Journal of Agricultural and Resource Economics 41(1):25–41 ISSN 1068-5502

Forecasting a Moving Target: The Roles of Quality and Timing for Determining Northern U.S. Wheat Basis

Anton Bekkerman, Gary W. Brester, and Mykel Taylor

While nearly instantaneous commodity futures price information provides price forecasts for national markets, many market participants are interested in forecasts of local cash prices. Expected basis estimates are often used to convert futures prices into local price forecasts. This study considers basis patterns in the northern U.S. hard red spring and hard red winter wheat markets. Using data on basis values across 215 grain-handling facilities, we empirically test the forecasting capabilities of numerous basis models. Contrary to basis models developed for other U.S. regions, we show that recent futures prices, protein content, and harvest information are more important for accurate basis forecasts than historical basis averages. The preferred basis models are used to develop an automated web-based basis forecasting tool, available at http://wheatbasis.montana.edu.

Key words: basis, forecast, protein, spring wheat, winter wheat

Introduction

Wheat producers, elevator managers, grain traders, exporters, and agricultural lenders frequently ask agricultural economists for forecasts of cash grain prices. Such information is important for production and marketing decisions as well as the implementation of risk management strategies. Although almost as many price-forecasting methods exist as the number of those making forecasts, research has generally shown that commodity futures markets provide the most consistent forecasts of national agricultural commodity prices (e.g., Colino and Irwin, 2010; Colino et al., 2012; Manfredo and Sanders, 2004; Tomek, 1997). Nonetheless, decision-makers are more often interested in forecasts of local rather than national prices.

Local price estimates are often developed by forecasting basis, which is defined as the difference between the cash price for a commodity in a given geographic location and a relevant futures contract price.[1] For many major commodity production regions (e.g., corn and soybean production in the Midwest, wheat production in the Central and Southern Plains, Midwest hogs and cattle), basis forecasts using historical moving averages of past basis outcomes have been found to be reasonable predictors of future basis outcomes (Hatchett, Brorsen, and Anderson, 2010; Kastens, Jones, and Schroeder, 1998). Furthermore, the U.S. Department of Agriculture has frequently used historical moving averages in basis-forecasting models (Hoffman, 2005). While the use of historical moving averages as a basis-forecasting model is relatively straightforward, recent research has found that

Anton Bekkerman is an associate professor and Gary W. Brester is a professor in the Department of Agricultural Economics and Economics at Montana State University. Mykel Taylor is an assistant professor in the Department of Agricultural Economics at Kansas State University.
This research was supported by the USDA Agricultural Marketing Service Federal-State Marketing Improvement Program 10.156.

Review coordinated by Christopher S. McIntosh.

[1] Basis can be calculated using the nearby futures price (referred to as nearby basis) or futures contract prices for other time periods.

such forecasts can be improved by incorporating current basis information, especially in cases when the time period for which the forecast is being made is relatively short (Tonsor, Dhuyvetter, and Mintert, 2004; Taylor, Dhuyvetter, and Kastens, 2006). However, the implementation of such models is often technically challenging for those market participants who lack econometric training.

Almost instantaneous price quotes from futures markets are available through various electronic sources at relatively low costs, but the collection of similar information regarding basis is more costly. Online commodity market subscription services typically do not provide historical cash prices by elevator location, necessitating daily or weekly data collection to develop a price series. In addition, basis forecasting is data intensive because it requires one to gather relatively lengthy cash and futures price time series, calculate appropriate basis measures, and establish an accurate forecasting framework. For many Midwest, Central, and Southern Plains markets, elevator-level cash price data are readily available through public sources such as the USDA Agricultural Marketing Service, but this is not the case for most grain-handling locations in the major northern wheat-producing states of Idaho, Montana, North Dakota, Oregon, and Washington.[2]

This northern wheat-production region is also characterized by several unique marketing features. First, wheat in this region is quality differentiated by both class and protein content levels. This region produces most of the U.S. high-protein spring and winter wheat crops. Prices for each class vary over time and space in response to local supply and demand conditions, transportation logistics, and storage availability. Second, wheat marketing in the northern states is also affected by production conditions in southern U.S. regions, where winter wheat harvest occurs several weeks earlier than in the north. This is not completely unique to wheat; for example, corn harvests start much earlier in the South than in the Midwest, and the earlier harvest data can provide important yield information to those markets. However, in the case of wheat, the earlier winter wheat harvest in the Southern Plains also offers information about wheat protein supplies (or lack thereof) for Northern Plains wheat markets. For example, when the protein content of the southern U.S. winter wheat crop is low, protein premiums for northern spring and winter wheat are high. In other years, these premiums are almost nonexistent. Hence, forecasting basis for the northern states has the added complexity of needing to incorporate available information regarding the supply of protein as determined by earlier southern wheat harvests.

We use a unique weekly dataset for 215 grain-handling facilities across Montana, North Dakota, and Washington between 2004 and 2010 to model variation in spring and winter wheat basis. We develop several alternative model specifications to evaluate whether information about historical and current basis, futures prices, seasonality, spatial attributes, and protein availability explains basis variation and helps improve basis forecasting accuracy for the northern production region. The model specifications are evaluated based on relative in-sample fit and out-of-sample forecasting capabilities. Using a large number of cross-sections and lengthy time series data, the empirical results indicate that the long-run market-level basis structure is almost entirely captured by elevator fixed effects and that recent market information has important impacts on basis predictions.

These findings are different from other basis-forecasting models developed for the Midwest, Central, and Southern Plains regions, which suggest that moving averages of historical basis outcomes are strong predictors of future basis values (Hatchett, Brorsen, and Anderson, 2010; Kastens, Jones, and Schroeder, 1998). The difference may be the result of a historically stable marketing environment for northern wheat crops due to consistent delivery locations and because of typically higher protein contents, which are differentially valued by buyers. In addition, current market information, such as futures price levels, futures price volatility, and protein-level information (revealed during the earlier harvest in southern wheat-production regions) are important factors for predicting northern U.S. wheat basis. Following previous research results for other commodities and regions, we show that models incorporating these elements result in more accurate out-of-sample basis forecasts than specifications that exclusively use historical basis information

[2] Regional average spot price data are available for Montana, but due to the expansive size of each region, substantial measurement error may bias basis calculations for any specific grain-handling facility in a region.

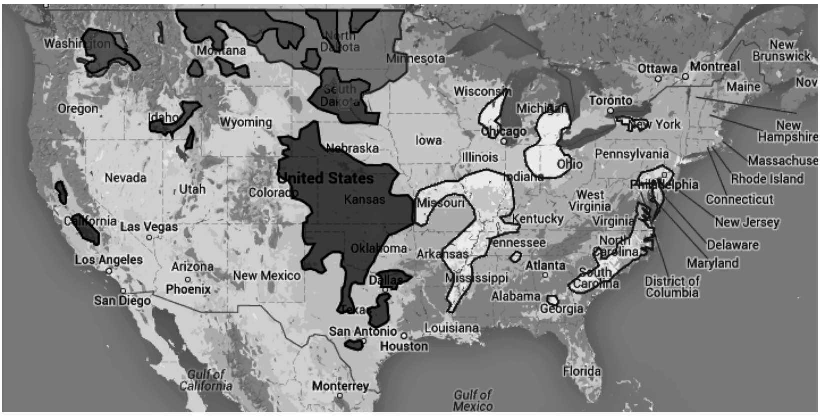

Figure 1. U.S. Spring and Winter Wheat Production Areas

Notes: White areas represents regions of soft red winter wheat production, dark gray areas represent regions of hard red winter wheat production, and light gray areas represent regions of hard red spring wheat production.
Source: U.S. Wheat Associates

(Tonsor, Dhuyvetter, and Mintert, 2004; Taylor, Dhuyvetter, and Kastens, 2006). Because such models are more difficult for many market participants to employ relative to the use of moving averages, our preferred basis model has been used to develop a web-based local wheat price forecasting tool for Montana and Washington, which has been widely used by industry participants over the past two years.

Industry Background and Literature Review

Over the past five years, U.S. wheat production has averaged 2.1 billion bushels and represented about 8% of world production. Hard red winter wheat (892 million bushels) and hard red spring wheat (502 million bushels) represent the majority of wheat produced in the United States and are generally used to produce flour for the production of breads, tortillas, rolls, pizza crust, and other high-gluten baked goods (U.S. Wheat Associates, 2013). The balance of U.S. production consists of soft red winter wheat (417 million bushels), white wheat (270 million bushels), and durum wheat (82 million bushels). Soft red and white wheat are used to produce products that require less gluten content than bread, such as cookies, crackers, and pastries, while durum wheat is used primarily for pasta production.

Figure 1 illustrates the major wheat-production regions in the United States. Most U.S. winter wheat is produced in the Central and Southern Plains, but the northern states of Montana, North Dakota, and Washington (along with the Canadian provinces of Alberta, Manitoba, and Saskatchewan) produce the majority of North America's high-protein spring and winter wheat. High-protein wheat is often blended with lower-protein wheat to improve gluten characteristics, which are essential for bread production. Over the past five years, Montana, North Dakota, and Washington produced 81.5% of U.S. hard red spring wheat; Minnesota (15%) and South Dakota (10%) were the other major producers. The largest producers of hard red spring wheat are North Dakota (a five-year average of 245 million bushels), Montana (90 million bushels), Minnesota (75 million bushels), South Dakota (51 million bushels), Idaho (44 million bushels), and Washington (30 million bushels).

The Central and Southern Plains states produce the majority of U.S. hard red winter wheat (81%), and Washington (7.5%), Montana (6%), Idaho (4%), and North Dakota (1.5%) produce the remainder. State-level production data do not distinguish between hard and soft red winter wheat classes. However, figure 1 shows that most winter wheat produced in the northern states is hard red winter wheat (dark gray regions), while soft red winter wheat is produced in the Ohio and Mississippi river regions and in eastern states (light regions).

Despite large spring wheat production in the northern states, much of the basis literature focuses on winter wheat in the Central and Southern Plains regions. Within this context, the use of historical moving average basis values and commodity futures prices as a means for forecasting local prices has a long history. Kastens, Jones, and Schroeder (1998) report that using five-year moving averages of historical basis measurements provides the most accurate forecasts for a variety of agricultural commodities. Hatchett, Brorsen, and Anderson (2010) find that somewhat shorter moving averages perform better for four agricultural commodities in Kansas and Oklahoma. This is especially true during periods of substantial structural change.

Tonsor, Dhuyvetter, and Mintert (2004) report that cattle basis forecasts can be improved by including current basis information with historical basis averages. The current information that is most useful is the nearby basis that exists at the time of making a forecast. Taylor, Dhuyvetter, and Kastens (2006) make a similar evaluation of grain basis forecasts in Kansas. They find that including current basis information along with relatively short historical averages reduces basis forecast errors. This is especially true for post-harvest (i.e., storage) price forecasts.

Wheat basis forecasting in the northern states is further complicated by spatial and temporal variation in protein content. For example, Goodwin and Smith (2009) find that changes in wheat protein stocks generate statistically significant responses in hard red spring and hard red winter wheat prices but not in soft red winter wheat prices. This is especially the case when deviations of protein stocks from normal levels are relatively large. Furthermore, the prices of various wheat classes respond asymmetrically to each other. For example, a shock to the price of hard red winter wheat has little effect on the price of hard red spring wheat. Conversely, a shock to the price of hard red spring wheat significantly affects the price of hard red winter wheat.

Protein premiums can also vary temporally because of the timing of U.S. wheat harvests. Climatic conditions allow harvest to begin as early as June in the Central and Southern Plains, while the northern states generally harvest winter wheat in late July and August and harvest spring wheat in late August and September. Consequently, the protein content of the majority of U.S. winter wheat production is revealed as harvest progresses northward from the Southern Plains. If protein levels are above normal in the Central and Southern Plains, protein premiums in the northern states shrink for both hard red winter and hard red spring wheat. The Minneapolis Grain Exchange spring wheat futures market is based on 13.5% protein wheat, and the Kansas City Board of Trade hard red winter wheat futures contract is based on 11% protein. Hence, substantial differences between futures prices and local prices can occur, not only because of usual supply, demand, and logistical reasons but also because of changes in expectations of wheat protein availability.

Data Description

The data are a pooled cross-section of average weekly cash bids between January 1, 2004, and December 31, 2010, for 215 elevators and processing facilities that purchase hard red spring wheat and/or hard red winter wheat in Montana, North Dakota, and Washington.[3] The data are collected from both public (the USDA Agricultural Marketing Service) and private (GeoGrain, Inc.) sources. Both spring and winter wheat price bids are reported across several protein levels, including 12%, 13%, 14%, 15%, and 16% protein spring wheat categories and 10%, 11%, 11.5%, and 12% protein winter wheat categories. In areas where premiums and discounts are attributed to differences in protein levels, 14% protein spring wheat and 11.5% protein winter wheat are typically considered the base level from which discounts or premiums are calculated.

Harvest-period weekly futures market price data are obtained from the Commodity Research Bureau. For hard red spring wheat, we use the September Minneapolis Grain Exchange (MGEX) futures contract; for winter wheat, we use the July Kansas City Board of Trade (KCBT) futures

[3] Although Idaho is a significant producer of hard red spring wheat, we were unable to obtain sufficient data to include that state in the analyses.

(a) Locations and relative basis strength of facilities accepting hard red spring wheat

(b) Locations and relative basis strength of facilities accepting hard red winter wheat

Figure 2. Locations and Relative Basis Strength of Grain-Handling Facilities

Notes: Dots represent grain elevators or processing facilities. Colors represent the harvest-time average (throughout the marketing year) basis strength at a location relative to the basis strength at other locations. For example, darker dots characterize locations where average harvest-period basis bid values are stronger (less negative or more positive) and lighter dots characterize locations with relatively weaker basis values.

contract. These contracts have the nearest expiration date to the harvest period for each wheat class in the northern states. Because of declining futures contract open interest and volume, futures market prices can become volatile near contract expiration dates. Hence, prices are rolled over to the following year's harvest contract fifteen days before the expiration of either the MGEX or KCBT futures contract.[4] Recent futures price volatility is represented by the standard deviation of a futures contract price in the preceding seven weeks, $Vol_{F,t} = STD[F_{t-1}, \ldots, F_{t-7}]$, and the spread between spring and winter wheat prices is calculated as the difference between the harvest time MGEX and the KCBT futures prices, $Sp_t = MGEX_t - KCBT_t$.[5]

A basis for each location i and week t is calculated as the difference between the cash price bid for protein level j for each location and week and the harvest-period futures contract price of the respective contract, $B_{it} = S_{ijt} - F_t$. Figure 2 shows the locations of the elevator and processing

[4] One could use other rollover dates such as the first day of the expiration month. Differences in model results between using the first day of the expiration month and the day fifteen days prior to expiration will depend upon whether changes in trading volume occur between the two points. Given the results of prior research (e.g., Szakmary et al., 2003; Manfredo and Sanders, 2004), these differences are not expected to make significant quantitative impacts in our analysis.

[5] We also calculate futures price volatility as the standard deviation of futures price returns from the preceding seven weeks. The alternative specification only trivially affects the quantitative results and has no impact on the overall analysis conclusions. The seven-week window was selected to ensure that the measure captured sufficient information about market uncertainty. The window corresponds to the period between futures contracts expirations and is expected to represent futures market activity associated with entry, exit, and reallocation of market participants between different futures contracts.

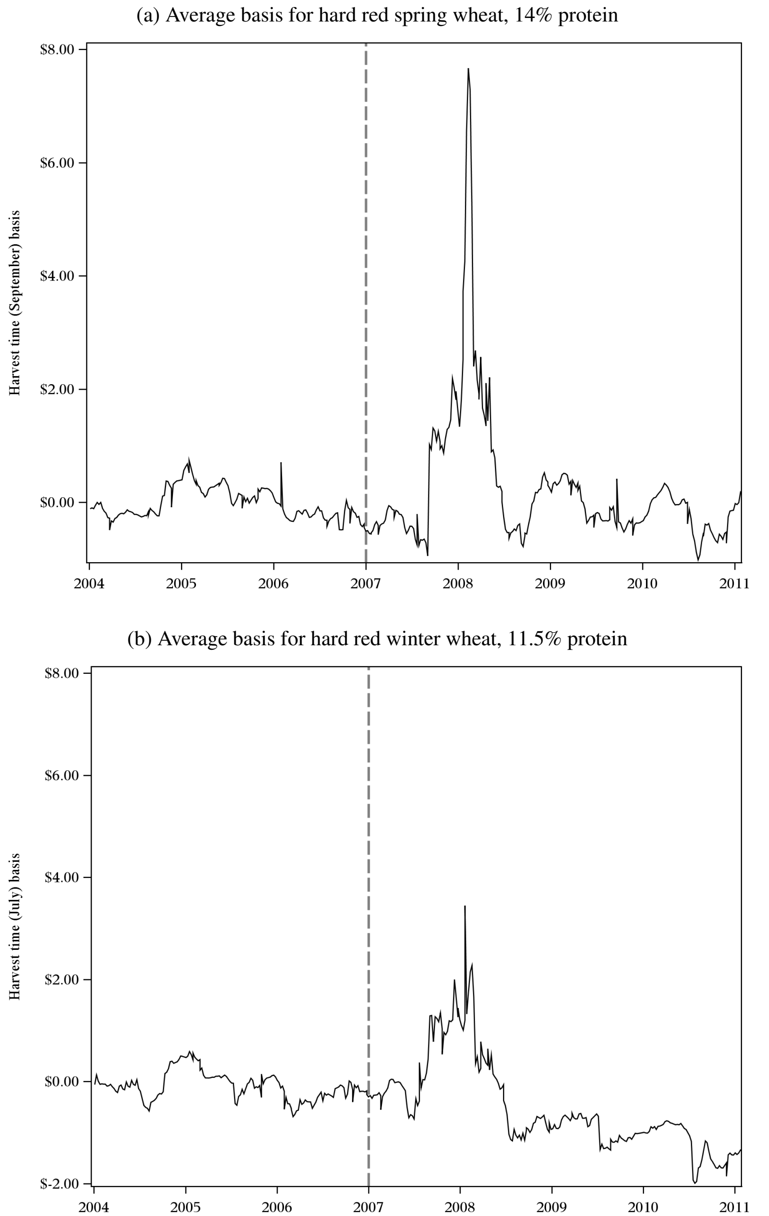

Figure 3. Time Series Plots of Average Harvest-Period Basis by Class, 2004–2010

facilities in the sample and characterizes the relative average basis for hard red spring wheat (14% protein) and hard red winter wheat (11.5% protein), respectively, at those locations. The color gradations indicate locations with stronger, more positive basis (darker) and weaker, more negative basis (lighter). Because the majority of northern wheat is shipped to Pacific Northwest export facilities, the figure shows an expected stronger basis relationship for grain-handling facilities that are closer to the Pacific Northwest ports (rather than closer to the commodity futures exchanges) because of lower transportation costs.

Figure 3 shows time series plots of average basis for hard red spring wheat (14% protein) and hard red winter wheat (11.5% protein) between 2004 and 2010. The plots show that basis patterns were relatively consistent between 2004 and 2007 (the latter indicated by a dashed vertical line in the

Table 1. Descriptive Statistics, 2004–2010

	Observations	Mean ($/bushel)	Std. Dev.
Basis			
Spring wheat			
12.0% protein	4,187	−$1.19	$1.47
13.0% protein	7,310	−$0.68	$1.06
14.0% protein	42,703	$0.04	$0.90
15.0% protein	8,926	$0.46	$0.94
16.0% protein	4,010	$0.77	$1.13
Winter wheat			
10.0% protein	1,802	−$1.26	$0.89
11.0% protein	5,319	−$1.16	$0.83
11.5% protein	20,141	−$0.69	$0.88
12.0% protein	4,608	−$0.65	$0.70
Futures			
Sept. HRS (MGEX)	368	$5.73	$1.97
July HRW (KCBT)	368	$5.53	$1.90
Spread	368	$0.20	$0.25

Notes: Basis measures are for hard red spring wheat and hard red winter wheat classes. Observation counts for basis represent the total number of instances that grain-handling facilities in the sample reported cash price bids for a particular combination of wheat class and protein level. Observation counts for futures contract prices and spread are the total number of weeks in the sample period.

time series graphs). Since then, substantial changes in small grain crop production in the Northern Plains have occurred as changes in relative crop profitability and new short-season corn varieties have altered farmers' incentives to produce small grain crops. Hence, corn production has replaced wheat production in some traditional wheat-production regions. The resulting decrease in both the production and stocks of small grains has likely contributed to increased price uncertainty in these markets.

Another reason for increased variability in wheat markets is a potential structural change in basis behavior following a significant lack of convergence between cash and futures prices in 2008. Irwin et al. (2011); Aulerich, Fishe, and Harris (2011); Adjemian et al. (2013); and Garcia, Irwin, and Smith (2014) provide several reasons for this structural change, such as disparities between actual storage costs for wheat and storage costs revealed in futures prices. Regardless of the reasons, basis data provide suggestive evidence of potential changes. For example, the standard deviation of spring wheat basis increased from $0.62 per bushel before 2007 to $1.33 per bushel after 2007, and the standard deviation of winter wheat basis increased from $0.63 per bushel before 2007 to $0.81 per bushel after 2007. This change could affect the manner (and effectiveness) in which historical information can be used to forecast basis behavior. A recent study by Taylor, Tonsor, and Dhuyvetter (2014) finds that an increase in Kansas wheat basis volatility since 2007 has substantially increased the costs of risk management through forward contracts. Hence, more recent basis information (occurring after 2007) may be the most appropriate for making accurate basis forecasts.

Table 1 presents descriptive statistics of the variables used for model estimation. The data show that the average basis for hard red winter wheat is largely negative, that lower-protein wheat is discounted, and that price premiums occur for higher-protein wheat. Average basis outcomes for spring wheat also include protein discounts and premiums, but the premiums for the 14% protein level are substantial enough to result in positive basis outcomes, a phenomenon typically observed in importing markets. Futures contract prices also reflect quality differences across the two wheat classes, characterized by the $0.28 per bushel average spread between the spring wheat and winter

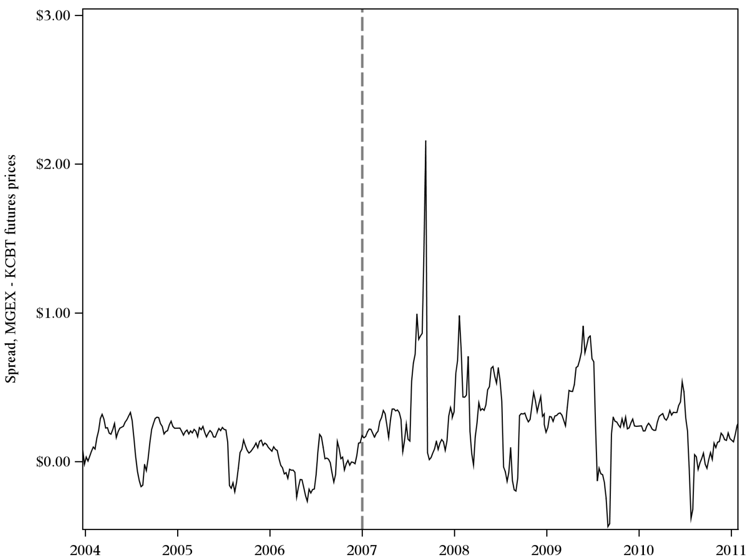

Figure 4. Spread Between MGEX and KCBT Harvest-Period Futures Contract Prices

Notes: The spread represents the difference between Minneapolis Grain Exchange (MGEX) September spring wheat futures contract price and the Kansas City Board of Trade (KCBT) July winter wheat futures contract price. Prices roll over to the next year's contract fifteen days before expiration of the current year's contract.

wheat contracts. Figure 4 presents weekly average spread values across the sample. Typically, the spread increases throughout the marketing year, suggesting that premiums for higher protein spring wheat rise over time. The variation between the futures price spreads across these two wheat classes signals the market's willingness to pay for higher-protein wheat and is likely an important factor for basis forecasting. The spread between the MGEX and KCBT harvest contracts may also reflect transportation costs and availability between the two regions, differences between end-uses, and other supply and demand factors unique to the two wheat classes.

Estimation and Model Forecast Evaluation Strategies

We model basis variation across spring and winter wheat handling facilities in Montana, North Dakota, and Washington. We construct a portfolio of alternative specifications based on previous studies and factors that are expected to affect basis in the northern states. A general model of wheat harvest-period basis at grain-handling facility i in week t during year y for wheat class c is

$$B_{ityc} = \boldsymbol{\theta}^k \boldsymbol{X}^k_{ity} + \phi \mathrm{I}(2008) + \delta_i + \delta_t + \varepsilon_{ityc}, \tag{1}$$

where $\boldsymbol{X}^k_{ity}$ represents the kth specification of a vector containing exogenous or predetermined variables, $\mathrm{I}(2008)$ is an indicator variable for 2008, δ_i is a facility-specific fixed effect that controls for unobservable, time-invariant factors affecting basis in location i, δ_t is a weekly fixed effect that accounts for seasonal basis behavior over the marketing year, and ε_{ity} is an idiosyncratic error term. The terms $\boldsymbol{\theta}^k$ and ϕ are the associated parameter vectors.

We estimate thirteen specifications of the $\boldsymbol{X}^k_{ity}$ vector. These specifications include combinations of one-, two-, and three-year lagged basis ($B_{it,y-1,c}$, $B_{it,y-2,c}$, $B_{it,y-3,c}$); the current futures price associated with wheat class c (F_{tyc}); the volatility of the relevant futures price (Vol_{tyc}); the spread between MGEX and KCBT futures contract prices (Sp_{ty}); and protein-level indicators (P_{ityc}). Table 2 presents the thirteen specifications. Each specification is estimated using two sample-period assumptions. The first assumption is that a longer time series provides additional historical information for making more informed forecasts. Under this assumption, we estimate the models

Table 2. Regression Model Specifications

Model Number	Model Specification
1	$B_{it,y-1,c}$
2	$B_{it,y-1,c}$, F_{ytc}
3	$B_{it,y-1,c}$, $B_{it,y-2,c}$, F_{ytc}
4	$B_{it,y-1,c}$, $B_{it,y-2,c}$, $B_{it,y-3,c}$, F_{ytc}
5	$B_{it,y-1,c}$, F_{ytc}, P_{ityc}
6	$B_{it,y-1,c}$, F_{ytc}, Vol_{tyc}, Sp_{ty}
7	$B_{it,y-1,c}$, F_{ytc}, Vol_{tyc}, Sp_{ty}, P_{ityc}
8	F_{ytc}
9	F_{ytc}, Vol_{tyc}
10	F_{ytc}, Sp_{ty}
11	F_{ytc}, P_{ityc}
12	F_{ytc}, Vol_{tyc}, Sp_{ty}
13	F_{ytc}, Vol_{tyc}, Sp_{ty}, P_{ityc}

Notes: The term B_{ityc} represents a harvest-period basis outcome at facility i in week t during year y for wheat class c, F is the futures contract price, Vol is the futures price volatility measured as the standard deviation of futures prices from the preceding seven weeks, Sp is the difference between MGEX and KCBT futures contract prices, and P is a protein-level indicator variable. All models include location fixed effects, weekly fixed effects, and an indicator variable for 2008.

using weekly harvest-period basis observations between 2004 and 2010. However, because of a potential structural change in basis behavior after 2007, a lengthier time series may encompass basis behavior that is no longer relevant for current markets and could reduce basis forecasting accuracy. Under the second assumption, we estimate basis models using weekly basis information from a shorter time period (2007–2010) and compare the resulting in-sample fit properties and out-of-sample forecasts for each of the thirteen model specifications to those obtained using the longer time series (2004–2010).

We estimate each of the model specifications using a pooled least squares estimator. In-sample model forecasting precision is evaluated using the estimated coefficient of determination (adjusted R-squared), the model root mean squared error (rMSE), the corrected Akaike information criteria (AICC), and the Schwartz Bayesian information criteria (SBC). Out-of-sample forecast errors are calculated as the difference between the predicted basis value for location i in week t for wheat class c and protein level j during the out-of-sample period and the actual observed value for that location, period, class, and protein-level combination. Forecasting accuracy is evaluated using forecast mean absolute error (fMAE) and forecast root mean squared error (fMSE) criteria.

To ensure that a model's out-of-sample forecasting capabilities are not biased by the choice or length of an out-of-sample time period, we use a cross-validation approach that is intended to minimize potential bias. Specifically, for each wheat class, period length (2004–2010 or 2007–2010), and thirteen model specifications, we perform the following iterative process:

1. Create a subsample that removes observations for one of the years (e.g., remove 2004 observations);
2. Use that subsample to estimate each of the thirteen specifications for each of the wheat classes;
3. Use the estimated parameters to make out-of-sample forecasts for the observations corresponding to the year that was removed in step 1;
4. Repeat steps 1–3 by iteratively removing each of the years in the overall sample.

Under the assumption of the longer time window (2004–2010), for example, the cross-validation approach results in ten in-sample and out-of-sample fit assessments for each wheat class and each model specification. Finally, we calculate average fit statistics across all of the cross-validation iterations.

To choose the "best" specification, we consider the model that provides a combination of the best in-sample fit and out-of-sample forecasting capability. Specifically, we use the cross-validation procedure average in-sample and out-of-sample forecasting precision rankings for each model relative to all other models by wheat class. For example, a spring wheat model specification that has the highest R-squared value and lowest rMSE, AICC, and BIC relative to all other spring wheat model specifications receives an in-sample rank of 1. Similarly, the highest out-of-sample rank is assigned to the model with the best relative out-of-sample forecasting accuracy. Finally, the specification with the lowest total rank (i.e., in-sample rank + out-of-sample rank) is deemed optimal. In cases for which two or more models have equal total ranks, the specification that provides the most accurate out-of-sample forecasts is selected.

Empirical Results

We estimate thirteen wheat harvest-period basis-forecasting models for each wheat class and for the longer and shorter time series—a total of fifty-two regression models. Tables 3 and 4 present the cross-validation average in-sample fit and out-of-sample forecast accuracy measure comparisons for the hard red spring and hard red winter wheat classes, respectively. In each table, the models are presented based on the combined in-sample and out-of-sample performance ranking, with the highest-ranked models presented first. For models of both spring and winter wheat basis, the top-ranked specifications indicate that using the full 2004–2010 time window provides the best fit and prediction accuracy. This suggests that basis behavior over this period is an important factor for making future basis forecasts. Furthermore, the top models indicate that basis predictions are affected by variation in futures market activity and information regarding protein content or associated premiums.

For spring wheat, the protein premium effect is largely expected because of the importance of wheat quality differentiation in the region. A less-expected result is that current futures market information improves basis forecasts while annual lagged basis values do not. There are at least two potential economic explanations for this outcome. The first is that grain-handling facility and weekly fixed effects are essentially capturing the long-run structural relationship between cash price bids and futures contract prices and can, therefore, proxy for lagged basis values. Previous studies (discussed in detail in the Industry Background and Literature Review section above) have shown that historical basis information is statistically and economically important for explaining basis variation and for making accurate basis predictions because this information accounts for relatively stable spatial and temporal transaction costs. In this study, fixed effects variables are likely capturing the stable, historical spatial and temporal basis relationships during harvest in northern wheat markets. This fixed-effects explanation is especially plausible because of the length of the sample, which can provide better insights about long-run basis consistencies at any particular location when predicting harvest-period basis.

The second reason is that this consistency may be somewhat unique to the northern U.S. wheat markets because of the consistency of market outlets. That is, northern U.S. wheat is primarily transported to Pacific Northwest ports for export to Asia (Bekkerman, 2013). This relative stability in the marketing structure differs from that of the Central and Southern Plains, where wheat flows change based on the demands of numerous competing sectors (e.g., different export markets, domestic animal feed, and U.S. flour needs).

The model comparisons for hard red winter wheat provide largely similar findings (table 4). In general, the average forecasting errors of the winter wheat models are lower than the spring wheat specifications, suggesting better forecasting capabilities in the winter wheat markets. The models with the four highest combined ranks support using a one-year lagged basis value, which is different from the results for the spring wheat models. This difference could be indicative of the distinctive characteristics of the northern U.S. spring wheat markets. Although the U.S. spring wheat market is

Table 3. Comparison of Hard Red Spring Wheat Regression and Forecast Model Fit Statistics

Regression Time Period	Explanatory Variables	Root MSE	Adj-R2	AICC	SBC	fMAE	Root fMSE
2004–2010	$F_{ytc}, Vol_{tyc}, Sp_{ty}, P_{ityc}$	68.52	0.47	776,735	697,021	65.53	107.34
2004–2010	F_{ytc}, P_{ityc}	67.16	0.49	765,015	686,229	68.25	112.35
2004–2010	F_{ytc}, Sp_{ty}	77.69	0.31	789,263	710,431	65.82	109.01
2004–2010	F_{ytc}	77.73	0.31	798,219	718,468	65.56	108.26
2004–2010	$B_{it,y-1,c}, F_{ytc}, Vol_{tyc}, Sp_{ty}, P_{ityc}$	70.78	0.48	518,675	466,507	73.16	118.21
2004–2010	$F_{ytc}, Vol_{tyc}, Sp_{ty}$	76.37	0.33	786,569	707,746	68.98	113.82
2007–2010	F_{ytc}, Vol_{tyc}	76.43	0.33	786,690	707,857	68.29	113.08
2004–2010	$B_{it,y-1,c}, F_{ytc}, P_{ityc}$	72.51	0.46	527,055	474,256	81.89	125.08
2004–2010	$B_{it,y-1,c}, F_{ytc}, Vol_{tyc}, Sp_{ty}$	78.00	0.37	529,639	477,436	73.85	120.29
2004–2010	$B_{it,y-1,c}$	80.84	0.32	539,400	486,557	67.59	117.52
2004–2010	$B_{it,y-1,c}, F_{ytc}$	79.72	0.34	537,938	485,104	81.23	125.90
2004–2010	$B_{it,y-1,c}, B_{it,y-2,c}, F_{ytc}$	84.08	0.33	364,910	329,675	85.12	127.90
2007–2010	F_{ytc}, P_{ityc}	85.29	0.57	301,990	272,992	93.71	140.92
2004–2010	$B_{it,y-1,c}, B_{it,y-2,c}, B_{it,y-3,c}, F_{ytc}$	83.60	0.34	256,061	231,547	108.50	145.14
2007–2010	$F_{ytc}, Vol_{tyc}, Sp_{ty}, P_{ityc}$	82.88	0.59	296,221	267,668	105.33	153.30
2007–2010	$B_{it,y-1,c}, F_{ytc}, Vol_{tyc}, Sp_{ty}, P_{ityc}$	84.55	0.59	218,510	197,904	176.00	222.37
2007–2010	$B_{it,y-1,c}, F_{ytc}, P_{ityc}$	87.21	0.57	223,178	202,210	191.78	237.90
2007–2010	F_{ytc}, Vol_{tyc}	101.42	0.37	309,432	280,837	103.06	152.21
2007–2010	F_{ytc}, Sp_{ty}	103.05	0.36	310,339	281,744	96.22	143.98
2007–2010	F_{ytc}	103.41	0.35	314,953	285,922	94.06	141.61
2007–2010	$F_{ytc}, Vol_{tyc}, Sp_{ty}$	101.08	0.38	309,251	280,665	106.85	155.35
2007–2010	$B_{it,y-1,c}, F_{ytc}, Vol_{tyc}, Sp_{ty}$	97.25	0.45	225,363	204,725	197.61	244.69
2007–2010	$B_{it,y-1,c}, B_{it,y-2,c}, B_{it,y-3,c}, F_{ytc}$	93.16	0.50	121,426	110,439	285.88	342.83
2007–2010	$B_{it,y-1,c}, F_{ytc}$	99.64	0.42	229,907	208,907	216.15	261.17
2007–2010	$B_{it,y-1,c}$	105.97	0.36	232,426	211,417	106.93	163.18
2007–2010	$B_{it,y-1,c}, B_{it,y-2,c}, F_{ytc}$	102.46	0.43	163,601	149,042	234.55	281.16

Notes: Values represent cross-validation procedure averages. The term B_{ityc} represents a harvest-period basis outcome at facility i in week t during year y for wheat class c, F is the futures contract price, Vol is the futures price volatility measured as the standard deviation of futures prices from the preceding seven weeks, Sp is the difference between MGEX September and KCBT July futures contract prices (with prices rolling over fifteen days prior to a contract's expiration), and P is a protein-level indicator variable. All models include a location fixed effects, weekly fixed effects, and an indicator variable for 2008. MSE represents the mean squared error, adj-R2 is the adjusted R-squared, AICC is the corrected Akaike information criterion, SBC is the Schwartz Bayesian information criterion, fMAE is the forecast mean absolute error, and fMSE is the forecast mean squared error. All out-of-sample forecasts are determined using observations in 2010.

Table 4. Comparison of Hard Red Winter Wheat Regression and Forecast Model Fit Statistics

Regression time period	Explanatory Variables	Root MSE	Adj-R2	AICC	SBC	fMAE	Root fMSE
2004–2010	$B_{it,y-1,c}, F_{ytc}, Vol_{tyc}, Sp_{ty}, P_{ityc}$	54.26	0.58	183,006	164,250	54.55	73.87
2004–2010	$B_{it,y-1,c}, F_{ytc}, Vol_{tyc}, Sp_{ty}$	55.08	0.57	183,623	164,843	52.08	72.83
2004–2010	$B_{it,y-1,c}, F_{ytc}, P_{ityc}$	55.65	0.56	186,551	167,500	59.01	77.61
2004–2010	$B_{it,y-1,c}, F_{ytc}$	56.42	0.55	187,133	168,059	56.24	76.23
2004–2010	$F_{ytc}, Vol_{tyc}, Sp_{ty}, P_{ityc}$	54.38	0.59	294,203	263,270	54.33	84.61
2004–2010	F_{ytc}, P_{ityc}	55.99	0.57	299,698	268,352	52.67	84.04
2004–2010	$F_{ytc}, Vol_{tyc}, Sp_{ty}$	55.31	0.58	295,348	264,389	56.71	87.00
2004–2010	F_{ytc}, Vol_{tyc}	56.97	0.55	297,254	266,288	51.84	81.86
2004–2010	$B_{it,y-1,c}$	57.75	0.53	188,238	169,156	56.62	80.71
2004–2010	F_{ytc}, Sp_{ty}	55.36	0.58	295,407	264,441	58.00	90.11
2004–2010	$B_{it,y-1,c}, B_{it,y-2,c}, F_{ytc}$	59.84	0.48	119,687	107,737	56.85	78.00
2004–2010	F_{ytc}	56.92	0.55	300,819	269,448	53.59	85.71
2004–2010	$B_{it,y-1,c}, B_{it,y-2,c}, B_{it,y-3,c}, F_{ytc}$	59.92	0.47	84,235	75,874	65.09	84.48
2007–2010	$B_{it,y-1,c}, F_{ytc}, Vol_{tyc}, Sp_{ty}, P_{ityc}$	58.85	0.58	85,943	77,460	97.98	121.72
2007–2010	$B_{it,y-1,c}, F_{ytc}, P_{ityc}$	62.13	0.53	88,489	79,838	87.49	114.46
2007–2010	$F_{ytc}, Vol_{tyc}, Sp_{ty}, P_{ityc}$	61.26	0.54	124,516	111,955	94.11	127.09
2007–2010	F_{ytc}, P_{ityc}	64.71	0.48	127,735	114,973	82.46	116.57
2007–2010	$B_{it,y-1,c}, F_{ytc}, Vol_{tyc}, Sp_{ty}$	61.16	0.55	86,974	78,470	106.95	130.97
2007–2010	$B_{it,y-1,c}, F_{ytc}$	64.19	0.50	89,354	80,682	96.11	123.05
2007–2010	F_{ytc}, Vol_{tyc}	66.61	0.46	126,963	114,373	84.68	118.75
2007–2010	$F_{ytc}, Vol_{tyc}, Sp_{ty}$	63.40	0.51	125,681	113,098	97.17	130.97
2007–2010	F_{ytc}, Sp_{ty}	63.61	0.50	125,791	113,201	96.22	130.50
2007–2010	$B_{it,y-1,c}, B_{it,y-2,c}, B_{it,y-3,c}, F_{ytc}$	61.70	0.56	42,903	38,864	152.63	180.08
2007–2010	$B_{it,y-1,c}$	65.15	0.48	89,612	80,933	91.84	121.79
2007–2010	F_{ytc}	66.82	0.45	128,837	116,053	84.96	119.57
2007–2010	$B_{it,y-1,c}, B_{it,y-2,c}, F_{ytc}$	64.94	0.50	58,309	52,931	130.72	159.10

Notes: Values represent cross-validation procedure averages. The term B_{ityc} represents a harvest-period basis outcome at facility i in week t during year y for wheat class c, F is the futures contract price, Vol is the futures price volatility measured as the standard deviation of futures prices from the preceding seven weeks, Sp is the difference between MGEX September and KCBT July futures contract prices (with prices rolling over fifteen days prior to a contract's expiration), and P is a protein-level indicator variable. All models include a location fixed effects, weekly fixed effects, and an indicator variable for 2008. MSE represents the mean squared error, adj-R2 is the adjusted R-squared, AICC is the corrected Akaike information criterion, SBC is the Schwartz Bayesian information criterion, fMAE is the forecast mean absolute error, and fMSE is the forecast mean squared error. All out-of-sample forecasts are determined using observations in 2010.

localized in the northern states and exhibits well-established annual grain storage and transportation patterns, the northern winter wheat market may be more heavily impacted by fluctuations in other U.S. winter wheat markets and therefore more reliant on historical information (Goodwin and Smith, 2009). However, only the most recent lagged basis value adds information, with spatial and temporal fixed effects likely explaining longer-run basis behavior.

The top-ranked winter wheat basis model result shows that, in addition to a one-year lagged basis variable, hard red winter wheat harvest-period futures prices, uncertainty, spread between MGEX and KCBT futures prices, and protein-level differentiation are also important. This suggests that winter wheat handling facilities consider both global market information and local demand and supply factors when making pricing decisions. Protein content may be especially important to facilities in the northern states—unlike those in southern wheat-production regions—because these facilities generally accept both spring and winter wheat.

As a robustness check, we use the modified Diebold-Mariano test (Harvey, Leybourne, and Newbold, 1997) to test whether the forecasts from any two competing models are statistically different. We consider the winter and spring wheat markets separately and compare thirteen alternative specifications within and across two assumed time periods (2004–2010 and 2007–2010).[6] For the hard red spring wheat basis models, the modified Diebold-Mariano tests indicate that the top-ranked model, which includes the explanatory variables F_{tyc}, Vol_{tyc}, Sp_{ty}, P_{ityc}, is statistically different from all but the F_{tyc}, P_{ityc} specification, which is simply a more parsimonious model that was ranked lower because of poorer in-sample fit. Similarly, the top-ranked winter wheat basis forecast model, $B_{it,y-1,c}$, F_{tyc}, Vol_{tyc}, Sp_{ty}, P_{ityc}, did not significantly differ from forecasts of the second-ranked specifications. Most importantly, these test results provide additional support for the use of our selected basis models for making accurate harvest-period wheat basis forecasts.

Marginal Effects for Selected Harvest-Period Basis Models

Table 5 presents the estimation results for the top-ranked spring wheat basis and winter wheat basis specifications. For each model, the marginal effects for each variable on basis are shown in level terms in the second column. After testing for and detecting spatial serial autocorrelation, we estimate the standard errors using 500 iterations of an overlapping block bootstrap (Carlstein, 1986; Kunsch, 1989; Lahiri, 1999).[7] Block bootstrapping has been shown to provide unbiased standard errors when data exhibit spatial and temporal serial autocorrelation (Wilks, 1997; Bekkerman, Goodwin, and Piggott, 2008). The bootstrapped standard errors for each variable are presented in the third column. All of the estimated coefficients, except for some of the location and week fixed effects variables (these parameter estimates are omitted for brevity) are statistically significant at the 1% level.

Standardized coefficient estimates, which are interpreted as the relationship between a one-standard-deviation change in each regressor and the change, in standard deviations, of the harvest-period basis are presented in the fourth column of table 5. These results are obtained by subtracting the mean value of each variable from its observed value and then dividing by the variable's standard deviation prior to estimation. Because the standardized coefficient estimates have identical scales, a comparison of the absolute values of the estimates' magnitudes provides insights about the relative importance (i.e., relative impact) of each regressor on changes in basis behavior.

Estimation results from the spring wheat model indicate that basis is strongly influenced by protein levels above 14%. Specifically, 1 and 2 percentage-point increases in protein levels are associated with approximately \$0.35 and \$0.55 per bushel stronger wheat basis (i.e., a higher cash price), respectively (table 5, column 2). Discounts for 12% and 11% protein levels are \$0.43 and \$0.74 per bushel, but, unlike premiums, grain-handling facilities' cash wheat bids are far

[6] The testing yielded 652 individual model comparison results. These are available from the authors upon request.

[7] Block sizes are determined using semi-variogram analyses to assess the distance from a grain-handling facility at which basis spatial autocorrelation dissipates. The distance is 340 miles for hard red spring wheat basis and 190 miles for hard red winter wheat basis.

Table 5. Estimation Results for Top-Ranked Wheat Harvest-Period Basis Models

Parameter	Estimate (cents per bushel)	Bootstrapped Std. Error	Standardized Estimate
	Hard Red Spring Wheat Model (2004–2010)		
Intercept	−29.48	16.06	−−
Futures price	0.14	0.01	0.25
Futures volatility	2.87	0.01	0.29
MGEX-KCBT price spread	−0.20	0.01	−0.05
12% protein-level indicator	−73.52	0.71	−0.16
13% protein-level indicator	−43.16	0.29	−0.13
15% protein-level indicator	35.49	0.18	0.52
16% protein-level indicator	54.85	0.51	0.61
Year 2008 indicator	11.91	1.51	0.04
Location fixed effects		Yes	
Week seasonality indicators		Yes	
	Hard Red Winter Wheat Model (2004–2010)		
Intercept	−69.39	9.72	−−
One-year lagged basis	0.12	0.01	0.11
Futures price	0.05	0.01	0.10
Futures volatility	0.21	0.04	0.02
MGEX-KCBT price spread	0.64	0.15	0.18
10% protein-level indicator	−33.04	7.11	−0.09
11% protein-level indicator	−18.66	6.71	−0.09
12% protein-level indicator	10.73	7.98	0.05
Year 2008 indicator	38.99	5.75	0.15
Location fixed effects		Yes	
Week seasonality indicators		Yes	

Notes: Futures prices for the hard red spring wheat model are of the Minneapolis Grain Exchange September contract and for the hard red winter wheat model are of the Kansas City Board of Trade July contract (with prices rolling over fifteen days prior to a contract's expiration. The MGEX-KCBT spread represents the difference between the prices of these two contracts. Standard errors are estimated using 500 iterations of a block bootstrap to account for spatial serial autocorrelation.

less affected by lower protein spring wheat. Changes in harvest-period MGEX futures prices and volatility both have a positive relationship with basis. A marginal change in the futures price level is associated with a small \$0.0014 per bushel change in the basis. An increase in the volatility of futures prices is associated with a larger, although still small, \$0.03 per bushel effect on basis, suggesting that greater uncertainty in global spring wheat markets could provide incentives for grain-handling facilities to increase their current demand for wheat, perhaps to secure against future large or unexpected price increases. The spread between MGEX and KCBT harvest-period futures prices is negatively correlated with basis, which could be indicative of MGEX futures prices rising faster than both KCBT and cash prices. While the increase in the futures price spread could be considered a market signal regarding protein supply, the disproportionate rise in spring wheat futures prices relative to cash prices is observed as a negative correlation between the two basis and MGEX futures price variables.

The standardized parameter estimates (table 5, column 4) show that hard red spring wheat protein levels have the largest impacts on harvest-period basis values, as indicated by the standardized parameter estimates being largest for the 15% and 16% protein-level indicators. Interestingly, protein discounts for lower protein levels are among the least important basis predictors, perhaps signaling markets' nonlinear valuation of protein content. Current market information represented by the futures price and volatility measures have the next largest impact on basis values, while the standardized parameter estimate associated with the futures price spread variable indicates that marginal changes in this variable have a relatively small impact on basis behavior.

Estimated parameters in the hard red winter wheat model indicate the relative importance of both local and futures market information. The absolute value of the standardized parameter estimates for the one-year lagged basis, futures price level, and the MGEX and KCBT futures price spread are the largest among other variables of interest. All of these variables are positively correlated with the winter wheat basis level. Similar to the spring wheat market, the positive unstandardized coefficient estimate associated with the spread variable suggests that as the relative price of spring wheat increases, winter wheat prices will respond to re-equilibrate the spread relationship. Interestingly, the results suggest that this response is stronger for winter wheat than for spring wheat. Changes in harvest-period KCBT futures contract prices are also positively correlated with basis but have a smaller ($0.0002 cents per bushel) impact on winter wheat basis behavior than the spring wheat market. Estimated discounts for wheat below 11.5% protein and premiums for wheat above 11.5% protein have the expected signs and indicate an approximately linear schedule, similar to estimates of the spring wheat basis model.

Conclusions and Market Applications

Wheat production in the northern United States is characterized by a relatively stable marketing environment, a later harvest period, and a particular focus on product differentiation based on wheat protein levels. These traits make grain marketing in the northern region unique relative to other U.S. wheat production areas with multiple market destinations, earlier harvests, and where less emphasis is placed on quality differentiation. Most studies of grain basis behavior have focused on the Central and Southern Plains markets, but this study shows that previous research on wheat basis in these areas is only partially applicable to the northern U.S. wheat-production region.

Hard red spring wheat and hard red winter wheat harvest-period basis behavior in the northern United States is affected by protein content considerations, harvest-period futures price levels and volatility, and the changes in market demands after production information becomes available from southern regions. Furthermore, using a relatively large, spatially and temporally disaggregated data sample, we show that historical basis values can be superfluous in markets with a well-established, consistent marketing structure because long-run relationships between a grain-handling facility's cash price bids and futures contract prices are sufficiently consistent within and across marketing years. Models that use fixed effects and recent exogenous changes in futures market prices outperform alternative specifications in out-of-sample forecasting.

This research provides some direction for appropriate responses to requests by wheat producers, elevator managers, grain traders, exporters, and agricultural lenders who seek forecasts of future northern U.S. cash wheat prices. In the case of wheat production in the northern United States, the unique, stable marketing structure and continuously updated futures markets information provide an opportunity to offer reasonable answers. The foundation of this research was used to develop an automated web-based basis forecasting tool (available at http://wheatbasis.montana.edu) that uses the combination of estimated basis model parameters and futures market information. The implementation of this web-based basis forecasting tool provides a direct link between academic research and its application to the U.S. wheat industry by incorporating regression results into a basis-forecasting model. Moreover, the tool eliminates market participants' costs of acquiring futures and local prices, developing forecasting models, and identifying and appropriately weighting relevant market factors.

[Received November 2014; final revision received November 2015.]

References

Adjemian, M. K., P. Garcia, S. H. Irwin, and A. Smith. "Non-Convergence in Domestic Commodity Futures Markets: Causes, Consequences, and Remedies." Economic Information Bulletin 115, U.S. Department of Agriculture, Economic Research Service, Washington, DC, 2013. Available online at http://www.ers.usda.gov/publications/eib-economic-information-bulletin/eib115.aspx.

Aulerich, N. M., R. P. H. Fishe, and J. H. Harris. "Why Do Expiring Futures and Cash Prices Diverge for Grain Markets?" *Journal of Futures Markets* 31(2011):503–533. doi: 10.1002/fut.20483.

Bekkerman, A. "The Changing Landscape of Northern Great Plains Wheat Markets." *Choices* 28(2013):1–6.

Bekkerman, A., B. K. Goodwin, and N. E. Piggott. "Spatio-Temporal Risk and Severity Analysis of Soybean Rust in the United States." *Journal of Agricultural and Resource Economics* 33(2008):311–331.

Carlstein, E. "The Use of Subseries Values for Estimating the Variance of a General Statistic from a Stationary Sequence." *Annals of Statistics* 14(1986):1171–1179. doi: 10.1214/aos/1176350057.

Colino, E. V., and S. H. Irwin. "Outlook vs. Futures: Three Decades of Evidence in Hog and Cattle Markets." *American Journal of Agricultural Economics* 92(2010):1–15. doi: 10.1093/ajae/aap013.

Colino, E. V., S. H. Irwin, P. Garcia, and X. Etienne. "Composite and Outlook Forecast Accuracy." *Journal of Agricultural and Resource Economics* 37(2012):228–246.

Garcia, P., S. H. Irwin, and A. Smith. "Futures Market Failure?" *American Journal of Agricultural Economics* 97(2014):40–64. doi: 10.1093/ajae/aau067.

Goodwin, B. K., and V. H. Smith. "Harvest-Time Protein Shocks and Price Adjustment in U.S. Wheat Markets." *Journal of Agricultural and Resource Economics* 34(2009):237–254.

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

Hatchett, R. B., B. W. Brorsen, and K. B. Anderson. "Optimal Length of Moving Average to Forecast Futures Basis." *Journal of Agricultural and Resource Economics* 35(2010):18–33.

Hoffman, L. A. "Forecasting the Counter-Cyclical Payment Rate for U.S. Corn: An Application of the Futures Price Forecasting Model." Electronic Outlook Report No. FDS05a01, U.S. Department of Agriculture, Economic Research Service, Washington D.C., 2005. Available online at http://www.ers.usda.gov/publications/FDS/JAN05/fds05a01/fds05a01.pdf.

Irwin, S. H., P. Garcia, D. L. Good, and E. L. Kunda. "Spreads and Non-Convergence in Chicago Board of Trade Corn, Soybean, and Wheat Futures: Are Index Funds to Blame?" *Applied Economic Perspectives & Policy* 33(2011):116–142.

Kastens, T. L., R. D. Jones, and T. C. Schroeder. "Futures-Based Price Forecasts for Agricultural Producers and Businesses." *Journal of Agricultural and Resource Economics* 23(1998):294–307.

Kunsch, H. R. "The Jackknife and the Bootstrap for General Stationary Observations." *Annals of Statistics* 17(1989):1217–1241.

Lahiri, S. N. "Theoretical Comparisons of Block Bootstrap Methods." *Annals of Statistics* 27(1999):386–404. doi: 10.1214/aos/1018031117.

Manfredo, M. R., and D. R. Sanders. "The Value of Public Price Forecasts: Additional Evidence in the Live Hog Market." *Journal of Agribusiness* 22(2004):119–131.

Szakmary, A., E. Ors, J. K. Kim, and W. N. Davidson III. "The Predictive Power of Implied Volatility: Evidence from 35 Tutures Markets." *Journal of Banking & Finance* 27(2003):2151–2175. doi: 10.1016/S0378-4266(02)00323-0.

Taylor, M. R., K. C. Dhuyvetter, and T. L. Kastens. "Forecasting Crop Basis Using Historical Averages Supplemented with Current Market Information." *Journal of Agricultural and Resource Economics* 31(2006):549–567.

Taylor, M. R., G. T. Tonsor, and K. C. Dhuyvetter. "Structural Change in Forward Contracting Costs for Kansas Wheat." *Journal of Agricultural and Resource Economics* 39(2014):217–229.

Tomek, W. G. "Commodity Futures Prices as Forecasts." *Review of Agricultural Economics* 19(1997):23–44.

Tonsor, G. T., K. C. Dhuyvetter, and J. R. Mintert. "Improving Cattle Basis Forecasting." *Journal of Agricultural and Resource Economics* 29(2004):228–241.

U.S. Wheat Associates. "Wheat Classes." 2013. Available online at http://www.uswheat.org/wheatClasses.

Wilks, D. S. "Resampling Hypothesis Tests for Autocorrelated Fields." *Journal of Climate* 10(1997):65–82. doi: 10.1175/1520-0442(1997)010<0065:RHTFAF>2.0.CO;2.