from the well-developed and liquid United States futures markets. This research provides a benchmark of results for research into the determinants of returns and volatility. An approach for validating the results of previous research is to examine whether the conclusions of previous research also hold for different markets. This study explores this issue by an examination of the determinants of returns and volatility in the Kuala Lumpur crude palm oil futures market. This market is important to analyse because (i) it has not been the subject of much previous academic research; (ii) it is in a country with an emerging capital market, thus its development has been important to financial deepening in the Malaysian economy; (iii) the Malaysian economy has been in a prolonged period of high economic growth. Thus the research will likely reflect whether the different features of the Malaysian economy impact on the results.

The purpose of this study is to measure and analyze the determinants of daily returns and volatility in the Kuala Lumpur crude palm oil futures market using ARCH/GARCH techniques to model the time varying behavior of returns and volatility. There are very few studies which have explicitly studied any aspects of the Kuala Lumpur crude palm oil futures market. A notable exception is Kok and Goh's (1994) study of the random walk hypothesis in the Kuala Lumpur crude palm oil futures market. Their results fail to find strong evidence against the random walk hypothesis.

THE PREVIOUS LITERATURE

Milanos (1986) studied seasonal effects in five agricultural commodity futures markets, three metals futures markets, and three financial futures markets. Using an ANOVA approach he found evidence of month effects, year effects, and contract month effects in these eleven futures markets.

Gay and Kim (1987) studied seasonal effects in the Commodity Research Bureau (CRB) futures index. The CRB index is a geometric average of prices on 27 commodity futures markets. Using ANOVA and a dummy variable regression model approach they found significant evidence of day of the week effects and month effects. Consistent with evidence on the stock market they found low returns on Monday, high returns on Friday, high returns in January and low returns in December. Milanos (1991) has criticised the Gay and Kim (1987) study, arguing that the analysis of commodity price indices is potentially misleading. Milanos (1991) points out that such an index mixes together commodities with and without seasonal cycles and also mixes commodities with different seasonal cycles. This makes the identification of true seasonalities in the data extremely difficult.

Malick and Ward (1987) studied seasonal effects in the frozen concentrated orange juice market. Using a regression-based approach they found that the basis was a function of seasonal variation in monthly stock levels. They also found evidence of a market depth effect with respect to volume and open interest.

Milonas (1991) extended his earlier work to study year, month, and half-month effects in five agricultural commodity futures markets, namely: Corn, wheat, soybeans, soybean meal, and soybean oil. He points out that careful analysis is needed to separately identify each of these effects. He finds that the year effect dominates the month effect. After allowing for year and month effects, a half-month effect is detected although no explanation is offered for this occurrence.

Khoury and Yourougou (1989) studied seasonal effects in the Canadian wheat market and found evidence of monthly effects. Khoury and Yourougou (1993) then extended this research to study six Canadian commodity futures markets: canola, rye, barley, wheat, flaxseed, and oats. Using the methodology of Milanos (1986) they found little evidence of a year effect, which they attributed to the price support system of the Canadian wheat board.

Kenyon et al. (1987) attempted to move beyond the mere identification of seasonal patterns and searched for the theoretical causes. They tried to explain observed seasonality in five agricultural commodity futures markets, namely: soybeans, corn, wheat, live cattle, and live hogs, as a function of seasonal variation in production levels and interest rates on agricultural loans. Replacing seasonal dummies with these variables leads to a substantial drop in the explanatory power of their econometric equations and mis-specification problems. Their results suggest that identification of the factors that drive seasonal effects is a difficult exercise.

A promising technique for the further analysis of seasonal effects in commodity futures markets is the use of ARCH-type techniques. Baillie and Myers (1991) used a GARCH framework to analyze distributions and determine the optimal hedge in six commodity futures markets: beef, coffee, corn, cotton, gold, and soybeans. They used a GARCH(1,1) model and allowed for the residuals to follow a conditional t distribution. They found strong evidence of shocks to the volatility being very persistent.

Yang and Brorsen (1993) extended the use of GARCH type models by conducting a comparison between the GARCH class of models and models of deterministic chaos. They conducted their analysis for seven agricultural futures markets, five metals futures markets, and three financial futures markets. They also made explicit allowance for seasonal effects in their analysis. Yang and Brorsen (1993) found GARCH effects in 13 of the 15 markets, a day of the week effect in 13 of the 15 markets, and a seasonal effect in 9 of the 15 markets. These results provide little evidence on the usefulness of the deterministic chaos models in this type of application.

A possible explanation of the presence of GARCH effects in the data could be linked to variations in trading volume. Lamourex and Lastrapes (1990) explored this possibility for stock returns data and found that trading volume does provide and explanation of GARCH effects in stock returns data. However Najand and Yung (1991) found that GARCH effects persist for treasury bond futures even after volume is taken into account. This result is also supported by Foster (1995), who found that volume did not account completely for GARCH effects in crude oil futures. Bessembinder and Seguin (1993) extended this line of research to analyze the role of both open interest and volume in the determination of returns and volatility in eight futures markets. They found evidence of both volume and open interest having a significant effect and suggested that this provides evidence of a market depth effect. Ragunathan and Peker (1997) produced similar results for Australian financial futures.

EMPIRICAL FRAMEWORK AND RESULTS

We gathered daily data on settlement prices, contract volume, market volume, and open interest for crude palm oil futures traded on the Kuala Lumpur Commodity Exchange over the period 1980 to 1994. The settlement price is derived by the clearing house, based on the last minute of trading in the day, and represents the price per tonne for a futures contract of 25 tonnes. The importance of how a continuous series of futures prices is constructed has been noted by Ma, Mercer, and Walker (1992). Ma, Mercer and Walker (1992) point out that any research into futures markets is difficult because contracts mature at regular intervals. Typically researchers desire a long time series to analyze. In futures markets this is done by splicing together data on individual futures contracts. This creates an issue of how the data should be spliced together at the rollover date. Ma, Mercer, and Walker (1992) identify different choices around the point at which the rollover is made and with regard to whether the prices are adjusted.

In the present article we use the approach of rollover at the delivery date without any adjustment to the price. This is because the Kuala Lumpur crude palm oil futures market is relatively illiquid, and the majority of volume is concentrated in the near future. At maturity of the futures contract this volume then switches to the next maturing contract. We constructed a continuous series of data by using the price of the contract nearest to maturity, whereas both market volume and open interest refer

TABLE I

Descriptive Statistics for the Returns Series for the Full Sample of 1980 to 1994

Mean	0.00685
Median	0.00000
Variance	5.37312
Skewness	−5.11020
Kurtosis	125.775
$Q_{20}(r)$	555.000
$Q_{20}(r)$	729.000

to all contracts traded at the different maturities. We rollover our data series on the delivery date. For crude palm oil futures on the KLCE the delivery date is the 15th of each month. Over this sample period a total of 162 contracts were used. We do not model the price series directly but instead approximate returns as

$$r_t = \log(P_t/P_{t-1}) \tag{1}$$

where P_t is the daily closing price on day t.

In Table I we present a number of descriptive statistics for the returns series. We observe a mean return that is not significantly different from zero. Our returns series exhibits severe negative skewness and severe excess kurtosis. The Box-Pierce (Box and Pierce, 1970) Q statistics for autocorrelation in the returns and squared returns exhibit significant evidence of autocorrelation. In Table II we extend this descriptive analysis to examine the daily, monthly, and weekly effects by calculating the mean and variance for each of these series. Our results show a significant day of the week effect with returns negative on Tuesday, Wednesday and after holidays but positive on Monday, Thursday and Friday. The lowest return for the week is observed on a Wednesday and the highest return for the week is observed on a Friday. The holiday returns are calculated consistent with all other returns, as the difference in prices from successive trading days. The monthly results are broadly consistent with the seasonal cycle in crop production. In February and July the months where there is the greatest uncertainty about production levels, average returns are strongly negative and the variance is relatively high. The behavior of yearly returns and volatilities primarily reflects influences in world markets that would be expected, given that the bulk of crude palm oil production is exported. The year 1985 exhibits extreme behavior in both returns and volatility due to a dramatic rise in the world price of all edible oil asso-

TABLE II

Descriptive Statistics for the Returns Series Where the Returns Are Classified by (1) Day of the Week, (2) Month, and (3) Year

	Mean	*Variance*
Mon	0.085192	0.006137
Tue	−0.070790	0.006029
Wed	−0.115990	0.015089
Thu	0.030747	0.000571
Fri	0.109950	0.010629
Hol	−0.070400	0.005968
Jan	0.116360	0.011992
Feb	−0.523930	0.281730
Mar	0.031213	0.000593
Apr	0.082541	0.005729
May	0.074210	0.004537
Jun	−0.066540	0.005386
Jul	−0.390680	0.158030
Aug	0.035831	0.008400
Sep	0.162450	0.024209
Oct	0.080852	0.005476
Nov	0.142210	0.018321
Dec	0.409710	0.162300
1981	−0.041690	0.002357
1982	−0.044820	0.002670
1983	0.299080	0.085395
1984	−0.186230	0.037282
1985	−1.329190	1.785000
1986	−0.517970	0.003440
1987	0.186180	0.032160
1988	−0.058390	0.004257
1989	−0.167160	0.030279
1990	0.135780	0.016623
1991	0.011757	0.000002
1992	0.022301	0.000239
1993	0.012420	0.000003
1994	0.193450	0.034818

ciated with a cutback in soybean planting in the U.S., the failure of the oil seed crop in Pakistan, and a shortage of edible oil in India.

Our general model for returns takes the form,

$$r_t = \gamma_0 + \sum_j \theta_j r_{t-j} + \sum_i \lambda_i d_i + \sum_i \rho_i m_i + \sum_i \phi_i y_i + \gamma_1 \text{ CVOL}_t + \gamma_2 \text{ MVOL}_t + \gamma_3 \text{ OPIN}_t + \varepsilon_t \qquad (2)$$

where (γ, θ, λ, ρ, ϕ) are unknown parameters to be estimated, d_i is a day of the week dummy, m_i is a monthly dummy, y_i is a yearly dummy, $CVOL_t$

is the volume in the near future, $MVOL_t$ is the volume in all contracts traded, $OPIN_t$ is the open interest and ε_t is a random shock assumed to be distributed $IN(0\sigma^2)$.

The results of estimating this model are presented in Table III. We observe that the first four lagged returns are statistically significant, there are seasonal effects in that four months of the year (Feb, Mar, Jun, and Jul) are statistically significant and there are significant year effects in 1985 and 1994. Further we find that open interest is a significant variable. Interestingly the day of the week effect and the volume effects are found to be statistically insignificant. This is despite the apparent differences in the mean returns for different days reported in Table II. Thus, these differences can be attributed to other factors in the regression.

Having examined the significance of individual parameter estimates we now turn our attention to testing the joint significance of various effects. The results of these F tests are presented in Table IV. Overall these results are broadly consistent with the individual parameter results. However as a joint test the year effect is not statistically significant. Accordingly a more parsimonious model for returns could be estimated as,

$$r_t = \gamma_0 + \sum_j \theta_j r_{t-j} + \sum_i \rho_i m_i + \gamma_3 \text{ OPIN}_t + \varepsilon_t \tag{3}$$

The results of estimating this model are presented in Table V and show significant effects for lagged returns, open interest and monthly effects in two months (Feb and Jul).

Having determined the model for the mean of returns we now turn our attention to modeling volatility. Our primary technique for modeling volatility is the class of ARCH/GARCH models. The earliest model is the ARCH(q) model suggested by Engle (1982), where

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \ldots + \alpha_q \varepsilon_{t-q}^2 \tag{4}$$

A number of generalizations of this model have been suggested, the most popular being Bollerslev's (1986) GARCH(p,q) model, where

$$\sigma_t^2 + \alpha_0 + \sum_{i=1} \alpha_1 \varepsilon_{t-i}^2 + \sum_{j=1} \beta_j \sigma_{t-j}^2 \tag{5}$$

These relatively simple ARCH and GARCH can now be readily estimated as a standard feature of most econometric software. However, they are still more complex than a model where the variance is constant over time. This suggests that we need to use econometric tests designed to test for the presence of ARCH and GARCH effects. A simple test in this regard

TABLE III

Results of an OLS Regression to Model the Returns Series Where the Explanatory Variables Are Lagged Returns, Day of the Week Dummy Variables, Monthly Dummy Variables, Yearly Dummy Variables, Volume, and Open Interest

Variable	*Coefficient*	*t-stat: Coeff = 0*
Con	0.92328	1.784
r_{t-1}	−0.57864	31.150
r_{t-2}	−0.32768	15.350
r_{t-3}	−0.15240	6.936
r_{t-4}	−0.06170	2.894
r_{t-5}	−0.00889	0.480
Mon	−0.04161	0.131
Tue	−0.02513	0.080
Wed	−0.04000	0.127
Thu	0.38600	1.231
Hol	−0.11428	0.296
Jan	−0.06820	1.400
Feb	−2.10682	4.164
Mar	−1.02400	2.148
Apr	−0.84031	1.761
May	−0.82863	1.698
Jun	−1.23210	2.507
Jul	−1.82238	3.716
Aug	−0.86729	1.763
Sep	−0.66763	1.362
Oct	−0.52093	1.066
Nov	−0.79760	1.661
1981	−0.15000	0.298
1982	−0.08166	0.169
1983	0.60759	1.255
1984	0.61097	1.111
1985	−2.78425	2.767
1986	−0.06788	0.134
1987	0.37510	0.769
1988	−0.17934	0.368
1989	−0.36309	0.746
1990	0.25295	0.521
1991	−0.01755	0.036
1992	0.01459	0.030
1994	1.63555	2.075
CVOL	0.00006	0.055
MVOL	0.00548	0.275
OPIN	−0.06919	4.362
R^2	0.25733	
D-W	2.00650	

TABLE IV

Results of F Tests to Test the Joint Significance of Various Combinations of Parameter Estimates Representing Seasonal and Market Depth Effects from Table III

Variables	*F statistic*	*F critical*
Year Effect	1.617	1.670
Month Effect	2.468	1.750
Day Effect	0.582	2.370
CVOL, MVOL, OPIN	6.509	2.600
r_{t-i}	194.860	2.210
Day, Year CVOL, MVOL	1.269	1.570
r_{t-i} OPIN Month Effect	58.210	1.570

TABLE V

Results of Restricted OLS Regression to Model the Returns Series

Variable	*Coefficient*	*t-stat: Coeff=0*
Con	0.49813	1.628
r_{t-1}	−0.57119	30.890
r_{t-2}	−0.31706	14.930
r_{t-3}	−0.14078	6.446
r_{t-4}	−0.05227	2.463
r_{t-5}	−0.00181	0.097
Jan	−0.25441	0.565
Feb	−1.56449	3.336
Mar	−0.48379	1.102
Apr	−0.30966	0.705
May	−0.29412	0.654
Jun	−0.40040	1.084
Jul	−1.33360	2.878
Aug	−0.38799	0.832
Sep	−0.18539	0.399
Oct	−0.06859	0.148
Nov	−0.44602	0.977
OPIN	−0.69095	4.543
R^2	0.25081	
D-W	2.00063	

The explanatory variables are lagged returns, monthly dummy variables and open interest.

is the LM test for ARCH effects suggested by Engle (1982). This tests the hypothesis that $\alpha_1 = \ldots = \alpha_q = 0$ and can be easily calculated from an auxiliary regression and is distributed as χ^2_q. Lee (1991) has shown that this test is also the LM test for GARCH disturbances, where the hypothesis being tested is $\alpha_1 = \ldots = \alpha_q = \beta_1 = \ldots \beta_p = 0$. Although these tests are relatively simple to compute, they may lack power in detecting ARCH/GARCH effects. This is because the parameters of ARCH/GARCH models must be strictly non-negative in all cases of ARCH(q) and in GARCH(1,1) models. For higher order GARCH models Nelson and Cao (1992) show that not all parameters must be non-negative. However, the dominant parameters must still be non-negative. This suggests that testing for ARCH/GARCH effects is a one-sided testing problem. Accordingly LM tests will not fully exploit this property. As a result Lee and King (1993) developed a new test for ARCH/GARCH effects which they denote as the LBS test. This test does exploit the one-sided nature of the testing problem. Lee and King (1993) suggest two versions of their test, a standard test LBS_1 and a test which is robust to non-normal disturbances LBS_2. Both of these tests have distributions which are standard normal. Lee and King (1993) show that significant increases in power can be attained by using LBS tests rather than LM tests.

We therefore now have a strategy to test for ARCH/GARCH effects applying both the standard LM and more powerful LBS tests. We find significant ARCH effects using all three tests. The calculated value of the LM statistic is a statistically significant 3.191, the calculated value of the LBS_1 statistic is a statistically significant 12.420 and the calculated value of the LBS_2 statistic is a statistically significant 1.787.

Therefore we are able to identify the presence of ARCH/GARCH effects. However it is very likely that any number of ARCH or GARCH models are likely to be good candidates for modelling these effects. Accordingly a method is needed for selecting a particular model from the family of ARCH/GARCH models. In this regard we use Akaike's (1974) information criterion. This essentially involves comparing the maximized log-likelihood of the different models with a penalty attached to the models with extra parameters.

To determine the optimal model for volatility we estimated ARCH models ranging from ARCH(1) through to ARCH(20) and GARCH models ranging from GARCH(1,1) through to GARCH(3,3). Detailed results for each of these models are available from the authors on request. To determine the optimal model we took the following steps. First we excluded all models where the parameter estimates failed to converge. Second we excluded all models which converged but where a parameter failed to estimate due to singularity problems. Third we excluded all models where a parameter estimate was insignificant using a conventional t test. Finally for the remaining subset we applied the Akiake (1974) information criteria (AIC) to determine the preferred model.

For the ARCH models the ARCH(1) model and the ARCH(10) through to ARCH(20) models are ruled out due to non-convergence, singularity and insignificant t-statistics. Therefore we now apply AIC to the models ARCH(2) through to ARCH(9). The application of the AIC chooses the ARCH(9) model as the preferred model. For the GARCH models only three of the nine models converge and have statistically significant parameter estimates. These models are the GARCH(1,1), GARCH(2,1) and the GARCH(3,2). Of these models the preferred model chosen by the AIC is the GARCH(3,2) model.

We now use the volatility estimates generated by the ARCH(9) and GARCH(3,2) models as the dependent variable in a secondary regression. We analyze whether this estimated volatility can be explained by daily dummies, monthly dummies, yearly dummies, volume and open interest effects.

Thus, the estimated equation is

$$\hat{h}_t = \gamma_0 + \sum_j \theta_j r_{t-j} + \sum_i \lambda_i d_i + \sum_i \rho_i m_i + \sum_i \phi_i y_i$$
$$+ \gamma_1 \text{ CVOL}_t + \gamma_2 \text{ MVOL}_t \; \gamma_3 \text{ OPIN}_t + \varepsilon_t \qquad (6)$$

where (γ, θ, λ, ρ, ϕ) are unknown parameters to be estimated, d_i is a day of the week dummy, m_i is a monthly dummy, y_i is a yearly dummy, CVOL_t is the volume in the near future, MVOL_t is the volume in all contracts traded, OPIN_t is the open interest and ε_t is a random shock assumed to be distributed IN(0, σ^2).

The results of this analysis are presented in Table VI. We find that all of the day of the week dummies are statistically insignificant. In contrast the holiday dummy is significantly negative, suggesting a dampening of volatility after a holiday. There are seasonal effects on volatility in eight months of the year (Jan, Feb, Mar, Jun, Jul, Aug, Sep, and Nov). In all of these months there is a significant positive effect on volatility. There are also five years (1983, 1984, 1985, 1986, and 1988) where there is a significant positive effect on volatility. There also appear to be volume and market depth effect on volatility with both market volume and open interest statistically significant. In Table VII we present the results of F tests of the significance of the seasonal and market depth effects. These results show a clear statistically significant effect for all groups of variables.

CONCLUSIONS

This article has investigated the determinants of daily returns and volatility in the Kuala Lumpur crude palm oil futures market over the period

TABLE VI

Results of an OLS Regression to Model the Generated Volatility Series from the ARCH (9) and GARCH (3,2) Models

	ARCH(9)		*GARCH(3,2)*	
Variable	*Coefficient*	*t-stat: Coeff = 0*	*Coefficient*	*t-stat: Coeff = 0*
Con	−4.60613	1.941	−4.05255	2.128
Mon	1.46661	1.002	1.41691	1.208
Tue	1.04622	0.722	1.10693	0.952
Wed	1.77793	1.224	1.70156	1.461
Thu	1.15844	0.804	1.26950	1.098
Hol	−4.88647	2.754	−4.20457	2.952
Jan	4.57548	2.046	3.53034	1.966
Feb	8.93549	3.823	8.09013	4.361
Mar	6.71579	3.076	6.19447	3.534
Apr	3.62025	1.653	3.11530	1.772
May	3.29323	1.470	2.60536	1.449
Jun	5.03642	2.237	4.01945	2.223
Jul	4.89980	2.191	4.19739	2.338
Aug	6.98218	3.094	5.94950	3.284
Sep	5.14886	2.288	4.90645	2.716
Oct	3.97786	1.772	3.14900	1.747
Nov	12.19770	5.539	10.78280	6.098
1981	2.09625	0.895	1.91197	1.029
1982	0.63785	0.287	0.67131	0.376
1983	5.87058	2.642	5.92417	3.320
1984	26.89500	10.652	27.13840	13.387
1985	90.01720	19.544	90.91650	24.586
1986	7.59550	3.264	7.60232	4.070
1987	2.21016	0.986	2.16452	1.203
1988	5.08106	2.272	5.19505	2.893
1989	2.22708	0.996	2.26772	1.263
1990	0.48281	0.216	0.51466	0.287
1991	0.57539	0.259	0.58647	0.328
1992	−0.43657	0.196	−0.43799	0.245
1994	−1.54022	0.426	−0.64423	0.222
CVOL	−0.00170	0.305	−0.00027	0.060
MVOL	−0.02378	2.601	−0.02293	3.126
OPIN	0.27391	3.765	0.22935	3.927
R^2	0.18305		0.25756	
D-W	1.03903		1.15594	

The explanatory variables are day of the week dummy variables, monthly dummy variables, yearly dummy variables, volume and open interest.

over the period 1980 to 1994. Broadly speaking our results can be summarized as follows. First we find significant evidence of month and open interest effects in returns. Second the econometric evidence is consistent with the presence of ARCH effects in the data.

TABLE VII

Results of F Tests to Test the Joint Significance of Seasonal and Market Depth Effects in the Equations with Estimated Volatility as an Explanatory Variable

Variables	*F statistic ARCH(9)*	*F statistic GARCH(3,2)*	*F critical*
Year Effect	42.747	67.614	1.670
Month Effect	3.767	4.883	1.750
Day Effect	1.820	2.188	2.370
CVOL, MVOL, OPIN	7.196	8.398	2.600

Estimated volatility is calculated by either an ARCH(9) or GARCH(3,2) model.

Third we find strong evidence of daily, monthly, yearly, volume and open interest effects in volatility when ARCH/GARCH models are used to estimate volatility. Our results are useful because they provide evidence about a market that has not been the subject of much analysis and thus provides additional supporting evidence to previous research on U.S. markets.

In a broad sense our results generally support the conclusions of previous research on U.S. markets as regards the importance of market depth (volume and open interest) effects on volatility. Consistent with Najand and Yung (1991) and Foster (1995) there are GARCH effects even after market depth effects are taken into account. Further, the results strongly support the presence of seasonal effects in volatility.

BIBLIOGRAPHY

Akaike, H. (1974): "A New Look at the Statistical Model Identification," *IEEE Transactions on Automatic Control,* 19, 716–723.

Baillie, R. T., and Myers, R. J. (1991): "Bivariate GARCH Estimation of the Optimal Commodity Futures Hedge," *Journal of Applied Econometrics,* 6, 109–124.

Bessembinder, H., and Seguin, P. J. (1993): "Price Volatility, Trading Volume and Market depth: Evidence from Futures Markets," *Journal of Financial and Quantitative Analysis,* 28, 21–39.

Bollerslev, T., (1986): "Generalised Autoregressive Conditional Heteroscedasticity," *Journal of Econometrics,* 31, 307–327.

Bollerslev, T., Chou, R. Y., and Kroner, K. F. (1992): "ARCH Modelling in Finance: A Review of the Theory and Empirical Evidence," *Journal of Econometrics,* 52, 5–59.

Box, G. E. P., and Pierce, D. A. (1970): "Distribution of Residual Autocorrelations in Autoregressive Integrated Moving Average Time Series Models," *Journal of the American Statistical Association,* 65, 1509–1526.

Engle, R. F. (1982): "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica,* 50, 987–1008.

Foster, A. J. (1995): "Volume-Volatility Relationships for Crude Oil Futures Markets," *The Journal of Futures Markets,* 15, 929–951.

Gay, G. D., and Kim, T. H. (1987): "An Investigation into Seasonality in the Futures Market," *The Journal of Futures Markets,* 7, 169–181.

Kenyon, D., K., Kling, J., Jordan, W. Seala, and McCabe, N. (1987): "Factors Affecting Agricultural Futures Price Variance," *The Journal of Futures Markets,* 7, 73–91.

Khoury, N., and Yourougou, P. (1989): "Price Discovery Performance and Maturity Effects in the Canadian Feed Wheat Market," *The Review of Futures Markets,* 8, 402–418.

Khoury, N., and Yourougou, P. (1993): "Determinants of Agricultural Futures Price Volatilities: Evidence from Winnipeg Commodity Exchange," *The Journal of Futures Markets,* 13, 345–356.

Kok, K. L., and Goh, K. L. (1994): "Crude Palm Oil Futures Price Behaviour in the Kuala Lumpur Commodity Exchange," *Proceedings of the First Annual Conference of the Asia Pacific Finance Association,* 1, 32–55.

Lamourex, C. G., and Lastrapes, W. D. (1990): "Heteroskedasticity in Stock Return Data: Volume versus GARCH Effects," *Journal of Finance,* 45, 221–229.

Lee, J. H. H. (1991): "A Lagrange Multiplier Test for GARCH Models," *Economic Letters,* 37, 265–271.

Lee, J. H. H., and King, M. L. (1993): "A Locally Most Mean Powerful Based Score Test for ARCH and GARCH Regression Disturbances," *Journal of Business and Economic Statistics,* 11, 11–27.

Ma, C. K., Mercer, J. M., and Walker, M. A. (1992): "Rolling Over Futures Contracts: A Note," *The Journal of Futures Markets,* 12, 203–217.

Malick, W. M., and Ward, R. W. (1987): "Stock Effects and Seasonality in the FCOJ Futures Basis," *Journal of Futures Markets,* 7, 157–167.

Milonas, N. T. (1986): "Price Variability and the Maturity Effect in Futures Markets," *The Journal of Futures Markets,* 6, 443–460.

Milonas, N. T. (1991): "Measuring Seasonalities in Commodity Markets and the Half-Month Effect," *Journal of Futures Markets,* 11, 331–345.

Najand, M., and Yung, K. (1991): "A GARCH Examination of the Relationship between Volume and Price Variability in Futures Markets," *The Journal of Futures Markets,* 11, 613–621.

Nelson, D. B., and Cao, C. Q. (1992): "Inequality Constraints in the Univariate GARCH Model," *The Journal of Business and Economic Statistics,* 10, 229–235.

Ragunathan, V., and Peker, A. (1997): "Price Variability, Trading Volume and Market Depth: Evidence from the Australian Futures Market," *Applied Financial Economics,* 7, 447–454.

Yang, S-R., and Brorsen, B. W. (1993): "Nonlinear Dynamics of Daily Futures Prices: Conditional Heteroscedasticity or Chaos?," *The Journal of Futures Markets,* 13, 175–191.