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

by

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Basis behavior has a direct affect on hedging and pricing decisions. Here, *ex ante* basis risk for selected live hog cash markets is analyzed from 1985 through 1994. Econometric, time series, and naive (three year average) models are used to forecast a nearby live hog basis. Measures of basis risk are based on mean squared forecast errors and market timing ability. The findings suggest that regardless of the forecasting method basis risk has not increased nor has basis predictability declined relative to historical levels. The recent decline in demand for futures contracts is likely attributable to other structural changes in the industry.

INTRODUCTION

Forecasting the cash-futures basis for agricultural commodities is an important aspect of a successful marketing strategy (Bobst, 1974; Chicago Mercantile Exchange, 1988). Short hedgers are long the basis and unanticipated basis movements can adversely affect the net price received, increasing risk and altering 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 stable and 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 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 the live hog contract, and the usefulness of the contract (Unnevehr, 1988; Hurt and Rice, 1991; Eihorn, 1994). The difficulty is attributed to the changing nature of cash markets, i.e., higher levels of vertical integration and by-passing of the traditional terminal markets with more direct sales to processors. Cash sales and prices in direct markets also are subject increasingly to quality, timing, and locational factors important to specific cash transactions. Furthermore, cash prices at terminal markets, which have declined in importance, are influenced less by fundamental supply and demand. Clearly, if the basis risk increased, the ability of futures contracts to transfer risk is reduced, it becomes more difficult to assess cash forward pricing opportunities, and the use of the futures contract itself can decline.

The purpose of this paper 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 to 1994. Basis risk is measured in a traditional mean squared error framework and the ability to correctly predict the sign of the basis. Because basis risk is generally viewed in an *ex ante*

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context, econometric and time series forecasting models are developed to assess basis behavior. Rather well established modeling procedures are used which can be readily implemented. Two forecast horizons are considered in the analysis: a long-term (five-month) forecast, which reflects the pricing decision of the producer during the planning stages of production; and a short-term (one-month) forecast, which represents the marketing decision and provides information on whether to sell animals immediately or wait for a strengthening of the basis. The out-of-sample forecasting ability of the basis models is assessed by examining their statistical behavior relative to naive forecasting models (Allen, 1994; Kolb and Stekler, 1993). Differences in basis risk over time, across terminal and direct markets, as well as implications for the successful use of futures markets are addressed. Additionally, analyses are performed to identify if 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; Leuthold and Peterson, 1983; Tomek, 1980), and those addressing forecastability have met with limited success. In a rational expectations framework, Naik and Leuthold (1988b) show that the basis for nonstorable commodities is a function of lagged values of the basis, cash prices, futures prices, as well as relevant supply and demand shifters. Naik and Leuthold (1988a) have moderate success in empirically explaining the cash-futures basis for live cattle and hogs. Although no explicit out-of-sample forecasting is performed, models explaining the maturity basis ahead of time (i.e., with lagged explanatory variables) fit the data poorly, suggesting that forecasting would be difficult.

Liu, Brorsen, Oellermann, and Farris (1994) explicitly address the forecastability of the nearby live cattle basis. Extending Naik and Leuthold's (1988a) work, the nearby basis is modeled as a function of delivery costs and expected changes in cash prices. Liu, et al. (1994) indicate 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 are 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 has the highest adjusted R-squared in-sample. The statistically important variables are lagged values of futures spreads, the basis, futures open interest, the consumer price index, and the price of chicken. However, evaluating thirty out-of-sample, one-step-ahead forecasts from 1987-1991, the four models perform similarly on the criteria of root mean squared error and in predicting turning points. The authors conclude that the ambiguity of out-of-sample results may stem from structural changes, and that the performance of the joint supply and demand model may not justify modeling costs. Furthermore, short-term dynamics (i.e., the lagged basis) are at least as important as fundamental variables in predicting the nearby basis.

This research utilizes the work of Naik and Leuthold (1988a) and Liu, et al. (1994) to identify potentially relevant supply and demand variables for an econometric forecasting model. The econometric model is specified from a set of economic 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, we define the basis over a relatively short temporal unit, one week, to minimize intra-observation variability and to represent a realistic marketing period. Additionally, previous studies have made only one-period-ahead 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 one- and five-months ahead, corresponding to the marketing and pricing/production decisions of producers, respectively. We also specifically consider the timing of data releases and their availability to a forecaster.

Data and Markets

The basis is defined as the difference in natural logarithm of cash and futures prices, $basis_t = \log(cash_t) - \log(nearby\ futures_t)$, so that cash is expressed as a percent premium or discount to futures.[1] Following Liu, et al. (1994) we focus 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 doesn't 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, and out-of-sample forecasts 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 econometric model expresses the basis as a function of supply and demand factors, delivery costs, and monthly dummy variables. Special attention is given to making the economic forecasting models realistic and implementable. For instance, distinct models are specified for generating one- and five-month forecasts. At the one-month horizon, all variables must enter the model with lags of at least 2 periods. Since 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 one-month models with lags of at least three periods. Similarly, for the five-month model these variables can only enter the model with lags of 7 months or greater, while those variables that are immediately observed (i.e., prices) need only be lagged 6 months.

The full live hog basis forecasting model is specified as:

where $lhbasis_t$ is the live hog basis (lh_t - $lhfut_t$); 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

[1] Preliminary analyses also were performed on the nonlogged basis data. In general, the characteristics and initial forecasting performance are consistent with the results presented below. The logged data are used as they closely reflect the percentage errors in returns.

$$lhbasis_t = f(dv2\text{-}dv12,\ cldpk_{t-i},\ slthg_{t-j},\ dcorn_{t-j},\ dretck_{t-j},\ dretbf_{t-j},\ dinccap_{t-i},\ dtb_{t-j},\ dcpi_{t-i})$$

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 dv1-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 was specified and estimated for the period 1975.01-1984.12. The full model incorporated all theoretically relevant variables with the minimum permissible lag for each forecasting horizon. The full model was then tested down--systematically eliminating variables insignificant at the 5% level--to a final specification. A Chow-test indicated a structural change in 1979. After examining the initial model, rolling samples of 60 observations are used for out-of-sample estimation and forecasting. During the forecast period, the econometric model is re-specified annually and re-estimated monthly. The models also are examined for autocorrelation in their estimated residuals.

Examples of the one-month Omaha econometric forecasting models for various samples are presented in table 1. 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^2s are reasonably high. While 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, ranged from .022 in early samples to a significant -.32 in others. Similarly, the CPI's estimated coefficient ranged 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, was 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, 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 five-month horizon, the econometric 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 has suggested that simple time series models may forecast as well as structural representations of the basis (Tomek, 1993; Hauser, Garcia, and Tumblin, 1990; Liu et al., 1994). As a distinct alternative to the pure economic models, the basis is modeled using 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 & Dickey, 1986). The seasonality and ARMA components are then jointly re-estimated. 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 econometric forecasts, time series models are estimated over rolling samples of 60 observations during the out-of-sample period. Time series models are re-specified annually and re-estimated 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 was an ARMA(4,0) or ARMA(2,1) with an occasional seasonal moving average term specified. Relative to the econometric models, the ARMA model specifications were fairly stable across subsamples. Adjusted R^2s were reasonably high and comparable to those of the econometric models.

Naive Model

Naive forecasts are a standard of comparison against which econometric and time series forecasts are often measured. The naive model is the three-year seasonal moving average, $f_t = 1/3(x_{t-12}+x_{t-24}+x_{t-36})$. This simple 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). Hence, this model provides forecasts that if improved upon would be useful to practitioners and academics alike. Further, it provides a view of basis risk with forecast procedures commonly used by many industry participants.

RISK MEASUREMENT PROCEDURES

Root Mean Squared Error

Tomek (1993) and Peck (1975) suggest the mean 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.[2] Define a forecast of x_t as f_t and

[2] 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. Thus, in this framework, changes in the proportion of the production hedged should be attributable primarily to changes in the basis risk.

the forecast error $e_t = x_t - f_t$, then the root mean squared forecast error (RMSE) over n forecasts can be expressed as,

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

The RMSE measures forecast accuracy based on a quadratic loss function which 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 using the procedure set forth by Ashley, Granger, and Schmalensee (1980).

Henriksson-Merton Timing Test

The MSE provides quantitative information concerning the accuracy of forecasts. However, it is often the case that 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 using the timing test proposed by Henriksson and Merton (1981).

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

$$FS_{t-i} = \alpha_1 + \beta_1 AS_t + \epsilon_t \qquad (1)$$

where, FS_{t-i} = 1 if a positive basis is forecasted for time t at time t-i
= 0 otherwise
AS_t = 1 if the actual basis is positive at time t
= 0 otherwise.

The null hypothesis of no timing ability, H_O: $\beta_1=0$, 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' sign.

RESULTS

Basis Variability

Table 2 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 both in terms of price level, price changes, and basis levels (panel B).[3] This results in similar basis models and forecasts for each market. Thus, emphasis is placed on the Omaha forecasting results 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 non-delivery months (table 2, panel A).[4]

Figure 1 shows the Omaha live hog basis from 1975 through 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 finds 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 through May 1994. However, basis variance as a measure of risk is limited in that 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 one to five months; hence, direct comparisons are not made across the different horizons. Similarly, for purposes of brevity, the discussion focusses on the one-month horizon findings, noting significant differences with the five-month results.

Root Mean Squared Error

Table 3 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 three-year moving average (3MA), with p-values of 0.0861 and 0.0287, respectively (Ashley, et al., 1980). At the five-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 three-year moving average's (3MA) RMSE at the 10% level. Similar RMSE rankings hold for delivery and non-delivery month forecasts.[5]

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[3] 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; Leuthold, Garcia, and Chaherli, 1992).

[4] The basis is characterized by time dependent variance, but it is not of the ARCH type. Basis variance increases in non-delivery 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 useable and tractable models, but nonetheless it is of practical concern to hedgers. The presence of this type of time dependent variance should not influence the comparative findings of the analysis.

[5] While 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 3), the one-month economic forecasts of the non-delivery basis provide the greatest potential for generating positive returns

To investigate how RMSEs and, thus, basis risk change through time, the RMSE for each forecasting method is calculated over rolling three-year (thirty-six month) periods.[6] A series of forecasts that outperforms another series would have a lower RMSE in all evaluation periods. At a one-month horizon the economic model clearly dominates the three-year moving average model (figure 2). The time series model produces a lower RMSE than the three-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 1988 and 1990. Similar tenuous relationships are revealed at the five-month horizon (figure 3), where no model dominates for an extended time period although the economic model provides the most consistent accuracy.

Over time, the RMSEs are not trending upward. At the one-month horizon, the RMSEs for the econometric and time series models have been relatively stable through time in a narrow band around 4% of the futures price. The RMSEs for the naive forecasting model have declined somewhat through time suggesting that seasonality has become more important in recent years. At the five-month horizon, the econometric and time series models again demonstrated rather stable RMSEs through time, while the RMSEs from naive model declined modestly. It is clear that these results provide little evidence of increasing basis risk using any of the forecast models.

Timing Tests

The Henriksson-Merton regression (equation 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 H-M test also are presented in table 3, where the percent 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. Due to strong seasonality in the basis, the timing is fairly consistent across markets and methods. The sign predictability of delivery and non-delivery months are roughly equivalent.

Again, rolling samples of thirty-six months are utilized to examine temporal changes in predictability. The H-M test is estimated over these rolling samples and the percent correct sign forecasts $((1+\beta_1)/2)$ are plotted in figures 4 and 5. At the one-month horizon (figure 4), the time series forecasts dominate the three-year moving average in nearly all samples; whereas, the relative timing ability between the time series and economic model is 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 five-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 one- and five-month horizons. Thus, the ability to forecast the sign of the basis using any of the forecast procedures did not decline over the period 1985 through 1994.

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over the use of the naive model.

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

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 through May 1994. In general, the economic and the time series models provided superior basis forecasts relative to the naive three-year moving average procedure, with the most dramatic improvements evidenced at the one-month horizon. Examining the results of out-of-sample basis forecasts across the three procedures, it is evident that mean squared errors did not increase from 1985 to 1994. Further, the ability to predict the sign of the basis, as measured by the Henriksson-Merton test, increased steadily through the period. In sum, live hog basis variability has not increased relative to historical levels and there is almost no evidence that 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. First, 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 variance reduction. However, once the forward pricing decision has been 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. Clearly, the economic value of the forecasts must be determined within the decision framework of the individual users and deserves additional consideration.

Second, 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.[7]

EVRs based on rolling thirty-six month intervals are shown for the Omaha market at the one-month horizons in figure 6.[8] EVRs that trend higher may be indicative of a basis that

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[7] 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 one-month horizon, regression results indicated that the various models provided rational forecasts. At the five-month horizon, rationality of the forecasts was rejected.

[8] The figure for comparable five-month EVRs is not presented for brevity. The rankings of the various models are much more tenuous, but the general pattern of the predictability

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 thirty-six month subperiods. The variance of the forecast errors are less than sixty percent 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 simply returned to normal levels (or perhaps is in the process of going lower 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 econometric 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, our findings indicate that live hog basis risk has been 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. Our analysis suggests that the usefulness of the live hog contract has not declined due to unfavorable basis behavior. Moreover, our results call into question the efficacy of recent efforts to modify contract design and specification which 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 towards 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 futures as a hedging instrument.

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Table 1. **One-Month Horizon Economic Models: Omaha Terminal Market Live Hog Basis**

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

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

Table 2. **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, non-delivery 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, non-delivery 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, non-delivery months	0.986

Table 3. Risk Measures, Live Hog Basis, 1985.01-1994.05

	Root Mean Squared Errors					Percent Sign Correct Forecast				
	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
Non-Delivery 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
Non-Delivery 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 statisically different from 0.50 at the 1% significance level.

Figure 1. Omaha Live Hog Basis, 1975-1994

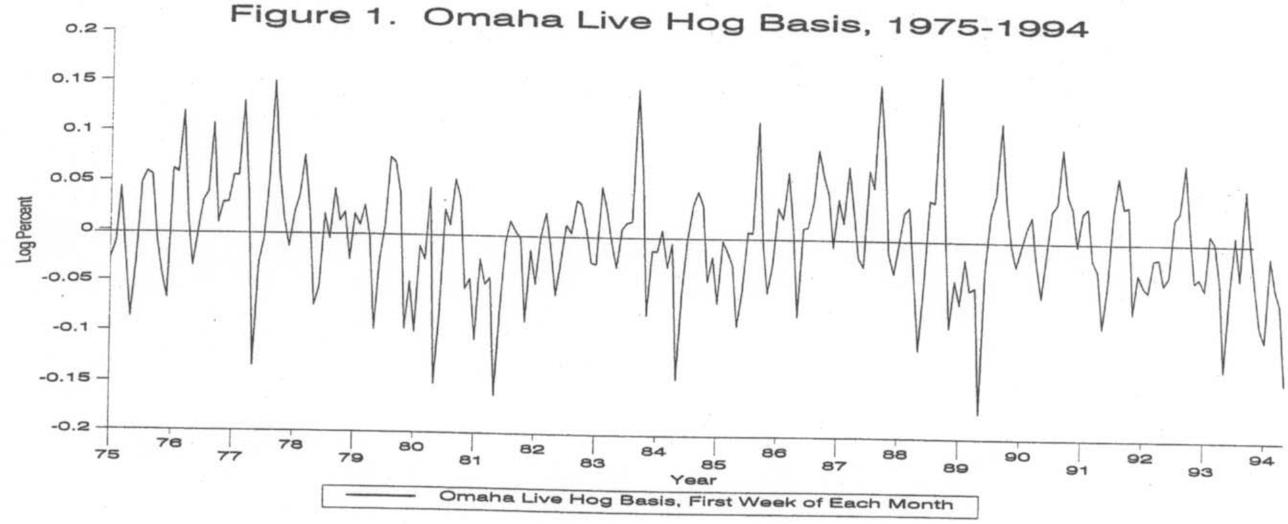

Figure 2. Root Mean Squared Errors, Rolling Thirty-Six Observations
One-Month Horizon

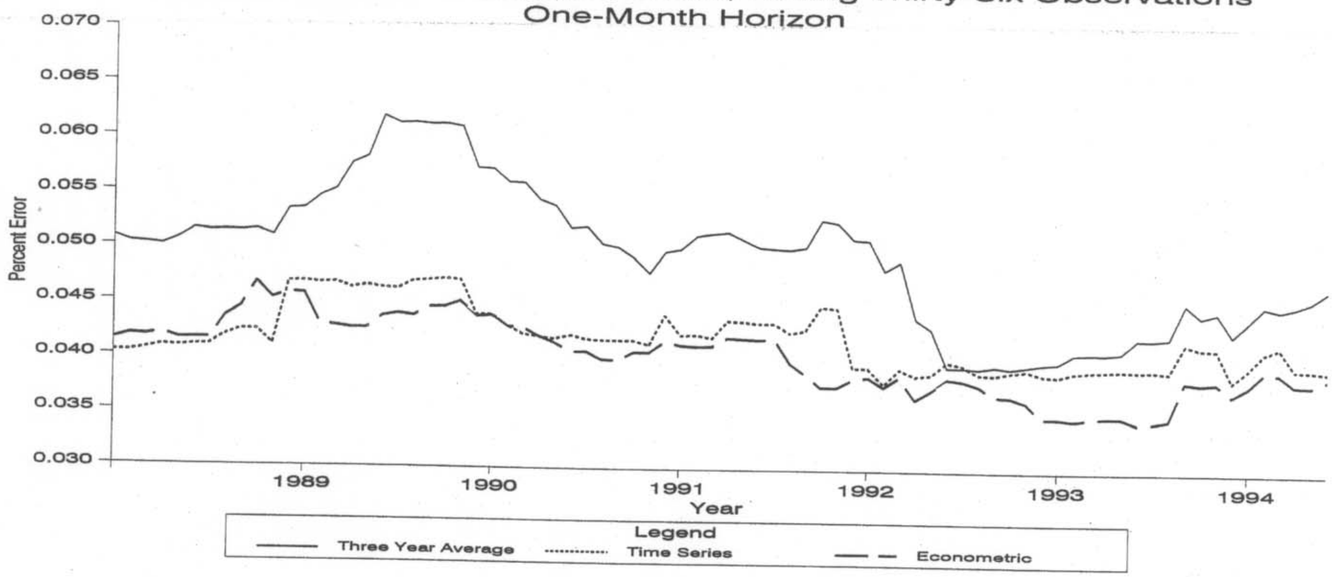

Figure 3. Root Mean Squared Errors, Rolling Thirty-Six Observations
Five-Month Horizons

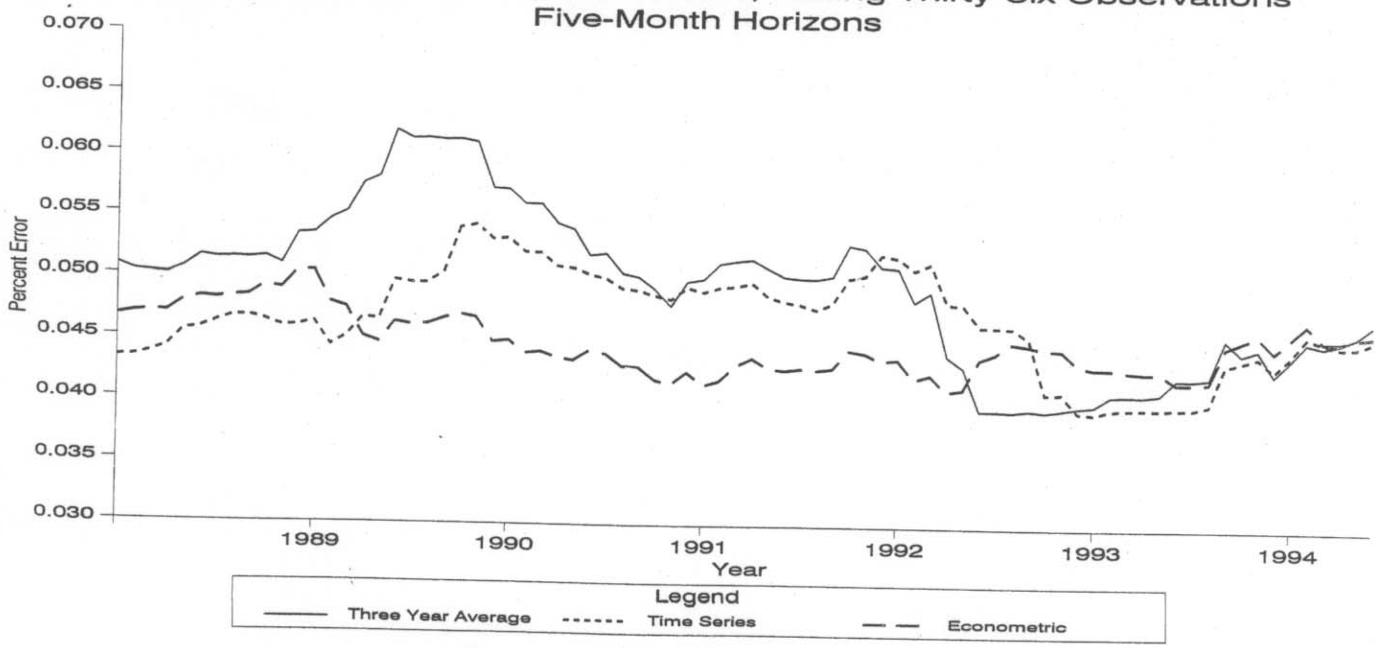

Figure 4. Percent Sign Correct Forecasts, Rolling Thirty-Six Observations
One-Month Horizon

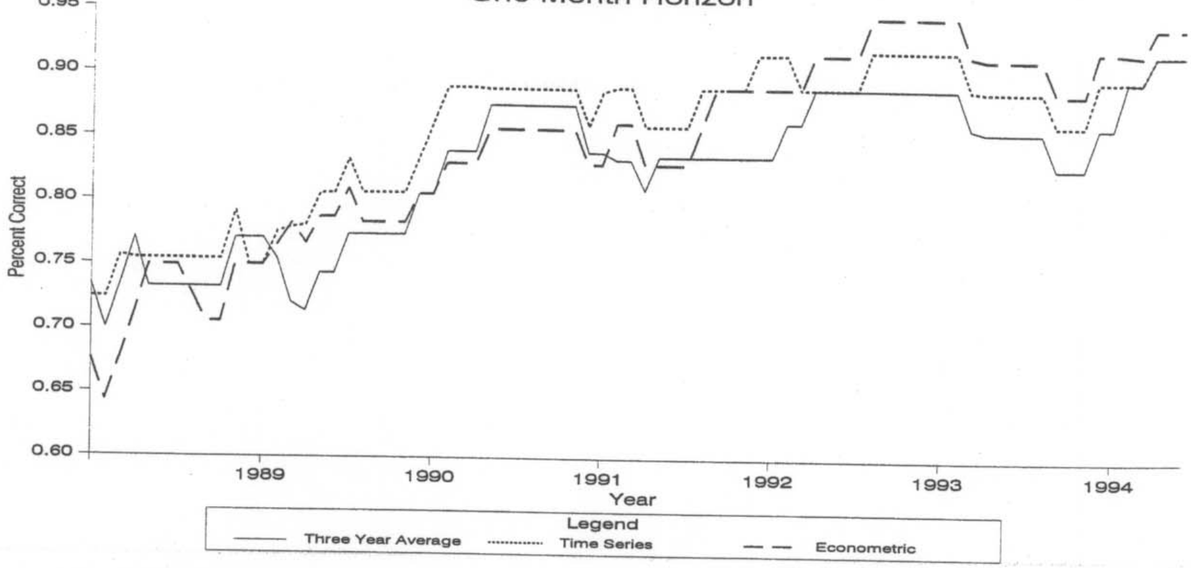

Figure 5. Percent Sign Correct Forecasts, Rolling Thirty-Six Observations
Five-Month Horizon

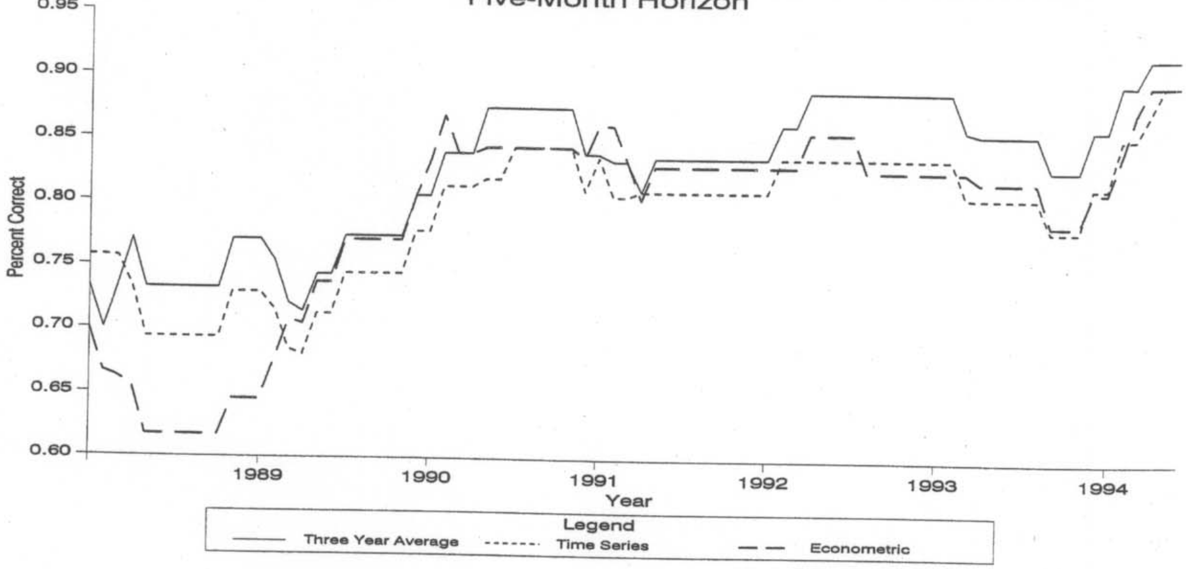

Figure 6. Error Variance Ratios, Rolling Thirty-Six Observations
One-Month Horizon