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Forecasting Nearby Corn Basis: An Empirical Approach

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Background

- Basis represents the difference between the futures price and the local cash price.
- The ability to forecast crop basis is essential for marketing decisions.
- Combined with information from the futures market, improving knowledge of how basis may evolve over a short period of time into the future can provide valuable insights, ultimately leading to improved farmer financial performance.

Objective

Develop models to forecast the nearby corn basis for elevators with varying attributes and highlight the tradeoffs in forecast accuracy between simple and complex models.

Data

- Elevator-level nearby daily basis data were collected from the Data Transmission Network (DTN).
- The nearby basis is the difference between the spot price and the nearby futures price, excluding the delivery month
- Data were collected from nine elevators chosen based on attributes and data availability.
- Three of the selected elevators were ethanol plants with varying capacities.
- Models were estimated using daily observations from May 25, 2009, to October 25, 2020
- The performance of the estimated models was tested using daily observations from October 26, 2020, to September 7, 2023.
- Models were estimated daily using data available up to the point the forecast was made, without altering the initially identified structure of the model.
- In total, 201,204 forecasts were generated by the nine models across nine locations over forecast horizons ranging from one week to four weeks

Model

Nine models were identified and estimated

Historical Averages: The first five models use basic historical averages for forecasting, each utilizing data from different time spans ranging from one to five years.

Historical Average Supplemented with Current Information: The sixth model uses a two-year historical average, enhanced with current market information. Current market information is defined as the deviation of the current nearby basis from its historical average.

This approach is based on methods by Dhuyvetter & Kastens (1998) and Taylor et al. (2006).

A neural network auto-regressive model with a single hidden layer was fitted following the approach of Shmueli & Lichtendahl (2018).

Results

Table 1 Mean Absolute Errors for Corn Basis Forecasts, Nov 2020 - Sep 2023

Method	Forecast Horizon (Weeks)				Horizon Average
	1	2	3	4	
Ethanol Plants					
2 Year Average	40.44	40.44	40.44	40.44	40.44
Historical Average with Current Information	9.84*	14.34*	17.43*	20.16*	15.44
Holt-Winter	10.40*	15.18*	18.52*	21.46*	16.39
ARIMA	8.14*	12.65*	15.96*	18.91*	13.92
Artificial Neural Network	8.71*	13.37*	16.94*	19.81*	14.71
Non Ethanol Plants					
2 Year Average	31.38	31.38	31.38	31.38	31.38
Historical Average with Current Information	8.05*	12.25*	15.27*	17.86*	13.36
Holt-Winter	8.69*	13.12*	16.19*	18.85*	14.21
ARIMA	6.51*	10.65*	13.74*	16.42*	11.83
Artificial Neural Network	7.66*	12.42*	15.87*	18.83*	13.70

The presence of an asterisk (*) indicates a statistically significant difference in mean absolute error when compared to the two-year average (2YR) at the 5% significance level. The difference in MAE between ethanol and non-ethanol plants was significant for all methods except the Artificial Neural Network

Table 2 Improvement in Forecast Accuracy Relative to 2-Year Average Benchmark Forecasts (%)

Method	Forecast Horizon (Weeks)				Horizon Average
	1	2	3	4	
A Year Ago	-2.61	-2.61	-2.61	-2.61	-2.61
3 Year Average	-2.67	-2.67	-2.67	-2.67	-2.67
4 Year Average	-12.74	-12.74	-12.74	-12.74	-12.74
5 Year Average	-22.04	-22.04	-22.04	-22.04	-22.04
Historical Average with Current Information	74.85	62.36	53.50	45.85	59.14
Holt-Winter	73.07	59.85	50.67	42.65	56.56
ARIMA	79.47	67.08	57.89	49.84	63.57
Artificial Neural Network	76.69	62.97	52.81	44.29	59.19

The improvement in forecast accuracy is calculated as a percentage change in forecast accuracy from the 2-year average to an alternative model. Results presented in Table 2 are averages computed across all elevators

Discussion

- Forecasting basis for ethanol plants is more challenging than for non-ethanol plants, as evidenced by consistently higher mean absolute values across all methods
- The optimal forecasting method remains consistent across different elevator attributes, although method accuracy varies by attribute
- Using MAE as the metric, the ARIMA model was identified as the optimal model, showing the smallest forecast error across all locations and horizons.
- The results show poor performance from the historical average models except for the historical average supplemented with current market information.

Policy Implication

- The results show that the historical average model, enhanced with current market information, significantly improves forecast accuracy compared to traditional historical average models, with only a negligible loss in accuracy compared to complex time series models (ARIMA and Artificial Neural Network).
- This suggests that the supplemented historical average model could be a practical, simpler alternative, particularly in extension settings where ease of adoption is essential.

References

- Dhuyvetter, K. C., and T. L. Kastens. 1998. "Forecasting Crop Basis: Practical Alternatives." Proceedings of the NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. Chicago, IL. [<http://www.farmdoc.uiuc.edu/nccc134>].
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