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Thin Trading and Mispricing Profit Opportunities in The Canadian Commodity Futures

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This study examines whether thin trading problems in the Canadian futures market can create mispricing profit opportunities for canola and feed wheat futures traded over the period 1981 through 1993. A forecasting model is developed using historical and publicly available information to predict futures closing prices for these contracts, then two trading rules (a confidence interval and a percentage price change filter) are used to determine their profit potentials. The size of profits generated from trading canola futures under either rule during the period 1987-1993 is consistent with C. Carter's (1989) earlier results that no market inefficiency was detected during the 1980-1987 period. Similarly, profits from the Canadian feed wheat thinly traded contracts and from a control group using the highly-liquid American soybean oil and wheat contracts do not violate the efficiency theory. The average gross profit per trade analysis further suggests that net positive profits may not be viable for marginal investors.

Technical analysts believe that futures have for many years exhibited highly repetitive and predictable price cycles or price patterns. Many scholars find evidence in support of technical analysis that price patterns do exist (for example, Lukac, Brorsen, and Irwin, 1988). These patterns, however, must be strong enough to make a trading profit, including covering transaction costs. Some futures markets have indeed shown greater tendencies toward patterns than others. For example, grains have more pronounced seasonal fluctuations in supply (across different countries) than in demand. Uncertainty about supply of grains during growing seasons produces some of the largest movements in basis points for grain futures contracts. The extent that these movements may present mispricing profit opportunities using trading rules across different markets are unknown and therefore are examined in this study. Further, the presence of excessive profits may have some implications with regard to the Efficient Market Hypothesis (EMH) in these markets.[1] Similarly, predictability of futures prices may not necessarily imply profitability (Bessembinder, Coughenour, Seguin, and Smoller, 1995). Therefore, mispricing profit opportunities and predictability of futures prices are tested here.

For the most part, agricultural commodity futures markets are presumed efficient in the weak-form. For instance, the American evidence on the weak-form efficiency of these futures is relatively established.[2] The evidence for the semi-strong form of efficiency is, however, inconclusive.[3] Also, there are some futures contracts (for example, canola and feed wheat) that trade only in the Canadian market. Yet, the efficiency of these Canadian futures contracts has not received the same attention as the American commodity futures. In addition, Canadian futures experience lower trading volume compared to American markets (as can be seen from the Winnipeg Commodity Exchange Statistical Annuals and the CRB Commodity Year Books). The thin trading problem has already been documented by Fowler, Rorke, and Jog (1979) for Canadian stocks, but not for futures. Thus, comparing the more-liquid American market to the much smaller Canadian markets can be of interest particularly to practitioners since they may use this phenomenon to identify additional profit opportunities.

Carter (1989) finds no evidence of weak-form market inefficiency for canola, soybean oil, corn and barley futures in the Canadian markets during the 1980-1987 period. However, he suggests that arbitrage opportunities exist between the American and Canadian markets for long-term government bonds. In this study, we examine mispricing of canola and feed wheat futures traded at the Winnipeg Commodity Exchange (WCE). Mispricing due to thin trading may or may not present profit opportunities.

Unlike Carter (1989), this study tests the weak and semi-strong forms of market efficiency jointly using a different testing methodology. It first constructs an econometric model to predict next-day futures prices. The forecasting model in its full form includes variables that were shown in the literature to have some relative predictive power. Next, the paper produces a reduced model from the variables that have the highest predictive power in the forecasting process. This model is used solely for forecasting and not to draw any inferences. The forecasted price (or its confidence interval) is then compared to a benchmark price (for example, actual closing price or opening price) to identify any mispricing opportunities, that is to find undervalued or overvalued futures. The comparison is performed using two trading rules, a confidence interval and a percentage price change filter, to initiate a position in these contracts. A position taken early in the day is then offset using two methods: either at the close of the same day it starts or by using the same trading rule. This study chose as the control group soybean oil and wheat futures heavily traded contracts at the Chicago

Board of Trade (CBOT) futures market as the closest substitutes to the Canadian canola and feed wheat futures, respectively.[4]

The main contribution of this study is that it provides new evidence on the Canadian feed wheat, and replicates Carter's (1989) tests of wheat, soybean oil and canola futures efficiency using different methodology and sample period (namely for the period 1987-1993). This study also calculates an average gross profit per trade to determine a ceiling for transaction costs below which floor traders may achieve profits.

Results for the sample period (1987-1993) support the hypothesis that the markets for the Canadian canola and feed wheat futures and the American soybean oil and wheat futures are efficient. This finding holds true despite thin trading problems Canadian markets suffer from.

Section I discusses the methodology used here. The findings are reported in Section II, followed by summary and conclusions in Section III.

I. TESTING METHODOLOGY

A. Data Description

The sample period extends from 1 January 1981 to 31 December 1993. Since the presence of nonsynchronous observations is a problem for Canadian data, for each trading day we follow Fama and French (1987), Bailey and Chan (1993), Bessembinder and Seguin (1993), and Bessembinder, Coughenour, Seguin and Smoller (1995) in using the nearby contract with the closest maturity. Following Carter (1989) and Lukac and Brorsen (1990), on the last trading day before the delivery month (during which the contract expires), the nearest contract is rolled over to the next contract, thus avoiding increasing volatility in the delivery month.[5] Observations that do not match in either market (the Chicago or Winnipeg markets) are omitted. For example, when there is a holiday in one market but not in the other market, that day is dropped from the final sample. This filter is used to ensure that there are observations for each trading day in both markets.

The sample period is divided as follows. We use the data from 1981-1985 period to select the variables that are most useful in predicting the closing prices of each commodity and to derive the optimal estimation period. Next, the forecasting model is tested for its predictive power during the 1986 year. Finally, the forecasting model predicts closing prices of the nearest contract for each trading day from 1987 through 1993, based on which position is either started or offset. The forecasting model is used for the period 1987 through 1993 with the data rolled one year at a time, and the coefficients are re-estimated every year.

The main goal of the forecasting model is to identify profit opportunities stemming from significant differences between model prices and actual prices for each commodity. These differences can be due to disequilibrium or noise (for more details on this issue, see Capozza and Seguin, 1996). To price futures contracts accurately, factors that are likely to cause changes in the corresponding commodity prices are tested. Following various studies in the futures literature, we identify a total of eight variables for their possible ability to forecast the closing prices of the commodities studied. Some of the chosen variables are measured daily, but others are moving average of daily data in the past month. The eight variables are:

1. **Seasonality Dummy Variable**: Following Stevens' (1991) emphasis on the importance of the growing season in determining the supply of agricultural commodities, we use a dummy variable that is set to equal one in the growing season between 1 May and 31 October, and zero otherwise.[6] We propose that the coefficient parameter for seasonality would have a negative relationship with the forecasted closing price, as more price uncertainty is expected during the growing season (due, for example, to unpredictable changes in weather condition).
2. **Daily Opening Price**: According to Carter (1989), the opening price reflects whatever relevant information was revealed overnight. Thus, we predict a positive correlation between daily opening price and the forecasted closing price expected to prevail at the close of the day.[7]
3. **Daily Open Interest**: Bessembinder and Seguin (1993) show that large open interest of a monthly-specific contract mitigates volatility, and as such, it proxies for market depth. By implication, lower outstanding open interest contracts would associate with high uncertainty, and would probably have a negative influence on the forecasted closing prices.
4. **Daily Total Open Interest**: This variable represents all contracts of all maturities (compared to daily open interest of a monthly-specific contract). Once again, following Bessembinder and Seguin (1993), we suggest that the sign of the relationship between the total of all open interest contracts (that is, all contracts on the underlying commodity) and volatility is negative.
5. **Average Daily Trading Volume**: This is a moving average of daily trading volume in the last 30 days for the nearest-maturity contract. Karpoff (1987) argues that misspecified regressions lead to no linear relationship between volume and price in equity markets. On the other hand, Mohammad and Yung (1991) find a positive relation between price changes and volume. Those arguments are put here to test for the Canadian futures. As with Mohammad and Yung (1991), we expect that, once we correct for heteroscedasticity and multicollinearity, the correlation between the average daily trade volume in the past month and daily price to be positive.

6. **Average Daily Total Trading Volume:** This is a moving average of daily total trading volume in the last 30 days for all contract maturities. The coefficient for this variable is expected to be positive.
7. **Average Daily Open Interest:** This is a moving average of daily open interest in the last 30 days for the nearest-maturity contract. This variable is selected as a testable alternative to daily open interest. The expected sign for the monthly average open interest coefficient is negative.
8. **Average Daily Total Open Interest:** This is a moving average of daily total open interest in the last 30 days for all contract maturities. This variable is selected as a testable alternative to the daily total open interest variable. Therefore, we anticipate its coefficient to be negative.

From this set of eight variables, we, in addition, use one day lag on daily open interest, daily total open interest, average daily trading volume, average total trading volume, and daily closing price (as a substitute for yesterday's opening price). The lag operator is used to test the predictive power of these variables, and to account for any delayed price adjustment. Some of the above-mentioned 13 variables may be positively correlated, and therefore some variables may be redundant. For example, Bessembinder, Chan, and Seguin (1996) find positive association between open interest and trading volume. The stepwise regression technique (described below) would, however, eliminate any redundancy.

B. Data Description and Sources

Data for the 1981-1993 period on opening prices, closing prices, open interest, and trading volume for each futures contract, and data on total open interest and total volume for all futures contracts on each commodity, are obtained from Tick Data Inc. of Lakewood, Colorado. The futures contracts are: the WCE feed wheat (spring wheat variety), the WCE canola, the CBOT wheat (winter wheat variety), and the CBOT soybean oil.

In order to compare the results for the Canadian to the American contracts, we use Canadian/$ US exchange rates to convert the data to its value in American dollars. The foreign exchange rates data are obtained from Scotia McLeod in Toronto, Ontario, and they are weekly quotations of average closing rates from January 1981 to December 1993.[8]

C. Testing Methodology

The original full forecasting model, given in Equation 1 includes thirteen variables as follows:

$$\hat{Y}_t = \alpha + \beta_1 X_{1,t} + \beta_2 X_{2,t} + \beta_3 X_{3,t} + \beta_4 X_{4,t} + \beta_5 X_{5,T} + \beta_6 X_{6,T} + \beta_7 X_{7,T} + \beta_8 X_{8,T} + \beta_9 X_{9,t-1} + \beta_{10} X_{10,t-1} + \beta_{11} X_{11,t-1} + \beta_{12} X_{12,t-1} \beta_{13} X_{13,t-1} \quad (1)$$

where, $\hat{Y}_t$ = Forecasted Closing Price for the t^{th} Day
α = Intercept or Constant Term From the Regression
$X_{1,t}$ = Seasonality Dummy Variable for the t^{th} Day
$X_{2,t}$ = Daily Opening Price for the t^{th} Day
$X_{3,t}$ = Daily Open Interest for the t^{th} Day
$X_{4,t}$ = Daily Total Open Interest for the t^{th} Day
$X_{5,T}$ = Average Daily Trading Volume for the period T where T= t-1, . . . , t-30
$X_{6,T}$ = Average Daily Total Trading Volume for the period T where T= t-1, . . . , t-30
$X_{7,T}$ = Average Daily Open Interest for the period T where T= t-1, . . . , t-30
$X_{8,T}$ = Average Daily Total Open Interest for the period T where T=t-1, . . . , t-30
$X_{9,t-1}$ = Daily Open Interest Lagged One Day
$X_{10,t-1}$ = Daily Total Open Interest Lagged One Day
$X_{11,t-1}$ = Daily Trading Volume Lagged One Day
$X_{12,t-1}$ = Daily Total Trading Volume Lagged One day
$X_{13,t-1}$ = Closing Price Lagged One Day

In the first data period, 1981-1985, the stepwise regression technique is used to find a subset of the examined variables in Equation 1 that has the highest explanatory power. As some of these variables are co-linear, stepwise regression would reduce multicollinearity, and improve the parsimony of the forecasting model.[9]

Following the stepwise regression (using forward selection method), the subset of selected variables is then included in the regression to determine the optimal estimation sub-period for each commodity. In the first data period, 1981-1985, there are five sub-periods under consideration (these are: one year, two years, three years, four years, and five years). Each sub-period has several possible combinations (these are: five 1-year units, four 2-year combinations, three 3-year combinations, two 4-year combinations, and only one 5-year combination), on which regressions are conducted. For example, the 4-year sub-period has two combinations: 1981-1984 or 1982-1985. Next, for each combination in a sub-period, we run the reduced (stepwise) regression model to forecast closing prices during 1986. Thus, data from 1986 are used to test the accuracy of the forecasting model. From these regressions, we calculate the RMSE for each combination in a sub-period, then we compute an average Root Mean Squared Error (RMSE) statistic for all combinations in that sub-period. The optimal estimation period is the sub-period that has the lowest average RMSE for the commodity. The idea here is to optimize the predictive power of the forecasting model by choosing the sub-period with the minimum average RMSE statistic. For example, by using the stepwise regression, it is determined for canola that four variables (seasonality, X_1, average daily trading volume, X_5, average daily total trading volume, X_6, and opening price, X_2) result in the highest R^2 WITH Mallows' C_p statistic that is closest to four (four is the number of estimated parameters). Using the four independent variables and the closing price as the dependent variable, we calculate the RMSE for each combination in a sub-period to forecast closing prices in 1986. The optimal estimation period is the sub-period that results in the smallest RMSE of any combination; in this case it is determined to be four years (the 1982-1985 period).

Once the optimal forecasting model (that is, the model that has the selected variables from stepwise regression and has the optimal estimation period) is chosen for each commodity, we then use 1987 as the first year for forecasting closing prices (Y_t). For example, the selected model for canola (described earlier) is then used to forecast closing prices for canola for each trading day during the year 1987. Of course, we roll the data one year using data from 1983-1986 to re-estimate the coefficients for the four variables. So while the parameters are re-estimated, the optimal estimation period of four years and the identity of the four variables selected for canola remain the same throughout the forecasting period (1987-1993).[10] This procedure is repeated for the period 1988 through 1993 with the data rolled one year at a time, and the coefficients are re-estimated every year.

Fowler, Rorke, and Jog (1979) argued that the prices of stocks that are thinly traded can exhibit heteroscedasticity and low R^2. So, since futures price data can also suffer from heteroscedasticity, they may result in misspecified residuals and misstated R^2.[11] Therefore, we use the correction for the standard error of the estimates for an unknown form of heteroscedasticity in the forecasting model. Thus, stationarity of the data in the forecasting model is ensured.

Now that forecasted closing prices are calculated for each commodity for each trading day in 1987 (and thereafter), two trading methods are used to take a position. In method one, a two-tailed 95% confidence interval range (formed based on the forecasted closing price) is calculated separately for each day by using Equation 2.[12]

$$C_i = (\alpha + \beta_1 X_1 + \ldots + \beta_p X_p) \pm \left[t_{\left(1-\frac{\alpha}{2};n-p\right)} \times \sqrt{(MSE + \sigma^2)} \right] \qquad (2)$$

Where: C_i = Upper and lower confidence intervals calculated based on the forecasting model;

t = Critical value at a 95% significance level for n observations and p regressors;

$(\text{MSE} + \sigma^2)$ = The standard deviation of the new predicted closing price at the specified levels of X (where MSE is the

Mean Squared Error of the closing price estimate, and δ^2 is the variance of the mean closing price estimate.)

The strategy under method one is that if the actual closing price lagged one day is greater (lesser) than the upper (lower) value C_t of the confidence interval, the futures contract is considered overvalued (undervalued), and therefore, the closing price of next day is expected to fall (rise).[13] So, the futures contract is sold (purchased) at the opening price of next day regardless of any price correction overnight.[14] Alternatively, we compared the opening price to the confidence interval. It turned out that 100% of the observed opening prices on the morning of the suggested trade for all four commodities fall within the calculated confidence intervals (implying that the market adjusts to information overnight), so we dropped this alternative. In another strategy, if the actual lagged closing price falls within the confidence interval, no buy or sell position is taken. This strategy is repeated every day. It must be noted here that neither strategy permits holding an offsetting (long and short) position at the same time. In other words, the outstanding position must be reversed first before a position in the opposite direction is undertaken.

To offset a position under method one, we apply two strategies: (1) offset at the same day the contract starts (purchased or sold), or (2) offset when the market price has moved one percent or two and a half percent from the sale or purchase price. The intuition behind the first strategy is that futures position is marked-to-market daily; therefore, the position is theoretically closed at the end of the same day the position starts. The second strategy presumes a certain desired return (or tolerance for a certain level of loss) on the futures position that must be realized before the position is reversed. Alternatively, if the price does not change significantly, the position is forced to be offset as the contract reaches the last trading day prior to its month of maturity. Under any of these strategies, however, the number of trades is the same, but the profit levels can differ.

Method two uses the forecasting model and a filter rule (rather than a confidence interval) to take a position in the futures market. An actual opening price at the beginning of day t is compared with the closing price forecasted to prevail at the end of day t (note that the forecast is estimated at the beginning of day t or at the end of day t-1 depending on the time dimension of the forecasting variables).[15] An actual opening price that differs from the forecasted closing price by 1% (or 2.5%) signals that a position should be taken in the futures contract. For instance, a buy position starts when the actual opening price is below the forecasted closing price by 1% (or 2.5%). Alternatively, a sell position starts if the actual opening price is greater than the forecasted closing price by 1% (or 2.5%). Again, the premise is that the actual opening price is expected to increase in a buy position or decrease in a sell position. Thus, the main difference between method one and method two is about whether the whole market forecasts price changes and whether it results in price adjustments at the opening.[16] Unlike method one (using a confidence interval), all positions are offset at the same day the futures positions start.[17]

In order to test the above strategies, the following testable hypotheses are formulated.

H1: *After transaction costs, there are no excess profits from trading canola, soybean oil, wheat, or feed wheat futures using the confidence interval trading rule.*

H2: *After transaction costs, there are no excess profits from trading canola, soybean oil, wheat, or feed wheat futures using the forecasting model and percentage price change rule.*

II. RESULTS AND ANALYSIS

Following the stepwise regression procedure described in Section I, the predicting variables for canola and feed wheat (in the test group), and soybean oil and wheat (in the control group) are displayed in Table 1. Also, displayed in the table is the optimal estimation period derived from regressions using 1981-1985 data.[18]

Interestingly, Table 1 shows that the daily opening price is consistently the most statistically important predicting variable for all four commodities. It is also clear from Table 1 that the number of predicting variables and the optimal estimation periods are different for each commodity.[19] For example, seasonality is a predicting factor for canola and soybean oil but not for feed wheat and wheat. Also, the estimation periods for canola and soybean oil are longer than those of the other two commodities.

Testing the strength of the forecasting model for each commodity in the year 1986, the results show that 96.8%, 97.8%, 98.4%, and 93.1% of the actual closing prices for canola, feed wheat, soybean oil, and wheat, respectively, fall within the calculated 95% confidence intervals. This observation suggests that confidence intervals calculated from the forecasted closing prices provide an accurate boundary of where closing prices should be at the close of the day.

Using the same forecasting models for 1987 and onward, we calculate the confidence interval method (method one) for each day, and positions are then started or offset according to the strategies described earlier. Table 2 reports the results for this method. The table is divided into four panels (one panel for each community). Each panel shows gross profits, average profits per trade, standard deviation of profits, number of trades, and number of positions forced to be offset for the entire (total) sample, and then by separating trades to buy or sell positions to determine whether up-market are more profitable than down-market.

Table 1. **The Results of Stepwise Regression Used to Select the Set of Predictive Variables to Be Included in the Forecasting Model for Each Commodity Futures, and the Results for the Optimal Estimation Period**

A total of thirteen variables are used in the forecasting regression (1). Stepwise regression technique is used to identify the most relevant predicting variables for each commodity. The level of significance the stepwise procedure uses to allow entry of variables into the model is 15%, and 5% to remain within the model. The selected variables are then used to determine the optimal estimation period. The optimal estimation period is the one that has the lowest root mean squared error (RMSE). Forecasting accuracy presents in percent how frequent the observed closing price falls within the calculated confidence intervals for the forecasted closing price. R-Squared is the coefficient of determination. The C(P) Statistic determines which model is most parsimonious (it is the one that is closest to the number of regressors in the forecasting model). The estimation period is January 1, 1981, through December 31, 1985.

Commodity	Variables Found To Be Significant	Optimal Estimation Period	Forecasting Accuracy	R-Squared	C(P) Statistic
Canola	Seasonality	4-Year	96.8%	0.9952	4.4044
	Average Daily Trading Volume				
	Average Daily Total Trading Volume				
	Daily Opening Price				
Soybean Oil	Seasonality	5-Year	98.4%	0.9957	1.3264
	Daily Opening Price				
Feed Wheat	Lagged Daily Total Open Interest	3-Year	97.8%	0.9942	3.0454
	Average Daily Trading Volume				
	Daily Opening Price				
Wheat	Lagged Average Daily Total Volume	1-Year	93.1%	0.9939	1.8516
	Daily Opening Price				

Table 2. **The Results From Positions Initiated by Method One (Confidence Interval) For All Commodities Futures, Buy, or Sell Trades Over the Period 1987-1993, Then Closed Either on the Same Day They Are Initiated or When the Observed Closing Price Increases or Decreases by 1% or 2.5%**

The strategy in method one is to compare the forecasted closing price to the observed closing price lagged one day. If the observed price is higher (lower) than the upper (lower) value of the confidence interval as shown in model (2), a futures contract is sold (purchased) because it is overvalued (undervalued). The position is offset either at the close of the same day or if the price decreases (increases) by 1% or 2.5%. Profit ($) is the total profit from all trades combined, buy, or sell trades transacted for that period; Average Profit Per Trade is total profit divided by the number of total trades for that period; Standard Deviation of Profit is the standard deviation of total profit; Number of Trades is the total number of trades (initiated and offset); and Offset Forced is the number of trades that are forced to offset at the end of the month before the futures contract expiration. No transactions costs are considered in this analysis. The estimation period for the forecasting parameters is January 1, 1981 to December 31, 1985. The model is then tested in 1986. The forecasting period is January 1, 1987, to December 31, 1993.

Offset	Profit ($)	Average Profit Per Trade	Standard Deviation Of Profit	Number Of Trades	Offset Forced
1. Canola Buy, Sell, and Totals For The Period 1987-1993					
Total					
Same Day	−66260.25	−487.21	801.45	136	Same Day
± 1%	12874.14	94.66	1089.95	136	60
± 2½ %	5116.16	37.62	1328.71	136	76
Buy					
Same Day	−46046.43	−590.34	984.66	78	Same Day
± 1%	10073.26	129.14	1013.48	78	40
± 2½ %	5579.01	71.53	1142.71	78	51
Sell					
Same Day	−20213.82	−348.51	421.22	58	Same Day
± 1%	2800.88	48.29	1192.61	58	20
± 2½ %	−462.84	−7.98	1553.62	58	25
2. Soybean Oil Buy, Sell, and Totals For The Period 1987-1993					
Total					
Same Day	−2550.61	−127.53	322.21	20	Same Day
± 1%	−5406.21	−270.31	974.99	20	10
± 2½ %	−3895.21	−194.76	1033.71	20	13
Buy					
Same Day	−1926.61	−148.21	372.12	13	Same Day
± 1%	−3558.01	−273.69	9.08	13	7
± 2½ %	−3295.21	−253.48	1146.59	13	9
Sell					
Same Day	−624.01	−89.14	221.69	7	Same Day
± 1%	−1848.01	−264.01	678.66	7	3
± 2½ %	−600.01	−85.71	856.29	7	4

(continued)

Table 2. **Continued**

Offset	Profit ($)	Average Profit Per Trade	Standard Deviation Of Profit	Number Of Trades	Offset Forced
3. Wheat Buy, Sell, and Totals For The Period 1987-1993					
Total					
Same Day	-18975.33	-558.09	3022.92	34	Same Day
± 1%	-413.01	-12.15	582.91	34	21
± 2½ %	-2812.55	-82.72	807.29	34	22
Buy					
Same Day	-18399.95	-799.99	3673.77	23	Same Day
± 1%	600.05	26.09	436.26	23	14
± 2½ %	2488.01	108.17	536.69	23	15
Sell					
Same Day	-575.41	-52.31	217.11	11	Same Day
± 1%	-1013.05	-92.09	831.97	11	7
± 2½ %	-5300.55	-481.87	1121.59	11	7
4. Feed Wheat Buy, Sell, and Totals For The Period 1987-1993					
Total					
Same Day	-392.32	-7.13	204.06	55	Same Day
± 1%	-108095.87	-1965.38	14207.33	55	27
± 2½ %	-2200.44	-40.01	460.75	55	35
Buy					
Same Day	-179.54	-5.28	248.14	34	Same Day
± 1%	352.79	10.38	261.92	34	15
± 2½ %	2117.95	62.29	378.93	34	21
Sell					
Same Day	-212.77	-10.13	104.02	21	Same Day
± 1%	-108448.00	-5164.22	22967.31	21	12
± 2½ %	-4318.39	-205.64	538.21	21	14

The results for all (that is total buy and sell) positions show large losses in the Canadian markets, especially the case of canola with same-day offset strategy (first panel in Table 2) and feed wheat with the ± 1% offset strategy (fourth panel in Table 2). The remaining commodity futures also experience losses before transaction costs. The only two exceptions are canola futures positions closed using ± 2½% offset strategy resulting in a modest gross profit of $5,116 US before transaction costs, and the canola futures positions closed using the ± 1% offset strategy (first panel in Table 2) resulting in a net profit of $1,314.00 US after transaction costs of $85 per round turn, as charged by WCE dealers.

Now we turn to separate buy and sell positions. Table 2 shows that same-day offset positions (buy or sell) always result in losses. Similarly, all sell positions using the ± 1% and ± 2.5% filter rules incur losses. The only exception is canola and only when sell positions are offset at the ± 1% filter rule. On the other hand, all buy positions (except soybean oil) are profitable at both the ± 1% and ± 2.5% filter rules. In particular, the first panel in Table 2 shows that

78% of canola's profit comes from buying positions. Recall that buy positions occur when the lagged actual closing price is less than the lower value of the confidence interval, suggesting that the commodity futures contract is undervalued. One possible explanation for profits made from buy positions relates to the type of information entering the marketplace after the initiation of the position (for example, the release of Statistics Canada Acreage Reports). This explanation suggests that maybe not all information that affects price movement is received and endogenized in prices during business hours of the market operations.[20] Why this phenomenon is observed only for long position is not clear, however. Nevertheless, ignoring that gross profits come from buying or sell positions, the overall profits net of transaction costs are significantly low, thus confirming the null hypothesis one of no mispricing opportunities.

Next, the analysis uses the forecasting model and a percentage price change (method two) to take a position in the futures market. The results for each commodity are reported in Table 3 by year. One difference between this analysis and the analysis using the confidence interval method (method one) as reported in Table 2 is the many transactions taken when applying the percentage price change method (method two). One possible reason for this result is that the 1% filter rule can be very narrow so that more actual opening prices fall outside the range, thus triggering the start of so many positions that are unwarranted. Thus, this strategy permits a position (either long or short) be held at one point of time more frequently. For instance, Table 3 shows that the number of trades for soybean oil futures during 1988 is 248 (about one trade for every trading day), thus offering more trading opportunities to profit from.

The same table shows that before transaction costs, canola and soybean oil, and feed wheat contracts report positive profits (refer to first, second and fourth panel in Table 3). However, after transaction costs of $85 US per round turn, losses occur, thus confirming null hypothesis two of no exploitable mispricing opportunities.

Next we investigate whether floor traders can realize profits using the described strategy. Therefore, for each contract we calculate an average gross profit per trade to establish a ceiling for transaction costs below which floor traders may achieve profits when using a percentage price change of ± 1%.[21] The average gross profit per trade is simply the ratio of total profits to the number of total trades over the entire sampling period (1987-1993). Using total profits and number of trades highlighted in Table 3, the average profit before transaction costs associated with this strategy are: canola $15.96, soybean oil $12.69, wheat N/A (meaning negative profits), and feed wheat $4.36. Obviously, with these low average gross profits, net positive profits may not be viable. However, it remains possible for floor traders, who pay low transaction and execution costs (that is below the gross profit levels), to experience some net profits. Such profits, if they exist, are considered as rewards for the liquidity service provided by floor traders in efficient markets.

Table 3. **The Annual Results From Positions Initiated by Method Two (Percentage Price Change) Over the Period 1987-1993, Then Closed on the Same Day They Are Initiated**

The strategy in method two is to compare the forecasted closing price to the observed opening price. If the observed price is 1% higher (lower) than the forecasted closing price, a futures contract is sold (purchased) because it is overvalued (undervalued). The position is offset at the close of the same day. Profit ($) is the total profit from all trades transacted for that period; Average Profit Per Trade is total profit divided by the number of total trades for that period; Standard Deviation of Profit is the standard deviation of total profit; and Number of Trades is the total number of trades (initiated and offset). No transactions costs are considered in this analysis. The highlighted total profits and number of trades are used to calculate the average break-even point for each contract. The estimation period for the forecasting parameters is January 1, 1981 to December 31, 1985. The model is then tested in 1986. The forecasting period is January 1, 1987, to December 31, 1993.

Year	Profit ($)	Average Profit Per Trade	Standard Deviation Of Profit	Number Of Trades
1. Canola: 1% Change In The Opening Price				
1987	185.06	1.20	145.81	154
1988	4946.50	103.05	177.37	48
1989	4053.03	19.87	188.33	204
1990	3277.01	11.19	165.91	231
1991	-2442.21	-17.08	178.95	143
1992	2647.94	23.23	122.62	114
1993	5344.35	22.74	156.75	235
Total	**18,011.68**	15.96	162.25	**1,129**
2. Soybean Oil: 1% Change In The Opening Price				
1987	2286.05	15.04	103.52	152
1988	6497.95	26.20	259.49	248
1989	4224.01	17.24	146.25	245
1990	4421.99	18.05	150.54	245
1991	-588.07	-2.51	146.43	234
1992	2058.09	8.47	120.82	243
1993	1445.96	6.13	156.24	236
Total	**20,345.98**	12.69	154.76	**1,603**
3. Wheat: 1% Change In The Opening Price				
1987	1112.52	8.43	117.31	132
1988	-2437.59	-11.95	271.36	204
1989	1425.02	17.81	107.18	80
1990	-4200.00	-17.57	152.98	239
1991	-6925.05	-29.22	169.08	237
1992	-824.92	-3.37	216.88	245
1993	2274.98	13.62	133.43	167
Total	**-9,575.04**	-7.34	166.89	**1,304**

(continued)

Table 3. **Continued**

Year	Profit ($)	Average Profit Per Trade	Standard Deviation Of Profit	Number Of Trades
4. Feed Wheat: 1% Change In The Opening Price				
1987	719.96	4.24	48.86	170
1988	-1292.84	-8.86	77.66	146
1989	1356.46	8.12	88.68	167
1990	573.45	14.34	45.11	40
1991	2603.76	10.94	78.51	238
1992	3156.65	14.96	79.59	211
1993	-2167.62	-13.30	49.59	163
Total	**4,949.82**	4.36	66.85	**1,135**

Table 4 shows the source of profits (whether they are from buy or sell trades) under method two. The results from the percentage price change method differ from those of the confidence interval method. With the percentage price change method, 96% of the profits for canola and 61% of the profits for soybean oil are realized from the sell (rather than buy) positions. Recall that in a sell position, the actual opening price is greater than the forecasted closing price by at least 1%. This finding about the difference in profit patterns between the two methods deserve further investigation in the future.[22] Another interesting observation about the level of profits is the size of the difference between buy and sell profits. For example, although there are less canola contracts sold than bought in 1992 (61 versus 53 - third and fourth columns in first panel of Table 4, respectively), profits from sell positions of $2,143.21 US are significantly higher than $504.73 from buy positions (second column first panel of Table 4). Similar results are shown for soybean oil for the years 1988 and 1989 (second panel in Table 4).[23]

Finally, we compare the coefficient of variation statistic of profits generated by method one to those of method two using the same-day offset strategy. The confidence interval method consistently shows negative results, while the percentage price change displays positive returns. The only exception is wheat futures contract. The analysis also shows that canola and soybean oil futures have less risk per unit of return compared to wheat and feed wheat futures.[24]

III. SUMMARY AND CONCLUSIONS

This study explores mispricing profit opportunities for Canadian canola and feed wheat traded at the WCE futures market. In order to contrast the results with those of other commodities, we choose a control group of soybean oil and wheat traded at the CBOT futures market. These contracts are presumably more liquid and because they can be considered close substitutes for canola and feed wheat, respectively. The methodology applies two trading rules using historical

Table 4. **The Annual Results For Buy/Sell Categories for Method Two (Percentage Price Change)**

The strategy in method two is to compare the forecasted closing price to the observed opening price. If the observed price is 1% higher (lower) than the forecasted closing price, a futures contract is sold (purchased) because it is overvalued (undervalued). The position is offset at the close of the same day. Profit is the total profit from buy or sell trades transacted for that period; and Number of Trades is the total number of buy or sell trades (initiated and offset). No transactions costs are considered in this analysis. The estimation period for the forecasting parameters is January 1, 1981 to December 31, 1985. The model is then tested in 1986. The forecasting period is January 1, 1987, to December 31, 1993.

	Profit ($)		No. Of Trades	
Year	**Buy**	**Sell**	**Buy**	**Sell**
1. Canola: 1% Change In The Opening Price (Buy/Sell Breakout)				
1987	−44.69	229.75	3	151
1988	254.99	4691.51	11	37
1989		4053.03		204
1990		3277.01		231
1991		−2442.21		143
1992	504.73	2143.21	61	53
1993		5344.35		235
Total	**715.03**	**17,296.65**	**75**	**1,054**
2. Soybean Oil: 1% Change In The Opening Price (Buy / Sell Breakout)				
1987	2064.01	222.04	28	124
1988	1187.94	5310.01	124	124
1989	306.02	3917.99	120	125
1990	3108.04	1313.95	120	125
1991	−336.08	−251.99	110	124
1992	1452.01	606.08	121	122
1993	179.98	1265.98	78	158
Total	**7,961.92**	**12,384.06**	**701**	**902**
3. Wheat: 1% Change In The Opening Price (Buy/Sell Breakout)				
1987	1387.49	−274.97	103	29
1988	−575.03	−1862.56	16	188
1989	337.51	1087.51	21	59
1990	−1437.49	237.49	236	3
1991		−6925.05		237
1992	−824.92		245	
1993	2149.99	124.99	154	13
Total	**−1,962.45**	**−7,612.59**	**775**	**529**
4. Feed Wheat: 1% Change In The Opening Price (Buy/Sell Breakout)				
1987	345.68	374.28	105	65
1988	−435.23	−857.61	16	130
1989		1356.46		167
1990	460.77	112.68	28	12
1991	2603.76		238	
1992	1375.29	1781.36	179	32
1993	−936.71	−1230.91	73	90
Total	**3,413.56**	**1,536.26**	**639**	**496**

and contemporaneous data (thus testing jointly the weak and semi-strong forms of market efficiency).

Futures positions started using either a confidence interval (method one) or a percentage price change (method two). Under method one, the positions are offset at the closing price in two alternative ways: (1) at the close of the same day the futures position starts, or (2) using a filter rule (± 1% or ± 2.5%). Under method two, positions are only offset at the closing price on the same day the futures position is started.

The analysis using the forecasting model to form a confidence interval shows that, for the period 1987-1993, net profits after transaction costs are small (or even negative). Another finding is that, using the percentage price change method, sell positions outperform buy positions.

Overall, using trading rules, we find no profitable mispricing opportunities for all four commodities futures for the period 1987-1993. The finding related to canola and soybean oil is consistent with Carter's (1989) conclusions covering the earlier period (1980-1987). Therefore, we cannot disprove market efficiency for the examined commodities. Hence, after all, thin trading in the Canadian futures market may be not a problem. Alternatively, the forecasting model used here may be misspecified (in that other variables may be missing from the model), the optimization periods or trading prices are unrealistic, or that other trading rules may prove to be more profitable.

Finally, there are additional issues arising from the development of the forecasting model that require further investigation in the future. The daily opening price is the most important predicting variable for all four commodities prices, which renders our forecasting model particularly sensitive to any error in measuring this variable. In practice, a trade will not take place at the opening price, but rather at a price quoted later, which may result in a slippage. Our paper ignores this slippage; it assumes it exists in both markets so that its effect is either neutralized, canceled out over time, or small. This problem, however, needs to be addressed in future research probably using transactional data. Also, while each of the four commodities has its own distinct growing seasons, the variable seasonality is only significant for canola and soybean oil pricing but not for wheat and feed wheat. A better model may capture these various seasonality patterns. Further, it appears that the optimal estimation period for each commodity is dependent on whether seasonality is selected as a predicting variable. For instance, the estimation periods for wheat and feed wheat are much shorter than those for canola and soybean oil. This observation implies that, for canola and soybean oil, a longer estimation period is needed to determine the parameters that should be in the forecasting models. Furthermore, a more detailed analysis is needed to further explain why method one leads to more buy position profits while most profits from method two come from sell positions, especially when the forecasting model is identical.

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NOTES

1. One can argue that the absence of mispricing opportunities does not prove or disprove market efficiency altogether, since efficiency can take many aspects including informational, allocational and operational efficiency of the futures market. Hence, while one form of efficiency may not hold, others may. Moreover, as pointed out by one referee of this journal, there is no consensus among researchers that the existence of profitable trading techniques consistently means inefficiencies.

2. Some studies that use the OLS approach reject pricing efficiency for some futures contracts with distant delivery (Bigman, Goldfarb, and Schechtman, 1983). However, some studies relate futures market inefficiencies to biases inherent in using OLS (Maberly, 1985; Hudson, Leuthold and Sarassoro 1987), biases in OLS alpha and beta estimates (Elam and Dixon, 1988), or to the failure of the OLS approach to produce an appropriate hedge ratio (Castelino, 1990). Nevertheless, Viswanath (1993) recommends OLS regression to estimate an appropriate hedge ratio. Other studies use filter rules to find either that large profits can be available to floor traders (Rechner and Poitras, 1993) or that only distant futures contracts are inefficient (Johnson, Zulauf, Irwin, and Gerlow, 1991). These results are consistent with the non-random behavior of inefficient markets. In contrast, Lukac, Brorsen, and Irwin (1988) and Lukac and Brorsen (1990) argue that the existence of abnormal profits indicates the presence of a market disequilibrium rather than market inefficiency. Also, Junkus (1991) uses CAPM to find no evidence of any risk premiums in the futures markets.

3. The semi-strong form tests of the EMH exploit the predictive ability of futures prices using publicly available information. Garcia, Leuthold, Fortenbery, and Sarassoro (1988) find that the cattle futures market does not incorporate all of the latest public information, thus creating some profitable opportunities. Using a simultaneous forecasting model, Gross (1988), however, could not reject the EMH.

4. Wheat and feed wheat may be not good substitutes for one another because they are grown at different seasons and because of differences in their quality Nevertheless, they are compared here because they belong to the wheat group. Soybean and canola, however, are close substitutes. Soybean has been a better source of vegetable oil; yet, canola's popularity is increasing as it is low in erucic acid. Also, both products can be fed to dairy cattle. The growth of canola production, however, is limited while soybean is grown in abundance.

5. An anonymous referee of this journal correctly points out that this roll over is only justified for those futures markets with seasonalities and non-trivial costs-of-carry, which is the case here. This treatment is consistent with Bessembinder, Coughenour, Seguin, and Smoller (1996).

6. The alternative suggested by an anonymous referee of this journal is to use monthly dummy variables (Rausser and Carter, 1983). The authors chose a single indica-

tor because no major monthly differences are expected to occur within the growing season or outside it. Also, while a regression with larger number of explanatory variables may improve R^2, it may not improve the parsimony of the model.

7. Using opening (and closing) prices, which need not be actual transaction prices, may be problematic, especially that the opening price is the only variable common to each forecasting model. As pointed out by an anonymous referee of the journal, using our methodology, a trader must wait for the opening price, calculate the forecast, then conduct the trade. So the trade cannot occur at the opening price and therefore the slippage between the opening price and the next quoted price could be large (unless there was little or no change during this time). However, assuming that the forecasting model is incorporated in computer trading program, the time lag between opening price and quoted trading price would be reasonably short, and the slippage may be small. Further (and as noted by the same referee), the assumption here is that a similar slippage also occurs in the control (American) market, which would reduce its effect. Furthermore, the slippage can be in either direction so that the long-term positive and negative slippages would cancel each other out. Finally, since we did not have access to transactional data (especially for the Canadian contracts), we follow the common practice in similar studies (Carter, 1989) by using opening and closing prices as reported on the data base.

8. Daily exchange rates were not readily available for the entire sampling period.

9. The stepwise procedure selects the variables based on the highest R-squared of the regression, thus eliminating any redundant variables and avoiding multicollinearity among remaining variables. Testing for multicollinearity, the Variance Inflation Factor was found to be insignificant (for reference on the VIF test, see Kennedy, 1985, p. 153). The statistics from the regression analysis also test for autocorrelation using Durbin-Watson, Von Neumann, and Rho statistic. No autocorrelation problem was detected. Also, normality was tested and ensured using Normal, Coefficient of Skewness, Coefficient of Excess Kurtosis, and Correlation Matrix tests.

10. As pointed out by one referee of this journal, although the forecasting model is reestimated annually with new data, the model is not optimized with new data and no sensitivity analysis was done to assess any potential affect a structural change might have on the model. Nevertheless, the statistical significance of the forecasting model (represented by the F-Value and R^2) was strong for every year thereof.

11. As pointed out by an anonymous referee of this journal, the assumption here is that prices are conditionally heteroscedastic. This follows from Schwert and Seguin's (1990) finding that returns are usually heteroscedastic.

12. For a reference of the confidence interval, see Neter, Wasserman, and Whitmore's 1992, *Applied Statistics*, 3rd ed., Equations 20.18-20.21, pp. 671-672. Boston: Allyn and Bacon.

13. The closing price is likely to correlate with opening price. Thus, a more interesting test is the correlation between the change in the closing price and the opening price. Thanks to an anonymous referee of this journal for noting this point. The authors plan to test this relationship in future research.

14. The analysis thus far ignores transaction costs This issue is discussed later when calculating the average gross profit per trade.

15. As mentioned in footnote 7, this comparison is performed ex-post and only after the opening price is used in the forecast. Then a trade is undertaken after the opening at that price.

16. Thanks to an anonymous referee of this journal for pointing out this clear distinction between the two methods.

17. Using other windows would involve marked-to-market adjustments. Also, choosing a particular window is a subjective decision. We want to test the profitability of a simple one-day position.

18. Details of the RMSE statistics are not displayed here but are available upon request.

19. All four commodities have very high R^2-Adjusted of nearly 100%. Also, Durbin-Watson, Von Neumann, and Rho statistics for autocorrelation, and skweness and Kurtosis statistics for testing normality all fall within the acceptable limits.

20. Profit opportunities are not driven by differences in time zones as both the CBOT and WCE are in the Central Time Zone.

21. Cost of borrowed funds and the required rate of return of invested funds are assumed negligible and therefore were not considered since futures are marked-to-market daily.

22. An anonymous referee of the journal suggests that something is probably happening to prices overnight.

23. An analysis is also performed by using ± 2½% as the percentage change required to initiate a futures market position. Similar results are achieved.

24. The results of the coefficient of variation analysis are not shown here, but are available upon request.

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