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Futures-Based Price Forecasts for Agricultural Producers and Businesses

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The forecasting accuracy of five competing naive and futures-based localized cash price forecasts is determined. The third week's price each month from 1987–96 is forecasted from several vantage points. Commodities examined include those relevant to Midwest producers: the major grains, slaughter steers, slaughter hogs, several classes of feeder cattle, cull cows, and sows. Relative forecasting accuracy across forecast methods is compared using regression models of forecast error. The traditional forecast method of deferred futures plus historical basis has the greatest accuracy—even for cull cows. Adding complexity to forecasts, such as including regression models to capture nonlinear bases or biases in futures markets, does not improve accuracy.

Key words: basis, cash price forecasting, futures

Introduction

Futures prices are regularly used to construct agricultural commodity price forecasts. Both grain elevators and livestock packer buyers forward price "off the board," generally using a formula. Even commodities that are not deliverable on the underlying futures contract—such as milo (grain sorghum)—often are priced this way. However, if futures/cash differentials (bases) are not stable over time, gains in predictive accuracy may result from using bases which have proportional as well as differential components. Further, if deferred futures prices are biased estimates of future prices, modeling cash/deferred futures relationships may provide greater forecast accuracy than just adjusting futures prices for expected basis.

This research examines the accuracy associated with using deferred futures prices, along with historical average bases, to predict future cash prices of various crop and livestock commodities important to the Midwest. Several forecast horizon lengths, up to a year, are considered. Futures-plus-basis price forecasts are compared with naive cash price forecasts and to other futures-based forecasts. Simple regression-based forecasts also are included. Regression analysis is used to determine which factors affect forecast errors of competing models and to test which forecast methods are most accurate. The overall objective is to provide information about several simple, mechanical, futures-based grain and livestock price forecasting methods, so that forecasters

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might be better equipped to increase the accuracy of their cash price forecasts—and hence their relevance.

Background

Agricultural production is becoming increasingly differentiated in physical characteristics, time, and/or space. For example, corn is becoming segregated into several classes such as high oil or high lysine, and wheat is increasingly segregated according to baking qualities, especially protein. Livestock are becoming increasingly differentiated with price premiums and/or discounts associated with various characteristics. In addition, profit-maximizing cropping decisions now rely more on price projections because virtually no cropping constraints are imposed by the most recent farm legislation [the Federal Agricultural Improvement and Reform (FAIR) Act of 1996]—which means the accuracy of crop price projections is becoming more important. Together, these observations imply producers and agricultural businesses require price forecasts that are more product, location, and time specific.

Extension outlook price forecasts have not traditionally been product, location, or time specific. Rather, they have focused on broad-based price forecasts, such as quarterly or annual national commodity prices. In part, this may be because extension models regularly incorporate fundamental supply/demand data that would be prohibitively expensive to obtain at finer time and space distinctions. Also, extension forecasters attempt to maximize user audience around each forecast provided. Recent research has shown that extension grain price forecasts typically have been less accurate than those of the U.S. Department of Agriculture (USDA) (Kastens, Schroeder, and Plain). Considering that extension regularly forecasts many of the same price series as USDA, and that producers will demand more specific forecasts in the future, this research aids those economists wishing to enhance their appeal by providing more frequent and more localized cash price forecasts. Further, management-oriented economists often must make price expectations, even if not formally. This research should benefit them by demonstrating potential gains to using futures prices to project cash prices.

Grain and livestock businesses regularly forward price based on deferred futures, and futures prices *are* price expectations (Eales et al.). Futures prices are inexpensive to obtain and are at least as accurate as commercial and public providers of price forecasts (Just and Rausser; Marines-Filho and Irwin; Kastens, Schroeder, and Plain). Because they are virtually continuously available, futures prices could aid extension and forecast users directly in the development of more specific price forecasts. However, to assure timeliness, availability, and the potential for user development, futures-based cash price forecasts must be simple to construct and easy to understand.

Brorsen and Anderson have challenged extension forecasters by arguing that "the efficient market hypothesis and the law of one price should be the cornerstone of extension marketing programs" (p. 90). This research builds on their challenge by embodying those two economic concepts in procedures that can be used in real-time forecasting. Using futures prices to construct cash price forecasts depends on futures market efficiency. If a futures market is efficient, then a deferred futures price will, on average, be an unbiased estimate of delivery-time price of the underlying commodity. That means a cash price forecast can be made by adjusting futures price for expected basis, assuming basis can be accurately forecasted. Hauser, Garcia, and Tumblin concluded that simple historical average bases represented relatively good forecasts of harvest-time soybean bases in Illinois. On the other hand, tying an unbiased delivery-time basis to a biased deferred futures price will result in a biased cash price forecast.

The futures efficiency literature is large, with a variety of procedural approaches taken and diverse conclusions. Overall, the evidence favors futures efficiency. However, there is a greater tendency for research to find inefficiency in livestock futures than in grain futures (Garcia, Hudson, and Waller; Kolb 1992, 1996). In some contracts, most notably live cattle futures, reported inefficiencies were *biases*, meaning that economically significant trends persisted in futures prices (Kastens and Schroeder). Thus, it may be important that simple futures-based price forecasting procedures allow for possible underlying biases.

For some agricultural commodities, especially grains, locational price differences are more important than differences between cash commodity characteristics and related futures contract specifications, at least currently (grain classes and qualities may become more important in the future). Hence, in developing futures-based cash grain price forecast procedures, it is important to test historical data from many locations. For other commodities, especially livestock, where products vary by type of animal, weight, or sex, departures from futures contract specifications are especially important. Thus, in developing futures-based cash livestock price forecasts, it is important to incorporate historical data from several animal classes and weights, and from both sexes. Finally, to be of general value, forecasts need to provide information for numerous points in the future.

General Analytical Procedures

Five approaches are used to forecast future cash prices. The procedures are presented in order of increasing complexity.[1] The first approach, referred to as *NAIVE*1, uses last year's price to forecast price in the same week this year. Formally, in a model framework, this approach states that the cash price for commodity i, in location j, for week w of year T ($CP_{i,j,w,T}$) is equal to the cash price observed for the same commodity, location, and week in year $T-1$, plus an error: $CP_{i,j,w,T} = CP_{i,j,w,T-1} + \varepsilon_{i,j,w,T}$. This specification yields a one-step-ahead forecast of price in week w of year $T+1$, with that expectation taken h (for horizon) weeks prior to when the actual price is observed:

$$(1) \quad NAIVE1: \qquad E_{w-h}\left[CP_{i,j,w,T+1}\right] = CP_{i,j,w,T}.$$

[1] Models used here are ad hoc, but were designed to meet several criteria. First, they must range from especially simple to somewhat more complex, to test the gains to increasing complexity, and thus cost in real-time ongoing forecast construction. Second, to have something worth testing against, the simpler models must be representative of methods that may be currently used by producers and businesses. Third, the most complex models considered cannot be too complicated, so that their cost does not preclude everyday use. Single- and multiyear historical averages are included as benchmarks. More important, such simple averages might plausibly be called upon by nonforecasting management economists who routinely must incorporate price expectations in their management advice. Thus, it is important to consider futures-based forecast accuracy relative to such simple models. The purpose here is not to find the absolute best cash price forecasting method among all reasonable alternatives. Rather, it is to examine whether incorporating futures in a practical manner might improve the accuracy over simple nonfutures methods.

The $w-h$ is not included on the right-hand side of (1) because the price forecast for a particular week of year $T+1$ is the same for all forecast horizons.

The second approach, referred to as *NAIVE*5, assumes cash price returns to its multiple-year average. However, because policy and other changes can fundamentally alter long-term prices, the number of years considered is only five. Formally, this forecast specification is:

$$(2)\quad NAIVE5: \qquad E_{w-h}\left[CP_{i,j,w,T+1}\right] = \frac{1}{5}\sum_{t=T-4}^{T} CP_{i,j,w,t}.$$

As in (1), the forecasts from (2) are the same for all forecast horizons.

The third forecast approach, *FUTLBAS*, incorporates futures and basis with basis a fixed *level* (or differential), as in cents per bushel. Basis is defined here as cash price less nearby futures price, implying cash price equals nearby futures price plus basis. If basis does not trend over time, cash price can be defined as nearby futures price plus historical average basis plus some error. If futures are unbiased, deferred futures price (the current price of a contract that expires in the distant future, beyond the expiration of the nearby contract) provides a reasonable forecast of that futures price when it becomes the nearby contract at delivery time. Consequently, using five years to generalize historical basis information, the *FUTLBAS* forecast specification is:

$$(3)\quad FUTLBAS: \qquad E_{w-h}\left[CP_{i,j,w,T+1}\right] = FP_{i,w-h,T+1}^{w,T+1} + \frac{1}{5}\sum_{t=T-4}^{T}\left(CP_{i,j,w,t} - FP_{i,w,t}^{w,t}\right),$$

where the subscript i on the futures price variable, *FP*, refers to the contract nearest in specification to (or most likely to be used in hedging) cash commodity i; the j is omitted because it is assumed that the pertinent futures contract does not change across cash price locations. As with cash price, the remaining two subscripts of *FP* denote the week (w) and year (T). The superscripts on *FP* further specify the futures contract represented, i.e., $\{w, T+1\}$ specifies that the futures contract is the nearby contract in week w of year $T+1$. Equation (3) reads as follows. The expectation (or forecast) taken in week $w-h$, for the cash price of commodity i in location j that will be observed in week w of year $T+1$, is equal to the price, observed in week $w-h$ of year $T+1$, for the futures contract corresponding to commodity i that *will be* the nearby in week w of year $T+1$, plus the respective five-year moving average basis. Unlike *NAIVE*1 and *NAIVE*5, *FUTLBAS* forecasts are unique for each forecast horizon—because these forecasts incorporate current deferred futures prices.

The fourth forecast approach retains the "futures plus basis" idea embodied in *FUTLBAS*. However, it allows more flexibility by specifying basis in *level* and *proportional* components. This forecast method is called *FUTLPBAS*. The increased basis flexibility comes about by assuming that cash price equals some proportion of nearby futures price, plus an additive constant, plus an error. As with *FUTLBAS*, relationships in *FUTLPBAS* are assumed to hold over only the most recent five years. Formally, cash price is treated as a five-observation regression of cash price on nearby futures price plus an intercept, resulting in a first-order approximation of some higher order cash/futures relationship. Each commodity, location, week, and year (but not horizon) has its own unique regression and corresponding intercept and slope estimates. As with *FUTLBAS*, in forecasting, current deferred futures price is substituted for the unknown nearby futures price. Using parameter estimates from the underlying regression equation, the forecast specification is:

$$(4)\qquad FUTLPBAS\text{:}\quad E_{w-h}\left[CP_{i,j,w,T+1}\right] = \hat{\alpha}_{i,j,w,T} + \hat{\beta}_{i,j,w,T}FP^{w,T+1}_{i,w-h,T+1}.$$

FUTLPBAS forecasts are horizon specific because deferred futures prices are unique for each forecasting horizon. *FUTLPBAS* is inherently more complex than *FUTLBAS* or the two naive methods in that regression models must be estimated. However, because the parameter estimates are not horizon specific, the total number of regressions required is not excessive, and the potential forecasting accuracy gains could be large.

Where futures prices may have a tendency to be biased, it could be helpful to circumvent the idea of basis altogether and model cash price directly as a function of deferred futures price (not nearby). Thus, *MODFUT* forecasts arise from regressions of cash price on deferred futures price, where parameter estimates are unique across commodity, location, week, year, *and* horizon. *MODFUT* forecasts are specified as:

$$(5)\qquad MODFUT\text{:}\quad E_{w-h}\left[CP_{i,j,w,T+1}\right] = \hat{\alpha}_{i,j,w-h,T} + \hat{\beta}_{i,j,w-h,T}FP^{w,T+1}_{i,w-h,T+1}.$$

Equation (5) looks a lot like (4) with one important difference. The subscripts for the parameter estimates include the letter h. That means a separate model is estimated for each price forecasted and each forecasting vantage point, $w - h$. *MODFUT* involves many more regressions than does *FUTLPBAS*. The additional computation time and data basing required, though seemingly small in a research setting, could be enough to preclude real-time forecasters from using this approach. However, if forecasting accuracy gains are large, then the additional burden may be worthwhile.

Data Used and Forecasts Developed

Weekly prices for various cash commodities and locations were collected from the first week of 1982 through the last week of 1996. Locations selected were those relevant for Midwestern (with focus on Kansas) producers and businesses. Commodities examined were wheat, corn, milo, soybeans, slaughter steers, cutter cows, 7–8 cwt steers, 4–5 cwt steers, 7–8 cwt heifers, 4–5 cwt heifers, slaughter hogs, and sows. Price data were structured on the basis of four weeks per month (if a month had five weeks, the fourth and fifth weeks' prices were averaged). Nearby futures price data corresponding to the cash price series also were collected, with nearby defined as nearest to delivery but not in the delivery month. For some commodities, deferred futures prices were consistently available up to 11 months prior to the nearby period. For others, they were available only for shorter time periods.

Table 1. Cash Price Forecast Description for Third Week in Each Month, 1987–96

Cash Commodity[a]	Location No. or Name	Futures Market[b]	Forecast Horizons (months)	Total Forecasts[c]
Wheat	23[d,e]	KCBT wheat	1, ..., 8	110,400
Corn	11[d]	CBOT corn	1, ..., 11	72,600
Milo	17[d,f]	CBOT corn	1, ..., 11	112,200
Soybeans	13[d,g]	CBOT soybeans	1, ..., 11	85,800
Slaughter Steers	Western KS Direct	CME live cattle	1, ..., 9	5,400
Cutter Cows	Sioux City IA	CME live cattle	1, ..., 9	5,400
7–8 cwt Steers	Dodge City KS	CME feeder cattle	1, ..., 6	3,600
4–5 cwt Steers	Dodge City KS	CME feeder cattle	1, ..., 6	3,600
7–8 cwt Heifers	Dodge City KS	CME feeder cattle	1, ..., 6	3,600
4–5 cwt Heifers	Dodge City KS	CME feeder cattle	1, ..., 6	3,600
Slaughter Hogs	St. Joseph MO	CME live hogs	1, ..., 11	6,600
Sows	St. Joseph MO	CME live hogs	1, ..., 11	6,600

[a] All grain prices are for Wednesday (or Thursday if no market on Wednesday). Slaughter steers, hogs, and sows are weekly averages; other livestock prices are market day prices.
[b] All futures prices are Wednesday's close (or Thursday if no market on Wednesday).
[c] Total forecasts are obtained by taking the number of forecast methods (i.e., 5—*NAIVE*1, *NAIVE*5, *FUTLBAS*, *FUTLPBAS*, and *MODFUT*) times the number of weeks forecasted each year (12, or one for each month) times the number of years forecasted (10) times the number of locations (e.g., 23 for wheat) times the number of horizons considered (e.g., 8 for wheat).
[d] All grains share these Kansas markets: Colby, Dodge City, Emporia, Garden City, Great Bend, Hutchinson, Kansas City, Pratt, Scott City, Topeka, and Whitewater.
[e] Other Kansas wheat locations: Andale, Beloit, Concordia, Hays, Hoxie, Liberal, Marysville, Russell, Salina, St. Francis, Wellington, and Wichita.
[f] Other Kansas milo locations: Andale, Beloit, Hays, Liberal, Salina, and Wichita.
[g] Other Kansas soybean locations: Andale and Beloit.

*NAIVE*1, *NAIVE*5, *FUTLBAS*, *FUTLPBAS*, and *MODFUT* forecasts were developed for each commodity and location.[2] Because all but one method (*NAIVE*1) required five years of historical data, all forecasts were for weeks in the years 1987 through 1996. Because of the large volume of data, prices from only selected weeks were forecasted, and only at selected horizons. Prices were forecasted for the third week of each month in each year. The vantage points from which these prices were forecasted (the forecast horizons) were four weeks prior, eight weeks prior, and so on, stepping back in time as long as deferred futures prices were available. Because of the weeks selected, both forecasted periods and forecast horizons are one month apart. Missing data were extrapolated to ease the computational burden (the appendix describes missing data procedures and other data details). Table 1 provides a description of the cash price series forecasted, the associated underlying futures markets, the number of forecast horizons considered, and the total number of forecasts constructed.

[2] Ordinary least squares (OLS) was used in estimating underlying regressions for regression-based forecasts. Potential cointegration between cash and futures prices may cause underlying parameter estimate standard errors to be unreliable. However, cointegration considerations are not useful in these models that are estimated over only five observations ($t = T - 4$ to $t = T$) each year.

Forecast Evaluation Procedures

Competing forecasts are routinely compared pairwise using a test statistic such as sum of squared errors or mean absolute error. Unfortunately, to extract information of interest often requires numerous pairwise comparisons, making it difficult to generalize results. An alternative forecast comparison approach, that generalizes large amounts of information, collapses the information in a forecast error series into a regression model where forecast error is the dependent variable. In that framework, forecast errors from competing forecasts across time and space can be stacked, so that partial effects of interest can be isolated using appropriate independent variables. (For an example of this method of forecast comparison, see Kastens, Schroeder, and Plain.) Because the number of forecasts examined was large, varying across years, weeks within the year, horizon length, location, and commodity, the forecast error regression model approach to forecast comparison was selected. This approach considers that cash price forecast errors for a commodity are affected by forecast method, forecast horizon, time period forecasted, and the cash price location:

$$\text{(6)} \qquad \text{Forecast Error} = f(\textit{method, horizon, time period, location}).$$

A goal of this research was to determine relative accuracy for alternative cash price forecasting methods. The effect of forecast horizon on the accuracy of competing forecast methods is expected to vary widely. For example, forecasts using the two naive methods are constant across horizon, while the two futures methods are horizon specific. Thus, it is important to specify (6) so that the effects of horizon by method, on relative accuracy, can be measured—suggesting an interaction term. Prices for some time periods within the year, and for some locations, are likely to be inherently more difficult to forecast than other times or locations. It is important to isolate these inherent forecast accuracy differences so that they do not mask information sought, i.e., comparing relative accuracy across competing forecast methods. However, to generalize the results into usable forecast procedure recommendations, no interactions with method were considered for the time and location effects.

Focusing on error magnitude, forecast errors were measured as absolute values. Because the scale of cash price varies substantially across time and location, errors were computed as percentage errors (actual less predicted, divided by actual, and multiplied by 100). Thus, the dependent variables are absolute percentage forecast error (APE) series. The final model to be estimated separately for each commodity is:

$$\text{(7)} \qquad \begin{aligned} APE_{i,j,w,T,w-h} = {} & \alpha + \beta_1 NAIVE1 + \beta_2 NAIVE5 + \beta_3 FUTLPBAS \\ & + \beta_4 MODFUT + \beta_5 HORIZON + \beta_6 (FUTLPBAS * H) \\ & + \beta_7 (MODFUT * H) + \beta_8 JAN_w + \ldots + \beta_{18} NOV_w \\ & + \beta_{19} LOC_1 + \ldots + \beta_{J+17} LOC_{J-1} + \varepsilon_{i,j,w,T,w-h}. \end{aligned}$$

In equation (7), i represents forecast method providing the forecast (*NAIVE*1, *NAIVE*5, *FUTLBAS*, *FUTLPBAS*, *MODFUT*), and thus the APE; j represents location ($1 \ldots J$); w is the week ($3, 7, \ldots, 47$) of year T (1987–96) corresponding to the period forecasted;

h represents forecast horizon length in weeks, so that $w - h$ denotes a forecast made in week $w - h$. *NAIVE*1, *NAIVE*5, *FUTLPBAS*, and *MODFUT* are forecast dummies that equal 1 when the forecast was generated by that respective method, and 0 otherwise (the default method is *FUTLBAS*). *HORIZON* is a variable equal to h; (*FUTLPBAS* $*H$) and (*MODFUT* $*H$) are forecast horizon slope shifters equal to the product of *HORIZON* and the corresponding forecast dummy (the default is *FUTLBAS* $*H$). JAN_w through NOV_w equal 1 if week w is in the month specified, and 0 otherwise. LOC_j is 1 if the underlying forecast corresponds to the cash price in location j, otherwise 0.

Naive forecasts do not change with horizon. Thus, prior to estimation of (7), observations involving naive forecasts beyond one-month horizons were eliminated to prevent unnecessary degrees-of-freedom inflation. Also, model errors are likely heteroskedastic across horizon and method. Specifically, model errors likely have greater variance as forecast horizon (h) increases because more distant forecasts have larger and more variable APEs. Further, if some forecast methods have greater forecast variance, this will cause larger model error variances. Consequently, equation (7) models were estimated in a generalized least squares framework allowing for these cross-sectional heteroskedasticities. For each commodity, the error covariance, $V = E(\varepsilon\varepsilon')$, was specified as a block diagonal matrix where each method-horizon combination was associated with a separate block. Using the wheat model as an example, each block is of the form $\sigma^2 \mathbf{I}_{2,760}$. The identity matrix dimension, 2,760, is from 12 months each year for 10 years across 23 locations. There are 26 blocks for the wheat model: eight horizons by each of three futures-using methods, plus one for each of the two naive methods.[3] Because estimations assumed no autocorrelation of errors, standard errors of parameter estimates may have been underestimated.

Results

As a general background, table 2 shows mean absolute percentage error (MAPE) and maximum absolute percentage error (maxAPE) by forecast method and commodity. The minimum APE was always near zero, so not reported. As judged by average MAPEs, *FUTLBAS* (futures plus level basis) and *FUTLPBAS* (futures plus level and proportional basis) provide the greatest accuracy across the forecast methods. Forecasts based on last year's price (*NAIVE*1), while not particularly accurate, did not diverge too far from actual price either (low maxAPEs). The relatively more complex *MODFUT*, where cash price is modeled as a function of deferred futures price, was the worst method by maxAPE, which suggests *MODFUT* is associated with occasional large errors, especially in the grains.

Overall, in terms of MAPE, table 2 shows that *NAIVE*5 (five-year naive) was generally the least accurate forecast method. For the six cattle price series, *NAIVE*5 was the single worst method for MAPE and had the highest maxAPE for four out of six cattle series. Underlying cattle price cycles may be to blame for lower accuracy of *NAIVE*5, causing the five-year average price to be a poor predictor of future price. The rightmost

[3] Equation (7) models involve multiple measurements of overlapping data. For a discussion of multilevel, or hierarchical, modeling (the techniques used to deal with such error dependencies), see Goldstein. We used the "repeated" command in PROC MIXED in the SAS/STAT modeling procedures of SAS to implement our heteroskedasticity corrections. For a discussion of these procedures, see *Getting Started with PROC MIXED* from SAS Institute, Inc.

Table 2. Mean and Maximum APEs by Commodity and Forecast Method, 1987–96

Commodity		Forecast Method					Average by Commodity
		*NAIVE*1	*NAIVE*5	*FUTLBAS*	*FUTLPBAS*	*MODFUT*	
Wheat	MAPE	20.25	18.99	10.73	10.89	12.95	14.76
	maxAPE	77.42	54.42	57.83	57.53	132.00	45.84
Corn	MAPE	19.33	18.48	11.58	12.32	15.23	15.39
	maxAPE	79.56	104.39	58.89	66.94	107.50	83.46
Milo	MAPE	20.43	20.03	12.47	13.13	16.39	16.49
	maxAPE	73.17	95.56	72.45	65.25	133.20	87.93
Soybeans	MAPE	15.42	11.51	9.41	9.15	10.29	11.16
	maxAPE	54.48	32.36	84.93	79.16	142.32	78.65
Slaughter Steers	MAPE	6.87	9.67	5.82	6.35	7.98	7.34
	maxAPE	20.78	30.17	19.47	22.75	49.17	28.47
Cutter Cows	MAPE	12.60	18.74	11.22[a]	10.77[a]	13.96	13.46
	maxAPE	59.62	85.00	67.27	66.89	82.36	72.23
7–8 cwt Steers	MAPE	9.57	15.47	6.12	5.83	8.15	9.03
	maxAPE	28.80	53.43	24.05	24.29	59.99	38.11
4–5 cwt Steers	MAPE	12.19	19.73	10.87	9.19	9.87	12.37
	maxAPE	53.22	81.61	51.81	46.05	50.39	56.62
7–8 cwt Heifers	MAPE	9.80	16.51	6.75[a]	6.76[a]	9.02	9.77
	maxAPE	29.76	64.23	27.34	22.11	57.98	40.28
4–5 cwt Heifers	MAPE	13.07	22.01	11.64	9.29	10.64	13.33
	maxAPE	53.95	94.04	58.39	39.38	54.62	60.08
Slaughter Hogs	MAPE	15.84	12.76[a]	10.22	10.45	13.32[a]	12.52
	maxAPE	49.73	56.37	65.95	65.30	79.35	63.34
Sows	MAPE	20.93	18.90[a]	13.66	14.17	18.94[a]	17.32
	maxAPE	79.02	89.21	103.75	104.02	117.96	98.79
Avg. by Method	MAPE	14.69	16.90	10.04	9.86	12.23	
	maxAPE	54.96	70.07	57.68	54.97	88.90	

[a] Same-row MAPEs that could not be distinguished from each other (at the 0.05 significance level) in pairwise tests using signed-rank Wilcoxon tests.

column of table 2 shows grains to have the least accuracy. The average MAPE for wheat, corn, milo, and soybeans is 14.45%, but 10.88% for the six cattle series. Across all commodities, slaughter steer price forecasts were the most accurate and sow price forecasts the least accurate.

Results of models explaining forecast errors [equation (7)] are presented in table 3. To conserve space, coefficient estimates for binary location and seasonal variables are not reported.[4] Chi-squared tests universally reject homoskedasticity null hypotheses in favor of the modeled error covariance structure. The models do not have particularly high explanatory power, as R^2s range from a high of 0.19 for 7–8 cwt feeder steers to a low of 0.04 for cutter cows.

[4] A total of 64 cash price locations were considered in grain price forecasts (wheat 23, corn 11, milo 17, soybeans 13). Among the 60 related location dummies, 15 had parameter estimates significant at the 0.05 level. Among the 132 total monthly dummies (12 commodities times 11 months), 76 were significant at the 0.05 level. Nonreported parameter estimates are available from the authors on request.

Table 3. Selected Regression Parameters with a Dependent Variable of Absolute Percentage Forecast Errors, 1987–96

	FORECAST ERROR MODELS											
Estimate	Wheat	Corn	Milo	Soybeans	Slaughter Steers	Cutter Cows	7–8 cwt Steers	4–5 cwt Steers	7–8 cwt Heifers	4–5 cwt Heifers	Slaughter Hogs	Sows
Intercept	3.41**	5.35**	6.91**	3.66**	2.37**	9.54**	3.15**	8.94**	3.97**	10.04**	4.24**	6.21**
	(0.20)	(0.24)	(0.24)	(0.19)	(0.33)	(1.01)	(0.46)	(0.93)	(0.50)	(0.98)	(0.57)	(0.85)
Forecast Method Dummies:												
*NAIVE*1	14.51**	12.86**	12.74**	10.48**	2.79**	2.65**	5.39**	2.55**	5.02**	3.00**	8.93**	10.80**
	(0.31)	(0.42)	(0.34)	(0.32)	(0.49)	(1.23)	(0.67)	(1.12)	(0.71)	(1.17)	(0.95)	(1.45)
*NAIVE*5	13.24**	12.02**	12.33**	6.57**	5.58**	8.80**	11.29**	10.08**	11.73**	11.93**	5.85**	8.78**
	(0.25)	(0.57)	(0.43)	(0.23)	(0.58)	(1.86)	(0.98)	(1.60)	(1.03)	(1.72)	(0.94)	(1.48)
FUTLPBAS	0.38**	1.06**	0.99**	-0.03	0.72**	-0.04	0.02	-1.63*	0.30	-2.36**	0.24	0.49
	(0.12)	(0.18)	(0.16)	(0.14)	(0.33)	(1.07)	(0.46)	(0.99)	(0.50)	(1.04)	(0.53)	(0.78)
MODFUT	2.15**	1.54**	2.32**	1.74**	0.87**	0.32	0.27	-2.28**	0.54	-2.56**	2.54**	2.57**
	(0.16)	(0.23)	(0.21)	(0.16)	(0.39)	(1.17)	(0.57)	(1.00)	(0.61)	(1.08)	(0.60)	(0.92)
HORIZON	1.42**	1.01**	0.94**	0.90**	0.43**	0.32**	0.78**	0.49**	0.79**	0.63**	0.65**	0.71**
	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.13)	(0.09)	(0.19)	(0.10)	(0.20)	(0.07)	(0.10)
Forecast Horizon Slope Shifters:												
*FUTLPBAS*H*	-0.05	-0.05	-0.04*	-0.04	-0.04	-0.08	-0.09	-0.01	-0.09	0.00	-0.00	0.01
	(0.03)	(0.03)	(0.03)	(0.02)	(0.07)	(0.18)	(0.13)	(0.27)	(0.14)	(0.28)	(0.10)	(0.14)
*MODFUT*H*	-0.02	0.36**	0.27**	-0.17**	0.26**	0.48**	0.50**	0.36	0.49**	0.44	0.06	0.42**
	(0.04)	(0.04)	(0.04)	(0.03)	(0.08)	(0.21)	(0.18)	(0.28)	(0.19)	(0.30)	(0.10)	(0.16)
No. of Observ.	71,760	46,200	71,400	54,600	3,480	3,480	2,400	2,400	2,400	2,400	4,200	4,200
χ^2 (j) Statistic	14,679**	11,197**	12,617**	6,665**	528**	196**	518**	166**	476**	181**	428**	503**
j	25	34	34	34	28	28	19	19	19	19	34	34
R^2	0.13	0.10	0.08	0.12	0.11	0.04	0.19	0.07	0.17	0.09	0.10	0.08

Notes: Single and double asterisks (*) denote significance at the 0.10 and 0.05 levels, respectively. Numbers in parentheses are standard errors. Models estimated with *PROC MIXED* in SAS, allowing for error variance to vary by method and horizon; χ^2 test is a test of the homoskedastic null; R^2 is squared linear correlation between observed and predicted values of dependent variable. Default forecast method is *FUTLBAS* (futures plus historical basis). All models included 11 monthly dummies. Grains models included these numbers of location dummies: wheat 22, corn 10, milo 16, and soybeans 12. Livestock series each have only one location.

The *HORIZON* estimate depicts the change in accuracy for a one-month increase in forecast horizon for the default forecast method, *FUTLBAS* (futures plus level basis). All *HORIZON* estimates are significantly positive, confirming that forecasting further into the future diminishes accuracy. *FUTLBAS* APEs increase more with lengthening horizons for grain than for livestock forecasts. *FUTLBAS* wheat price forecast accuracy diminished the most, at 1.42% for each one-month increase in horizon.

Naive forecasts are generally less accurate than *FUTLBAS* (all *NAIVE*1 and *NAIVE*5 estimates are statistically positive). However, this is only consistently true for sufficiently short forecast horizons since *FUTLBAS* forecast accuracy deteriorates with increased horizon while naive accuracy does not. In all but three cases, the horizon where this occurs is at or above the maximum horizon tested.[5] The three exceptions are *NAIVE*5 for soybeans (at 8.3 months), *NAIVE*1 for slaughter steers (7.5 months), and *NAIVE*5 for slaughter hogs (10 months). These findings for livestock are consistent with those of Koontz, Hudson, and Hughes, who noted that distant livestock futures prices often represent long-run average feeding costs rather than accurate price forecasts (because production decisions have time to alter futures-anticipated profits). That naive forecasts of soybean prices could be as accurate as futures forecasts is somewhat surprising. However, Kenyon, Jones, and McGuirk have noted that futures forecast accuracy has been poor for soybeans, especially since 1973—due partly to yield uncertainty.

Forecasts generated from regressing cash price on nearby futures price (*FUTLPBAS*), treating basis as having level and proportional components, generally were not more accurate than *FUTLBAS*, where expected basis was the simple five-year historical average basis. Nor did *FUTLPBAS* gain in relative accuracy over *FUTLBAS* as horizons grew (no *FUTLPBAS*$*H$ estimates in table 3 were significant at the 0.05 level). However, using the more complex basis definition improved accuracy over futures plus basis for 4–5 cwt steers and 4–5 cwt heifers.

MODFUT forecasts were based directly on regressions of cash price on deferred futures, not relying on the concept of basis. That increased complexity, requiring a separate regression model for each horizon-point forecast combination, did not generally improve accuracy over the default futures plus basis forecast (*MODFUT* forecasts were statistically *less* accurate than *FUTLBAS* for 7 out of 12 of the commodities). Further, relative to the default futures plus basis forecast, *MODFUT* forecasts typically diminish in accuracy as horizon expands (7 of 12 *MODFUT*$*H$ estimates were significantly positive). However, as with the proportional basis regressions, these regression forecasts were more accurate than futures plus basis for 4–5 cwt steers and 4–5 cwt heifers. This suggests that constructing regression forecasts for lightweight feeder cattle prices improves forecast accuracy over simply using futures plus basis.

Soybeans are somewhat anomalous. *MODFUT* forecasts at short horizons are less accurate than *FUTLBAS* counterparts. Model-predicted APE is 1.57 greater (1.74 − 0.17). Yet, beyond around 10-month horizons (1.74/0.17), *MODFUT* soybean forecasts are more accurate than *FUTLBAS* counterparts. Earlier it was noted that distant-month *NAIVE*5 soybean forecasts are more accurate than *FUTLBAS* counterparts. Why did the default futures plus basis approach (*FUTLBAS*) forecast so poorly at distant

[5] Dividing values in either the *NAIVE*1 or *NAIVE*5 rows by same-column values in the corresponding *HORIZON* row, and subsequently adding 1 (because naive forecasts have $h = 1$ throughout), yields the forecast horizon where naive accuracy equals *FUTLBAS* accuracy.

horizons? Neither *NAIVE*5 nor *MODFUT* depends on basis, but *FUTLBAS* does. Therefore, one possibility is that basis is less predictable for soybeans than other commodities. However, a broad look at basis variability (not shown) does not confirm this.[6] Apparently, the soybean anomaly is explained as difficulties with predicting delivery-time futures using deferred futures, as suggested by Kenyon, Jones, and McGuirk.[7]

The default forecast method (*FUTLBAS*) was typically superior to other methods reported in table 3. Among the 210 horizon-by-commodity combinations for *NAIVE*1 and *NAIVE*5, only six involved a naive forecast that was statistically superior to *FUTLBAS*. Among the 210 horizon-by-commodity combinations for *FUTLPBAS* and *MODFUT*, only 19 involved a sophisticated forecast that was statistically superior to *FUTLBAS* (all six horizons for *FUTLPBAS* on 4–5 cwt heifers, all six horizons for *FUTLPBAS* and *MODFUT* on 4–5 cwt steers, and the 11-month horizon for *MODFUT* on soybeans). Together, if only one method must be selected, these results make a strong case for using deferred futures plus historical basis for forecasting future cash commodity prices—at least among the relatively simple forecast methods considered here. Little was gained by assuming basis is more complex than simple historical levels (*FUTLPBAS*), or that futures market biases (inefficiencies) are systematic enough to be picked up in historical regressions of cash price on deferred futures price (*MODFUT*). However, there is evidence that adding such complexities might improve lightweight feeder cattle cash price forecasting.

An interesting question revolves around *MODFUT*. Why was that method typically less accurate than *FUTLBAS*? After all, *MODFUT* accounts for persistent biases that may be present in the underlying futures market and should not be unduly hampered if biases are not present. Furthermore, it should simultaneously account for cash prices that are consistently below futures (i.e., basis). However, the relatively large maximum APEs reported for *MODFUT* in table 2 suggest this method forecasts some prices especially poorly. Regressions may impose too much structure on the data. That is, the relationship between a futures contract's current price and its price several months prior may be highly unstable. This points to an age-old problem faced by empirical economists: How can historical data best be generalized for making future decisions? Or, how can the real-time forecaster be restrained from making too much of historical data? There is, of course, no simple answer. Here, at least, combining the concept of futures efficiency with the simplest of models, the mean of five-year historical basis, resulted in more accurate forecasts of cash commodity prices than did using more complex models involving regressions.

Conclusions

This study has examined the accuracy of five competing naive and futures-based localized cash price forecasts. The third week's price for each month of 1987 through 1996 was forecasted out of sample from vantage points of 1–11 months preceding the observed

[6] Taking the standard deviation of weekly basis over 1987–96 for each location, dividing by the average nearby futures price for the same time period, and averaging the quotients across all cash price locations, results in soybean basis variability that is 3% of futures price. Yet, comparable computations for wheat locations results in basis variability of 4%.

[7] When nearby soybean futures were treated as the cash price series, forecast accuracy results were similar to those in table 3. In short, deferred futures are merely poor predictors of eventual nearby futures when time gaps are large (favoring *NAIVE*5). Moreover, biases in distant soybean futures persist long enough that historical regressions of nearby on deferred futures can capitalize on them (favoring *MODFUT*).

price. Commodities examined were wheat, corn, milo, soybeans, slaughter steers, cutter cows, 7–8 cwt steers, 4–5 cwt steers, 7–8 cwt heifers, 4–5 cwt heifers, slaughter hogs, and sows. Locations selected are important to Midwestern producers and businesses. Only simple-to-construct forecasting methods were considered—methods that could easily be adopted for real-time forecasting by practitioners, producers, and businesses. Naive methods involved one-year lagged price and most recent five-year average price. Futures-based methods involved the traditional deferred futures plus historical basis (the most recent five-year average), deferred futures plugged into the estimates from a regression of cash price on nearby futures (assumes basis has both proportional and level components), and deferred futures plugged into the estimates from a regression of cash price on deferred futures (captures persistent futures trends as well as historical cash/futures relationships directly in a model).

Relative forecasting accuracy across forecast methods was compared in regression models of forecast error. Although regression-based forecasts for lightweight feeder cattle prices were more accurate, for most commodity prices the traditional deferred futures plus historical basis method was superior. That method was either statistically more accurate or not statistically less accurate in 395 of 420 commodity-by-forecast horizon combinations. In general, the added sophistication of regression models was not merited. Although considering other forecast methods or other historical data lengths may have altered conclusions, the best models were generally those that used the economic principle of futures market efficiency along with one of the simplest models—the mean of historical basis. The implication is that forecasters would do well to provide historical localized basis values directly to producers and businesses, and instruct them to simply add current deferred futures.

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Appendix: Additional Data Details

A number of missing data points were approximated to expedite computations. Futures problems were limited to feeder cattle, where a few missing points would have precluded considering horizons beyond 14 weeks. Thus, in weeks 23 and 24 of 1983, January 1984 feeder cattle futures were not yet trading and were replaced with corresponding averages over 1982, 1984, 1985, and 1986 (only used in forecast model initialization). In week 19 of 1992, the January 1993 feeder cattle futures, which was not yet trading, was assumed to be 0.987 times the week 22 price (when it was trading), which was the same proportion observed in the November 1992 contract over the same time span.

For cash series, missing data problems were more severe, although typically less than 2% over the entire 1982–96 time period for a particular commodity in a location, and typically less than 1% for the period forecasted, 1987–96. Missing data were filled in using proportional changes in corresponding nearby futures prices before and after the missing points. For example, if a cash price in week 2 were missing, but weeks 1 and 3 were present, then the cash price was the average: [(week 2 futures / week 1 futures × week 1 cash) + (week 2 futures / week 3 futures × week 3 cash)] / 2.

If contiguous cash prices were absent, the adjustment process was iterated until convergence within $0.00001. In one case, cutter cow prices, missing data were severe during the forecast initialization period (1982–86), where 72% of the data were missing. However, during the period forecasted (1987–96), only 0.6% were missing. Consequently, because we wished to be consistent in both series length and in procedures, we used the same missing data computations. We recognize that this may introduce error in the cutter cow price forecasts, at least early in the 1987–96 time period.

Hog futures contracts changed exclusively to lean hogs with the February 1997 contract. This involved four weeks of nearby futures in December 1996, as well as the deferred futures prices associated with the various forecast horizons. To be consistent with the preceding data, prices for the lean hog contract were converted to old contract equivalents by multiplying by 0.74.