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FORWARD-PRICING MODELS FOR FUTURES MARKETS: SOME STATISTICAL AND INTERPRETATIVE ISSUES†

Econometric analyses of the forward-pricing efficiency of futures markets have involved both the aggregation of observations over contract months and disaggregation for individual contract months. If the equations are fully disaggregated (specifying a single contract month with a fixed lag), the equations have just one observation on each variable per year. For example, an analysis of the March corn contract six months prior to maturity would use annual observations on the March corn futures prices observed in September. Given frequent intervention by the government in grain markets and the relative newness of other futures markets, the number of years available for analysis is likely to be small. Even if the underlying price series is generated by a random walk process, a small sample from such a series may give potentially misleading results. Thus, pooling of observations over different contract months may seem reasonable.

As is well-known, however, the introduction of new information into a market influences the entire constellation of prices, not just those for a single contract month (Working, 1942, 1948). Consequently, to some degree, the pooling of prices from different contract months does not add new information; these data are not generated by separate, independent experiments. Thus, the common method of pooling can also be misleading, and the problem can be compounded if the sample spans a time period with aberrant observations evident in all contract months trading.

The seemingly unrelated regressions framework is appropriate for pooling forward pricing equations. This framework takes account of the degree of correlation among regressors in the different equations as well as among the error terms. But the seemingly unrelated regressions framework is not a panacea for short data sets or the uncritical pooling of outliers.

In this paper we discuss some methodological issues in testing the forward-pricing efficiency of futures markets. We first review a few of the implications of the random walk model of price behavior, which provide the basis for market efficiency tests. Then, we specify a forward-pricing (efficient market) model and discuss the possible effects of influential time periods or outliers. Finally, an empirical analysis of live cattle, corn, and soybean futures is presented to illustrate the problems of interpreting results.

IMPLICATIONS OF RANDOM WALKS

In a random walk, the price series evolves according to the equation

$$P_{t+1} = P_t + e_{t+1}, \tag{1}$$

where e_{t+1} is a random variable with a zero mean and is drawn independently each time period. A rationale for this model is contained in Working's classic paper on anticipatory prices (1958). Namely, in an efficient market, current price P_t reflects known information; truly new information is unexpected and occurs randomly; when the unanticipated does occur, it is reflected promptly in the new price, and hence the price changes are random, $P_{t+1} - P_t = e_{t+1}$.

The random walk model is perhaps an over-simplification of reality (Samuelson, 1965, 1976). Futures prices are not free to wander anywhere; they will terminate in a maturity month at a price that is determined by economic conditions. Samuelson also hypothesizes that the variance of e_t may increase as the maturity month approaches. But, both the random walk and Samuelson's martingale models assume that the expected price changes are serially independent.

In these models, the current price is the market's best estimate of the maturity month price, and price changes cannot be forecast. Of course, unexpected events occur each year, and the sequence of random events can create a price series with upward and downward "trends" (Working, 1934). That is, the random walk model does not preclude the possibility of new information flowing in such a way as to cause prices to move in a systematic fashion over some particular time span. If the price changes are random, however, the pattern of movement in one time period cannot be used to forecast the movement in another.

Since a random walk can generate prices which seem to have systematic components, it may be exceedingly difficult to discriminate between prices from an efficient market and those from an inefficient market, especially when sample sizes are small. This also helps explain why technical trading rules can coexist

with prices that are generated by a random walk or martingale process. An analysis of a historical price series often can identify a trading rule that is profitable for a particular period. Of course, if the series is indeed random, the rule developed for one time period will not work, on average, for a longer period. It is not truly predictive. (These points are illustrated in Tomek and Querin, 1984.)

Some analysts (for example, Houthakker, 1961; Stevenson and Bear, 1970) have used profits based on technical trading rules as evidence of nonrandomness of price changes. However, as the foregoing discussion suggests, such rules can be profitable over certain time spans when applied to a random series. Thus, one must be exceedingly cautious about drawing conclusions concerning nonrandomness from such analyses.

TESTING FOR WEAK FORM MARKET EFFICIENCY

To test for market efficiency, many researchers have estimated the traditional forward pricing (weak form efficiency) model which makes the maturity time price a function of a prior futures price (Fama, 1970; Tomek and Gray, 1970).

$$P_{jt} = \alpha_{ji} + \beta_{ji} \, P_{jt-i} + \varepsilon_{jit}, \tag{2}$$

where

P = futures price,

$t = 1, 2, \ldots,$ T years,

$i = 1, 2, \ldots,$ I lags,[1]

$j = 1, 2, \ldots,$ J contract maturities,

      e.g., $J = 5$ for corn, and the price for the

      t^{th} period is treated as the maturity price.

For a given i and j—a single equation—the ε_{jit} are typically assumed to have the classical properties of a zero mean, constant variance, and zero covariances over the $t = 1, \ldots,$ T observations.

In an efficient market, $\alpha_{ji} = 0$ and $\beta_{ji} = 1$ for all i and j if one assumes zero transaction costs. Thus, one can test for market efficiency

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[1] Monthly observations will be assumed for convenience. The maximum lag depends on how soon trading starts before maturity. Currently, trading in agricultural commodities often starts 12 to 15 months before maturity, but historically the maximum I is usually six to ten months, depending on the commodity and historical period. Also, in contrast to Equation (1), many lags, rather than a single lag, are being explored.

by testing whether $\alpha_{ji} = 0$ and $\beta_{ji} = 1$.[2] If all I lags and J contracts are considered, then there are $I \times J$ equations to be fitted. In practice, some analysts have fitted a subset of the total as separate equations (for example, Tomek and Gray, 1970). Other analysts have pooled subsets of the data, typically pooling data for the same lag length across different contract months (Leuthold, 1974).

A variant of Equation (2) also deserves comment, namely,

$$P_{jt} - P_{jt-i} = \alpha_{ji} + \delta_{ji} \, P_{jt-i} + \varepsilon_{jit}, \qquad (3)$$

where $\delta_{ji} = \beta_{ji} - 1$. In this version, the null hypothesis of an efficient market is $\alpha_{ji} = \delta_{ji} = 0$. Firch (1982) fitted this model (using deflated prices) without pooling, while Kolb et al. (1983) pooled observations over a large number of contracts. The Kolb et al. analysis, rather than being in a regression framework, tests the hypothesis $\alpha_{ji} = 0$, using the computed differences based on the $P_{jt} - P_{jt-i}$; they test the null hypothesis both for a contract with varying lags and for different contracts with a fixed lag.[3]

Aggregating or Not Aggregating the Data

As discussed earlier, it seems natural to pool the price data from the various contract months trading simultaneously to increase the number of observations relative to the number of parameters to be estimated. However, the prices for the various contract months for a particular market are correlated. Thus, the pooling of such observations carries the danger of biasing tests toward finding inefficient markets.

A hypothetical example in which additional observations merely duplicate the original information—no new information is added—illuminates the problem (Table 1). The example involves testing the null hypothesis $\mu = 0$ based on samples of n observations. The t-ratio grows as the sample size n grows. This is the expected and intended result, assuming the added data represent new information; that is, we should become more and more confident, given the hypothesized data, that the true mean is not zero. On the other hand, if the true mean is zero and if, as in the example, a small sample is merely

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[2] Of course, transaction costs are never zero. As a result, "any nonrandom elements that are too small to permit superior traders to profit by eliminating them, after paying transactions and other costs, might be expected to persist. ...[A more realistic random walk hypothesis is] that any dependencies in the series of price changes are too small to provide opportunities for traders to profit from eliminating them after paying transactions costs and other expenses" (West and Tinç, 1971, pp. 175–76). Analysts who test for market efficiency without adjusting for transaction costs apparently assume that transaction costs are insignificant. Transaction costs are assumed to be insignificant throughout this paper also.

[3] In practice, the hypothesis is formulated somewhat differently by Kolb et al. (1983), but this difference is not important to the point of our paper.

Table 1.—Effect of Duplicating Data
on the Test of Hypothesis $\mu = 0^*$

n	$\bar{x}$	s	$s_{\bar{x}}$	t
3	1	1.00	0.58	1.72
6	1	0.89	0.36	2.78
9	1	0.87	0.29	3.45
12	1	0.82	0.24	4.17
15	1	0.82	0.21	4.76

*The observations ($n = 3$) are 0, 1, 2. Subsequent samples merely duplicate this sample. $t = \bar{x}/s_{\bar{x}}$ under the null hypothesis that the true mean (μ) equals zero, $\bar{x}$ is the arithmetic mean, and $s_{\bar{x}}$ the standard deviation of the mean.

being duplicated, then this "pooling" is increasing our confidence in the wrong answer.

In practice, prices for the different contract months are not perfectly correlated and the example is an exaggerated analogy. The price for each contract month contributes some new information, and the correlation among prices for different contract months varies from commodity to commodity. Prices for the different corn contracts are, for example, likely to be more highly correlated than those for the different potato contracts (Tomek and Gray, 1970). Ultimately, the amount of independent information in the price series for each contract month is an empirical question.

Aggregating observations may also exaggerate the importance of exceptional observations caused by factors external to the market. For example, an embargo could influence an entire constellation of futures and spot prices over a particular time span. This effect might appear as a single outlier in one equation, but appear in multiple observations of a pooled data set. Thus, pooling could amplify the influence of a single event (time span) on the overall results. The market may be efficient, and the rejection of the efficient market hypothesis may be a consequence of aberrant observations (forgivable errors) from a limited time period.

The effect of the 1973 soybean embargo on soybean price relations is illustrated in Charts 1 and 2. The plots represent the data for the July and August soybean futures contracts with an eight-month lag. Since the market could hardly have anticipated the embargo, the case can be made that the forecasting errors in 1973 do not represent a market failure. The observations in Charts 1 and 2 make clear that pooling, without deleting observations, could compound the problem of outliers. In addition, the observations in Charts 1 and 2 show the apparent correlation between the residuals for the two relationships. Thus, problems can arise when futures prices across contract months are pooled in one equation.

In addition, the aggregation of data requires an assumption that market efficiency does not vary from contract month to contract month or from time

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Chart 1.—Change in the Price of July Soybean
Futures Contract from November to July as a
Function of the Price in November: 1973–82
(Dollars per bushel)
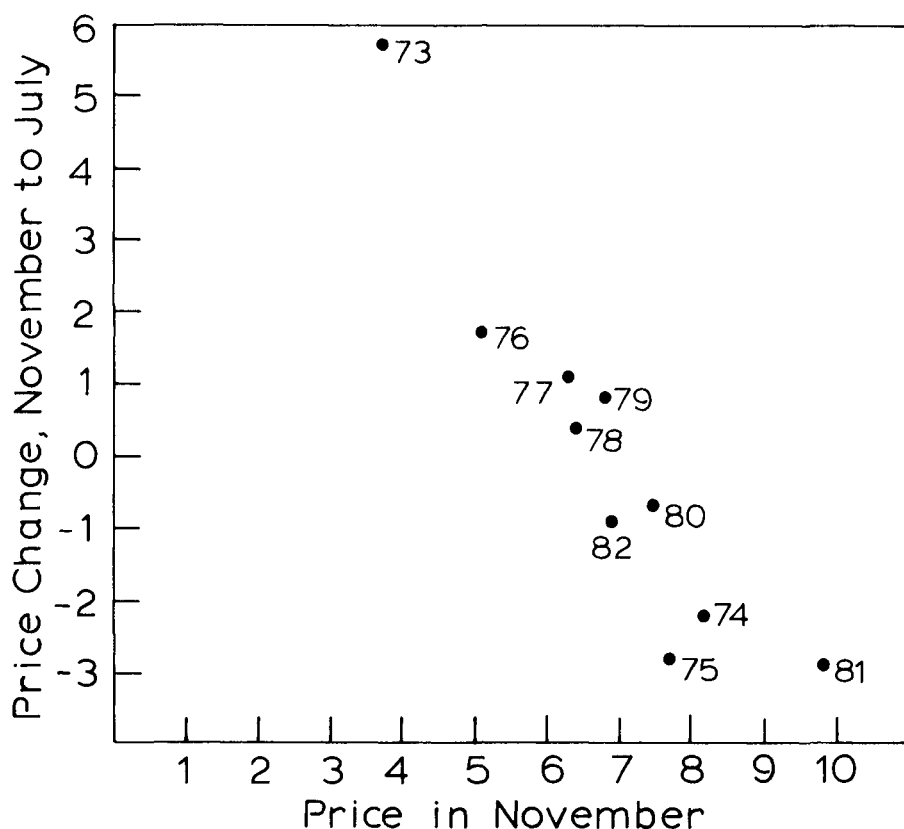
to time. This assumption seems plausible. No strong reasons exist for the degree of market efficiency to differ from contract month to contract month. However, Leath and Garcia (1983) found differences in the predictive reliability of the various corn contract months at different months prior to maturity, and Leuthold (1975) and Martin and Garcia (1981) suggest that seasonality in volume of trading in cattle futures could have a differential effect on efficiency.

Because of the problems with aggregating data, one may conclude that disaggregated data should be used. However, when disaggregated data are used, one frequently has few degrees of freedom. Data limitations (because the futures contract has not traded many years or because of changes in contract specifications) may reduce the reliability of results. In addition, by using disaggregated data, one may be ignoring additional relevant information that is available.

Chart 2.—Change in the Price of August Soybean
Futures Contract from December to August as a
Function of the Price in December: 1973–82
(Dollars per bushel)
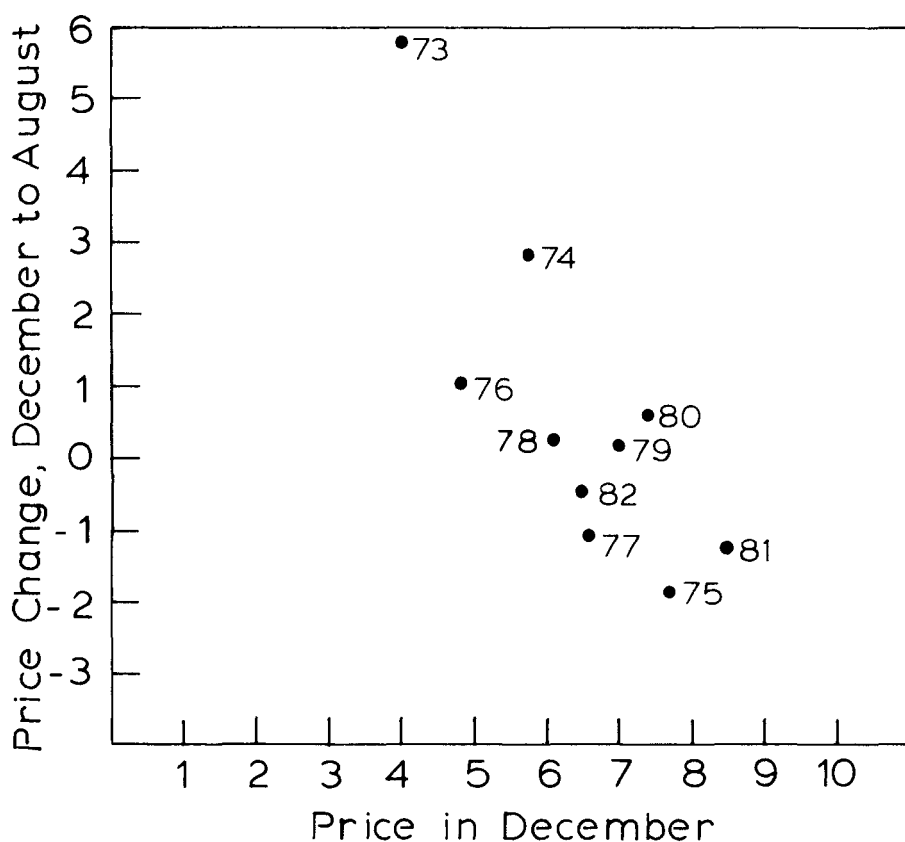
Recommended Methodology

The seemingly unrelated regressions model is theoretically superior both to pooling the data across contract months and estimating equations for each contract month and each lag independently. Seemingly unrelated regressions does not artificially increase the degrees of freedom, and it uses the additional relevant information that is available. Generalized least squares applied to a system of equations is statistically more efficient than ordinary least squares applied to the individual equations, provided that the contemporaneous covariances are indeed not zero, and that the explanatory variables differ across equations (Zellner, 1962).[4]

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[4] We do not consider the possibility of non-zero lagged covariances, i.e., if i and j are constant, the possibility that t and $t - i$ are correlated. Given the monthly data,

The contemporaneous covariances for the ε_{jit} across equations for the different i and j are not likely to be zero in the market efficiency application. For example, let j be constant, say $j = 1$ represent the February live cattle contract, then as the lag i varies, the equations clearly have a certain time span in common. The equation for lag $i = 4$ covers two-thirds of the same period as the equation for lag $i = 6$. Thus they will have certain errors in common. Likewise, if we consider different contracts, say $j = 1$ and 2, with the same or different lag lengths, they often will have a sufficient time period in common that their residuals will have common components.

The explanatory variables may also be quite highly correlated across equations. However, the degree of correlation among the lagged prices (the regressors) will vary with the particular commodities being considered as well as with the nature of the lags used within particular market analyses. Thus, the improvement in efficiency generated by generalized least squares is an empirical matter, but in essence the seemingly unrelated regression model formalizes the issues related to cross-equation correlations in the regressors and error terms.

Rather than test $\alpha_{ji} = 0$ and $\delta_{ji} = 0$ as separate hypotheses, it is preferable to test $\alpha_{ji} = \delta_{ji} = 0$ (Martin and Garcia, 1981). If $\delta_{ji} \neq 0$, then typically $\alpha_{ji} \neq 0$; that is, if the slope is not zero, then projecting the regression back to the price-change axis typically would result in an intercept different than zero. The critical question in the framework of Equation (3) is, does the price level at time $t - i$ have predictive power? Specifically, is

$$E[P_{jt} - P_{jt-i}|P_{jt-i}] = 0?$$

Conditional on a particular P_{*t-i}, the estimated price change is $\hat{\alpha}_{ji} + \hat{\delta}_{ji} \, P_{*t-i}$, and under the null hypothesis that the price change is zero, the test statistic is the foregoing conditional mean divided by its standard error, which is a standard error of forecast. For ordinary least squares estimation, a t test is assumed appropriate; for seemingly unrelated regression estimation, Hotelling's T^2 statistic is used (Johnston, 1972).

EMPIRICAL ANALYSIS

Equation (3) was estimated using both ordinary least squares and seemingly unrelated regressions using futures price data for corn and soybeans traded at the Chicago Board of Trade and live cattle traded at the Chicago Mercantile Exchange.[5] Price data were used for all futures contract months maturing in crop years 1972–81 for corn and soybeans and in calendar years 1969–81 for

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it seems unlikely that the errors will be autocorrelated for an individual equation, and hence we would not expect the lagged covariances across equations to be nonzero.

[5] The empirical results for live cattle have been published by Barton and Tomek (1984).

live cattle.[6] The closing futures price on the first trading day of the maturity month was assumed to be the maturity price (i.e., the price for the tth period).[7] The equation was estimated using data for representative lags of two, four, six, and eight months prior to maturity.[8] Closing futures prices on the fifteenth day of the month (or the closest business day to the fifteenth day) were selected as representative of prices during these lagged months.

Ordinary Least Squares Results

Ordinary least squares was used to estimate Equation (3) for each futures contract for each lag. Twenty equations were estimated using corn data, because there are five corn futures contract months and we selected four lags. Twenty-eight soybean equations (seven contracts, four lags) and twenty-four cattle equations (six contracts, four lags) also were estimated. There were ten observations for each corn and soybean regression and thirteen observations for each cattle regression. The results for selected regressions are given in Table 2.

In almost all cases, the intercept is positive and the slope is negative for all three commodities.[9] The corrected coefficient of determination and the

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[6] Corn price data were collected for all December futures contracts maturing in 1972–81 and for all March, May, July, and September futures contracts maturing in 1973–82. Soybean price data were collected for all September and November futures contracts maturing in 1972–81 and all January, March, May, July, and August futures contracts maturing in 1973–82.

[7] Alternatively, one could have used the price on the last trading day of the maturity month or an average of the prices on the last few trading days as the maturity price. The use of the futures price on the first trading day of the maturity month as the maturity price reduces the problems of using prices obtained from thinly traded markets.

[8] Only four representative lags were selected in an attempt to illustrate the different empirical results obtained from using different methodologies without an overwhelming set of numbers.

[9] The intercept is positive in 26 out of 28 soybean regressions, 19 out of 20 corn regressions, and in all 24 cattle regressions. The slope is negative in 26 out of 28 soybean regressions, 19 out of 20 corn regressions, and 22 out of 24 cattle regressions. These results are consistent with the regression results obtained by Leath and Garcia (1983) for the December, March, May, and July corn contract months one to eleven months prior to maturity. Leath pand Garcia estimated Equation (2) using the closing futures price at maturity for P_{jt} and the closing futures price on the last trading day of the month for P_{jt-i}. During the 1953–66 period, 39 out of their 44 regressions had positive intercepts. During the 1966–80 period, 41 out of the 44 regressions had positive intercepts. Because Leath and Garcia estimated Equation (2) instead of Equation (3), it is necessary to subtract one from their estimated slope to obtain an estimate of δ_{ji} in Equation (3). Estimates of δ_{ji} obtained from Leath and Garcia's results were negative in 39 out of 44 regressions for both periods analyzed. A plausible explanation of this pattern of results is given by Maberly (1985).

Table 2.—Regression Results for Selected Cattle,
Corn and Soybean Contracts
for Two- and Eight-Month Lags

Equations	Ordinary least squares				Seemingly unrelated regression	
	Intercept	Slope	$\bar{r}^2$	Durbin-Watson	Intercept	Slope
Summer						
2-month lag						
June beef	7.49	−0.14	.14	2.39	14.72	−0.29
	(1.80)[a]	(1.69)			(3.87)	(3.87)
July corn	0.88	−0.30	.14	1.83	1.97	−0.71
	(1.66)	(1.56)			(6.68)	(6.67)
July beans	3.17	−0.47	.30	1.91	4.80	−0.70
	(2.12)	(2.20)			(5.70)	(6.09)
8-month lag						
June beef	14.45	−0.23	.16	1.61	24.82	−0.47
	(2.35)	(1.77)			(4.73)	(4.26)
July corn	1.89	−0.69	.71	2.71	2.47	−0.90
	(4.48)	(4.79)			(11.37)	(13.01)
July beans	9.84	−1.43	.86	1.70	7.78	−1.13
	(7.30)	(7.49)			(11.01)	(12.06)
Fall						
2-month lag						
Dec. beef	4.03	−0.09	.08	2.28	9.27	−0.20
	(1.31)	(1.40)			(3.30)	(3.54)
Dec. corn	0.19	−0.08	−.02	2.35	0.63	−0.25
	(0.72)	(0.90)			(2.94)	(3.25)
Nov. beans	−0.43	0.06	−.10	2.95	1.39	−0.23
	(0.41)	(0.38)			(1.83)	(1.95)
8-month lag						
Dec. beef	6.86	−0.16	.09	3.03	13.57	−0.30
	(1.30)	(1.44)			(2.79)	(3.04)
Dec. corn	1.50	−0.54	.19	1.82	2.28	−0.85
	(1.85)	(1.75)			(5.72)	(6.21)
Nov. beans	2.69	−0.38	.07	3.10	4.59	−0.71
	(1.49)	(1.30)			(5.36)	(5.52)

[a] t-ratios.

intercept tend to increase and the slope tends to increase in absolute value
for each contract month as the lag increases. In addition, the t-statistics for

both the intercept and the slope tend to increase in absolute value for each contract month as the lag increases. The intercept and slope are significantly different from zero in almost half of the corn and soybean regressions.[10] The large *t*-values tend to occur more often in regressions having longer lags and in regressions for particular contract months. For example, the *t*-values for the intercept and the slope are significant for all soybean contract month regressions having eight-month lags except for the November contract. All of the significant *t*-values for the intercept and slope of the corn regressions occur in the March, May, and July contract months. Although the *t*-values for the intercept and slope are not significant in any of the cattle regressions, the *t*-values tend to be larger in absolute value for the longer lags and for particular contract months, as in the corn and soybean regressions. Thus, the results demonstrate some "seasonality." However, the observed seasonality may be unique to the sample period used in this analysis.

The Durbin-Watson statistics also show some evidence of seasonal behavior, although little or no evidence of positive autocorrelation exists. The hypothesis of positive autocorrelation is rejected in 24 of the 28 soybean regressions, in all corn regressions, and in 21 of the 24 cattle regressions. The hypothesis could not be rejected for all four regressions for the August soybean contract and two of the four regressions for the February cattle contract. As noted above, the seasonality of results may be an artifact of the time pattern of events observed in the particular samples, arising because of the correlation across commodities within the sample period selected.

The ordinary least squares results also show the increased *t*-statistics when data are pooled across contract months. The *t*-statistics for both the intercept and the slope are higher when the July and August soybean data are pooled than when the model is estimated using the July and August data separately (Table 3). In addition, the importance of a single aberrant observation is demonstrated by the results in Table 3. As discussed earlier, the market would not be expected to be able to predict the soybean embargo in the summer of 1973. The estimated coefficients in Equation (3) change substantially when the 1973 observation is deleted. If the 1973 observation is in fact an aberrant observation, pooling the data across contract months increases one's confidence in the inaccurately estimated coefficients.

Estimates of the correlation coefficients show a strong positive correlation between the disturbances of some of the ordinary least squares equations for each commodity. In general, the residuals are highly correlated if the data for the two equations cover a common time period. For example, the correlation between the residuals for the February cattle contract with a lag of six months and the April contract with a lag of eight months is .880. The data for these

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[10] The intercept is significantly different from zero in 13 of the 28 soybean regressions and 8 of the 20 corn regressions. The slope is significantly different from zero in 12 soybean regressions and 9 corn regressions. All significance is determined at the 95 percent confidence level.

Table 3.—Regression Results for the July
and August Soybean Contract Months
Eight Months Before Maturity

Period	Contract month	Intercept	Slope	$\bar{r}^2$	Durbin-Watson
1973–82	July	9.84	−1.43	.86	1.70
		$(7.30)^a$	(7.49)		
	August	9.76	−1.41	.62	.78
		(4.15)	(3.96)		
	July and August pooled	9.83	−1.43	.77	1.27
		(8.18)	(8.11)		
1974–82	July	7.58	−1.14	.79	1.52
		(5.03)	(5.54)		
	August	5.87	−0.87	.36	1.47
		(2.31)	(2.33)		
	July and August pooled	7.00	−1.05	.64	1.29
		(5.31)	(5.63)		

^{a}t-ratios.

two equations cover a common time period of six months (i.e., from August to February). The correlations between the residuals for data without a common time period are often low and sometimes negative. For example, the correlation between the residuals for the January soybean contract with a two-month lag and the July contract with a two-month lag is −.375. In general, the correlations between the residuals for all three commodities are highest for those equations involving different lags for a particular contract month. It was impossible to estimate a full seemingly unrelated regressions system because of data limitations.[11] Thus, we fit the four equations (i.e., four lags) for each contract month as separate seemingly unrelated regressions models.[12]

The efficiency gains from using seeming unrelated regressions instead of ordinary least squares are greatest when the residuals are highly correlated but the independent variables are uncorrelated. Although the estimated correlations between the residuals for certain equations are relatively high, the independent variables are expected to be highly correlated as well. Estimates

[11] A full seemingly unrelated regressions system can be estimated only if the number of observations exceeds the number of equations. In the soybean, corn, and cattle examples in this paper, the number of equations in the full system exceeds the number of observations.

[12] As noted earlier, data have generally been pooled across contract months holding the lag length constant. In this paper, the data are pooled across different lags holding the contract month constant. The decision to pool the data across lags was based on the generally higher correlations between the residuals for these equations.

of the correlation coefficients between the independent variables show strong positive correlations for at least some of the regressors for each commodity. Correlations between the cattle prices were very high (.753 or greater). Much less correlation was observed between the corn and soybean prices. (Negative correlations were even observed in some cases.)

Seemingly Unrelated Regressions Results

As discussed above, seemingly unrelated regressions was used to estimate the four equations (i.e., lags) for each contract month for each commodity (corn, soybeans, and cattle). The results for selected regressions are given in Table 2.

In general, the estimated coefficients using seemingly unrelated regressions are farther from the theoretical values of zero than the ordinary least squares estimates and the *t*-statistics are larger in absolute value. The patterns evident in the ordinary least squares results are also apparent in the seemingly unrelated regressions results. The intercept is positive in all regressions for all commodities, and the slope is negative for all corn and cattle regressions and all but one soybean equation.

Given the consistent pattern of signs and the frequency of large *t* ratios on individual coefficients, it is tempting to conclude that these markets are inefficient. However, the hypothesis that $E[P_{jt} - P_{jt-i}|P_{jt-i}] = 0$ was tested for cattle and could not be rejected for P_{jt-i}'s within the range of historical observations. That is, the confidence interval around the estimated price change contains zero.[13]

In contrast to seemingly unrelated regressions (four equation system for four lags for a given contract), the common approach to pooling has combined prices with a fixed lag length for different contracts into one equation. This approach "averages" the coefficients of the separate equations. For example, the slope coefficients for July and August soybeans for the 1974–82 sample period are −1.14 and −0.87, respectively, while the pooled observations give a slope of −1.05 (Table 3). Analogous results (not shown) occur for corn and live cattle. The seemingly unrelated regressions estimator, of course, gives separate estimates of the coefficients of each equation.

Also, the fact that the seemingly unrelated regressions slope coefficient for July soybeans for the 1973–82 sample period (−1.13) almost equals the ordinary least squares slope with 1973 deleted (−1.14) is accidental. Seemingly unrelated regressions is not a remedy for the effects of aberrant observations on slope and intercept coefficients. Rather, seemingly unrelated regressions is the preferred

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[13] Tests in the seemingly unrelated regressions framework were made using a 25 percent level of significance rather than a typical 5 or 10 percent level, and the computed test statistics were less than the critical values based on this conservative approach. For example, the test statistic for the June beef equation with an eight-month lag (Table 2) using a price of $60 per hundredweight was 1.91. The critical value of the test statistic at the 25 percent level of significance is 3.27. For more detail on the test criterion and the results, see Barton and Tomek (1984, Appendix C).

estimator, from the viewpoint of statistical efficiency, when the residuals of the equations are correlated. But, to the extent that these correlations depend on outliers, the seemingly unrelated regressions variances can be misleadingly small.

CONCLUDING REMARKS

Price data for different futures maturity months are highly correlated. Thus, it is not surprising that the residuals of the ordinary least squares equations are correlated and that patterns are evident in the results. Theoretically, seemingly unrelated regressions is the appropriate methodology when analyzing price data for different futures contract months because it takes into account the correlation among the residuals of the equations. However, the efficiency gains from using seemingly unrelated regressions instead of ordinary least squares may be limited empirically by the high correlation among the regressors of the equations.

No methodology can overcome the problem of a small sample. The results of our research and those of others are highly sample specific. The similarities in the results of the three commodities presented here may be simply a function of the sample period selected.

The results of this paper are, in a sense, negative about weak form market efficiency tests. Short samples from highly variable price series simply do not lend themselves to definitive conclusions about market efficiency, at least in the weak form framework, even if appropriate methods are used. The results do illustrate, however, how pooling over different contract months or different lags, and particularly how pooling outliers can dramatically exaggerate the possibility of obtaining results that markets are inefficient.

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