Forecasting Local Grain Prices: An Evaluation of Composite Models in 500 Corn Cash Markets

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MOTIVATION

The forecasting of future cash grain prices is a central concern for producers, processors, and brokers. Further, the forecasting information required by these actors is highly location specific. While futures markets reflect expectations of future prices at a set of central delivery locations, spatial basis varies widely across producing and consuming areas. This paper takes advantage of a proprietary daily cash grain data set from nearly 500 widely dispersed locations to evaluate the performance of a large number of forecasting models, including 10 composite forecasts derived from 31 more basic individual models. Most of the models use recent histories of cash prices from the forecasted location as well as recent histories of nearby futures prices, thus allowing both broad market and locally idiosyncratic forces to enter in.

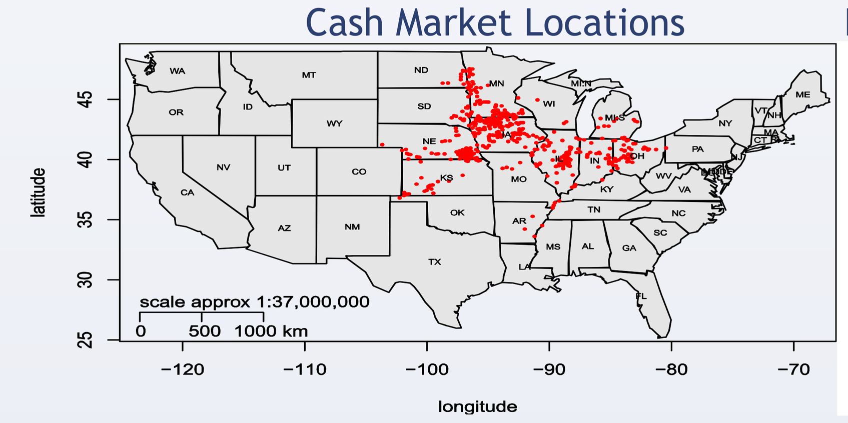
FORECAST MODELS CONSIDERED

Individual Models	
1	No-change
2	AR(5)-fixed autoregressive order-parameter update
3	AR(5)-fixed autoregressive order-rolling window with 1038 observations-parameter update
4	AR(5)-fixed autoregressive order-rolling window with 831 observations-parameter update
5	AR-recursively estimated autoregressive order-parameter update
6	AR-recursively estimated autoregressive order-rolling window with 1038 observations-parameter update
7	AR-recursively estimated autoregressive order-rolling window with 831 observations-parameter update
8	VAR in differences-fixed lag order-parameter update
9	VAR in differences-fixed lag order-rolling window with 1038 observations-parameter update
10	VAR in differences-fixed lag order-rolling window with 312 observations-parameter update
11	VAR in differences-recursively estimated lag order-parameter update
12	VAR in differences-recursively estimated lag order-rolling window with 1038 observations-parameter update
13	VAR in differences-recursively estimated lag order-rolling window with 312 observations-parameter update
14	Bayesian VAR in difference-fixed lag order-parameter update (Minnesota-style priors)
15	Bayesian VAR in difference-fixed lag order-rolling window with 1038 observations-parameter update
16	Bayesian VAR in difference-fixed lag order-rolling window with 312 observations-parameter update
17	Bayesian VAR in difference-recursively estimated lag order-parameter update
18	Bayesian VAR in difference-recursively estimated lag order-rolling window with 1038 observations-parameter update
19	Bayesian VAR in difference-recursively estimated lag order-rolling window with 312 observations-parameter update
20	VECM-fixed lag order-parameter update
21	VECM-fixed lag order-rolling window with 1038 observations-parameter update
22	VECM-fixed lag order-rolling window with 831 observations-parameter update
23	VECM-recursively estimated lag order-parameter update
24	VECM-recursively estimated lag order-rolling window with 1038 observations-parameter update
25	VECM-recursively estimated lag order-rolling window with 831 observations-parameter update
26	Bayesian VECM-fixed lag order-parameter update
27	Bayesian VECM-fixed lag order-rolling window with 1038 observations-parameter update
28	Bayesian VECM-fixed lag order-rolling window with 831 observations-parameter update
29	Bayesian VECM-recursively estimated lag order-parameter update
30	Bayesian VECM-recursively estimated lag order-rolling window with 1038 observations-parameter update
31	Bayesian VECM-recursively estimated lag order-rolling window with 831 observations-parameter update
Composite Models	
32	Previous Best Forecast
33	Equal-Weighted Average
34	Inverse MSE
35	Least Squares Estimates of Combination Weights (Unrestricted with Constant)
36	Least Squares Estimates of Combination Weights (Unrestricted without Constant)
37	Least Squares Estimates of Combination Weights (Constrained without Constant)
38	Bias-Adjusted Mean
39	Shrinkage (κ=0.25)
40	Shrinkage (κ=1)
41	Odds Matrix Approach

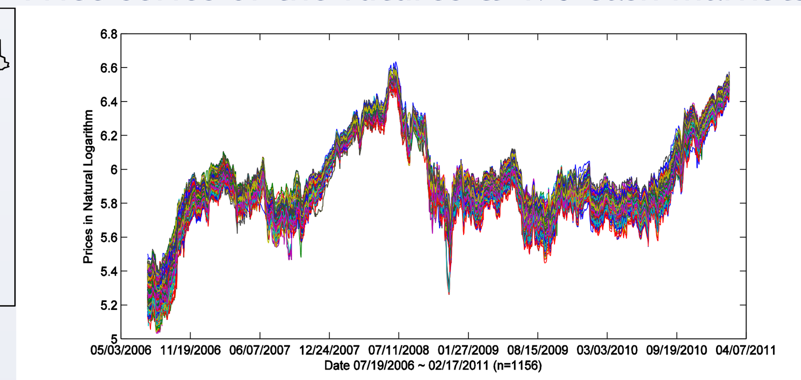
- Composite models, #32 ~ #41, are outlined by Capistrán and Timmermann (2009).
- $Y^c_{t+h|t} = \sum_{i=1}^{m} \omega^i Y^i_{t+h|t}$, where $Y^c_{t+h|t}$ and $Y^i_{t+h|t}$ are the h-step ahead forecasts of a composite model and the i-th individual model.

DATA

Cash Market Locations



Price series of the futures & 496 cash markets

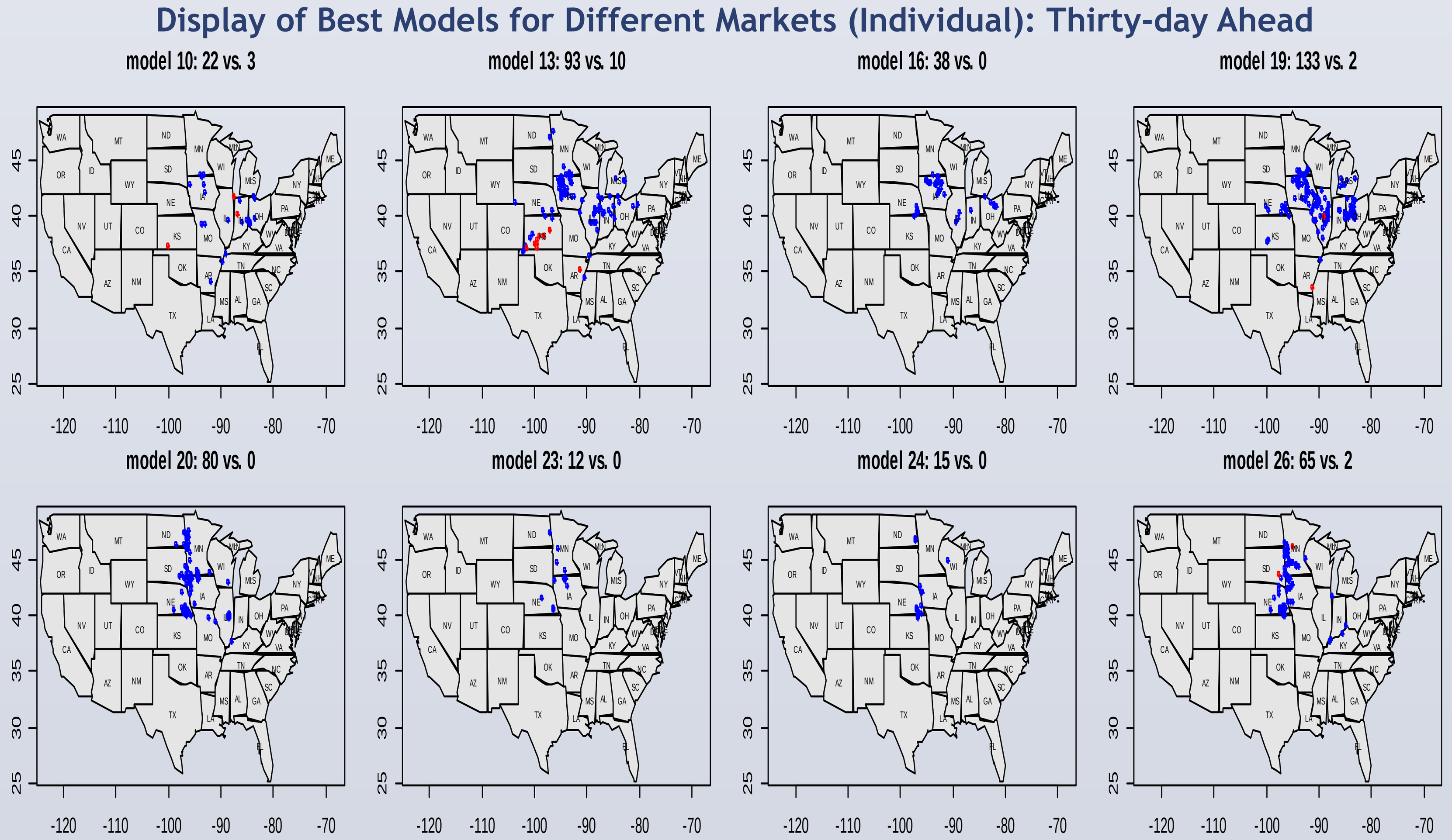


- Futures prices of the nearest maturity contract are used until the first day of the delivery month and then those of the next nearest maturity contract are used.

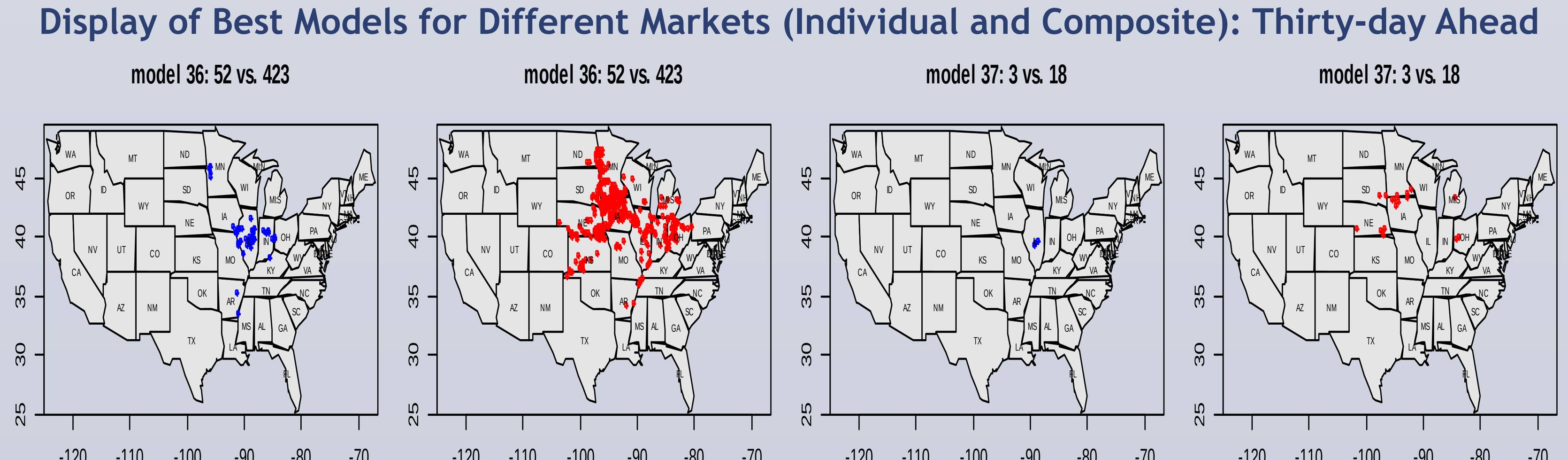
FORECAST PERFORMANCE COMPARISONS FOR THIRTY DAYS

- Five-, ten-, and thirty-day ahead forecasts are evaluated over 09/01/2010 ~ 02/17/2011.
- Model forecast accuracy comparisons are based on the modified Diebold-Mariano (MDM) test of significant differences in MSEs (Harvey *et al.*, 1997).
- Each figure is titled "model j: x vs. y", where:
  1. model j is the best model for the cash markets plotted in that figure based on the MSE
  2. x is the number of cash markets (plotted in blue) for which the MSE of the best model is significantly different from MSEs of at most other 16 (22) models for individual (all) model comparisons based on the MDM test
  3. y is the number of cash markets (plotted in red) for which the MSE of the best model is significantly different from MSEs of at least other 17 (23) models for individual (all) model comparisons based on the MDM test

Display of Best Models for Different Markets (Individual): Thirty-day Ahead

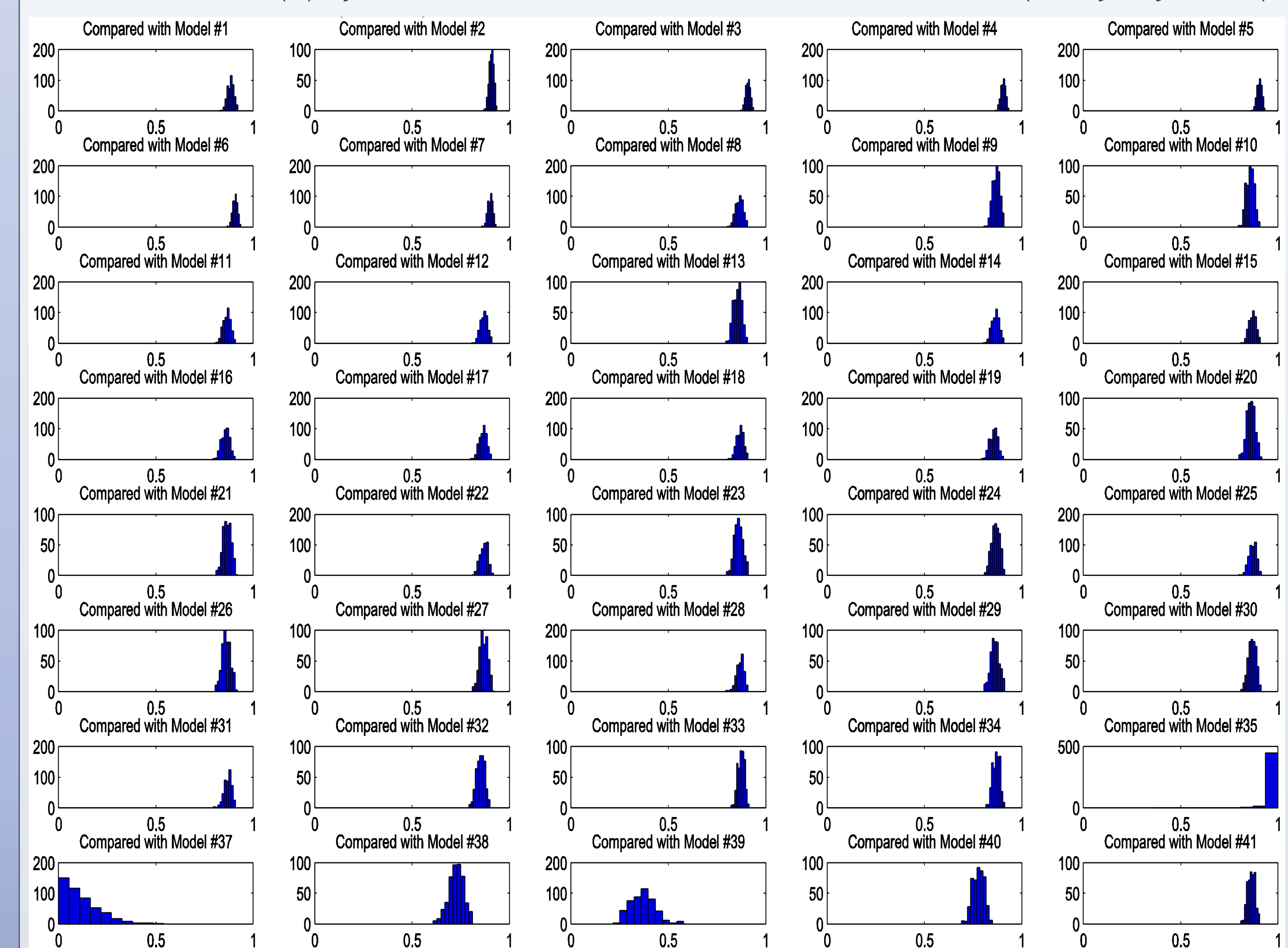


Display of Best Models for Different Markets (Individual and Composite): Thirty-day Ahead



COMPARISONS OF THE BEST MODEL WITH THE OTHERS BASED ON RMSE

RMSE Reductions (%) by Market of the Best Model #36 over Other Models (Thirty-day Ahead)



- RMSE reductions of a specific model except for #35, #37, #38, #39, and #40 achieved through switching to the best model #36 for different markets are generally around 0.40%, 0.55%, and 0.87% at horizons of five-, ten-, and thirty-day ahead, respectively.
- Similar Results are found when the best model is identified to be #37.
- As the forecast horizon increases, larger RMSE reductions are to be expected by using the best model.

IMPLICATIONS & CONCLUSIONS

- Futures prices help improve cash price forecasts. The no-change and AR-type models never result in the lowest RMSE for a single market across horizons.
- Comparing models #10 and #13 (#16 and #19), it can be seen that lag structure re-estimation for VAR (BVAR) type models is more necessary at long horizons than at short ones.
- Considering models #10, #13, #16, and #19 (#20, #23, #24, and #26), it is evident that a small rolling window size (a large model fitting sample size) is preferable for VAR and BVAR models (VECMs and BVECMs).
- It is also worth noting that, based on the results of models #20, #23, #24, and # 26, rolling window forecasts and lag structure re-estimation are not essential in producing good forecasts under the VECM and BVECM framework for the majority of markets.
- The forecast error series of the best model, #36 or #37, tends to fall inside ranges of those of other models and be less variable. These models are easy to implement and do not require much effort in upkeep, suggesting their usefulness to market participants.

REFERENCES

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Harvey, D., S. Leybourne, and P. Newbold. 1997. "Testing the Equality of Prediction Mean Squared Errors." *International Journal of Forecasting* 13:281-291.

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