Re-examination of the Pricing Efficiency of the Hog Futures Market

by

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A research topic of continual interest to economists is an assessment of whether markets perform efficiently. Inefficient markets can lead to erroneous price signals, and consequently, a misallocation of resources. Within the context of futures markets, forward pricing abilities are of particular interest since producers and other market participants use futures prices for production and marketing decisions (Gardner; Hurt and Garcia).

Numerous investigations on commodity futures markets have attempted to assess the degree and source of market inefficiencies using a variety of approaches (Kamara). Results have been mixed (Goss). The underlying theme of most price efficiency studies on futures markets is whether the market incorporates all available information. While many of these studies have found that futures do not incorporate "available" information in the pricing process, their findings may be limited due to the approaches used in the analysis as well as the evaluation of results.

In this study, a conventional semi-strong form analysis is used to examine the pricing efficiency in the live hog futures market within a mean squared error (MSE) framework. This approach provides an initial procedure for examining market efficiency by assessing the forecasting ability of the futures market versus alternative forecasters. However, the assessment of relative MSE provides only an indication of the potential of market inefficiency. It also is necessary to determine if the forecasting method is capable of generating risk-adjusted profits which exceed the costs of its usage (Rausser and Carter). This analysis tests and evaluates the pricing efficiency of the hog futures markets by comparing it to out-of-sample econometric, ARIMA, and composite forecasts. Evaluation is based on both MSEs and risk-return results generated from trading strategies which implement the most accurate forecasts.

Relevant Literature

The conventional approach for assessing futures market efficiency begins with the premise that a market is efficient relative to an information set if the price correctly reflects the information in the relevant set (Fama). In a forecasting sense, an efficient futures market provides the most accurate representation of subsequent spot prices. In this framework, finding a more accurate forecasting model than the futures market leads to the conclusion that the market is not processing information as effectively as might be expected and therefore is relatively inefficient.

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This method of efficient market evaluation can be limited by its failure to take into consideration factors which may explain why futures prices are biased expectations of subsequent spot prices. Several reasons are listed elsewhere (Garcia et al.), but maybe most important among them is that futures markets may not reflect all available information due to costs of gathering and processing information (Grossman and Stiglitz). Traders buy information to earn a higher return in the market, and in equilibrium the extra returns earned are just sufficient to offset the cost of information.

Thus, even if a particular model's forecast is more accurate than the forecasts of the futures markets, inefficiency does not necessarily follow due to risk and information costs. Joerding has recently shown that in an efficient market in which agents have rational expectations, market forecasts do not necessarily have a smaller MSE than every individual forecast. He shows that the discovery of a forecasting method with lower MSE than the futures market does not assure that an agent can earn abnormal profits and thus is not sufficient to conclude that the futures market is inefficient. Rausser and Carter argue that evaluation of MSE is only a necessary condition, and that a sufficient condition for inefficiency is to examine the risk-adjusted profits relative to the modeling and information costs.

Considerable empirical work exists on developing and estimating models on cash hogs which could be used for forecasting (e.g. Brandt and Bessler 1981, 1984). Relatively less work has been done on evaluating the out-of-sample forecasting accuracy of hog futures markets in a MSE framework. Just and Rausser examined on a quarterly basis the forecasting accuracy of the hog futures market for the period December 1976 through 1978 and found that the futures market outperformed commercial forecasts one quarter forward, but just the opposite for four quarters forward. Leuthold and Hartmann (1979, 1981) examined the forecasting accuracy of the live hog futures market using both monthly and quarterly econometric models of the hog market. While there existed periods where the futures market outperformed the econometric models, on balance their results suggested that the econometric representations were superior forecasters. Using a time series approach Shonkwiler suggests that hog futures prices more than two months from maturity do not represent rational forecasts.

In this paper the evaluation is carried beyond the traditional MSE framework, and a sufficiency test of market efficiency is performed. The next section discusses the model specification, data, and estimation results.

Econometric Modeling

The econometric model hypothesized to act as a performance norm is a demand-supply model of the live hog market using monthly data for 1976 through 1982. The initial objective was to portray the hog market accurately while attempting to keep the model as parsimonious as possible for forecasting. Supply, represented by hog slaughter, is a function of expected price, represented by lagged prices, and prices of inputs. Previous research noted above has demonstrated the importance of including sow farrowings from the previous 2 quarters and a set of seasonal monthly dummy variables.

Since the objective of the model is to forecast prices, the hog sector is assumed recursive and the demand equation is modeled as price dependent. Cattle slaughter, broiler slaughter and income per capita were also incorporated as shifters in the demand equation.

Preliminary results of the estimated model were not satisfactory with low R^2s and numerous insignificant variables. The changing hog cycle and possible changes in meat consumption patterns might explain these findings. In an attempt to improve the forecasting potential of the model, a practical approach was taken to identify its structure. Time series and correlation analyses were used to identify important lags between independent and dependent variables. Once important variables and their tentative lagged structures were identified, the Schwartz Bayesian information criterion (SBIC) was used to specify the exact nature of the relationships.[1]

The supply and demand models estimated by ordinary least squares are as follows (standard errors are in parenthesis):

$$
\begin{aligned}
SHOGS_t = {} & \underset{(165.86)}{130.09} + \underset{(.007)}{.071}FAR_{t-6,9} + \underset{(2.21)}{18.12}PHOGS_{t-13} - \underset{(1.63)}{7.59}PHOGS_{t-21} \\
& - \underset{(1.53)}{7.95}PHOGS_{t-34} + \underset{(.07)}{.30}SHOGS_{t-12} + \underset{(.081)}{.436}SHOGS_{t-14} - \underset{(.074)}{.246}SHOGS_{t-25} \\
& - \underset{(.072)}{.209}SHOGS_{t-27} - \underset{(.066)}{.259}SHOGS_{t-36} - \underset{(37.73)}{128.17}FEB + \underset{(38.82)}{175.34}MAR \\
& + \underset{(47.86)}{344.68}APR + \underset{(43.72)}{172.17}MAY + \underset{(41.24)}{158.42}JUN + \underset{(40.86)}{6.33}JUL + \underset{(38.57)}{77.77}AUG \\
& + \underset{(43.18)}{78.25}SEP + \underset{(52.55)}{220.03}OCT + \underset{(49.28)}{291.12}NOV + \underset{(38.29)}{117.02}DEC
\end{aligned}
$$

$\bar{R}^2 = .92$ SBIC = 1004.31
D.W. = 2.28

$$
\begin{aligned}
PHOGS_t = {} & - \underset{(27.90)}{57.81} - \underset{(.0025)}{.022}SHOGS_t - \underset{(.0028)}{.016}SHOGS_{t-1} - \underset{(.0033)}{.0072}SHOGS_{t-13} \\
& + \underset{(.0027)}{.0074}SHOGS_{t-17} + \underset{(.0024)}{.0097}SHOGS_{t-18} + \underset{(.0028)}{.0058}SHOGS_{t-23} \\
& + \underset{(.0042)}{.0085}SHOGS_{t-27} + \underset{(4.17)}{34.51}I/N - \underset{(.25)}{1.91}(I/N)^2 - \underset{(.087)}{.441}PHOGS_{t-13} \\
& + \underset{(.049)}{.206}PHOGS_{t-21} - \underset{(.089)}{.154}PHOGS_{t-27} - \underset{(1.38)}{7.01}FEB - \underset{(1.48)}{7.39}MAR - \underset{(1.52)}{5.71}APR \\
& - \underset{(1.75)}{4.24}MAY - \underset{(1.31)}{6.66}JUN - \underset{(1.52)}{8.18}JUL - \underset{(1.35)}{5.73}AUG - \underset{(1.81)}{4.41}SEP + \underset{(1.93)}{1.22}OCT
\end{aligned}
$$

$$+ \underset{(1.67)}{1.96NOV} + \underset{(1.51)}{1.99DEC}$$

$\bar{R}^2 = .90$ SBIC = 429.55
D.W. = 1.29

where SHOGS is hog slaughter, U.S., million pounds; FAR is sow farrowings, 10 states, 1,000 head; PHOGS is price of barrow and gilts, 7 markets, dollars for hundredweight; I/N is personal income per capita, U.S., dollars; FEB through DEC represent binary dummy variables. Sow farrowings are the average of the previous second and third quarters. The data were collected from standard public (government) sources. Prices and income are not deflated as our goal is to evaluate the performance of actual price-level forecasts.

The residuals from the estimated equations were examined and were found to be nonspherical. To incorporate this information for forecasting, the following ARIMA models were estimated from the residuals (U_t) of the supply and demand equations respectively:[2]

$$(1 - \underset{(.106)}{.229B^3} + \underset{(.110)}{.222B^{12}})\, U_t(\text{SHOGS}) = \underset{(6.27)}{.129}$$

$\chi^2(24) = 22.38$[3] SBIC = 912.9

$$(1 - \underset{(.102)}{.268B} + \underset{(.125)}{.365B^{12}})\, U_t(\text{PHOGS}) = - \underset{(.156)}{.024}$$

$\chi^2(24) = 21.85$ SBIC = 318.02

ARIMA Modeling

Initial identification efforts led to the specification of an ARIMA (2,0,0) model for hog prices. The estimated model, called ARIMA-I, is

$$(1 - \underset{(.0972)}{1.304B} + \underset{(.0970)}{.487B^2})\text{PHOGS}_t = \underset{(2.146)}{8.11}$$

$\chi^2\ (24) = 24.21$ SBIC = 408.34

The adequacy of the model was tested using an LM test proposed by Godfrey. The procedure tests the ARMA(2,0) specification against the hypothesis that the true specification is ARMA(2+m,0) or ARMA(2,m). In the case of a pure autoregressive null hypothesis, the test statistic is calculated by regressing the estimated residuals from the ARMA (2,0) on the dependent variable lagged up to 2+m periods. The statistic is nR^2, which is distributed as a χ^2 with m degrees of freedom.

We fail to reject the null hypothesis that the model is correctly specified for m = 1,2,...,10. However, for values of m greater than 10, we reject the null hypothesis at the .10 critical level. The LM test suggests an alternative model, however, "it will not help us distinguish between the desireability of additional autoregressive and additional moving average parameters" (Granger and Newbold, p. 101).

Further examination of the autocorrelations and partial autocorrelations, along with the results from the LM tests, led to the selection of an ARMA (13,0) model. This leads to potentially $2^{13} = 8,192$ different restricted models from which to choose. A subset of lags to include were selected based upon the size of autocorrelations and significance from the LM tests to reduce the number of choices. Over 125 different models were then estimated and compared.

The residuals from each estimated model were first checked for white noise using a modified Box-Pierce Q-statistic (Ljung and Box). Next, the SBIC was computed for each model in which the residuals exhibit white noise. Four models were virtually identical based on the SBIC criterion. The model, designated ARIMA-II, with the lowest SBIC over the January 1976 to December 1982 sample period is:

$$\underset{}{(1} - \underset{(.094)}{1.171B} + \underset{(.092)}{.383B^2} - \underset{(.055)}{.119B^{11}} + \underset{(.057)}{.237B^{13}})PHOGS_t = \underset{(2.84)}{14.587}$$

$$\chi^2(24) = 16.97 \qquad \text{SBIC} = 399.70$$

This model and the original ARMA (2,0), ARIMA-I, are re-estimated each period during the out-of-sample market simulation. Details are presented below.

Updating and Forecasting

In order to utilize potentially new information about market relationships in subsequent observations which may affect later forecasts, all the models were re-estimated each period incorporating new observations in the data set. The procedure followed in this study was to drop the oldest observation as each new observation was added, keeping constant the number of observations in each estimation. This procedure limits the memory of the system by totally discounting the most distant information (Harvey, p. 194). This discounting permits the estimates of the structure to respond more quickly to the fundamental structural changes than when old observations are retained.[4]

Each month new out-of-sample forecasts are obtained for horizons 1 to 6 months for each model and mean squared errors calculated. This updating, re-estimating and subsequent forecasting procedure continues from January 1983 through December 1985. In the econometric model, only the unlagged variable, I/N, needs to be forecasted exogenously. This is done using a simple trend model.

All the models (and error structure of the econometric model) were checked for appropriate specification at each time period. ARIMA-I maintained the same specification throughout the forecasting period, although during 1985 it failed the test for white noise residuals. ARIMA-II changed specification once through the period. The econometric model and associated error structure changed frequently while updating. The errors of both the demand and supply equations were forecasted for each period and horizon and then incorporated into the econometric forecasts. The econometric model forecasts were combined separately with each ARIMA model forecast with equal weight to generate composite forecasts. Each composite is labeled appropriately in the results table.

The purpose for forecasting is to compare the performance of these models to that of the live hog futures market. The method of evaluation used here is to compare across models the mean squared errors, MSE, defined as:

$$MSE = [\Sigma(P-A)^2/n]$$

where P and A are predicted and actual values, respectively, and n is the number of forecasts. MSE can be viewed as a quadratic loss function, and is a commonly used measure in the literature for evaluation.

The MSEs reported later contain only the forecasting errors for those seven months in which there exists a corresponding futures contract. For example, since there is no January contract, the January forecasts produced by the above cash models are ignored in the evaluation procedure. However, there is a significantly positive basis for hogs which must be taken into account. One method is to compare cash model errors (forecasted cash price relative to the final cash price) with the futures errors (past futures price relative to the final futures price).[5] With the significant basis, evaluations could then be made with percentage MSE. Alternatively, we chose to adjust the futures prices according to an expected basis so that the errors just described could be compared directly with each other within the MSE context. Following the procedure in Holt and Brandt, the expected basis for each contract is a simple average of the actual delivery month basis for that corresponding month for the most recent three years. Now the MSEs can be compared directly with each other. The cash model MSEs can be tested for significant difference from the futures market MSEs, but specific tests were not performed here. Nevertheless, our experience would suggest that several, but not all, are significantly different from each other (see Garcia et al.).

Simulation and Evaluation

Table 1 presents the MSEs of the 5 forecast models and 6 time horizons. Also listed for comparison are the MSEs for the futures contracts in indicating maturity month prices. Although MSEs are available after each monthly update, only those through 1983 and through 1985 are shown as examples. These two are representative of the intervening MSEs.

For each horizon there is usually at least one model, and often more, which has a lower MSE than the futures market for the same horizon. Sometimes all 5 forecast models have smaller MSEs than the futures market. When doing the simulation described below, only once did we encounter a situation where no model had a lower MSE than the corresponding futures market MSE.

Regarding the relative forecasting abilities of the 5 models, the econometric model begins as the most accurate forecaster in the short run of 1 and 2 months. However, by the end of 1984 the econometric--ARIMA-II composite becomes the most accurate nearby horizon forecaster. For longer horizons of 3 to 6 months the econometric--ARIMA-I composite is almost always the best forecaster except for early in the forecasting time period when ARIMA-I was occasionally the best. Composite models incorporate information from multiple sources and it is not uncommon for them to provide more accurate forecasts than individual models (Brandt and Bessler 1981).

Using the traditional MSE method of evaluation, these results would lead to the conclusion that the hog futures market is relatively inefficient in a semi-strong form sense. Specifically, the hog futures market does not seem to be incorporating all available information at the time of forecast since alternative models demonstrate smaller forecast errors.

However, the typical evaluation procedure in the literature of forward pricing efficiency of the futures markets, as discussed earlier, may not be a sufficient condition for market inefficiency. A model can demonstrate smaller MSEs than the futures market, but that does not necessarily mean a trader can turn such information into profitable trading opportunities. Rausser and Carter argue that the sufficiency condition depends on an evaluation of the benefits and costs. As an approximation of this, trading in the futures market is simulated using the forecast information from the models. This provides a direct measure of the benefits. Since the futures contracts exist for alternate months, forecasts with horizons of 2, 4 and 6 months are used.[6]

The general trading rule adopted here is to buy futures if the forecast exceeds futures, and sell if the forecast is below futures. Specifically, starting with the 2-month forecasts, if the most accurate forecast for the next delivery month is more than $.15 per hundredweight[7] above (below) the average corresponding futures price during the forecasting month, a futures contract is purchased (sold) at the closing price of the next trading day and held until the close of either the 1st or the 10th day of the delivery month.[8] If the forecast is within $.15 of the futures,[9] no action takes place. For example, at the end of December, forecasts become available for February. If the forecast is more than $.15 above or below the average of the February closing prices during the month of December, a trade occurs with a contract being initiated on the first trading day of January and liquidated on the 1st or 10th (or nearest trading day) of February. The profit or loss of this trade is recorded after deducting a commission cost of $.15.

The forecast from the model with the lowest MSE up to the date of the market decision is used in the analysis. Specifically, the MSEs based on the 1983 forecast errors are used to begin the first set of trading exercises for 1984. Updated MSEs are calculated after each forecast and are used to select the most accurate model for that period. Forecasts and resulting trading decisions then are made from this model for subsequent periods. The above procedure is followed for all the contracts maturing during the 1984-1985 period.

The same procedure and signals are followed for the 4-month forecasts. The forecast for the most accurate model (lowest MSE) at the time of the market decision is compared to the average price of the futures contract 4 months forward for a potential trading signal. However, here, there are 2 alternative procedures for liquidation. In the first case, the contract position based on the initial signal is held until the maturity month, a period of over 3 months, ignoring any new information. This case is called "fixed market strategy". In the second case, the initial position is held until the 2-month forecasts are available at which time the most accurate forecast at that time is compared to the then existing average futures price. If the signal remains the same, no new action occurs. However, if the signal is different, then the original position is liquidated and a new one established on the first trading day following the 2-month forecast. Of course, it is possible that the old position is liquidated and no new position is taken if the futures price and forecast are within $.15 of each other, or a new position may be established if none were held from 4 months to 2 months for the same reason. This case is called "flexible market strategy". It is designed to take advantage of the most recent information.

The procedures for the 6-month forecasts are the same as for the 4-month forecasts. Both the "fixed market strategy" and "flexible market strategy" situations are examined. However, under the latter situation we could update and change positions at 4 and at 2 months prior to maturity.

Table 2 shows the means, variances, standard deviations and number of observations for the trading simulations. Results for the two liquidation dates are shown separately. All the means are positive indicating profits could be generated from the trading simulation. The 4-month forecasts generate the highest profits. The standard deviations are greater than their respective means in all cases but one, the 4-month fixed market strategy when liquidating on the 10th day. However, in only four cases does the standard deviation exceed its respective mean by more than 2 times, and only in one of these case is the ratio more than 2.66 (6-month flexible, 1st day). In all cases mean returns are higher with usually a lower variance if trades are held until the 10th of the month instead of the 1st. This means that prices during the spot month generally moved the direction forecasted. Unexpectedly, the flexible market strategy has a lower mean return than the fixed market strategy for both the 4 and 6 month forecasts. Since the flexible strategies incorporate more recent information, they would be expected to outperform the fixed strategies. However, because the 2-month forecasts have a relatively lower mean, this poorer performance must be influencing the flexible market results. One explanation for varying performance for different horizons could be changing trader mix, but data are not readily available to analyze that possibility.[10]

These results suggest that the live hog futures market is semi-strong form inefficient, judged on both necessary and sufficient criterion. That is, econometric and time series models based on existing and available public information can be formulated which have smaller MSEs than the futures market and which also generate positive trading profits. It appears that the risk-return ratios shown in table 2 could be attractive to many risk-averse traders; that is, the benefits may be substantial.

However, some caveats need to be mentioned. First, these results are preliminary in the sense that the simulation results are based on only 2 years of data. The analysis needs to be extended to provide more assurance of the results. Second, we have ignored the possibility of receiving and meeting any margin calls. At least one trade occurred where the price moved against us by $10 before recovering back to near its initial level.

This would be difficult to ignore when watching the market on a daily basis and meeting margin calls. Third, a full test of the sufficiency condition should include all the costs and benefits. The costs have not been itemized here. The benefits may look quite large, but the personnel and computing costs in building the above models were not trivial. Incorporation of these costs would make the benefits relative to the costs less attractive. Nevertheless, the cost of future model upkeep will be considerably less than the initial costs.

On the other hand, our results are not out of line with previous work. The model MSEs reported in table 1 for the 2-month horizon are probably not significantly smaller than the MSE for the futures market, while for 4- and 6-month horizons there are model MSEs which are likely significantly smaller than the corresponding futures market MSE. This conforms with Shonkwiler's results that futures beyond 2 months are not rational forecasts. Also, Just and Rausser found futures to be more accurate than commercial forecasting services for 1 quarter ahead. It could be that hog futures at the 2-month horizon are relatively more efficient than at longer horizons, a feature supported by our risk-return results.

Summary and Conclusions

Previous research on the performance of futures markets in a semi-strong form forecasting framework have resulted in inconclusive results. However, some have raised the possibility of the hog futures market being inefficient. In this paper, structural econometric and ARIMA models were developed to forecast monthly hog prices. Employing a mean square prediction error criterion, forecasts from these models and their composites were compared to the futures market.

Departing from previous studies, this paper obtains out-of-sample forecasts for 6 horizons while updating the models with new information each period and re-estimating them in a recursive fashion. This updating allows for parameter coefficients to adjust to recent information. Also, the sufficiency condition of the efficiency test is examined by simulating trading results based on the most accurate forecast for horizons of 2, 4, and 6 months.

In terms of the MSE criterion, usually at least one model exists, and sometimes all of them, which forecasts more accurately than does the futures market. Most often one of the composite models is the best forecaster.

The simulation results based on the most accurate forecast demonstrated positive profits without unreasonably high risk-return ratios. Many risk-averse traders would act on the signals provided here if they expected risk-return ratios of the magnitude shown. This is not a complete test of the sufficiency condition because the total costs have not been itemized, but the benefits do seem attractive. This study has demonstrated one procedure for measuring the benefits and noted the importance of analyzing markets beyond the MSE. The results would suggest that the live hog market may be inefficient based on the criterion established here. However, these results are preliminary in the sense that the forecasting period has not been extensive, and any concern over margin calls has been ignored. Further work in both of these areas, along with carefully examining the robustness and costs of our models, needs to be done before more conclusive statements can be provided.

Table 1. Mean Squared Errors for Various Forecasting Models and Futures for Horizons of 1 through 6 Months Ahead

Forecast Technique	Horizon (Months Ahead)	1983	1983-1985
ARIMA-I	1	11.90	8.27
	2	46.16	26.21
	3	17.82	18.34
	4	10.64	15.00
	5	12.51	15.45
	6	6.70	13.43
ARIMA-II	1	8.89	5.59
	2	34.34	21.15
	3	26.86	20.23
	4	16.40	20.95
	5	23.19	27.41
	6	20.40	26.90
Econometric	1	2.66	13.20
	2	17.03	32.86
	3	26.66	29.76
	4	40.88	40.61
	5	54.40	42.76
	6	18.11	32.97
Econometric--ARIMA-I Composite	1	5.21	6.79
	2	23.36	19.20
	3	13.58	13.99
	4	16.31	15.23
	5	19.03	16.35
	6	3.99	12.02
Econometric--ARIMA-II Composite	1	4.41	5.32
	2	21.96	18.09
	3	21.28	16.00
	4	20.96	16.58
	5	26.00	18.44
	6	10.20	14.81
Basis Adjusted Futures	1	23.84	13.74
	2	27.69	19.36
	3	29.85	22.78
	4	23.77	26.33
	5	32.77	25.86
	6	32.20	21.94

Table 2. Results of Simulated Market Activities, 1984-1985

	Mean	Variance	Standard Deviation	N
	Trade liquidated on 10th of Delivery Month			
2 - Month Forecasts	2.26[a]	14.22	3.77	10
4 - Month Forecasts				
Fixed Market Strategy	3.87	14.13	3.76	11
Flexible Market Strategy	2.67	15.72	3.96	11
6 - Month Forecasts				
Fixed Market Strategy	2.62	18.37	4.29	8
Flexible Market Strategy	1.61	16.11	4.01	10
	Trade liquidated on 1st of Delivery Month			
2 - Month Forecasts	1.28	11.66	3.41	10
4 - Month Forecasts				
Fixed Market Strategy	3.77	15.96	3.99	11
Flexible Market Strategy	2.07	16.50	4.06	11
6 - Month Forecasts				
Fixed Market Strategy	2.32	22.62	4.76	8
Flexible Market Strategy	0.91	20.87	4.57	10

[a]Units are in dollars per hundredweight. To find the results per futures contract, multiply the numbers by 300. N represents the number of contracts used in the simulations under the trading rules specified in the text.

Footnotes

[1]SBIC = n (log (2π) +1) + n log $\hat{\sigma}^2$ + log (n) K, where n = the number of observations, K = the number of lags included in the model, and $\hat{\sigma}^2$ = (the sum of squared errors)/n.

[2]This procedure was employed because of its simplicity and the limited capability of available computer programs to correct for such nonspherical errors with long lag structures of the dependent variable. In the strictest sense, the occurence of autocorrelation with lagged dependent variables produces biased and inconsistent estimates of the coefficients. Incorporation of short-term lagged dependent variables reduces the autocorrelation problems but makes short-term forecasting more difficult due to compounding forecast errors. Granger and Newbold (p. 200) indicate that forecasts obtained through such procedures can be far from optimal if the autocorrelation is not also taken into account when the model is estimated. However, at least in the short term, the adjustment procedure is superior to ignoring the problem altogether.

[3]Ljung-Box Q-Statistic. The critical value at the 0.10 significance level is 33.2.

[4]People who follow the hog market have recognized that the hog cycle in the last 15 years has been changing from its previously regular 4-year pattern. Work by Shonkwiler and Spreen has documented this change, although that specific documentation would not have been known in January 1983 when forecasting in this paper would have begun.

[5]These data refer to monthly averages of daily prices.

[6]For this simulation the July futures contract is ignored for the convenience of constant forecasting and trading horizons.

[7]Fifteen cents represents approximately the commission costs.

[8]Examined are two alternative liquidation dates. First, the models forecast the monthly price, so for a representative of the monthly average the trading day closest to the 10th of the month is selected. This is midway between the first day of the month and the last trading day. A single day is selected because market participants cannot trade the monthly average. For comparison, results are also generated assuming that trades are liquidated on the 1st day of the delivery month. This day is selected because many view holding speculative positions into the spot month is risky, and many traders are urged to leave the market then.

[9]All units are on a per hundredweight basis.

[10]Over all the trades made, the number of long positions and number of short positions was approximately equal, indicating no particular bias in futures contract values relative to our models.

References

Brandt, J. A. and D. A. Bessler. "Composite Forecasting: An Application with U.S. Hog Prices." Am. J. Agr. Econ. 63(1981):135-140.

Brandt, J. A. and D. A. Bessler. "Forecasting with Vector Autoregression Versus a Univariate ARIMA Process: An Empirical Example with U.S. Hog Prices." No. Centr. J. Agr. Econ. 6(1984):29-36.

Fama, E. F. "Efficient Capital Markets: A Review of Theory and Empirical Work." J. Finance. 25(1970):383-417.

Garcia, P., R. M. Leuthold, T. R. Fortenbery and G. F. Sarassoro. "Pricing Efficiency in the Live Cattle Futures Market: Further Interpretation and Measurement." Mimeo. Department of Agricultural Economics, University of Illinois, 1987.

Gardner, B. L. "Futures Prices in Supply Analysis." Amer. J. Agr. Econ. 58(1976):81-85.

Godfrey, L. G. "Testing the Adequacy of a Time Series Model." Biometrika. 66(1979):67-72.

Goss, B. A. "The Semi-Strong Form Efficiency of the London Metal Exchange." Applied Econ. 15(1983):681-698.

Granger, C. W. J. and P. Newbold. Forecasting Economic Time Series. New York:Academic Press. 1986.

Grossman, S. J. and J. E. Stiglitz. "On the Impossibility of Informationally Efficient Markets." Amer. Econ. Rev. 70(1980): 393-408.

Harvey, A. C. Time Series Models. Oxford, England: Philip Alan Publishers Limited. 1981.

Holt, M. T. and J. A. Brandt. "Combinging Price Forecasting with Hedging of Hogs: An Evaluation Using Alternative Measures of Risk." J. Futures Markets. 5(1985):297-309.

Hurt, C. A. and P. Garcia. "The Impact of Price Risk on Sow Farrowings, 1967-78." Amer. J. Agr. Econ. 64(1982):565-568.

Joerding, W. "The Model Dependence of Relative Mean-Square Error Tests for Market Efficiency." J. Econ. Busn. 38(1986):227-236.

Just, R. E. and G. C. Rausser. "Commodity Price Forecasting With Large-Scale Econometric Models and the Futures Market." Amer. J. Agr. Econ. 63(1981):197-208.

Kamara, A. "Issues in Futures Markets: A Survey." J. Futures Markets. 2(1982):261-294.

Leuthold, R. M. and P. A. Hartmann. "An Evaluation of the Forward-Pricing Efficiency of Livestock Futures Markets." No. Centr. J. Agr. Econ. 3(1981):71-80.

Leuthold, R. M. and P. A. Hartmann. "A Semi-Strong Form Evaluation of the Efficiency of the Hog Futures Market." Am. J. Agr. Econ. 63(1979):482-489.

Ljung, G. M. and G. E. P. Box. "On a Measure of Lack of Fit in Time Series Models." Biometrika. 65(1978):297-303.

Rausser, G. C. and C. Carter. "Futures Market Efficiency in the Soybean Complex." Rev. Econ. Stat. 65(1983):469-478.

Schwartz, G. "Estimating the Dimension of a Model." Annals of Stat. 6(1978):461-464.

Shonkwiler, J. S. "Are Livestock Futures Prices Rational Forecasts?" West. J. Agr. Econ. 11(1986):123-128.

Shonkwiler, J. S. and T. H. Spreen. "A Dynamic Regression Model of the U.S. Hog Market." Can. J. Agr. Econ. 30(1982):37-48.