Ex Ante Basis Risk in the Live Hog Futures Contract: Has Hedgers' Risk Increased?

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Forecasting the cash-futures basis for agricultural commodities is an important aspect of a successful marketing strategy [Bobst (1974), Garcia and Good (1983), Chicago Mercantile Exchange (1988)]. Short hedgers are long the basis and unanticipated basis movements can adversely affect the net price received which can increase risk, and alter producer behavior [Peck (1975)]. Forecasting the basis permits producers to assess alternative forward pricing mechanisms such as futures hedging, cash forward contracts, and basis contracts. The latter two have become increasingly important as the marketing systems for agricultural commodities, particularly livestock, have become more integrated. The success of a futures contract also hinges on a predictable basis. Increased basis risk relative to price risk can reduce the attractiveness of the futures market as a risk management vehicle.

Recently, concern has been expressed over the changing nature of

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the basis for agricultural commodities. It has been suggested that the basis risk has increased, as the basis has become more volatile and difficult to predict [Tomek (1993)]. In particular, some anxiety has developed over the level of basis risk, the recent decline in the volume of futures trading in live hog contracts and the usefulness of the contract [Unnevehr (1988), Hurt and Rice (1991), Einhorn (1994)]. The difficulty is attributed to the changing nature of cash markets, that is, higher levels of vertical integration and bypassing of the traditional terminal markets with more direct sales to processors. Cash sales and prices in direct markets also are increasingly subject to quality, timing, and locational factors important to specific cash transactions. Furthermore, cash prices at terminal markets, which have declined in importance, may be influenced less by fundamental supply and demand. Clearly, if the basis risk increases, (a) the ability of futures contracts to transfer risk is reduced, (b) it becomes more difficult to assess cash forward marketing and pricing opportunities, and (c) the use of futures contracts can decline.

The purpose of this article is to investigate the changing nature of live hog basis risk for a direct (non-par delivery) and a terminal (par delivery) market over the period 1975–1994. Basis risk is measured in a traditional mean-squared-error framework, and the correct prediction of the sign of the basis (which is an important part of basis risk) is included. Because basis risk is generally viewed in an *ex ante* context, economic and time-series forecasting models are developed to assess basis behavior. Well-established modeling procedures that are easily implemented are used. Two forecast horizons are considered in the analysis: a long-term (5-month) forecast, which reflects production decision; and a short-term (1-month) forecast, which represents marketing decisions. The out-of-sample forecasting ability of the basis models is assessed by examining their statistical behavior relative to naive forecasting models that have been employed by Kolb and Stekler (1993) and Allen (1994). Differences in basis risk over time and across terminal and direct markets, as well as implications for the successful use of futures markets, are addressed. Analyses also are performed to identify whether basis volatility has increased over the last decade at selected terminal and direct markets.

MODELING THE LIVE HOG BASIS

Most work concerning the cash-futures livestock basis has been explanatory in nature [e.g., Leuthold (1979), Tomek (1980), Leuthold and Peterson (1983), and Garcia, Leuthold, and Sarhan (1984)]. In a rational expectations framework, Naik and Leuthold (1988b) showed that the basis for nonstorable commodities is a function of lagged values of the basis, cash prices, futures prices, and relevant supply and demand shifters. Naik and Leuthold (1988a) had moderate success in empirically explaining the cash-futures basis for live cattle and hogs.

Liu, Brorsen, Oellermann, and Farris (1994) extended the Naik and Leuthold work by explicitly addressing the forecastability of the nearby live cattle basis. They modeled the nearby basis as a function of delivery costs and expected changes in cash prices. They found that the expected impact of supply, demand, and delivery cost variables on the basis is ambiguous because changes in these factors may differentially impact cash and futures prices. Four different models were specified and estimated: a model using futures market variables, a model using lagged basis and delivery costs, a model using lagged supply and demand variables, and a joint model encompassing all variables. Not unexpectedly, the joint model exhibited the highest in-sample adjusted R-squared. The statistically important variables were lagged values of futures spreads, the basis, futures open interest, the consumer price index, and the price of chicken. However, in evaluating 30 out-of-sample, one-step-ahead forecasts from 1987 through 1991, the four models performed similarly on the criteria of root-mean-squared error and in predicting turning points. The authors concluded that the ambiguity of out-of-sample results may have stemmed from structural changes, and that the performance of the joint supply and demand model may not justify modeling costs. Furthermore, they concluded that short-term dynamics (i.e., the lagged basis) are at least as important as fundamental variables in predicting the nearby basis.

This research extends the work of Naik and Leuthold (1988a) and Liu et al. (1994) to identify potentially relevant supply and demand variables for an economic forecasting model. The economic model is specified from a set of variables reflecting supply, demand, and delivery costs for live hogs. Liu et al. (1994) stress the importance of short-run dynamics in predicting the basis; thus, an ARMA time-series model serves as a second model to generate out-of-sample forecasts. In contrast to the above studies and after discussions with industry participants, the basis is defined over a relatively short temporal unit, 1 week, to minimize variability within the unit of aggregation and to represent a realistic marketing period.[1] Additionally, previous studies have made only one-period-ahead

[1]Interestingly, there is no evidence of cash-futures convergence in the first week of the delivery month. Hurt and Rice (1991) document that convergence is sporadic and often does not occur until well into the delivery month.

forecasts and have not given sufficient attention to the availability of secondary data at the time of the forecast. In this analysis, forecast horizons are 1 and 5 months ahead, corresponding to the marketing and pricing/production decisions of producers, respectively. The timing of data releases and their availability to a forecaster also are considered.

Data and Markets

The basis is defined as the difference in natural logarithm of cash and futures prices, $\text{basis}_t = \log(\text{cash}_t) - \log(\text{nearby futures}_t)$, so that cash is expressed as a percent premium or discount to futures.[2] Following Liu et al. (1994) focus is placed on forecasting a nearby basis, the difference between cash and nearby futures at time t. The cash and nearby futures prices are weekly averages of daily prices for the first week of each month where the 1st does not fall on Friday. For instance, the March basis is calculated with the prevailing cash and the April futures price (nearby contract) during the first week of March. The basis is calculated for each month from January, 1975 to May, 1994. The subperiod from January, 1975 through December, 1984 serves as the in-sample period. Out-of-sample forecasts based on updated models are made over 113 observations from January, 1985 through May, 1994.

Two markets are examined: a par delivery terminal cash market (Omaha) and a non-par delivery direct market (Illinois direct). The Omaha market, although relatively low in volume compared to direct markets and some other auction markets, is a nationally quoted terminal market and a par delivery point for the live hog contract.

Futures data are provided by the Office for Futures and Options Research, University of Illinois. Cash data are taken from various USDA publications: *Livestock, Meat, and Wool Weekly Summary* and *Livestock and Poultry Situation and Outlook Report*. Macroeconomic variables are from *The Economic Report of the President*.

Economic Forecasting Models

The economic model expresses the basis as a function of supply and demand factors, delivery costs, and monthly dummy variables. Special attention is given to making these models realistic and implementable.

[2]Preliminary analyses performed on the nonlogged basis data found, in general, that the characteristics and initial forecasting performance are consistent with the results presented in this article. The logged data are used, as they closely reflect the percentage errors in returns.

For instance, distinct models are specified for generating 1- and 5-month forecasts. At the 1-month horizon, all variables must enter the model with lags of at least two periods. Because the basis is defined for the first week of the month, a one-period lag would result in a meaningless forecast horizon. Furthermore, many of the economic variables are not immediately available to the forecaster. Most notably, cold storage, personal income, and the consumer price index for month t are all released via government reports in the middle of month $t + 1$. Consequently, these variables must enter the 1-month models with lags of at least three periods. Similarly, for the 5-month model these variables can only enter the model with lags of 7 months or greater, whereas those variables that are immediately observed (i.e., prices) need only be lagged 6 months.

The full economic live hog basis forecasting model is specified as

$$\begin{aligned} \text{lhbasis}_t = f(&\text{dv2} - \text{dv12}, \text{cldpk}_{t-i}, \text{slthg}_{t-j}, \text{dcorn}_{t-j}, \text{dretck}_{t-j}, \\ &\text{dretbf}_{t-j}, \text{dinccap}_{t-i}, \text{dtb}_{t-j}, \text{dcpi}_{t-i}) \end{aligned}$$

where lhbasis_t is the live hog basis ($\text{lh}_t - \text{lhfut}_t$); lh_t is the price ($/cwt, 220–240#, US 1–2) of live hogs; and lhfut_t is the nearby futures price for the live hog contract. The supply variables include cldpk_t the total pork (millions of pounds) in cold storage at the end of month t (information becomes available during the middle of month $t + 1$); slthg_t, the federally inspected hog slaughter (thousand head) during month t; and dcorn_t the change in the monthly average price of corn (No. 2, yellow, Central Illinois) from month $t - 1$ to month t. The demand variables are dretbf_t, the change in the average monthly retail price of beef ($/cwt) from month $t - 1$ to t; dretck_t, the change in the average monthly retail price of chicken ($/cwt) from month $t - 1$ to t; and dinccap_t, the change in U.S. personal income per capita (thousand dollars) from month $t - 1$ to month t (information is not released until the middle of month $t + 1$). The delivery cost variables examined are: dtb_t, the change in the monthly average Treasury bill rate from month $t - 1$ to month t; and dcpi_t, the change in the consumer price index from month $t - 1$ to month t (information is not released until the middle of month $t + 1$). The subscripts i and j refer to the availability of the data such that $i = 3$ and $j = 2$ for the one-period forecast model, and $i = 7$ and $j = 6$ for the five-period forecast model. Monthly intercept shifters are represented by dv2–dv12, and all variables are first put into natural log form, so that levels are log levels and changes (indicated by the d prefix) are percent changes.

An initial full model is specified and estimated for the period,

TABLE I
One-Month Horizon Economic Models: Omaha Terminal Market Live Hog Basis

Independent Variables	*Sample Period* 1975.01–1984.12	1985.01–1989.12	1989.01–1993.12
Constant	0.526	1.7333	0.5428
	(5.69)[a]	(2.30)	(2.98)
DV2[b]	0.0490	0.0241	0.0191
	(3.20)	(1.31)	(0.94)
DV3	0.0618	0.0332	0.0145
	(4.02)	(1.79)	(0.72)
DV4	0.0406	−0.0155	−0.0014
	(2.69)	(−0.70)	(−0.07)
DV5	−0.0607	−0.0743	−0.0623
	(−4.07)	(−4.00)	(−3.09)
DV6	−0.0034	−0.0081	−0.0019
	(−0.23)	(−0.67)	(−0.09)
DV7	0.0701	0.0529	0.0686
	(4.43)	(2.59)	(3.23)
DV8	0.0974	0.0479	0.0716
	(5.97)	(2.03)	(3.42)
DV9	0.1355	0.1291	0.1104
	(8.39)	(5.32)	(5.50)
DV10	0.0531	0.0489	0.0544
	(3.57)	(2.45)	(2.80)
DV11	−0.0276	−0.0173	−0.0097
	(−1.87)	(−0.94)	(−0.51)
DV12	−0.0241	−0.0084	−0.0186
	(−1.59)	(−0.42)	(−0.968)
$cldpk_{t-3}$	−0.0977	−0.0649	−0.0997
	(−5.68)	(−2.93)	(−3.09)
$dretck_{t-2}$	−0.3114		
	(−2.86)		
$dcpi_{t-3}$	−0.0367	−0.0444	
	(−4.09)	(−4.62)	
$slthg_{t-2}$		−0.1562	
		(−1.68)	
Adj. R squared	0.686	0.777	0.692

[a]t statistics in parentheses.
[b]Variables are defined in text.

1975.01–1984.12. The full model incorporates all theoretically relevant variables with the minimum permissible lag for each forecasting horizon. The full model is then tested down—systematically eliminating variables insignificant at the 5% level—to a final specification. A Chow test indicates a structural change in 1979. After examining the initial model, rolling samples of 60 observations are used for estimation and out-of-sample forecasting. During the forecast period, the economic model is respecified annually and reestimated monthly. The models also are examined for autocorrelation in their estimated residuals.[3]

Examples of the 1-month Omaha economic forecasting models for various samples are presented in Table I. The economic forecasting models' variables and summary statistics are representative of the other models estimated through the sample. During the initial estimation period, increased cold storage and inflation widened the basis, which can be explained in an inventory context. However, increased chicken prices also resulted in a widening of the basis, somewhat surprisingly suggesting that chicken and pork are complements rather than substitutes. Overall, the adjusted R^2's are reasonably high. Although autocorrelation is not a significant problem for the estimated forecasting equations, the model specification is tenuous and highly sample sensitive. For instance, the estimated coefficient on the retail price of chicken, a demand variable, ranges from 0.022 in early samples to a significant $-.032$ in others. Similarly, the CPI's estimated coefficient ranges from -0.037 to 0.060, both statistically significant. Furthermore, many proposed explanatory variables (e.g., income per capita and T-bill rates) never entered the forecasting models. Only the supply variable, cold storage, is consistently important with a reasonably stable coefficient. Seasonality in the live hog basis is pervasive, with a weak basis in the November, December, January, May, and June contracts, and a strong basis in July, August, September, October, February, March, and April. The strong seasonality accounts for much of the explanatory power and similarities across models. At the 5-month horizon, the economic results confirm the importance of cold storage and seasonality, the only factors consistently affecting the basis (results not shown). The importance of cold storage and seasonality are consistent with the results of previous explanatory analyses of the hog basis [Leuthold and Peterson (1983), Naik and Leuthold (1988a)]. Previous research on the hog basis speaks little to the constancy of the estimated structure over time, but Liu et al. (1994) do suggest the possibility of structural changes in the basis during the out-of-sample period, creating ambiguity in their findings.

Time-Series Models

Previous research and analysis have suggested that simple time-series models are as good at forecasting as are models based on structural representations of the basis [Hauser, Garcia, and Tumblin (1990), Tomek

[3]Initially, nondelivery-month slope shifters also are examined, but are not significant. Apparently, potential differences between delivery and nondelivery months are captured by the monthly dummy variables.

(1993); Liu et al. (1994)]. As a distinct alternative to the pure economic models, the basis is modeled here with the use of a set of monthly dummy variables to account for seasonality, with the residuals from the dummy variable regression being used to identify an ARMA process following standard Box-Jenkins procedures [Brocklebank and Dickey (1986), and Strobl, Fortenbery, and Fackler (1992)]. The seasonality and ARMA components are then jointly reestimated. For both the Omaha and Illinois Direct live hog basis, an ARMA (2,0) fit the sample, 1975.01–1984.12, but it was found to be unstable in subperiods (Chow test). Thus, consistent with the information set used for the economic forecasts, time-series models are estimated over rolling samples of 60 observations during the out-of-sample period. Time-series models are respecified annually and reestimated monthly. Five-month forecasts are formed by iterating the forecasting model and using forecasted values as proxies for actual values. The typical time-series specification is an ARMA (4,0) or ARMA (2,1) with an occasional seasonal moving average term specified. Relative to the economic models, the ARMA model specifications are fairly stable across subsamples. Adjusted R^2s are reasonably high and comparable to those generated by the economic models.

Naive Model

Naive forecasts provide a standard of comparison against which economic and time-series forecasts are often measured. The naive model used here employs a 3-year seasonal moving average, $f_t = 1/3(x_{t-12} + x_{t-24} + x_{t-36})$, where f represents the forecast and the x's represent past basis levels. The naive model is widely used in the literature as an estimate of the basis [Leuthold, Garcia, Adam, and Park (1989)] and is commonly used by industry participants (personal discussions). It provides a view of basis risk with the use of forecast procedures commonly used by many industry participants.

RISK MEASUREMENT PROCEDURES

Root-Mean-Squared Error

Peck (1975) and Tomek (1993) identify the mearr-squared forecast error (MSE) as a measure of basis risk. In a hedging context, the risk in returns from a completely hedged position is directly proportional to the basis forecast error.[4] Define a forecast of x_t as f_t and the forecast error, $e_t = x_t - f_t$. Then, the root-mean-squared forecast error (RMSE) over n forecasts can be expressed as

$$\mathrm{RMSE} = \left[\frac{1}{n}\sum_{t=1}^{n} e_t^2\right]^{1/2}$$

The RMSE measures forecast accuracy based on a quadratic loss function that has desirable statistical properties. In natural logarithms, the RMSEs provide a measure of the percent error in the basis forecast relative to the futures price, which is consistent with risk measures from traditional mean-variance decision models. Differences in mean-squared errors and, hence, RMSE can be tested across alternative forecasting models with the use of the procedure set forth by Ashley, Granger, and Schmalensee (1980).

Henriksson-Merton Timing Test

The MSE provides quantitative information concerning the goodness of fit of forecasts. Often, however, detecting directional changes or timing is much more crucial to the practitioner. When considering the basis and its role in forward pricing, the relevant question is whether the basis will be positive or negative. That is, will the effective marketing price be above or below the futures price at which hedges are placed? The ability to correctly forecast the sign of the basis can be evaluated with the use of the timing test proposed by Henriksson and Merton (1981).

The Henriksson-Merton (HM) test evaluates the ability to correctly predict the sign (or direction) of a variable through estimating the following model [Breen, Glosten, and Jagannathan (1989)]:

$$\mathrm{FS}_{t-i} = a_1 + \beta_1 \mathrm{AS}_t + \varepsilon_t \tag{1}$$

where

$$\begin{aligned} \mathrm{FS}_{t-i} &= 1 \text{ if a positive basis is forecasted for time } t \text{ at time } t - i \\ &= 0 \text{ otherwise} \\ \mathrm{AS}_t &= 1 \text{ if the actual basis is positive at time } t \\ &= 0 \text{ otherwise} \end{aligned}$$

[4]In an efficient market, the hedge ratio is affected by the basis and price forecast errors, and their covariance [Peck (1975)]. Based on ARMA modeling of the live hog prices, the price forecast error variance does not appear to change appreciably through time, nor are the forecast errors correlated with the basis errors. In this context, changes in the proportion of the production hedged should be attributable primarily to changes in the basis risk.

TABLE II
Summary Statistics for Live Hog Prices and Basis, 1975–1994

Panel A

	Mean	*Standard Deviation*
Omaha terminal market		
Price level	46.66	6.79
Δ log (prices)	0.0000	0.0824
Basis, all months	−0.0032	0.0566
Basis, delivery months	0.0013	0.0357
Basis, nondelivery months	−0.0098	0.0768
Illinois direct market		
Price level	47.71	6.75
Δ log (prices)	0.0000	0.0838
Basis, all months	−0.0194	0.0569
Basis, delivery months	−0.0147	0.0357
Basis, nondelivery months	−0.0262	0.0768

Panel B

Omaha and Illinois direct markets	*Correlation Coefficient*
Price level	0.995
Δ log (prices)	0.983
Basis, all months	0.965
Basis, delivery months	0.892
Basis, nondelivery months	0.986

The null hypothesis of no timing ability, H_0: $\beta_1 = 0$, is tested against the alternative hypothesis, H_A: $\beta_1 \neq 0$, where $\beta_1 > 0$ indicates superior timing ability, and $\beta_1 < 0$ is perverse timing ability. Rejection of the null hypothesis indicates that the forecasts have a significant probability of correctly predicting the sign of subsequent basis, where $(1 + \beta_1)/2$ is the expected probability of correctly anticipating the basis's sign.

RESULTS

Basis Variability

Table II presents the summary statistics for the live hog basis and cash prices at the Omaha and Illinois direct markets. Simple F tests reveal that neither price nor basis variance differs across the two markets. Further, the two markets are highly correlated in terms of price level, price

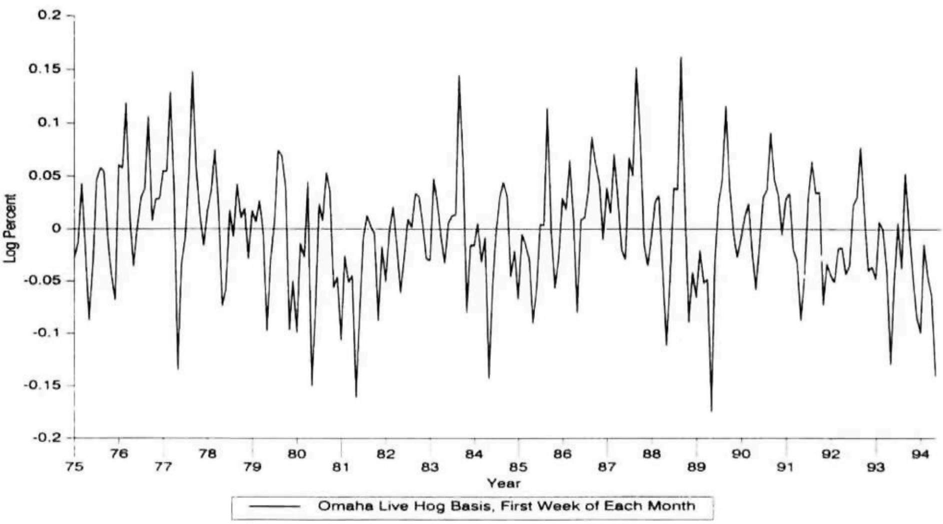

FIGURE 1

Omaha live hog basis, 1975–1994.

changes, and basis levels (panel B).[5] This results in similar basis models and forecasts for each market. Thus, the Omaha forecasting results are presented here, with Illinois direct results discussed only when markedly different. Not surprisingly, in both markets, basis variability is significantly greater (0.001 level, F test) for nondelivery months (Table II, Panel A).[6]

Figure 1 shows the Omaha live hog basis from 1975 to May, 1994. Although quite volatile, with extremes of as much as 15% of live hog prices, there is no obvious visual break where basis variability either increases or decreases. Arbitrarily splitting the data set at the end of 1981 and 1988 reveals that the basis variance actually decreases across the three subperiods. Hence, there is little evidence that basis variability has increased at the Omaha or Illinois direct markets over the period 1975–May, 1994. However, basis variance as a measure of risk is limited in that

[5]The high degree of similarity between the two monthly series is not entirely unexpected. Previous research has registered high correlations among hog markets using both daily price levels and their changes, particularly for the markets in the important producing states [Stigler and Sherwin (1988), and Leuthold, Garcia, and Chaherli (1992)].

[6]The basis is characterized by time-dependent variance, but it is not of the ARCH type. Basis variance increases in nondelivery months, in general, and May and November, in particular. Modeling this type of conditional variance is not addressed here, because of the desire to generate easily usable and tractable models. Modeling conditional variances is, nonetheless, of practical concern to hedgers. Examination of basis risk by delivery and nondelivery months indicates that the presence of this time-dependent variance does not change the general findings of the behavior of basis risk through time.

it does not decompose basis movement into its predictable and random components, nor does it consider the sign of the basis.

Basis Risk

As discussed, basis risk is evaluated using root-mean-squared error (RMSE), and with the Henriksson-Merton test of timing ability. As expected, basis forecast errors increase as the forecast horizon increases from 1 to 5 months; hence, direct comparisons are not made across the different horizons. For purposes of brevity, the discussion focuses on the 1-month horizon findings, noting differences in the findings at the 5-month horizon where significant.

Root-Mean-Squared Error

Table III presents the RMSE for the forecast procedures in both markets. Concentrating on the Omaha results, the one-period-ahead economic model (EC1) produces a statistically smaller RMSE than either the time-series model (TS1) or the 3-year moving average (3MA), with p values of 0.0861 and 0.0287, respectively [Ashley et al. (1980)]. At the 5-month horizon, the economic model's forecasts (EC5) again produce the smallest RMSE, which is significantly less than both the time series (TS5) and the 3-year moving average's (3MA) RMSE at the 10% level. Similar RMSE rankings hold for delivery and nondelivery month forecasts.[7]

To investigate how RMSEs and, thus, basis risk change through time, the RMSE for each forecasting method is calculated over rolling 3-year (36-month) periods.[8] A series of forecasts that outperforms another series would have a lower RMSE in all evaluation periods. At a 1-month horizon, the economic model clearly dominates the 3-year moving average model (Figure 2). The time-series model produces a lower RMSE than the 3-year moving average model in nearly all periods. However, the superior RMSE performance of the economic model over the time-series model, although statistically significant, on average, is sample sensitive between

[7]Although the forecasts from the other models are statistically superior to the naive model, the economic value of generating alternative forecasts must consider the benefits and costs of their use. Based on the percentage reduction in RMSE (Table III), the 1-month economic forecasts of the nondelivery basis provide the greatest potential for generating positive returns over the use of the naive model.

[8]A 36-month interval is chosen because it is not unusual for an industry forecaster or consultant's performance to be evaluated over a 3-year (or shorter) period. Additionally, academic studies often use 30 out-of-sample forecasts for model evaluation. Clearly, as the interval is lengthened the RMSE series becomes smoother and converges to its mean.

TABLE III
Risk Measures, Live Hog Basis, 1985.01–1994.05

	Root-Mean-Squared Errors					*Percent Sign Correct Forecast*[b]				
	Forecasting Models[a]					*Forecasting Models*				
	TS1	*EC1*	*TS5*	*EC5*	*3MA*	*TS1*	*EC1*	*TS5*	*EC5*	*3MA*
Omaha terminal market										
All months	0.0331	0.0328	0.0372	0.0367	0.0399	0.838[b]	0.806	0.809	0.801	0.814
Delivery months	0.0248	0.0247	0.0266	0.0274	0.0270	0.812	0.827	0.818	0.812	0.845
Nondelivery months	0.0419	0.0413	0.0481	0.0463	0.0525	0.856	0.738	0.794	0.767	0.750
Illinois direct market										
All months	0.0356	0.0349	0.0415	0.0391	0.0400	0.811	0.743	0.819	0.793	0.826
Delivery months	0.0270	0.0272	0.0321	0.0323	0.0294	0.835	0.707	0.826	0.802	0.859
Nondelivery months	0.0447	0.0432	0.0515	0.0467	0.0510	0.775	0.792	0.808	0.778	0.778

[a]The models are defined in the text.
[b]The percent sign-correct forecasts are statistically different from 0.50 at the 1% significance level.

1988 and 1990. Similar tenuous relationships are revealed at the 5-month horizon (Figure 3), where no model dominates for a prolonged time period, although the economic model provides the most consistent forecast accuracy.

Over time, the RMSEs do not have an upward trend. At the 1-month horizon, the RMSEs for the economic and time-series models are relatively stable through time in a narrow band around 4% of the futures price. The RMSEs for the naive forecasting model decline somewhat through time, suggesting that seasonality is more important in recent years. At the 5-month horizon, the economic and time-series models again demonstrate rather stable RMSEs through time, whereas the RMSEs from the naive model decline modestly. It is clear that these results provide little evidence of increasing basis risk with the use of any of the forecast models.

Timing Tests

The Henriksson-Merton regression [eq. (1)] tests if the models have a statistically significant ability to predict if the basis will be positive or negative, an important consideration for break-even pricing. The results of the HM tests are presented in Table III, where the percent of sign-correct forecasts are calculated as $[(1 + \beta_1)/2]$. All of the forecasting methods demonstrate at the 1% level a statistical ability to correctly forecast the sign of the basis. Because of strong seasonality in the basis, the

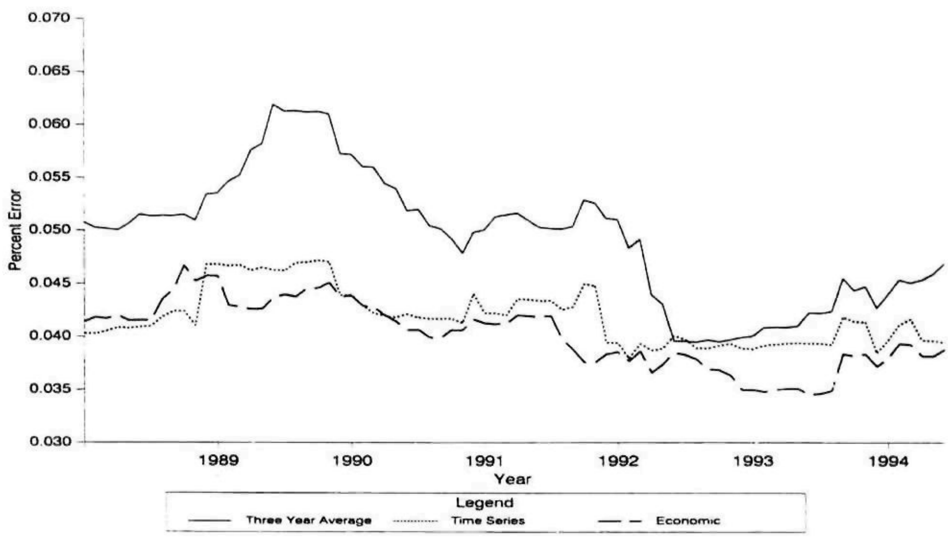

FIGURE 2

Root-mean-squared errors, rolling 36 observations, 1-month horizon.

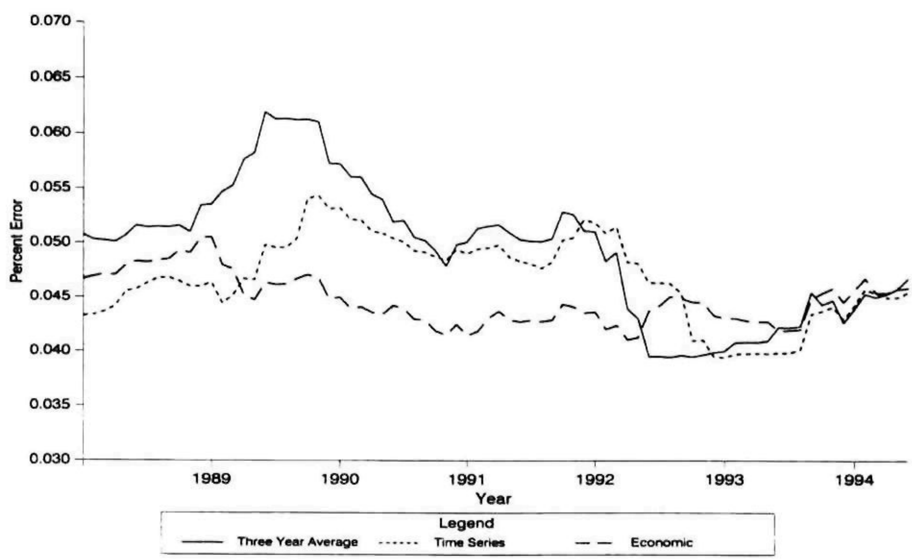

FIGURE 3

Root-mean-squared errors, rolling 36 observations 5-month horizons.

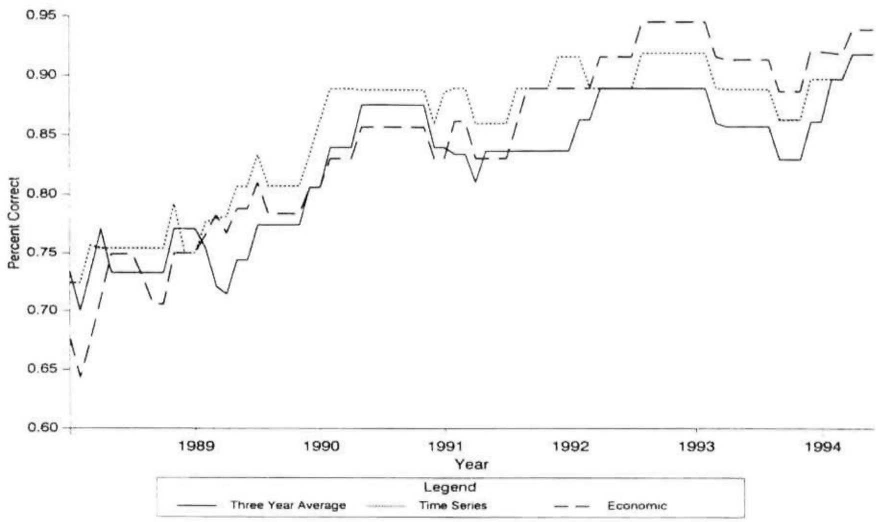

FIGURE 4

Percent sign-correct forecasts, rolling 36 observations 1-month horizon.

timing is fairly consistent across markets and methods. The sign predictability of delivery and nondelivery months are roughly equivalent.

Again, rolling samples of 36 months are utilized to examine temporal changes in predictability. The HM test is estimated over these rolling samples. The percent of sign correct forecasts $[(1 + \beta_1)/2]$ are plotted in Figures 4 and 5. At the 1-month horizon (Figure 4), the time-series forecasts dominate the 3-year moving average forecast in nearly all samples, whereas, the relative timing abilities of the time-series model and the economic model are quite sensitive to the period examined. As shown in Figure 5, the forecasting models provide little or no improvement in timing ability over the naive model at a 5-month horizon.

Over time, the sign predictability of the basis increases considerably, with the last set of forecasts correctly predicting the sign over 90% of the time at both the 1- and 5-month horizons. Thus, the ability to forecast the sign of the basis with the use of any of the forecast procedures does not decline over the period, 1985–1994.

DISCUSSION, FURTHER EVIDENCE, AND IMPLICATIONS

The results indicate that terminal (Omaha) and direct (Illinois) live hog prices behave similarly and that there is no meaningful difference in their basis. Monthly basis variance has not increased over the period, 1975–

FIGURE 5

Percent sign-correct forecasts, rolling 36 observations, 5-month horizon.

May, 1994. In general, the economic and the time-series models provide superior basis forecasts relative to the naive 3-year moving average procedure, with the most dramatic improvements evidenced at the 1-month horizon. If one examines the results of out-of-sample basis forecasts across the three procedures, it is evident that mean-squared errors have not increased from 1985 to 1994. Further, the ability to predict the sign of the basis, as measured by the Henriksson-Merton test, increases steadily through the period. In sum, live hog basis variability has not increased relative to historical levels. There is almost no evidence that either basis risk (as measured by the mean-squared error) or the ability to forecast the sign of the basis has increased.

The findings raise several points about the forecastability of the basis, basis risk and basis predictability, and the usefulness of live hog futures as hedging instruments. It has been suggested that extension economists' outlook and price forecasts are not an especially efficient use of state monies [Brorsen and Irwin (1994)]. Providing basis forecasts may be a viable and useful alternative. In this context, identifying the economic value of basis forecasts becomes more important. When used simply to form expected prices out of observed futures prices, utility is derived from a reduction in variability.[9] However, once the forward pricing decision is

[9]For an example of the reduction in variability, consider the RMSE of EC1 relative to the standard

made, forecasts can be used to time the lifting of hedges or to negotiate basis contracts, which can increase the mean of the price distribution. These decisions, in particular, benefit from short-horizon forecast accuracy. Thus, utilizing forecasts for basis trading is potentially profitable to industry participants, especially for those who perform frequent short-term transactions (i.e., packers). Clearly, the economic value of the forecasts must be determined within the decision framework of the individual users and deserves additional consideration.

The results raise a question regarding what might explain the popular concern about live hog basis risk. In part, the answer may rest on the fact that the RMSE may not completely capture changes in basis predictability when the variance of the underlying series changes through time. For a given RMSE, predictability increases (decreases) as the variance of the underlying series increases (decreases). In this context, Granger and Newbold (1977, p. 284) suggest the error variance ratio (EVR), which standardizes the forecast error variance by the variance of the forecasted variable, as a measure of predictability. The EVR is bounded by 0 and 1, where 0 represents perfect forecasting accuracy and 1 indicates no information contained in the forecasts.[10]

EVRs based on rolling 36-month intervals are shown for the Omaha market at the 1-month horizons in Figure 6.[11] EVRs that trend higher may be indicative of a basis that is becoming relatively more difficult to predict as the forecast error increases relative to the variance of the basis. The rolling EVRs reveal that the forecasts are useful at explaining a substantial portion of the basis variance in all 36-month subperiods. The variance of the forecast errors is less than 60% of the basis variance in nearly all subperiods.

The EVRs provide some weak evidence that the basis is becoming more difficult to predict. The EVRs reach a low in mid-1990 and trend higher through mid-1993, only to decrease sharply in late 1993 and 1994. However, it is difficult to say if predictability has permanently eroded, or has simply returned to normal levels, or is in the process of improving

deviation of a constant zero basis forecast (assuming that the average basis is zero, Table II), 0.0328% and 0.055%, respectively. In terms of the standard deviation, a hedger that always mistakenly forecasts a zero basis has 1.68 times the price risk of a hedger using the EC1 model.

[10]Granger and Newbold (1977) indicate that the EVR $= 1 - R^2$, where R^2 is the coefficient of determination from regression, $x_t = a + bf_t$, and f_t is a rational forecast ($a = 0, b = 1$). In general, at the 1-month horizon, regression results indicate that the various models provide rational forecasts. At the 5-month horizon, rationality of the forecasts is rejected.

[11]The figure for comparable 5-month EVRs is not presented for brevity. The rankings of the various models are much more tenuous, but the general pattern of the predictability over time is similar to the results presented in the text.

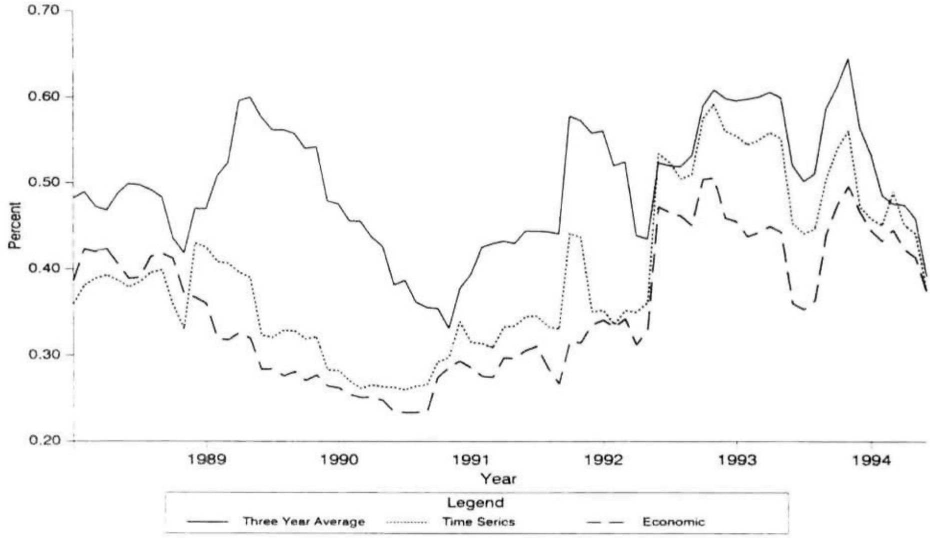

FIGURE 6

Error variance ratios, rolling 36 observations, 1-month horizon.

again. Regardless, the decline in relative predictability (rise in EVRs) since 1990 could underlie recent industry concerns about increased basis risk. Interestingly, based on the rather stable RMSEs (Figures 2 and 3) generated by the economic and time-series models, the source of the increasing EVRs appears to be a declining variability in the underlying basis rather than an increasing error in the basis forecast.

Finally, the findings indicate that live hog basis risk is rather stable, and the basis is not more variable nor appreciably less predictable than historical standards. This is in sharp contrast to the concerns expressed over declining deliveries at par markets, large basis variability, and the usefulness of the live hog contract. This analysis suggests that the usefulness of the live hog contract has not declined because of unfavorable basis behavior for the markets considered here. Moreover, the results call into question the efficacy of recent efforts to modify contract design and specification that emphasize the reduction of basis risk as a means of improving the performance and stimulating trading volume of the live hog futures contract. Alternative explanations not related to the performance of the contract may exist. Changes in the structure of the hog industry with movement toward alternative, less costly means of managing price risk, such as contracting or increased vertical integration, may have reduced the use of the futures contract. Similarly, the emergence of large-scale, high-volume, hog producers who market frequently, thereby receiving average price over the production cycle, also may have reduced the demand for the use of futures contracts as hedging instruments.

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