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Suggested citation format:

Bekkerman, A. and R. T. Worley. 2020. "Quality Forecasts: Predicting When and How Much Markets Value Higher Protein Wheat." Proceedings of the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. [http://www.farmdoc.illinois.edu/nccc134].

Quality Forecasts: Predicting When and How Much Markets Value Higher Protein Wheat

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Paper prepared for the NCCC-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management, 2020.

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Wheat markets stand out among other major crop commodity markets because pricing at the first point of exchange—typically a grain handling facility—is differentiated on specific quality characteristics. Moreover, the premiums and discounts that elevators offer to obtain grain of specific quality can be significant. Despite the relative importance of quality premiums and discounts to farm-level production and marketing decisions, almost no research has examined the factors underlying wheat quality pricing schedules. This study develops an informed expectation model of elevators' quality-based pricing strategies and empirically estimates the model a lengthy dataset of weekly price observations. As such, this research provides the first step toward developing a more accurate understanding of the wheat market and an opportunity to develop price forecasts as a function of wheat quality.

Keywords: discount, premium, prices, protein, quality wheat

Introduction

Wheat stands out among other major crop commodity markets. Unlike corn, soybeans, or cotton, for example, a large proportion of wheat is used directly for human consumption by being processed into flour and then into final consumer goods such as breads, pastas, pastries, among others. As such, wheat procurers assess and price-differentiate across wheat quality characteristics much earlier in the supply chain, assigning quality premiums or discounts at the time farmers deliver wheat to a grain handling or processing facility. The combination of wheat being used in wide variety of ways for producing consumer foods (and, thus, requiring much more precise quality valuation of the unprocessed farm-level product) and quality valuations being made so close to the farm level implies that prices faced by producers can be significantly affected by market supply and demand for particular quality components.

One of the most used characteristics for differentiating wheat quality is the protein content level in a wheat kernel, and millers require that they receive wheat shipments with consistent protein levels within and across marketing years. While protein levels are to some extent tied to specific wheat classes (e.g., soft winter, hard winter, hard spring, soft spring, etc.), there can be considerable annual variability in wheat protein availability because weather conditions during the wheat growing process also significantly impact protein levels. For example, hot and dry conditions typically lead to lower yields but higher protein content, while wet and cooler conditions are typically associated with higher yields but lower protein content. As such, in order to provide a consistent wheat supply of a particular protein level to millers, grain handling facilities offer price premiums and implement price discounts to acquire wheat that can be blended to create a desired protein quality level.

Because weather conditions typically impact large geographic areas, it is often the case that a deficit or surplus of higher-quality, higher protein wheat exists across an entire state or even across an entire country, rather than isolated locations. This implies that price premiums or discounts can represent a significant proportion of producers' farmgate price (i.e., a price that a farmer observes after delivering grain to an elevator and obtaining a premium or discount in addition to a base price). For example, during the 2016/17 marketing year—characterized by a widespread deficit of high-protein wheat—northern U.S. producers received an average of $1.00 per bushel premium for a 15% protein content spring wheat, relative to the price of the base-level 14% protein content, and a $1.75 per bushel discount for 13% protein content wheat. Given that an average market wheat price for base protein content was approximately $5.00 per bushel, these 2016/17 premiums and discounts represented, respectively, a 20% increase and a 35% decrease to the base price, which are significant in a period of relatively low commodity prices.

Farmers who can better anticipate and appropriately manage quality-based price variation (e.g., through intertemporal storage and/or wheat segregation and mixing strategies) may be able to capture additional value (and lower reductions in value) of their product. However, despite the relative importance of quality premiums and discounts to farm-level production and marketing decisions, almost no research has examined the factors underlying wheat quality pricing schedules nor developed models that could assist wheat producers, procurers, and public institutions (such as the USDA and university extension programs) to better anticipate the market equilibrium level of protein premiums/discounts during a marketing year. Our research begins to fill this knowledge gap.

First, we develop an economic model that represents a rational grain-handling facilities two-stage conditional decision-making process for developing a pricing schedule across wheat protein levels. The first stage represents the use of market-level information to determine whether there is an anticipated market-wide deficit or excess of high-protein wheat. Conditional on this determination, the second stage of the decision-making process is setting the price premiums and discounts across different protein levels.

The economic model is then used to develop a corresponding conditional regime-switching econometric framework that captures grain handling facilities' pricing decisions as a function of incoming production and marketing information throughout a marketing year. Specifically, the first stage models the probability of a deficit or surplus of high-protein wheat based on exogenous factors, including regional weather information, USDA wheat quality reports, futures market information, and likely level of high-quality wheat available in on-farm storage. Then, conditional on the first-stage regime, we estimate the level of price premiums/discounts observed across grain elevators for wheat with different levels of protein. Finally, because a main objective is to provide a forecasting tool, we develop out-of-sample analysis to assess the forecasting capabilities of the model.

Perhaps one reason that this type of research has not yet been attempted is the lack of available data describing variation in protein schedules across a diverse set of grain handling facilities and across time. We use a diverse set of information about weekly wheat prices and elevator-specific protein premium and discount schedules in Montana to describe, estimate, and develop forecasting models for differentiated wheat products. The empirical results indicate that elevators switch quickly from offering high premiums for higher protein wheat between marketing years, and that they maintain highly consistent pricing schedules throughout the remainder of a marketing year. Their decisions to offer a low or high premium schedule in the next marketing year is based on pricing variation throughout a current marketing year, as well as indicators from the spread between Minneapolis Grain Exchange and Kansas City Board of Trade futures contract prices and weekly USDA wheat quality reports.

Once elevators make a decision about offering a high or low premium, their pricing strategies are highly linear but are typically kinked at the protein level that represents the baseline protein level. The data indicate that the pricing strategies are based on an elevator's decision to set a high or low premium schedule, previous year's schedule, the level of the protein in delivered wheat, and the elevator's spatial location. We then show that this behavioral consistency allows for relatively accurate out-of-sample forecasting capabilities.

Wheat Protein Markets

Unlike many other crop commodities, the majority of U.S. wheat is used directly for human consumption, primarily in baked goods and pastas. Because there are so many different types of flour-based foods—each of which has specific production characteristics and requiring particular milling and baking traits—there are also a number of different wheat classes that are used in production of the goods. In the United States, the majority of produced wheat is of one of six classes: hard red winter, hard red spring, soft red winter, soft white, hard white, and durum (US Wheat Associates 2017). Each class is produced to create flour that can be used for making different foods. For example, hard red winter wheat is used for production of hard rolls, tortillas, breakfast cereal, and all-purpose flour; hard red spring wheat is used for items such as bagels, croissants, and pizza crusts; and durum is primarily used for traditional pastas. However, some of the classes can be blended together to adjust specific flour characteristics required by millers.

Millers, who source the wheat and sell flour to bakers, are concerned with two aspects of wheat procurement: obtaining wheat that has a particular set of characteristics and maintaining a stable supply of wheat that consistently possesses those characteristics. One of the most important wheat characteristic is the protein content in each wheat kernel. Flour derived from higher-protein wheat helps improves baking performed and dough strength, reduces adverse impacts of over-mixing doughs, and provides the necessary final-good characteristics such as the chewiness of breads, pizza crust, and bagels, or the consistency and "bite" of cooked pasta (Veraverbeke and Delcour 2002). As such, the demand for a consistent supply of higher-protein wheat is passed down the marketing channel from bakers, to millers, to elevators, and eventually to farmers. And while other baking characteristics are also important and can affect wheat pricing, protein level is used as a general proxy for characterizing overall wheat quality traits (Wilson and Dahl 2011).

Production and Pricing of Wheat Protein

The production of wheat with specific protein content largely depends on four factors: wheat class, wheat variety (within the class), precipitation and temperature, and nutrient availability to the wheat plant (primarily nitrogen). Certain wheat classes—such as the hard red winter, hard red spring, and durum—are particularly good at producing higher-protein kernels. However, these classes can only be grown in specific regions of the United States and Canada that have favorable climatic characteristics such as low humidity, particular timings of the beginning and end of winter, lowest temperatures during the winter and highest temperatures during the spring and summer, degree growing days, among others. Specifically, the majority of hard red winter wheat is grown in the Great Plains region and hard red spring is produced in the northern states west of the Mississippi river (US Wheat Associates 2017). Within those regions, farmers are assumed to plant wheat varieties (cultivars) that are expected to maximize both yield and protein content.

The northern U.S. region—comprised of western North Dakota, Montana, Idaho, western Washington, western Oregon—and the southern regions of the Canadian Prairie Provinces are particularly unique because this is one of the few regions in North America that has the potential to produce very high protein wheat. However, wheat protein levels in this region can vary significantly across years due to weather variability. Typically, conditions that are more favorable to higher wheat yields in semi-arid production climates—higher amounts of precipitation and more moderate temperatures—are also less favorable to higher protein content. That is, while more rain, for example, will result in more and larger kernels in a wheat plant, it can result in nitrogen run-off that results in higher starch levels rather than protein. In warmer, drier years, protein content relative to the kernel size is higher.

The production conditions and weather variability in the northern North American region are sufficient to cause significant differences in yield-to-protein trade-offs across marketing years, and markets reflect this variability by having a quality-based wheat pricing and marketing landscape. This is quite different than marketing landscapes in more southern North American wheat production regions, where weather conditions are sufficiently consistent to not trigger major trade-offs between wheat yield and protein content. For example, average rainfall in Kansas results in hard red winter wheat that contains a fairly uniform level of protein and the region is too far south to produce higher-protein spring wheats. In fact, levels are so uniform that elevators do not offer differential prices for wheat based on this quality characteristic.[1]

When elevators in the northern U.S. region make price bids for grain delivery, they can alter incentives for delivery of wheat with particular protein content by offering differential prices for that wheat. This is particularly useful for ensuring that elevators can deliver wheat with a particular protein content, because higher-protein wheat can often be blended with lower-protein wheat to

[1] Infrequently, the central Great Plains regions receives higher-than-average rainfalls (e.g., El Nino years), resulting in widespread yield increases but also reductions in protein content. During those years, some differential pricing may exist.

ensure that when the blend is milled, the resulting flour has the desired baking characteristics.[2] However, a profit-maximizing elevator will attempt to set the lowest possible bids that are high enough to incent delivery of the necessary amount of wheat with the desired protein level. Conversely, elevators can also reduce the delivery of wheat with protein content that is too low by placing sufficiently steep discounts based on wheat quality.

An elevator typically does not fully know the quality characteristics of a wheat crop until producers begin to deliver it at harvest (i.e., at the start of a marketing year). After elevators learn about the production outcomes in their delivery region and in other regions, they establish a protein pricing schedule that describes premiums to a baseline price for wheat that exceeds a baseline protein level, and discounts for wheat that contains protein levels below the baseline. Because wheat harvest occurs only once per marketing year and the underlying wheat quality does not change until the next new crop, elevators maintain a highly consistent schedule throughout the entire marketing year. That is, while the baseline price of wheat is usually pegged to the price of a futures contract—prices of a Minneapolis Grain Exchange hard red spring futures contract and the Kansas City Board of Trade hard red winter wheat futures contract—and those prices fluctuate throughout a marketing year, the premiums and discounts relative to that baseline price remain largely the same. For example, if at time $t = 1$ the bid for spring wheat with a baseline level of protein content (typically 14%) is \$5.00 per bushel and there is a \$0.50 per bushel premium for delivering wheat that contains 1 percentage point higher protein, then the farmer would receive a \$5.50 per bushel overall price for delivering the higher protein wheat. Then, if the baseline price at $t = 2$ changes to \$4.50 per bushel, a farmer delivering wheat with a 1 percentage point higher protein level will receive an overall price of \$5.00 per bushel.

Because weather is relatively systemic and tends to similarly affect large regions, all elevators within a region face similar marketing landscapes. For example, in a marketing year after high-precipitation production conditions, the majority of farmers are likely to have grown higher-yielding wheat with lower protein levels. As such, elevators would need to offer higher premiums for higher-protein wheat and larger discounts for lower-protein wheat in order to procure grain with the desired quality characteristics. We denote this a "high" type marketing year. Conversely, after a particularly warm and dry summer, the majority of farmers produce lower yielding but higher-protein wheat. As such, elevators do not need to offer large incentives to attract higher-protein wheat. We denote this a "low" type marketing year. It is important to note that because of a large on-farm storage capacity in the northern U.S. region, many farmers choose to store their higher-protein wheat (after a high protein production year) with the expectation that they may be able to sell it for a higher premium in the following marketing year. Therefore, even though weather conditions do affect production at the regional level, differential pricing is still an effective strategy

[2]Because hard red winter and hard red spring wheat classes are both of the hard red family—only differing in whether the plant overwinters after seeding or is seeded in the spring—these two classes can be blended together. This is particularly useful because hard red spring wheat typically has higher protein levels but hard red winter wheat has higher yields. By blending the two wheats, one can achieve higher yields with sufficient protein levels (i.e., the whole is greater than the sum of its parts).

for elevators to attract sufficient quantities of desired grain.[3]

Elevators' Decision Model

The quality-differentiated pricing structure of wheat implies that elevators must make two decisions. First, they must decide whether a marketing year will be of a "high" or "low" type. This decision is likely to be formed based on observable market characteristics leading up to the new marketing year. Then, conditional on that assessment, they must then decide how much of a premium to offer for wheat with higher-than-baseline levels of protein and how much to discount wheat with below-than-baseline protein. This decision is also expected to be formed based on known market factors and their perceived interactions in determining market equilibrium for protein. Elevators that can make these assessments sooner than their competitors may be able to increase their likelihood of procuring sufficient quantities of wheat with desired quality characteristics; more effectively manage their procurement, grain handling, storage, and transportation operations; and develop better hedging strategies for managing price risk (Wilson and Miljkovic 2013).

The two-step decision process can be conveniently summarized using a conditional premium (discount) expected value framework. For example, an elevator seeking to develop an informed expected value of wheat protein pricing in marketing year $T+1$ can be characterized by the decision model:

$$\begin{aligned} E[K_{\text{prem},T+1,r^+}] &= P[Y_{T+1} = \text{high}|\boldsymbol{Z_T}]\left(K_{\text{prem},r^+,\text{high}}\right) + P[Y_{T+1} = \text{low}|\boldsymbol{Z_T}]\left(K_{\text{prem},r^+,\text{low}}\right) \\ E[K_{\text{disc},T+1,r^-}] &= P[Y_{T+1} = \text{high}|\boldsymbol{Z_T}]\left(K_{\text{disc},r^-,\text{high}}\right) + P[Y_{T+1} = \text{low}|\boldsymbol{Z_T}]\left(K_{\text{disc},r^-,\text{low}}\right) \end{aligned} \tag{1}$$

The term $E[K_{\text{prem},T+1,r^+}]$ represents the expected value of the premium set in marketing year $T+1$ for a protein level that is r^+ percentage points above the baseline protein level; $P[Y_{T+1} = \text{high}|\boldsymbol{Z_T}]$ is the probability of observing a high type marketing year in $T+1$, conditional on an information set, $\boldsymbol{Z_T}$ available to the elevator in the current marketing year; and, $\left(K_{\text{prem},r^+,\text{high}}\right)$ and $\left(K_{\text{prem},r^+,\text{low}}\right)$ represent the protein premium pricing strategies that an elevator has chosen to implement in a high or low type marketing year, respectively. The term $E[K_{\text{disc},T+1,r^-}]$ represents the expected value of the discount set in marketing year $T+1$ for a protein level that is r^- percentage points below the baseline protein level, with all the other variables having complementary descriptions to those for price premiums.

There are several immediate insights from the model in equation 1. First, this characterization of elevators' decision-making helps directly inform the empirical strategy. That is, the empirical analysis must estimate the underlying regime-switching attributes that represent the distinct market behaviors occurring in each regime (i.e., the "high" or "low" market types). Second, the analysis requires estimating both the conditional probabilities of observing a particular year type and the

[3] There can arguably be more than two marketing year types, but as we discuss and show below, the empirical analysis indicates that there is evidence suggesting that two regimes sufficiently represent the market.

strategy for pricing wheat protein during that marketing year. And third, there is an assumption that elevators set different schedules for price premiums and price discounts.

The assumption about asymmetric premium and discount schedules is based both on economic factors underlying the structure of quality-differentiated wheat markets and on observed historical data in the market. First, the North American (and global) wheat market is dominated by the production of lower-protein wheat. As such, northern U.S. grain handling facilities—on which U.S. and increasingly global markets rely to supply higher-quality wheat for blending purposes—are more likely to create proportionately greater disincentives for producers to deliver lower-protein wheat. Stated more practically, because northern U.S. elevators are often expected to supply higher-protein wheat and this is more difficult to do when farmers deliver higher quantities of lower-quality wheat, these elevators are more likely to create greater penalties for delivering lower-protein wheat relative to the premiums offered to incentivize greater delivery of higher-quality wheat.

Second, the asymmetric pricing assumption is made because there is empirical evidence of this behavior. Figure 1 shows average protein pricing schedules for hard red spring and winter wheat classes across twenty Montana grain elevators between 2012/13 and 2016/17 marketing years.[4] These data provide several important insights. First, for each wheat class, there is a distinct pricing kink at the baseline protein level (14% for spring wheat and 12% for winter wheat). More importantly, in every year, the slope above the kink (i.e., premiums for wheat with protein levels above the baseline) is flatter than the slope below the kink (i.e., discounts for wheat with protein levels below the baseline). That is, higher protein levels are rewarded less than the penalty for lower protein wheat. Both the kink and the asymmetric pricing behaviors are persistent across every year of the sample.[5]

Data Description

To estimate the pricing decision model, we use publicly-available data of weekly prices for hard red spring (HRS) and hard red winter (HRW) wheat in five Montana regions between 1990 and 2016 (USDA Agricultural Marketing Service 2017). These data have been used before in numerous other commodity pricing studies that incorporate wheat quality components (see, for example Goodwin and Smith 2009; Bekkerman 2011; Miao et al. 2016), because these data provide prices at three protein content levels for HRS—12%, 13%, and 14% protein —and at four content levels for HRW—10%, 11%, 12%, and 13% protein. While these prices have relatively few protein levels, the overall length of these data, their relatively high frequency of reporting, and at least some differentiation across wheat quality levels provides an opportunity to model various characteristics about type of marketing year within which pricing decisions are made.

[4] This is a unique dataset, which has been assembled by the authors using annual phone surveys of grain elevator managers. Appendix A provides additional information about these data.

[5] A more rigorous, regression analysis of these data provide statistical evidence that elevators asymmetrically price wheat protein above and below the baseline levels. The analysis and results are described in the appendix.

Normalized Price Spread

To estimate the type of marketing year—the first step in the estimation process—we develop a measure that uses spreads between prices of wheat with different protein levels to help identify marketing years when there is a large supplies and and those with small supplies of wheat protein. That is, during years when wheat protein supplies are relatively high, price premiums for higher-protein wheat and discounts for lower-protein wheat will both be low, implying that the difference between the prices of the higher- and lower-protein wheats will also be small. Conversely, during years with wheat protein deficits, price differences will be relatively high. As such, empirically assessing market signals sent by price differences can provide a mechanism for estimating the marketing year type.

One concern, however, with simply calculating the spread between the price of a higher-protein wheat and the price of a lower-protein wheat is that this measure would be difficult to compare across time, because spreads are likely to be larger in years when wheat prices are higher and smaller when wheat prices are low. That is, protein schedules are heteroskedastic in the base price of wheat. Instead of using simple price differences, we define a normalized premium–discount spread variable. Specifically, after adjusting all prices to 2017 dollar values, we use the following function to calculate the spread, D, in protein valuations in time t:

$$D_t = \frac{P_{\text{high}} - P_{\text{low}}}{P_{\text{base}}} \,. \tag{2}$$

The term P_{base} represents the baseline price for which there is neither a protein premium nor discount. In most northern U.S. production locations, this baseline price is consistently set at 14% protein level spring wheat and 12% protein level winter wheat.[6] The variables P_{high} and P_{low} represent the prices of wheat with a 1 percentage point higher protein content and 1 percentage point lower protein content, respectively. Thus, the normalized premium–discount spread provides a measure of the protein content premium level in each marketing year after accounting for differences in the baseline prices across marketing years. This allows the measure to be comparable across marketing years.

Figure 2 presents a visual time-series summary of the normalized spread variable for Montana across 27 marketing years. First, the figure makes evident that there are clear distinctions between high and low year types, with well-defined peaks and valleys across time. Second, switches in the year types occur quickly and quite soon after a wheat harvest begins, as elevators begin to observe the majority of wheat that is marketed and delivered. And third,the pricing schedules persist throughout the remainder of the marketing year. These insights seem to imply a relatively consistent "feast-or-famine" marketing landscape for higher-protein wheat, with elevators having to consistently maintain a higher price premium to incent higher-protein wheat to be delivered throughout the year.

[6]In years when there is a particular deficit of higher protein wheat, the baseline price may occur at a slightly lower protein level. However, this occurs very infrequently and the baseline protein level is typically reduced by 0.25–0.50 percentage points.

The figure also shows that while there are many years in which pricing patterns are similar for spring and winter wheat classes, these markets are not identical and should not be treated as interchangeable. This is likely related to the fact that winter wheat is grown in many other U.S. regions, while spring wheat production is concentrated in the northern United States. As such, while localized protein supply issues are likely most influential in many years, production outcomes in other major winter wheat areas impact markets for wheat protein and the magnitude of this impact varying across time.

Protein Premiums and Discounts

Despite its length, the weekly price data are limited in an important way: they provide only minimal detail about the pricing distribution across wheat protein levels. The primary concern is whether these limited data can be used to effectively characterize the underlying functional form of elevators' protein pricing. For example, theoretical modeling of protein schedules characterizes farmers' blending strategies (which are assumed to based on producers' knowledge of elevators' protein pricing schedules) as a non-linear third-degree polynomial with an inflection point at the baseline price (Miao and Hennessy 2015; Hennessy 1996). If that is the case, then using the publicly-available data that only describes prices for three or four protein levels would unlikely be sufficient to fully identify and estimate the protein pricing schedules. However, if elevators' pricing schedules were closer to or exactly linear, then knowing only the baseline price and one price above and one below the baseline would be sufficient to characterize the entire schedule.

To determine the true form of elevators' protein schedules, we collected data about firms' pricing decisions directly, by conducting repeated phone surveys of twenty Montana elevators between the 2012/13 and 2016/17 marketing years.[7] Figure 1 shows the average pricing schedules for the two wheat classes and offers additional insights to the ones discussed above regarding asymmetric protein pricing. Specifically, the figure shows that elevators use relatively simple piecewise functions, which have two linear price schedule components that are kinked at the baseline protein level.[8]

The empirical evidence for linear protein pricing schedules suggests that only minimal guidance about pricing of wheat with above-baseline and below-baseline protein levels is sufficient to identify with relative confidence the entire protein pricing schedule. That is, although publicly-available data provide limited details about wheat prices across only a few protein levels, these data offer enough information about the magnitude of price premiums and discounts to estimate empirical models of these schedules.

[7] Appendix A provides additional information about these data.

[8] The pricing schedule is actually a four-component piecewise function because elevators either refuse to accept wheat below a certain protein level floor and do not pay any additional premiums for wheat above a certain protein level ceiling.

Additional Data

In addition to the two dependent variables used to estimate the two-stage pricing decision model, we collect data for a number of other variables that have been shown to aid in explaining variation in wheat price formation and, therefore, could also play a role in modeling the formation of strategies for pricing wheat quality. First, following Bekkerman, Brester, and Taylor (2016), we calculate futures spread variables between prices of the Minneapolis Grain Exchange (MGEX) spring wheat futures contract and the Kansas City Board of Trade (KCBT) winter wheat futures contract. Because spring wheat, on average, contains a higher protein level than winter wheat, the magnitude of the spread between the MGEX and KCBT futures contract prices would be indicative of the market demand for higher-protein wheat relative to the baseline winter wheat. For example, in years when the average protein level of winter wheat is relatively low, higher-protein spring wheat is expected to have a higher demand (and, thus, a higher price and wider MGEX–KCBT futures price spread), because the spring wheat would be necessary to blend with lower-protein winter wheat to ensure an industry-required protein content.

We create two MGEX–KCBT spread variables using historical weekly-average futures price data obtained from Quandl: one that uses nearby contracts for both markets and the second that considers the spread between harvest period contracts. The nearby contract spread helps characterize shorter-term market demand for higher-protein wheat. The harvest period spread exploits the temporal differences in the timing of U.S. wheat harvests. Warmer climatic conditions imply that winter wheat harvest begins as early as June in the Central and Southern Plains, while the northern states generally harvest winter wheat in late-July and August and spring wheat in late-August and September. As such, 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. Therefore, variation in the harvest period MGEX–KCBT spread (measured using September MGEX contract prices and July KCBT contract prices) helps characterize changes in expectations of market-wide wheat protein availability.

Using futures contract prices, we also create a "harvest carry" variable, which is the difference between the price of the harvest period contract price and the nearby contract price for each wheat class. Specifically, for spring wheat the harvest carry is the difference between prices of the September MGEX futures contract and the nearby contract, and for winter wheat, it is the difference between the prices of the July and nearby KCBT futures contracts. These variables help indicate the extent to which markets demand wheat in the short-run relative to waiting until the new crop. The lower the harvest carry value, the more the market demands wheat of a certain class in the short-run rather than waiting until the next harvest. For example, a low or negative harvest carry in the higher-protein spring wheat market may suggest a high demand for immediate delivery of high protein wheat.

Next, we obtain weekly data about spring and winter wheat quality conditions from the USDA Crop Progress reports. The reports describe the percent of wheat from field surveys that was rated a five-point Likert quality scale: very poor, poor, fair, good, and excellent. Similar to many industry publications, we group the "good" and "excellent" categories together to indicate the proportion of higher quality ratings and the remaining three categories as lower quality ratings. For winter wheat, quality reports begin in week 14 of a calendar year (March) and continue until shortly before harvest in July (week 27). For spring wheat, reports begin in week 20 (May) and conclude in week 33 (late August).[9] We use the reports to construct two variables for each wheat class: the proportion of higher-quality rated wheat in Montana and the proportion of higher-quality rated wheat in the United States. The expected relationship of the quality rating reports to the type of marketing year and protein pricing behavior is uncertain, because higher quality ratings may indicate the potential for higher yield (which is typically correlated with lower protein levels) or higher protein.

Lastly, we collect precipitation and temperature information for Montana from the NOAA National Centers for Environmental Information Climate Data Online tool. We use these data to calculate weekly cumulative precipitation (from January 1 to the week t) and average temperature observed in week t. Higher cumulative precipitation has been shown to increase wheat yields, which is typically inversely related with protein content in a wheat kernel. However, higher temperatures tend to decrease wheat yields, but also result in a higher protein content level.

Empirical Specification

The empirical modeling has three components, each of which is applied separately for the two classes of wheat, hard red winter and hard red spring. First, we empirically identify the type of marketing: high type (in which elevators offered higher protein premiums and steeper discounts) or a low type (in which elevators provide moderate premiums and discounts). Next, the empirically-identified marketing year type becomes the dependent variable in a model of next year's type as a function of numerous market and production factors in elevators' available information sets. The predicted values from this regression represent the probability estimates in an elevator's price decision model described in equation (1); that is, $P[Y_{T+1} = \text{high}|\boldsymbol{Z_T}]$ and $P[Y_{T+1} = \text{low}|\boldsymbol{Z_T}]$. Lastly, we estimate a regression model of historical pricing schedules. These models provide estimates of the expected premium and discount schedules in equation (1) under alternative marketing year types; that is, $(K_{\text{prem},r^+,\text{high}}, \ldots, K_{\text{prem},r^-,\text{low}}$. Combining insights from the second and third steps yields the conditional premium and discount expectations; that is, $E[K_{\text{prem},T+1,r^+}]$ and $E[K_{\text{prem},T+1,r^-}]$.

[9] There are several weeks of reports for winter wheat in the fall of the preceding year during first emergence and before the winter dormant period. To maintain consistency between the spring and winter wheat data, We do not consider those reports.

Marketing Type Estimation

The first step of the estimation process is to empirically identify the type of marketing year that occurred in year T. To do so, we implement a Markov-Switching Dynamic Regression (MSDR) regime switching model (Quandt 1972; Goldfeld and Quandt 1973; Hamilton 1989). MSDR models are used for time series data in which there may be numerous unobserved, latent states, between which transitions occur through time. These transitions are assumed to follow a Markov process and the duration between states is assumed to be random. Whether a process is in one state or another is not known with certainty, but the MSDR model estimates the probability that the time series process is in one of the states. The MSDR model estimation is similar to an updating algorithm of a Kalman filter. After the model is estimated, it is used to then predict the probabilities that a marketing year was of a high or low type, based on the normalized premium–discount spread.

Specifically, we model the normalized premium–discount spread, D in state s in week t as

$$D_t = \mu_s + \boldsymbol{Z}_t \boldsymbol{\theta}_s + \nu_s. \tag{3}$$

The term $\boldsymbol{Z}_t$ is a vector of exogenous variables, including the nearby futures MGEX–KCBT spread, harvest futures MGEX–KCBT spread, and either the MGEX or KCBT the futures price carry related (depending on whether the model is for the spring or winter wheat class), two USDA Crop Progress report variables that represent the proportion of excellent and good rate wheat in Montana and in the United States (for the appropriate wheat class), and weather variables, including cumulative precipitation up to week t and average temperature in week t. Because we expect (based on observed market behaviors) that states can change relatively quickly during the harvest period, we allow the models to adjust quickly between year types, $s \in (\text{low, high})$ by specifying state-dependent intercept (μ_s), coefficients (θ_s), and error terms (ν_s).[10]

After estimating the MSDR models and the associated state-transition probabilities, we estimate the predicted probabilities of being in a low or high marketing year type in week t of marketing year T. If the probability of a high (low) marketing year type exceeds 50% in week t, then it is classified as that year type. Finally, we use the modal value of predicted year type across all weeks in a marketing year to classify marketing year T as either high or low type. For example, if twenty-five of twenty-seven weeks in marketing year T were predicted as having low premiums/discounts, then we classify year T as a low type.

Forecasting Future Marketing Year Type

After classifying either marketing year as either a low or high premium/discount type using the MSDR analysis, we use the lead of each year type (i.e., Y_{T+1}) as the dependent variable for modeling the ability to use current-year's market and production information to predict next year's

[10] We consider whether more than two marketing year types (i.e., states) might exist. However, in all attempts, the optimization procedures fails to converge, which most likely indicates that the data cannot fit models with $s > 2$. We interpret this as empirical evidence against using more than two states.

marketing year type. That is,

$$Y_{T+1} = \beta_0 + \beta_1 \mathrm{Y}_T + \boldsymbol{\beta_F F}_{T,t} + \boldsymbol{\beta_Q Q}_{T,t} + \boldsymbol{\beta_W W}_{T,t} + \delta_t + \varepsilon_{T,t}. \tag{4}$$

The term Y_{T+1} represents the predicted year type in the upcoming marketing year $T+1$; Y_T is the predicted year type in the current marketing year, T; $\boldsymbol{F}_{T,t}$ is a vector of futures market variables, including the nearby futures MGEX–KCBT spread, harvest futures MGEX–KCBT spread, and either the MGEX or KCBT the futures price carry related (depending on whether the model is for the spring or winter wheat class); $\boldsymbol{Q}_{T,t}$ is a vector of two USDA Crop Progress report variables that represent the proportion of excellent and good rate wheat in Montana and in the United States (for the appropriate wheat class); $\boldsymbol{W}_{T,t}$ is a vector of weather variables, including cumulative precipitation up to week t and average temperature in week t; δ_t are week fixed effects that help control for unobserved seasonality effects; and $\varepsilon_{T,t}$ is an error term.

The above model is essentially a balanced panel data with $T = 26$ marketing years and N represented by the number of USDA Crop Progress report weeks in each marketing year, which depends on each wheat class (thirteen for spring wheat and fourteen for winter wheat). As such, the weekly fixed effects, δ_t, can be interpreted as individual fixed effects. Katz (2001) and Greene (2004) show that estimation of non-linear panel models, such as probit and logit specifications, with individual fixed effects results in biased and inconsistent estimates, even with a reasonably large T. Therefore, we estimate the model in equation 4 using a linear probability model (LPM). LPMs have been shown to provide consistent estimates in panel fixed effects models Angrist (2001). And while we certainly acknowledge the potential trade-offs of linear probability models (e.g., predictions outside of the [0,1] interval), we argue that the advantages of such models outweigh their weaknesses relative to alternatives.[11]

Modeling Protein Price Schedules

The last component is modeling variation in the actual protein pricing schedule under the low and high marketing year types. As discussed above, we show that elevators price protein using relatively linear schedules, but which have different slopes above and below the baseline protein level. As such, we model the protein schedule model of premium (discount) price P_T in marketing year T and week t as

$$P_{T,t} = \alpha_0 + \alpha_1 Y_T + \alpha_2 R + \alpha_3 (Y_T \times R) + \boldsymbol{\alpha_F F}_{T,t} + \boldsymbol{\alpha_Q Q}_{T,t} + \boldsymbol{\alpha_W W}_{T,t} + \eta_{T,t}. \tag{5}$$

The premium (discount) price, P_T is measured as the percentage above (below) the price of wheat with a protein level higher (lower) than the baseline level and R represents a binary indicator of whether the observation represents a protein premium or discount. The marginal effect associated with the interaction term $(Y_T \times R)$ is the coefficient of interest, because it represents the extent to

[11]In a small number of cases when predictions do fall outside the [0,1] interval, we evaluate those predictions based on whether they fall below or above 0.50.

which the premium (discount) will be steeper in a high type marketing year (i.e., $Y_T = 1$) relative to a low type marketing year (i.e., $Y_T = 0$). The terms $\boldsymbol{F}_{T,t}$, $\boldsymbol{Q}_{T,t}$, and $\boldsymbol{W}_{T,t}$ are the same as described for equation (4), and $\eta_{T,t}$ is the error term.

Estimation Results

Table 1 presents the summary statistics for the relevant variables. The data show that nearly 60% of marketing years had high premiums and large discounts for spring wheat, but only 35% of marketing years were "high" for winter wheat. Similarly, the average normalized premium–discount spread is nearly twice as high in the spring wheat market than it is for winter wheat. On average, the nearby futures market spread is larger than the harvest spread, suggesting that markets may over-estimate the amount of higher-protein wheat available in the new marketing year. Interestingly, spring wheat quality across the United States seems to be, on average, higher than in Montana for spring wheat, but lower for winter wheat. Differences in cumulative precipitation and average temperatures for the two wheat classes are a function of the fact that winter wheat is usually harvested in late July but spring wheat is harvested in late August and early September.

Results of MSDR Models

Figure 3 provides a visual summary of the estimated year type probabilities from the Markov-switching dynamic regression model. For each wheat class, the figure shows the weekly normalized premium–discount spread overlaid with the conditional predicted probability of the year being a high or low type. The estimation and predicted probabilities make quite evident that there is often little uncertainty between year types and that the signals provided by the normalized premium–discount spread variable are strong. The estimation also adds evidence to the fact that while the types marketing years in spring and winter wheat markets are certainly related and there are numerous periods when both markets are in a high type year or a low type year, there are also many cases when elevators used different pricing strategies for the two classes, even though an elevator accepts delivery of both wheat classes.

Table B1 of the appendix presents the detailed estimation results of the MSDR model. The results indicate that the exogenous factors included in the models explain a greater amount of variation for low protein premium/discount marketing year types, and that for both wheat classes, futures market dynamics and USDA Crop Progress quality reports are the primary explanatory variables in assessing variation in marketing year types. The results also show that there are statistically different variances across the low and high type marketing years. As to some extent expected, there is less variability in the normalized spread variable within low marketing year types, but approximately five times as much variance in the high marketing year types. This is similar to observing a higher variance in commodity prices in years when those prices are relatively high. Lastly, the results show that once a protein pricing schedules are established (i.e., once the model enters either the low or high state), there is a very low likelihood—approximately 3.3%—

of switching to the other type. This adds empirical support for the observed behavior that grain elevators establish their pricing schedules quickly and do not deviate from those schedules unless there is overwhelming market signals to do so (e.g., a new crop harvest).

Results of Marketing Year Predictive Models

Table 2 presents the estimation results of the linear probability model for the marketing year type forecast. The results show that in predicting whether the upcoming marketing year will have "high" or "low" premiums and discounts, information about the current year's marketing type, the harvest and nearby MGEX–KCBT spreads, USDA quality reports for Montana, and temperature provide predictive power in both the spring wheat and winter wheat models. As expected, markets look toward current conditions (i.e., the current marketing year type) to help inform next year's type. This measure may also provide insights about available inventories of higher-protein wheat, which can also drive expectations about the upcoming marketing year type.

Larger spreads between nearby MGEX and KCBT futures prices would lead to a higher probability of observing a high premium and discount marketing year in $T+1$. That is, higher spreads indicate either higher demand or lower quantities of higher-protein wheat in the current marketing year T, increasing the market value of higher-protein wheat in $T+1$. Conversely, increases in the harvest-period MGEX–KCBT spread signal higher value on higher-protein wheat later in the year, which may suggest that there is sufficient high-quality wheat in the current period and that sufficient inventories may carry over to $T+1$. Higher weekly temperatures during the growing condition typically imply that the $T+1$ crop will have higher protein levels, which would lower the probability of observing a high type marketing year. For winter wheat, the results also show that higher precipitation—which is associated with higher yields but lower protein levels—would be expected to increase higher-protein wheat's value in the upcoming marketing year.

Table 2 also shows that increases in the proportion of Montana wheat categorized as excellent or good by the USDA is associated with lowering the probability of observing a high marketing year type. This suggests that USDA quality reports may truly reflect quality characteristics. However, when the USDA increases the proportion of excellent and good winter wheat in other parts of the United States, the probability of higher protein premiums and discounts in Montana increases. Lastly, the year T spring–summer post-emergence weekly indicators show how markets incorporate information throughout the year to make predictions about the $T+1$ marketing year type. Early in the season, when current year's production information is scarce or uncertain, there is large predictive power derived from the current marketing year type. That is, markets simply assume that the marketing year type in $T+1$ will be similar to the current marketing year type. However, as the season progresses, the predictive power of weekly indicators dissipates, suggesting that markets rely more heavily on actual market and production information, rather than simple autoregressive forecasting.

Table 3 shows the marketing year type model's out-of-sample predictive accuracy. Predictions are generated using one-step-ahead forecasts of the marketing year type model. Forecasts are generated by using a subsample of years to estimate parameters and then using the following year's data to predict the next year's marketing year type. For example, 2007 predictions are generated by first using 1990–2005 data to estimate the marketing year type model, and then using observed information for the 2006 marketing year to predict the marketing year type in 2007. The results show that the winter and spring wheat models have relatively high predictive power, with the winter wheat model correctly predicting 70% and spring wheat 80% of marketing year types.

Results of the Protein Pricing Schedules

Table 4 shows the results of the protein pricing regression. First, while we specify the regression model in equation (5) using the restricted (interaction term) form, we test whether this form should be used or whether protein premiums and protein discounts should be modeled using separate regressions. For both winter and spring wheat, Chow test results provide evidence toward rejecting the null hypothesis of using a single equation.[12] As such, Table 4 presents the results for separate premium and discount subsample regressions.

The results show that, on average, protein premiums in high marketing year types increase by approximately 7 percentage points for both winter and spring wheat classes. However, discounts are less symmetric across the two classes. In high discount years, winter wheat discounts increase by approximately 6.3 percentage points. However, lower-protein spring wheat is discounted by nearly an additional 9 percentage points. This suggests that elevators develop pricing strategies that strongly respond to wheat markets that demand higher-protein wheat for blending during years when higher-quality wheat is at a deficit.

Conclusions

Wheat markets stand out among other major crop commodity markets because pricing at the first point of exchange—typically a grain handling facility—is differentiated on specific quality characteristics. Moreover, the premiums and discounts that elevators offer to obtain grain of specific quality can be significant. Despite the relative importance of quality premiums and discounts to farm-level production and marketing decisions, almost no research has examined the factors underlying wheat quality pricing schedules. This study develops an expected valuation model of elevators' quality-based pricing strategies and empirically estimates the model using data describing protein level premium and discount schedules. As such, this research provides the first step toward developing a more accurate understanding of the wheat market and an opportunity to develop price forecasts as a function of wheat quality.

[12] The F-test statistics is 18.967 for winter wheat and 22.392 for spring wheat, which are both greater than the critical value of 1.83.

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Table 1: Descriptive Statistics of Relevant Variables

Statistic	**Mean**	**St. Dev.**	**Min**	**Max**
	Spring Wheat			
"High" Marketing Year	0.585			
Normalized Premium–Discount Spread, HRS	0.153	0.120	0.003	0.464
Harvest MGEX–KCBT Spread, cents/bushel	17.652	33.026	−51.000	140.450
Nearby MGEX–KCBT Spread, cents/bushel	28.613	37.761	−36.600	247.500
MGEX Harvest Carry	2.971	19.024	−20.800	184.750
Percent HRS Wheat Rated Excellent/Good, MT	0.589	0.161	0.170	0.880
Percent HRS Wheat Rated Excellent/Good, US	0.681	0.106	0.320	0.880
Cumulative Precipitation, inches	5.936	4.739	3.081	10.782
Average Temperature, degrees F	55.476	7.187	37.081	71.526
	Winter Wheat			
"High" Marketing Year	0.347			
Normalized Premium–Discount Spread, HRW	0.088	0.086	0.002	0.339
Harvest MGEX–KCBT Spread, cents/bushel	23.113	33.616	−65.250	159.650
Nearby MGEX–KCBT Spread, cents/bushel	33.028	50.278	−45.050	343.850
KCBT Harvest Carry	−4.167	17.501	−82.938	68.650
Percent HRW Wheat Rated Excellent/Good, MT	0.533	0.184	0.000	0.820
Percent HRW Wheat Rated Excellent/Good, US	0.495	0.138	0.000	0.790
Cumulative Precipitation, inches	6.640	5.438	3.092	11.534
Average Temperature, degrees F	44.643	9.462	16.122	68.474

Table 2: Estimation Results of Next Marketing Year's Type Model

	Hard Red Winter		*Hard Red Spring*	
Variable	**Estimate**	**Std Err**	**Estimate**	**Std Err**
Marketing year type, current year	0.175***	(0.045)	0.168***	(0.048)
Futures price spread, harvest	-0.003***	(0.001)	-0.007***	(0.001)
Futures price spread, nearby	0.003***	(0.001)	0.007***	(0.001)
Futures price carry, harvest	0.001	(0.002)	0.001	(0.002)
Proportion good/exc quality, MT	-0.314**	(0.128)	-0.337*	(0.186)
Proportion good/exc quality, US	1.789***	(0.166)	0.212	(0.297)
Cumulative precipitation	0.124***	(0.027)	0.017	(0.016)
Average weekly temperature	-0.012***	(0.004)	-0.030***	(0.005)
Intercept	0.912***	(0.188)	-1.163***	(0.315)
Post-emergence week number, current crop				
Week 1	0.733*	(0.383)	0.351**	(0.159)
Week 2	0.684*	(0.378)	0.364**	(0.154)
Week 3	0.666*	(0.369)	0.351**	(0.149)
Week 4	0.640*	(0.358)	0.313**	(0.146)
Week 5	0.613*	(0.351)	0.211	(0.138)
Week 6	0.625*	(0.341)	0.174	(0.134)
Week 7	0.580*	(0.332)	0.156	(0.133)
Week 8	0.572*	(0.322)	0.117	(0.133)
Week 9	0.505	(0.315)	0.026	(0.134)
Week 10	0.475	(0.308)	0.020	(0.135)
Week 11	0.390	(0.304)	0.004	(0.136)
Week 12	0.300	(0.298)	0.040	(0.143)
Week 13	0.262	(0.294)	-0.040	(0.295)
Week 14	0.244	(0.295)		
Week 15	0.165	(0.330)		
Week 16	0.141	(0.390)		
Week 17	0.107	(0.390)		
Week 18	0.110	(0.390)		
Model R-square	0.372		0.353	

Notes: ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3: One-step-ahead Out-of-Sample Prediction Assessment of Marketing Year Type

	Hard Red Winter Wheat		*Hard Red Spring Wheat*	
Year	Actual Year Type	Predicted Year Type	Actual Year Type	Predicted Year Type
2007	Low	Low	Low	Low
2008	Low	Low	Low	Low
2009	High	Low*	High	High
2010	High	Low*	High	High
2011	High	High	High	High
2012	High	High	High	High
2013	Low	High*	Low	High*
2014	Low	Low	High	Low*
2015	Low	Low	High	High
2016	Low	Low	High	High
Prediction Accuracy	70%		80%	

Notes: Predictions are generated using one-step-ahead forecasts of the marketing year type model. Forecasts are generated by using a subsample of years to estimate parameters and then using the following year's data to predict the next year's marketing year type. For example, 2007 predictions are generated by first using 1990–2005 data to estimate the marketing year type model, and then using observed information for the 2006 marketing year to predict the marketing year type in 2007. * denotes years in which the forecast year type does not match the observed year type.

Table 4: Estimates of the Protein Price Premiums and Discounts Across Marketing Year Types

	Hard Red Winter Wheat		*Hard Red Spring Wheat*	
	Premium	**Discount**	**Premium**	**Discount**
Marketing year type	0.071***	-0.063***	0.070***	-0.088***
	(-0.003)	(-0.002)	(-0.005)	(-0.005)
Futures price spread, harvest	-2.7E-04***	-6.0E-05	-3.1E-04***	3.5E04***
	(-7.0E-05)	(-5.0E-05)	(-8.0E-05)	(-9.0E-05)
Futures price spread, nearby	1.6E04***	-1.3E-04***	-6.0E-05	7.0E-05
	(-4.0E-05)	(-3.0E-05)	(-9.0E-05)	(-1.0E-04)
Futures price carry, harvest	2.2E04***	1.6E04**	9.0E-05	-8.0E-05
	(-1.0E-04)	(-7.0E-05)	(-1.6E-04)	(-1.8E-04)
Proportion good/exc quality, MT	-0.013	0.009	0.005	-0.02
	(-0.009)	(-0.007)	(-0.018)	(-0.020)
Proportion good/exc quality, US	0.127***	-0.055***	0.147***	-0.168***
	(-0.012)	(-0.009)	(-0.029)	(-0.033)
Cumulative precipitation	0.002**	-0.002**	0.004***	-0.003**
	(-9.4E-04)	(-7.1E-04)	(-0.001)	(-0.002)
Average weekly temperature	-4.0E-05	2.0E-06	-0.001***	0.001
	(-2.3E-04)	(-1.8E-04)	(-3.4E-04)	(-3.9E-04)
Intercept	-0.040***	0.021**	-0.039	0.070**
	(-0.012)	(-0.009)	(-0.028)	(-0.032)
Model R-square	0.630	0.719	0.523	0.554

Notes: The dependent variable is measured in percentage price premium above (premium) and below (discount) the price of wheat with the base-level protein level (14% for spring wheat and 12% for winter wheat). ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

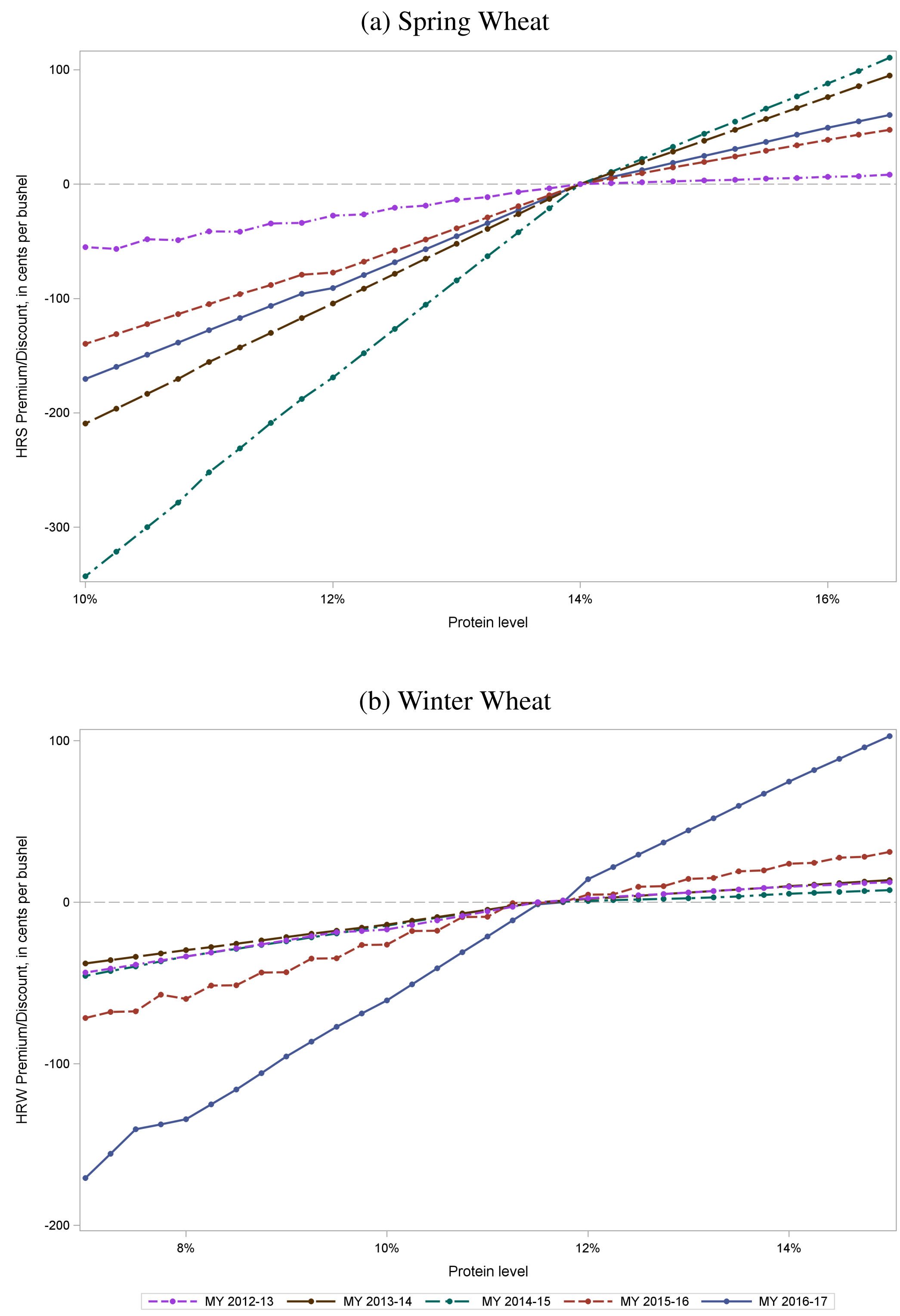


Figure 1: Annual Protein / Discount Schedules, 2012/13–2016/17 Marketing Years

Notes: Schedules represent averages across 20 Montana grain handling facility locations.

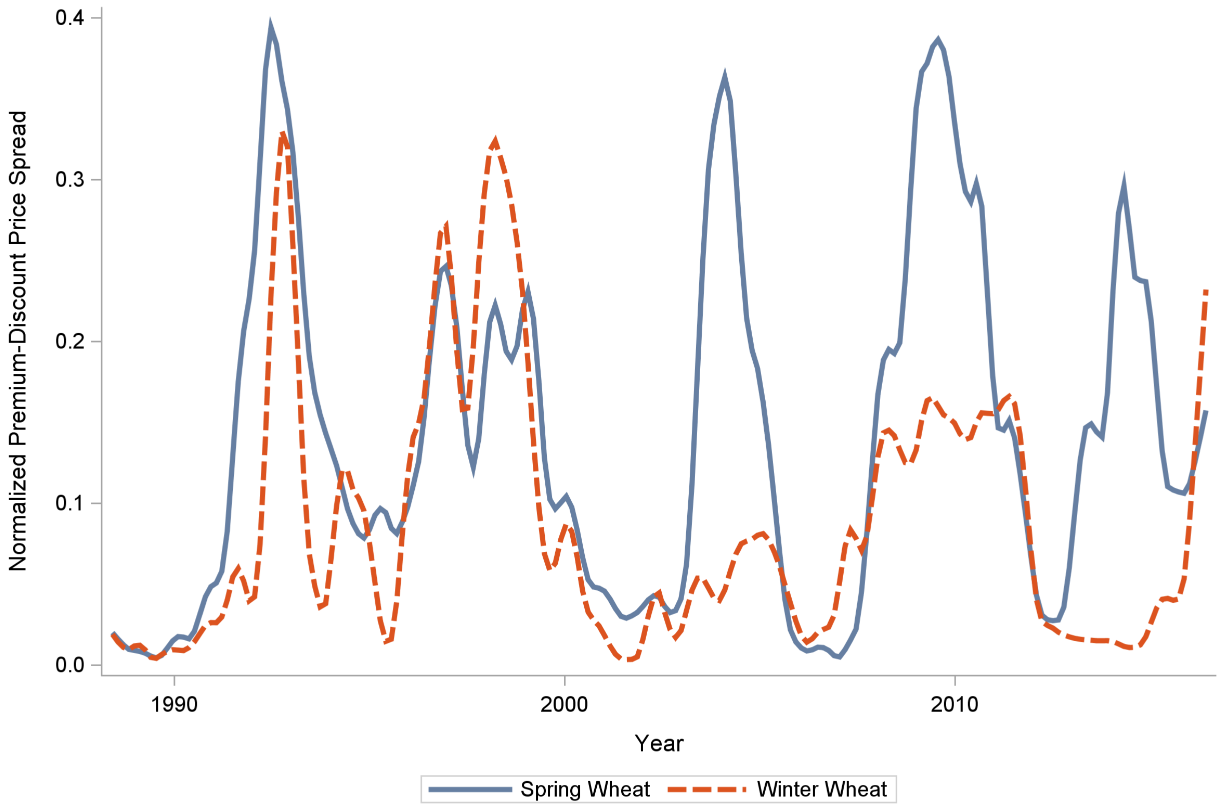
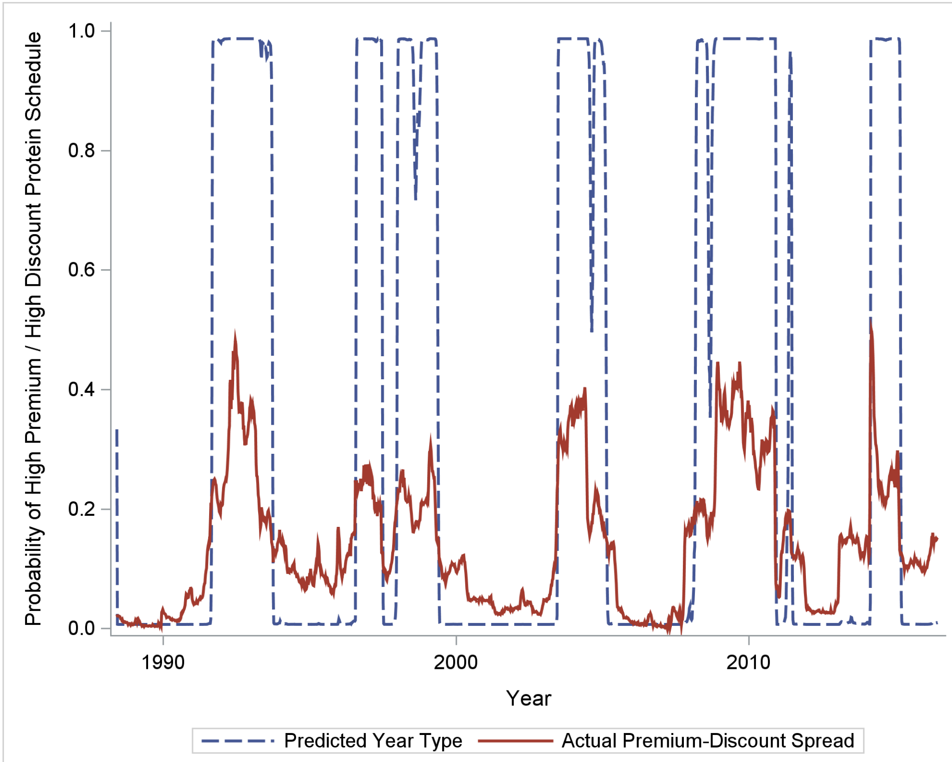


Figure 2: Normalized Price Premium–Discount Spread, 1990–2017

Notes: For spring wheat, the normalized spread is calculated as, $(P_{15\%} - P_{13\%})/P_{14\%}$, where $P_{14\%}$ is the baseline price for 14% protein spring wheat for which no premiums or discounts are provided by elevators. For winter wheat, the normalized spread is calculated as, $(P_{13\%} - P_{11\%})/P_{12\%}$, where $P_{12\%}$ is the baseline price for 12% protein winter wheat for which no premiums or discounts are provided by elevators. Before the spreads were calculated, all prices were adjusted to represent 2017 dollars.

(a) Spring Wheat



(b) Winter Wheat

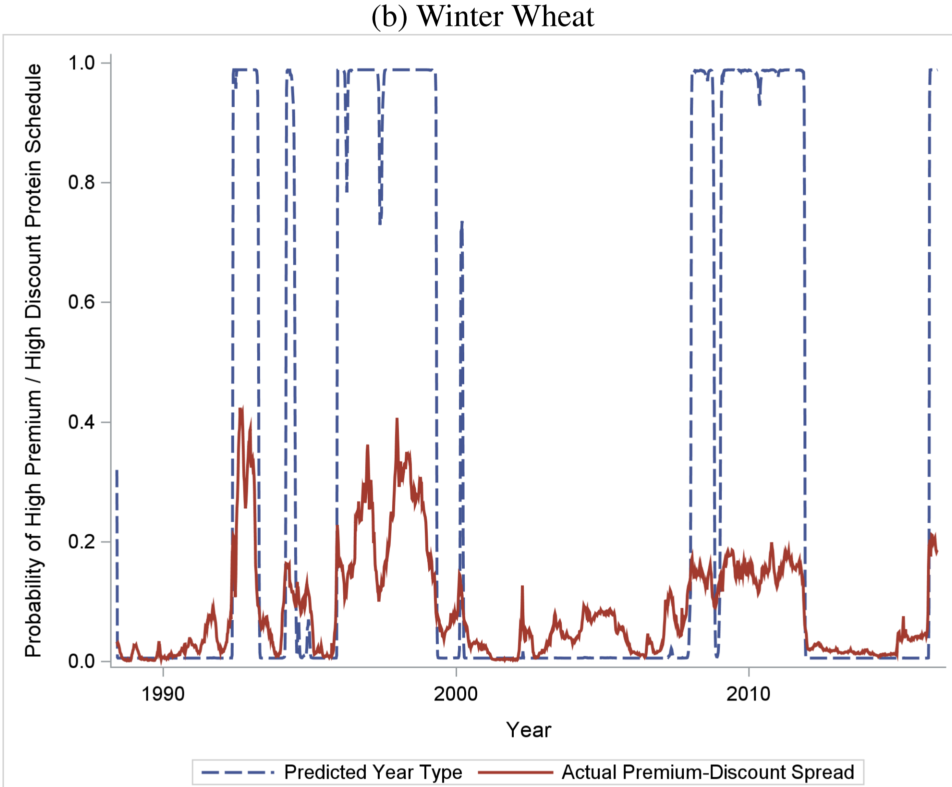


Figure 3: Estimated Marketing Year Types from Markov-Switching Dynamic Regression Model

Appendix A: Asymmetric Protein Pricing

We model variation in elevator-level protein pricing schedule using a unique dataset, which has been assembled by the authors using annual phone surveys of grain elevator managers. The elevators were chosen to characterize a representative cross-section of grain handling facilities across the state, both spatially and in terms of grain handling, ownership, and transportation factors. Table A1 of the appendix shows the comparison of elevator characteristics of all active Montana facilities and those used in the sample. Sampled locations are spatially distributed across the state, with some oversampling of facilities in the north-central and northeast part of the state to appropriately represent the primary wheat production areas in the state. Pricing was collected at the most granular level available to producers; that is, for every 0.25 percentage point of protein content. For spring wheat, elevators provided pricing information for protein levels between 10% and 16.5%, and for winter wheat, between 7% and 15%.

Figure 1 shows that elevators price protein using linear schedules but which have different slopes above and below the baseline protein level and those slopes vary across marketing year types. A regression model of price $P_{T,r}$ in marketing year T and protein level r is characterized as

$$P_{T,r,i} = \beta_0 + \boldsymbol{\beta_1}(\boldsymbol{r} \times \boldsymbol{Y}_T \times \boldsymbol{Y}_{T-1} \times \boldsymbol{K}) + \delta_i + \nu_{T,r,i}. \tag{6}$$

The term $(\boldsymbol{r} \times \boldsymbol{Y}_T \times \boldsymbol{Y}_{T-1} \times \boldsymbol{K})$ represents all of the interaction combinations between the four variables—protein level (r), marketing year type in the current year (Y_T), marketing year type in the preceding year (Y_{T-1}), and whether the protein level is above or below the baseline level (K)—as well as all of the four variables independently. The variable δ_i is an elevator-level individual fixed effect, which helps control for unobserved factors related to an elevator's location, grain handling technology, capacity, ownership structure, among other characteristics that could impact their protein pricing decisions. The individual fixed effects make the protein schedule model particularly powerful because they significantly reduce the potential for endogeneity and other issues that might bias the parameter estimates. Lastly, $\nu_{T,r,i}$ is an error term.

Table A2 shows the estimates of the protein pricing model. Both models have very high R-squared values, providing strong support for the hypothesis that elevators set protein schedules linearly. The spring wheat model seems to provide a better fit to the data better, which may be a result of greater variation in the types of years observed between the 2012/13 and 2016/17 marketing years (see, for example, Figure 1). As expected, protein premiums and discounts are, on average, larger in magnitude than for winter wheat. Additionally, as indicated by the estimated marginal effect associated with the (Protein Content $\times$ Premium Indicator) variable, elevators increase their discounts for lower-protein wheat disproportionately more than they increase their premiums for higher-protein wheat. That is, elevators seem to place more aggressive emphasis on reducing producers' incentives to deliver lower protein grain, rather than more assertively inducing delivery of higher protein wheat.

Table A1: Montana Grain Handling Facility Characteristics

	Population	**Sample**
Active facilities	63	20
Proportion co-op ownership	35%	30%
Average storage capacity	697,787	748,941
Rail capacity		
110+ car shuttle loader	33%	35%
40-110 car conventional loader	37%	53%
Fewer than 40 car conventional loader	16%	6%
No rail access (truck only)	14%	6%

Table A2: Estimation Results of the Protein Pricing Model

	Spring Wheat	*Winter Wheat*
Variable	**Estimate**	**Estimate**
Constant	-725.302^{***}	-128.299^{***}
	(11.714)	(4.323)
Protein Content Level	52.289^{***}	11.258^{***}
	(0.958)	(0.420)
Premium Indicator	199.877^{***}	69.196^{***}
	(34.444)	(9.038)
Marketing Year Type$_T$	-460.625^{***}	-289.672^{***}
	(17.243)	(7.744)
Marketing Year Type$_{T-1}$	538.549^{***}	22.762^{***}
	(17.246)	(8.089)
Protein Content $\times$ Premium Indicator	-14.289^{***}	-6.035^{***}
	(2.315)	(0.736)
Protein Content $\times$ Year Type$_T$	32.971^{***}	24.826^{***}
	(1.419)	(0.818)
Protein Content $\times$ Year Type$_{T-1}$	-38.539^{***}	-2.066^{**}
	(1.429)	(0.856)
Year Type$_T$ $\times$ Premium Indicator	372.094^{***}	7.936
	(49.222)	(17.966)
Year Type$_T$ $\times$ Year Type$_{T-1}$	113.839^{***}	–
	(23.170)	
Premium Indicator $\times$ Year Type$_{T-1}$	-52.877	21.992
	(51.625)	(19.875)
Protein Content $\times$ Premium Indicator $\times$ Year Type$_T$	-26.685^{***}	-0.318
	(3.315)	(1.459)
Protein Content $\times$Year Type$_T$ $\times$ Year Type$_{T-1}$	-8.348^{***}	–
	(1.911)	
Protein Content $\times$ Premium Indicator $\times$ Year Type$_{T-1}$	3.789	-1.571
	(3.469)	(1.608)
Premium Indicator $\times$ Year Type$_T$ $\times$ Year Type$_{T-1}$	-274.646^{***}	–
	(67.209)	
Protein $\times$ Premium $\times$ Year Type$_T$ $\times$ Year Type$_{T-1}$	19.952^{***}	–
	(4.523)	
Elevator Location Fixed Effects	Yes	Yes
Adjusted R^2	0.942	0.859

Notes: Protein content level is measured in 0.25 percentage point intervals. Premium indicator is a binary variable that is 1 for protein levels above the baseline protein level (i.e., wheat receiving price premiums) and 0 for protein levels below the baseline (i.e., wheat receiving discounts). Marketing year type in T is 1 if the current marketing year is identified as "high" and 0 if it is "low." Marketing year type in $T-1$ represents the previous year's type. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix B: Supplementary Tables

Table B1: Markov-switching dynamic regression results

	Hard Red Winter		*Hard Red Spring*	
	Estimate	**Std Err**	**Estimate**	**Std Err**
Low marketing year type				
Futures price spread, harvest	-1.6E-4***	4.8E-5	3.8E-4***	6.8E-5
Futures price spread, nearby	2.8E-4***	2.4E-5	-5.6E-4***	8.4E-5
Futures price carry, harvest	2.0E-4	7.6E-5	4.8E-4***	1.2E-4
Proportion good/exc quality, MT	-3.3E-2***	0.007	0.121***	0.019
Proportion good/exc quality, US	0.061***	0.010	-3.2E-1***	0.033
Cumulative precipitation	0.002	8.6E-4	-2.0E-3	0.002
Average weekly temperature	2.1E-4	1.7E-4	-1.1E-4	3.0E-4
Intercept	-6.7E-3	0.007	0.203***	0.025
High marketing year type				
Futures price spread, harvest	-1.0E-3***	3.3E-4	-8.3E-4***	3.2E-4
Futures price spread, nearby	0.001***	3.0E-4	9.5E-5	2.9E-4
Futures price carry, harvest	0.001***	3.9E-4	6.3E-5	8.0E-4
Proportion good/exc quality, MT	-1.3E-2	0.027	0.080	0.051
Proportion good/exc quality, US	0.338***	0.041	0.409***	0.087
Cumulative precipitation	-2.6E-3	0.003	0.008	0.004
Average weekly temperature	-3.3E-4	7.0E-4	-2.9E-3	0.001
Intercept	0.029	0.037	0.029	0.094
Variance, low marketing year type	0.014	8.2E-4	0.019	0.001
Variance, high marketing year type	0.058	0.004	0.085	0.004
Z-stat for difference in variances	10.776***		16.007***	
Likelihood to remain in low type year	0.974	0.011	0.959	0.019
Likelihood to switch from low type year	0.033	0.014	0.023	0.010

Table B2: Estimation Results of Next Marketing Year's Type Model, by Quartile of Spring–Summer Production Period

	Hard Red Winter Wheat				*Hard Red Spring Wheat*			
	Quartile 1	**Quartile 2**	**Quartile 3**	**Quartile 4**	**Quartile 1**	**Quartile 2**	**Quartile 3**	**Quartile 4**
Marketing yr type, current yr	0.187*	0.221**	0.191**	0.081	0.256**	0.198**	0.134	0.093
	(0.101)	(0.090)	(0.091)	(0.080)	(0.121)	(0.097)	(0.088)	(0.074)
Futures price spread, harvest	-0.006***	-0.004*	-0.003	-0.001	0.010	-0.005**	-0.008***	-0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.008)	(0.002)	(0.001)	(0.001)
Futures price spread, nearby	0.003***	0.004**	0.004***	0.001	-0.009	0.005**	0.006***	0.009***
	(0.001)	(0.002)	(0.001)	(0.002)	(0.008)	(0.002)	(0.002)	(0.002)
Futures price carry, harvest	-0.010*	0.005	0.009	-0.001	0.010	-0.006*	-0.003	0.004
	(0.005)	(0.008)	(0.005)	(0.003)	(0.008)	(0.003)	(0.010)	(0.009)
Prop. good/exc quality, MT	0.286	-0.177	-0.700***	-0.506**	-0.255	-1.078**	-0.283	0.505*
	(0.288)	(0.262)	(0.260)	(0.230)	(0.432)	(0.423)	(0.428)	(0.286)
Prop. good/exc quality, US	1.814***	1.824***	2.160***	1.816***	-1.436	0.012	0.185	0.519
	(0.340)	(0.333)	(0.371)	(0.347)	(0.993)	(0.626)	(0.556)	(0.420)
Cumulative precipitation	-0.001	0.115*	0.111***	0.114***	0.078	0.148***	0.029	0.001
	(0.107)	(0.059)	(0.039)	(0.030)	(0.076)	(0.047)	(0.029)	(0.016)
Average weekly temperature	-0.014*	-0.016**	-0.003	-0.021***	-0.023*	-0.020**	-0.025***	-0.011
	(0.008)	(0.007)	(0.008)	(0.007)	(0.013)	(0.009)	(0.008)	(0.009)
Intercept	-0.217	-0.149	-0.716	0.192	2.695***	1.751***	1.956***	0.650
	(0.354)	(0.342)	(0.493)	(0.464)	(0.914)	(0.622)	(0.662)	(0.637)
Model R-square	0.458	0.375	0.461	0.492	0.276	0.443	0.509	0.627

Notes: The spring–summer production period is defined to begin on the first date that a USDA Crop Progress report is issue in the spring of a marketing year, which generally corresponds with the first emergence after overwintering (winter wheat) or after seeding (spring wheat). The period ends after the last Crop Progress report, which generally corresponds to harvest. Because weather conditions change across years, the beginning and end of the spring–summer production period do not correspond to specific dates. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table B3: One-step-ahead Out-of-Sample Prediction Assessment of Marketing Year Type, by Quartile of Spring–Summer Production Period

Hard Red Winter Wheat, One-step-ahead Year Type Predictions				
Year	**Quartile 1**	**Quartile 2**	**Quartile 3**	**Quartile 4**
2007	Low	Low	Low	Low
2008	High*	High*	High*	High*
2009	Low*	Low*	Low*	High
2010	High	High	High	High
2011	Low*	Low*	High	High
2012	Low*	Low*	Low*	Low*
2013	Low	Low	Low	Low
2014	Low	Low	Low	Low
2015	Low	Low	Low	Low
2016	Low	Low	Low	Low
Prediction Accuracy	60%	60%	70%	80%

Hard Red Spring Wheat, One-step-ahead Year Type Predictions				
Year	**Quartile 1**	**Quartile 2**	**Quartile 3**	**Quartile 4**
2007	High*	Low	High*	Low
2008	High*	Low	High*	High*
2009	Low*	High	High	High
2010	High	High	High	High
2011	Low*	High	High	High
2012	Low*	High	High	High
2013	High*	High*	Low	High*
2014	Low*	Low*	Low*	Low*
2015	Low*	High	High	Low*
2016	Low*	High	High	High
Prediction Accuracy	10%	80%	70%	60%

Notes: The spring–summer production period is defined to begin on the first date that a USDA Crop Progress report is issue in the spring of a marketing year, which generally corresponds with the first emergence after overwintering (winter wheat) or after seeding (spring wheat). The period ends after the last Crop Progress report, which generally corresponds to harvest. Because weather conditions change across years, the beginning and end of the spring–summer production period do not correspond to specific dates. * denotes years in which the forecast year type does not match the observed year type.

Table B4: Estimation Results of Next Marketing Year's Type Model, Week-Dependent Weights

	Winter wheat	*Spring wheat*
Marketing year type, current year	0.154***	0.144***
	(0.043)	(0.045)
Futures price spread, harvest	-0.003**	-0.008***
	(0.001)	(0.001)
Futures price spread, nearby	0.003***	0.007***
	(0.001)	(0.001)
Futures price carry, harvest	0.001	-0.006***
	(0.001)	(0.002)
Proportion good/exc quality, MT	-0.378***	-0.072
	(0.115)	(0.174)
Proportion good/exc quality, US	1.856***	0.275
	(0.170)	(0.261)
Cumulative precipitation	0.083***	0.021*
	(0.013)	(0.012)
Average weekly temperature	-0.018***	-0.015***
	(0.003)	(0.004)
Intercept	0.109	1.222***
	(0.173)	(0.289)
Model R-square	0.424	0.436

Notes: Week-dependent weights are defined as the ratio of the week number within a spring–summer production period to the total number of weeks within the spring–summer production period in year T. The spring–summer production period is defined to begin on the first date that a USDA Crop Progress report is issue in the spring of a marketing year, which generally corresponds with the first emergence after overwintering (winter wheat) or after seeding (spring wheat). The period ends after the last Crop Progress report, which generally corresponds to harvest. Because weather conditions change across years, the beginning and end of the spring–summer production period do not correspond to specific dates. ***,**, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.