The Fallacy of Nearby Contract Commodity Futures Price Analysis: Intramarket Futures Contracts Are Not Identically Distributed

Christopher B. Barrett
JauRong Li
Dawn D. Thilmany

Presented at Western Agricultural Economics Association 1997 Annual Meeting
July 13-16, 1997
Reno/Sparks, Nevada

July 1997

The Fallacy of Nearby Contract Commodity Futures Price Analysis:

Intramarket Futures Contracts Are Not Identically Distributed

Christopher B. Barrett, JauRong Li,and Dawn D. Thilmany

September 1996; revised November 1996

Abstract: Researchers and analysts commonly use nearby contract futures prices series as a proxy for more distant contracts in empirical analysis and commodity hedging applications. This paper tests for equivalence between nearby and specific contract Chicago Board of Trade wheat futures price behavior.

JEL Codes: G13, Q1

The authors are assistant professor, graduate student, and assistant professor, respectively, in the Department of Economics, Utah State University, Logan, UT 84322-3530.
Seniority of authorship is shared equally. This work was supported by the Utah Agricultural Experiment Station and approved as journal paper 5033.

The Fallacy of Nearby Contract Commodity Futures Price Analysis:

Intramarket Futures Contracts Are Not Identically Distributed

Abstract: Researchers and analysts commonly use nearby contract futures prices series as a proxy for more distant contracts in empirical analysis and commodity hedging applications. This paper tests for equivalence between nearby and specific contract Chicago Board of Trade wheat futures price behavior.

The Fallacy of Nearby Contract Commodity Futures Price Analysis:

Intramarket Futures Contracts Are Not Identically Distributed

Commodity futures represent a substantial share of futures market activity and are an essential price discovery mechanism for the agricultural sector. Following the lead of the financial futures literature, nearby contract price series have become a standard for commodity futures price analysis, although financial and commodity futures may not follow similar price generating processes (Blank 1991; Yang and Brorsen 1995). Nearby contract futures price series are a composite of the maturing segments of all available seasonal contracts.[1]

Many uses of a nearby contract price series rely on the assumption that individual contracts are identically distributed. For instance, a farmer looking to hedge price risk for an expected September harvest or a baked goods manufacturer looking to do the same for year-end increases in flour demand wish to trade in September and December wheat futures contracts, respectively, and therefore to know the statistical properties of the data generating processes underlying the pricing of those contracts. A composite such as the nearby contract series offers a satisfactory proxy only if it evinces the same statistical characteristics as the specific contract of interest. The literature on commodity storage (e.g., Williams and Wright 1991; Deaton and Laroque 1992), however, suggests spot price distributions should vary with seasonal differences in storage volumes, information

1 For example, a nearby contract series on Chicago Board of Trade winter wheat futures would include prices on the March contract until it matured, at which time it would contain prices from the May contract until it matured, when it would roll to the July contract, and so on.

arrival, and the nature of supply and demand shocks. Since spot and futures markets are intrinsically linked, one might suspect significantly different statistical properties among intramarket futures contract price series. A composite series of futures prices may fail to capture the basic statistical properties of any or all of the underlying contracts. This paper uses winter wheat futures price data to test the appropriateness of analyzing nearby contract price series as a proxy for specific delivery contracts.

Futures Price Behavior

Nearby contract analysis' popularity is based on the assumption that the maturing contract is always an appropriate proxy for more distant contracts. The root of this assumption is the common belief that the maturing period of a contract experiences the greatest interest, and thus volume of transactions, generating superior liquidity and more efficient pricing. Although it is true that average daily trading volume is higher in the maturing period of a contract (Table 1), the majority of trading occurs outside of this period and daily trading volumes are substantial in the early period (i.e., that are not included in a nearby contract). Indeed, average daily trading volumes in the early period of some contracts (December) exceed those in the maturing period of others (May). Moreover, the maturing period appears to be of varying significance across contracts as evidenced by the absolute and relative differences in volume traded at the end of contracts.

If there are no significant differences between intramarket contracts,[2] a nearby

---

[2] We use the term "market" to refer to the underlying commodity on a particular exchange, e.g., soft red winter wheat on the Chicago Board of Trade. Within each futures market there are multiple contracts, each having a different delivery date.

contract price series should permit relatively smooth rolling of hedges across sequenced contracts, as is necessary for market participants undertaking anything other than short-duration hedging (i.e., 60 or fewer days). If, however, the specific contract prices do not follow the same data generating process, analysis of nearby contract price series will yield inconsistent estimates of the contract price distribution(s) of interest due to misspecification.

There are theoretical reasons to expect significant differences across individual contracts. While it does not offer a complete explanation of commodity price behavior, a rational expectations competitive storage model can nonetheless explain a number of empirical regularities in commodity spot price series, including positive skewness, the existence of rare but violent explosions in prices, and a high degree of price autocorrelation in more stable periods (Williams and Wright 1991; Deaton and Laroque 1992). But these properties result from underlying storage, information and innovation patterns that influence speculative agents' expectations and equilibrium pricing behavior and which may vary across seasonally distinct futures contracts.

Recent empirical findings also cast doubt on the appropriateness of composite, nearby contract prices as a proxy for specific commodity futures contract price series. For example, Thilmany, Li and Barrett (1996) found significant differences between May and September winter wheat futures prices. The latter matures following the U.S. harvest, during a season of considerable inventories, while the former matures just prior to harvest, when inventories hit seasonal lows. Contracts maturing at different points of the year may follow significantly different price generating processes, probably due to sharp seasonal differences in inventories, information availability, and the nature of demand and supply shocks.

Understanding intramarket differences in futures pricing has practical importance. Producers, elevators, processors or manufacturers hedging through futures markets to mitigate price risk tend not to use all contract delivery months uniformly. These agents need information on the price behavior and optimal hedging strategy related to a (few) particular contract(s), not to the composite nearby contract price series commonly studied by researchers. This is not always taken into consideration when developing appropriate analytical, hedging and general investment tools (CBOT 1984; Hull 1994). The recent controversy surrounding hybrid contracts is one relevant example. Hybrid contracts rely on hedgers' ability to roll nearby hedges across contracts and growing seasons. Recent negative publicity and legal action surrounding such contracts calls hybrids into question (Harl 1996).

Empirical Analysis

We use daily soft red winter wheat futures contract price data from the close of each trading day on the Chicago Board of Trade, January 1991 to December 1995 inclusive. We include each of the five different soft red winter wheat contracts—March, May, July, September and December—in the analysis along with the nearby contract series constructed from those data. Table 2 presents simple descriptive statistics of these six series. Although there are many similarities across the contracts (i.e., high autocorrelation and low persistence), the nearby contract series appears to be more variable, less positively skewed and less leptokurtic than any of its component contracts.

We model each futures price series as an autoregressive integrated moving average

(ARIMA) process. First, augmented Dickey-Fuller (ADF) tests indicated that each of the price series is integrated of order one in its logarithm, so henceforth we use first-differenced log price series ($\Delta \ln P$) as the dependent variables. We next used the Akaike information criterion (AIC) to identify the time-series dimensionality of the stationary $\Delta \ln P$ series. By including lags of up to five days in both the dependent variable and the residuals—i.e., fitting an ARIMA (5,1,5) model—as suggested by the AIC, the residuals from each contract price model follow a white noise process, as indicated by Ljung-Box-Pierce portmanteau Q-statistics. Finally, there is a point each year where the data set rolled over from the maturing year's to the next year's contract. We include the number of truncated days as a regressor on the day the rollover occurred; TRUN takes zero value all other days. Not only does this control for the time-series shock of the truncation, but it accommodates contract arrival effects on futures price behavior.[3] Each contract price series thus is specified as in equation (1), where $Y_t = \Delta \ln P_t$.

$$(1)\ Y_t = \alpha_0 + \alpha_1 TRUN + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \phi_3 Y_{t-3} + \phi_4 Y_{t-4} + \phi_5 Y_{t-5} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \theta_3 \varepsilon_{t-3} + \theta_4 \varepsilon_{t-4} + \theta_5 \varepsilon_{t-5}$$

Next we tested for GARCH effects using the Q-statistic on the squared residuals. Where GARCH effects were found, the time-series dimensionality of the conditional variance was identified following Bollerslev (1988). The sufficiency of these GARCH specifications were verified by a Q-test of the squared

---

[3] Not all contracts begin, or "arrive", on the same date each year. Shocks to demand for futures contracts not only influence pricing, they may also cause a new futures contract to arrive earlier or later than other years. Thilmany, Li and Barrett (1996) find significant variation in contract arrivals and durations in September winter wheat futures.

normalized residuals.

Tables 3 and 4 report significant differences in price behavior among the contracts.[4] Table 3 offers three key indicators of these differences. For instance, there is considerable difference in magnitude and sign of day-to-day (i.e., first-order) autoregression coefficient estimates. Unlike the July and September contract price series which exhibit GARCH effects, the March, May and December contracts do not exhibit autocorrelation in conditional variance. This is likely attributable to lower inventories and lesser importance of crop information shocks, and hence less intertemporal transmission of shocks to contract price risk in these pre-harvest contracts. Most fundamentally, for each of the five delivery contracts, χ^2 tests overwhelmingly reject the null hypothesis that all the coefficients are equal to those of the nearby contract series. Indeed, Table 4 shows that statistical tests overwhelmingly reject the hypothesis that any pair of the delivery contracts evince identical time series properties.

Conclusions

The primary objective of this paper was to test the statistical validity of price analysis or hedging strategies based on nearby futures contract price series. Our findings suggest that research, marketing and risk management techniques which rely heavily on nearby contract price analysis should be reconsidered. No two series of Chicago Board of Trade winter wheat futures contract prices follow the same data generating process, highlighting the importance of differences in underlying market conditions—e.g., storage

[4] An appendix available from the authors contains full details of the empirical results.

and information patterns—on equilibrium pricing.

Table 1. Trade Volume Data, CBOT Soft Winter Wheat Futures, 1991-1995

5000 Bushel Contracts	Average Daily Volume of Early Period[1]	Average Daily Volume of Maturing Period[2]	Average Daily Trading Volume Entire Contract	Maturing Period's Share of Total Trading Volume
March	1,857	5,849	2,700	45.70%
May	1,057	2,300	1,228	26.30%
July	2,021	5,769	2,417	27.31%
Sept.	1,073	3,212	1,328	33.39%
December	2,525	7,377	3,373	38.93%

[1] The early period is that not included in a nearby contract price series.
[2] The maturing period is that included in a nearby contract price series.

Table 2. Descriptive Statistics for Individual Contracts

	Autocorrelation (days)				Coeff. of	Persistence (days				
	1	2	3	4	Variation	60	90	120	Skewness	Kurtosis
March	0.995	0.990	0.986	0.982	0.146	0.0026	0.0025	0.0024	0.720	3.776
May	0.995	0.990	0.986	0.982	0.128	0.0016	0.0017	0.0017	0.640	3.613
July	0.993	0.987	0.980	0.973	0.114	0.0013	0.0012	0.0012	0.771	3.461
Sept.	0.994	0.988	0.982	0.976	0.123	0.0016	0.0014	0.0014	0.988	3.702
Dec.	0.994	0.989	0.984	0.979	0.139	0.0019	0.0020	0.0020	1.234	4.321
Nearby	0.995	0.990	0.985	0.981	0.158	0.0032	0.0034	0.0034	0.611	3.448

Note: The persistence is the normalized spectral density at zero. The relative skewness measure is $\mu_3/(\mu_2)^{1.5}$, and the relative kurtosis measure is $\mu_4/(\mu_2)^2$, where μ_i is the ith central moment.

Table 3. Estimation Results for Wheat Futures Contracts

Estimated Properties	Futures Contract					
	Mar	May	JulSep	Dec	Nearby	
AR(1) coefficient	0.57	0.37	0.27	-0.32	0.44	-0.18
GARCH effects?	No	No	Yes	Yes	No	No
χ^2 (12) stat of H_0: $\underset{\sim}{\beta}_i = \underset{\sim}{\beta}_{nearby}$ (critical value= 26.22 at .01 level)	88,204	107	209	73	400	

Table 4. Joint Test Statistics for Structures of Different Contracts
(H_0: $\underset{\sim}{\beta}_i = \underset{\sim}{\beta}_j$ for contracts i and j)

	March	May	July	September	December	Nearby
March	–	183.24*	502.54*	110.70*	1,572.78*	88,204.00*
May		–	69.65*	73.41*	539.05*	107.24*
July			–	307.44*	1,315.36*	208.63*
September				–	219.89*	72.59*
December					–	399.69*

Note: The joint tests follow χ^2 (12) distribution, for which the critical value=26.22 at .01 significance level.

Technical Appendix

Table A1. ARIMA(5,1,5) Results for March Contract

Dependent Variable: Y_t	Coefficient	t-Statistic
α_0	0.0006	1.7420
α_1	-0.0004	-3.2102*
ϕ_1	0.5707	10.6177*
ϕ_2	-0.1900	-5.0062*
ϕ_3	0.5070	14.0130*
ϕ_4	0.2271	6.0408*
ϕ_5	-0.5849	-11.8068*
θ_1	-0.5720	-12.2903*
θ_2	0.1289	5.7302*
θ_3	-0.4989	-16.7721*
θ_4	-0.2707	-9.9795*
θ_5	0.6408	14.9269*
F-statistic	2.9100	p-value=0.0008
Box-Pierce Q for $\lrcorner_t$	8.3869	p-value=0.9960
Box-Pierce Q for $\lrcorner_t^2$	0.9857	p-value=1.0000

Table A2. ARIMA(5,1,5) Results for May Contract

Dependent Variable: Y_t	Coefficient	t-Statistic
α_0	0.0005	1.4441
α_1	0.0000	-0.1212
ϕ_1	0.3693	1.0883
ϕ_2	-0.7259	-1.7805
ϕ_3	-0.2057	-0.3964
ϕ_4	-0.0497	-0.1391
ϕ_5	-0.5231	-2.0415*
θ_1	-0.3173	-0.9360
θ_2	0.6422	1.6218
θ_3	0.2276	0.4769
θ_4	0.0430	0.1309
θ_5	0.4498	1.9533
F-statistic	2.7995	p-value=0.0013
Box-Pierce Q for $\lrcorner_t$	8.0990	p-value=0.9910
Box-Pierce Q for $\lrcorner_t^2$	3.6708	p-value=1.0000

Table A3. ARIMA(5,1,5) Results for July Contract

Dependent Variable: Y_t	Coefficient	t-Statistic
α_0	0.0005	1.5386
α_1	-0.0002	-7.1368*
ϕ_1	0.2733	0.7579
ϕ_2	-0.5280	-1.2147
ϕ_3	-0.5518	-1.4539
ϕ_4	0.0891	0.3514
ϕ_5	-0.3246	-1.7880
θ_1	-0.2273	-0.6299
θ_2	0.5001	1.1919
θ_3	0.6149	1.7729
θ_4	-0.0952	-0.3936
θ_5	0.2958	1.5776
F-statistic	6.2232	p-value=0.000
Box-Pierce Q for $\lrcorner_t$	9.1506	p-value=0.9810
Box-Pierce Q for $\lrcorner_t^2$	45.0980	p-value=0.0010

Table A4. ARIMA(5,1,5) Results for September Contract

Dependent Variable: Y_t	Coefficient	t-Statistic
α_0	0.0005	1.4852
α_1	-0.0005	-5.9939*
ϕ_1	-0.3159	-0.7270
ϕ_2	-0.4678	-1.5169
ϕ_3	-0.2671	-0.8841
ϕ_4	0.4104	1.5804
ϕ_5	-0.2138	-0.6061
θ_1	0.3640	0.8303
θ_2	0.4201	1.3271
θ_3	0.1924	0.6331
θ_4	-0.4355	-1.6694
θ_5	0.1416	0.4024
F-statistic	6.2648	p-value=0.9960
Box-Pierce Q for $\lrcorner_t$	15.5390	p-value=0.8020
Box-Pierce Q for $\lrcorner_t^2$	167.99	p-value=0.0000

Table A5. ARIMA(5,1,5) Results for December Contract

Dependent Variable: Y_t	Coefficient	t-Statistic
α_0	0.0007	2.2361*
α_1	-0.0009	-19.1162*
ϕ_1	0.4445	2.1994*
ϕ_2	-0.7884	-5.6133*
ϕ_3	-0.1275	-0.5740
ϕ_4	0.1526	1.0722
ϕ_5	-0.6049	-5.6613*
θ_1	-0.4025	-1.9497
θ_2	0.7313	5.4651*
θ_3	0.1565	0.7493
θ_4	-0.2015	-1.4766
θ_5	0.5708	5.1660*
F-statistic	35.3826	p-value=0.0000
Box-Pierce Q for ε_t	21.1870	p-value=0.3860
Box-Pierce Q for ε_t^2	27.2270	p-value=0.1290

Table A6. ARIMA(5,1,5) Results for Nearby Contract

Dependent Variable: Y_t	Coefficient	t-Statistic
α_0	0.0009	2.0523*
α_1	-0.0001	-4.7563*
ϕ_1	-0.1764	-0.5756
ϕ_2	-0.3093	-2.0288*
ϕ_3	-0.3129	-2.3955*
ϕ_4	0.5443	3.9901*
ϕ_5	-0.2098	-0.8868
θ_1	0.2128	0.6904
θ_2	0.2600	1.6807
θ_3	0.3164	2.4506*
θ_4	-0.5670	-4.0825*
θ_5	0.1513	0.6334
F-statistic	3.5697	p-value=0.0000
Box-Pierce Q for ε_t	9.9658	p-value=0.9690
Box-Pierce Q for ε_t^2	2.4419	p-value=1.0000

Bibliography

Blank, S.C. (1991): "Chaos in Futures Markets? A Nonlinear Dynamical Analysis," *Journal of Futures Markets*, 11:711-28.

Bollerslev, T. (1988): "On the Correlation Structure for the Generalized Autoregressive Conditional Heteroskedastic Process," *Journal of Time Series Analysis*, 9:121-31.

Chicago Board of Trade (CBOT) (1984): *Introduction to Hedging*. Chicago: CBOT Press.

Deaton, A., and Laroque, G. (1992): "On the Behavior of Commodity Prices," *Review of Economic Studies*, 59:1-23.

Harl, N.E. (1996): "Hedge-to-Arrive Contracts," *AgriFinance*: 28-30.

Hull, J.C. (1995): *Introduction to Futures and Options Markets*, 2nd edition. Prentice-Hall Business Publishing.

Thilmany, D., J. Li, and C. Barrett (1996): "Wheat Futures Price Behavior: Theoretical and Empirical Considerations." *Proceedings of NCR-134 Conference on Applied Commodity Price Analysis, Forecasting and Market Risk Management*. Chicago, IL: Chicago Mercantile Exchage.

Williams, J.C., and Wright, B.D. (1991): *Storage and Commodity Markets.* New York: Cambridge University Press.

Yang, S.R., and Brorsen, B.W. (1995): "Nonlinear Dynamics of Daily Futures Prices: Conditional Heteroskedasticity or Chaos?," *The Journal of Futures Markets*, 13:175-91.