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

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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 a rational expectation model of elevators' quality-based pricing strategies and empirically estimates the model using a unique elevator-level 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.

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JEL classification codes: Q11, Q13, L15

Introduction

Wheat markets stand out among other major crop commodity markets. Unlike corn, soybeans, or cotton, for example, a large proportion of wheat is used directly 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 marketing channel, assigning quality premiums or discounts at the time a farmer delivers 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 farm-level pricing can be significantly affected by market supply and demand for particular quality components.

One of the most important wheat quality characteristics is the protein content level in a wheat kernel. Protein content levels are closely tied to a wheat class (e.g., soft winter, hard winter, hard spring, soft spring, etc.) as well as weather conditions during the wheat growing process (hot and dry conditions typically lead to lower yields but higher protein content, while wet and cooler conditions are associated with higher yields but lower protein content). The latter makes the premiums and discounts—set by grain handling facilities such that they are able to acquire wheat of a desired protein quality level—uncertain across marketing years. Moreover, because weather conditions typically impact large geographic areas, it is often the case that a deficit or surplus of high quality, higher protein wheat exists across an entire state or even across an entire country, rather than isolated locations.

The implication of a geographically widespread deficit or surplus is that quality-driven price premiums or discounts can represent a significant proportion of a 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 current 2016/17 marketing year—characterized by a widespread deficit of high-protein wheat—Montana producers receive an average of $1.00 per bushel premium for a 1 percentage point higher protein content spring wheat (above a 14% content base), and a $1.75 per bushel discount for a 1 percentage point lower protein content wheat. Given that an average market wheat price for base protein content is approximately $5.00 per bushel, these 2016/17 premium and discount represent a 20% increase and a 35% decrease to the base price, which are significant in a period of already low commodity prices. Consequently, farmers who were not able to anticipate or appropriately manage for these types of markets (e.g., through intertemporal storage or wheat segregation and mixing strategies) may either not be able to capture substantial revenue increases or suffer large declines to farm-level profitability.

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. This research begins to fill this gap.

First, I develop a rational-expectation economic model that represents a 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 a market-wide deficit or excess of high-protein wheat. Conditional on this determination, the second stage of the decision-making process is setting the schedule.

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 such as regional weather information, USDA wheat quality reports, and likely level of high-quality wheat available in on-farm storage. Then, conditional on the first-stage regime, the model estimates the level of price premiums/discounts observed across grain elevators for wheat with different levels of protein. We use factors such as weather, planted acres, futures prices spreads across wheat classes, and fixed effects to estimate the second stage model. Finally, because a main objective is to provide a forecasting tool, we use a foundation of standard in-sample and out-of-sample assessment techniques and apply them to the regime-switching framework to ensure unbiased insights.

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. First, I use a 27-year dataset of daily wheat prices across several Montana regions and across three protein levels to estimate the first-stage in the regime-switching model. Montana represents one of the largest wheat producing states and one in which both low and high protein wheat are sourced. Next, I use a unique, five-year panel dataset of highly disaggregated pricing information based on protein levels across grain elevators in Montana to estimate the second stage model. These facilities represent those that typically handle between 60 and 80% of all grain marketed in Montana, and are also diverse in their size, loading capacity, ownership type, and geographic location, enabling us to control for this type of variation (which could be correlated with an elevators' decision to set differential protein schedules). Each elevator cross-section provides precise, highly disaggregated information about quality pricing schedules for winter and spring wheat classes. These two datasets provide both the power, variation, and consistency to accurately develop the predictive model.

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 MGEX and KCBT 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 decision, the level of the protein in delivered wheat, and the elevator's spatial location.

An Elevator's Price Decision Model

Unlike most other crop commodities, most wheat produced in the United States is used directly for human consumption, primarily in baked goods and pastas. Because there are so many different types of flour-based goods, 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, six classes of wheat are produced: 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.

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 characteristics 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 supply chain from bakers, to millers, to elevators, and eventually to farmers. Protein levels have also been shown to be a fairly useful proxy for characterizing other wheat quality traits (Wilson and Dahl 2011).

The production of wheat with specific protein content characteristics 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 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, there, the production of wheat with certain protein content can vary significantly with weather and input factors, because most wheat is produced on non-irrigated land. Typically, conditions that are more favorable to higher wheat yields in semi-arid production climates—higher amount 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.

In most years, weather conditions in many North American wheat production regions is 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. In fact, levels are so uniform that elevators do not offer differential prices for wheat based on this quality characteristic.[1] However, in the northern U.S. and southern Canada regions, weather variation across years is sufficient to cause significant differences in yield–protein trade-offs across marketing years. Moreover, because this is one of the few regions in North America that has the potential to produce very high protein wheat, markets reflect this characteristic by having a quality-based pricing and marketing landscape.

When elevators in the northern U.S. region make price bids for grain delivery, they can alter incentives for wheat with particular protein content to be delivered 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 be blended with lower-protein wheat to 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 is high enough to incent delivery of the necessary amount of wheat with the desired protein level.

[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.

[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).

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 know the availability of wheat with sufficient protein levels until wheat begins to be delivered at harvest (i.e., at the start of a marketing year). After the elevator learns about the production outcomes in their delivery region and in other regions, they establish a protein pricing schedule that describes premiums that are added 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, 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. I 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 offer large incentives to attract higher-protein wheat. I 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 for elevators to attract sufficient quantities of desired grain.

This quality-differentiated pricing structure implies that elevators must make two decisions. First, they must decide whether a marketing year will be of a “high” or “low” type. Then, conditional on that assessment and other factors, they must 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. 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). Therefore, an elevator that seeks to develop a forecast of a pricing strategy for wheat with protein level in marketing year $T+1$ could be characterized using a rational expectations 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 in the preceding sentence.

To develop conditional expected premiums and discounts, equation (1) makes evident that empirical models are necessary to estimate both the conditional probabilities of observing a particular year type and the strategy for pricing wheat with certain protein levels during that marketing year.

Data Description

The pricing decision model indicates that two sets of data are required to estimate the empirical model: one set that can help estimate the probability of an upcoming marketing year's type (high or low), and a second that could help model the specific pricing premium and discounts within different marketing year types. Ideally, these data would be a lengthy panel of elevators who provide highly disaggregated price premium and discount information across a wide range of protein levels. Unfortunately, such an ideal public dataset does not exist and two alternative sets of data are combined and used instead.

Data for Identifying Marketing Year Types

The first data are 27-years of weekly price data for hard red spring (HRS) and hard red winter (HRW) wheat in five Montana regions (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; 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—ordinary, 11%, 12%, and 13% protein. While having access to prices at so few protein levels would be insufficient to estimate the specific pricing schedules that elevators choose to set, the overall length of these data, their relatively high frequency of reporting, and at least some differentiation across wheat quality levels does provide an opportunity to model various characteristics about type of marketing year within which pricing decisions are made.

To determine the type of marketing year, I consider the spread between the price of a higher-protein wheat and a lower-protein wheat. In years when spreads are larger, higher-protein wheat is valued relatively more than in years when spreads are closer to zero; that is, larger spreads imply a general shortage of higher-quality wheat and a relative excess supply of lower-quality wheat. An issue with simply calculating the protein value spread as the difference 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.

I define a normalized premium–discount spread variable. Specifically, after adjusting all prices to 2017 dollar values, I 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.[3] 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 compared across marketing years.

Figure 1 presents a visual time-series summary of the normalized spread variable for Montana across 27 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 the wheat harvest begins, as elevators begin to observe the majority of wheat that is marketed and delivered, and that the pricing schedules persist throughout the remained 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.

The figure also shows that while there are certainly 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

[3] 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.

outcomes in other major winter wheat areas impact markets for wheat protein and the magnitude of this impact varying across time.

Data for Identifying Protein Valuations

Despite its length, the weekly price data are limited in two important ways: they provide only minimal detail about the pricing distribution across wheat protein levels; and they are spatially aggregated, making it difficult to exploit variation in geographic, grain handling capacity, rail access, and other elevator-level differences that have been shown to affect basis (Bekkerman et al. 2014). As such, I have collected data from twenty Montana elevators. These 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 1 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 larger wheat producing areas.

Beginning in the 2012–13 marketing year, managers at the sampled elevators were contacted by phone and asked to provide protein premium and discount schedules at the location; these surveys were continued through the current 2016–17 marketing year. During the data collection period, no elevators exited the sample, implying that the data represent a balanced panel. For spring wheat, elevators provided pricing information for protein levels between 10% and 16.5%, and for winter wheat, between 7% and 15%. Prices were reported for every 0.25 percentage points.

Figure 2 shows average pricing schedules for the two wheat classes across the sampled elevators for the five marketing years. These data provide several important initial 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.

These data provide some of the first empirical evidence to support theoretical modeling of protein schedules in the literature (Miao et al. 2016; Hennessy 1996). However, unlike the theorized pricing model, which describes the farmers' blending strategies (that are assumed to based on their knowledge of elevators' protein pricing schedules) to be characterized as a non-linear third-degree polynomial with an inflection point at the baseline price, these data show that elevators' pricing strategies are largely linear. These data also show that standard linear panel regression specifications are likely to perform well in modeling these pricing schedules across the elevator sample.

Additional Data

In addition to the two dependent variables used to estimate the two-stage pricing decision model, I 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), I 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.

I 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, I 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, I 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, I 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).[4] I 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, I collect precipitation and temperature information for Montana from the NOAA National Centers for Environmental Information Climate Data Online tool. I 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.

Table 2 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%

[4] 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, I do not consider those reports.

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.

Empirical Specification

The empirical modeling has three components, each of which is applied separately for the two classes of wheat. First, I 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, I use these estimates to model the year type as a function of a number of market and production factors that are in the information set available to elevators. The predicted values from this regression represent the probability estimates in an elevator’s price decision model described in equation (1). Third, I estimate a regression model of historical pricing schedules. Combining these estimates with the year type probability estimates from the second empirical modeling component provides the estimates of the conditional premium and discount expectations.

To first estimate the type of marketing year, I implement the Markov-Chain Dynamic Regime (MCDR) switching model (Quandt 1972; Goldfeld and Quandt 1973; Hamilton 1989). MCDR models are used for time series data in which there may be numerous unobserved states between which transitions occur through time. These transitions are assumed to follow a Markov process and the duration of remaining in a state is assumed to be random. Whether a process is in one state or another is not known with certainty, but the MCDR model estimates the probability that the time series process is in one of the states. The MCDR 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, based on the normalized premium–discount spread data, a marketing year was of a high or low type.

If the probability of a certain marketing year type (high or low) exceeds 50% in week t, then it is classified as that year type. These estimates are then used as the dependent variable, Y_{T+1}, for the model:

$$Y_{T+1} = \beta_0 + \beta_1 \mathrm{NS}_{T,t} + \boldsymbol{\beta_F} \boldsymbol{F}_{T,t} + \boldsymbol{\beta_Q} \boldsymbol{Q}_{T,t} + \boldsymbol{\beta_W} \boldsymbol{W}_{T,t} + \delta_t + \varepsilon_{T,t}. \tag{3}$$

The term Y_{T+1} represents the predicted year type in the upcoming marketing year $T+1$; $\mathrm{NS}_{T,t}$ is the normalized premium–discount spread in week t of 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, I estimate the model in equation 3 using a linear probability model (LPM). LPMs have been shown to provide consistent estimates in panel fixed effects models Angrist (2001). And while the potential weaknesses of linear probability models are certainly acknowledged (e.g., predictions outside of the [0,1] interval), there are no cases for these data in which predicted probabilities exceed the theoretical range.

The last component is modeling variation in the actual protein pricing schedule. Because the data show that elevators price protein using relatively linear schedules but which have different slopes above and below the baseline protein level and those slopes vary across marketing year types. Furthermore, the data show that schedules are established once during the marketing year (at harvest) and remain relatively constant throughout the remainder of the marketing year. As such, I do not model within-marketing year temporal variation of pricing schedules.

The protein schedule model of price $P_{T,r}$ in marketing year T and protein level r is

$$P_{T,r,i} = \beta_0 + \boldsymbol{\beta_1}(\boldsymbol{r} \times \boldsymbol{Y}_T \times \boldsymbol{Y}_{T-1} \times \boldsymbol{K}) + \delta_i + \nu_{T,r,i}. \tag{4}$$

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. As is the case with estimating the marketing year type model in equation (4), the individual fixed effect makes the protein schedule model particularly powerful because it significantly reduces the potential for endogeneity and other issues that might bias the parameter estimates. Lastly, $v_{T,r,i}$ is an error term.

Estimation Results

Figure3 provides a visual summary of the estimated year type probabilities from the Markov-Chain Dynamic Regime switching model. For each wheat class, the figure shows the weekly normalized premium–discount spread overlaid with the predicted probability of the year being a high or low type. The estimation and predicted probabilities make quite evident that there is 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 3 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 normalized premium–discount spread, the nearby MGEX-KCBT spread, harvest period carry, and temperature provide predictive power in both the spring wheat and winter wheat models. As expected, higher levels of normalized spread—which indicate lower supplies of higher-protein wheat in the current marketing year—increase the likelihood of another "high" type marketing year because there is a higher probability that high-protein wheat deficits may continue. This result represents the classic storage rationale. Similarly, 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, and there is a higher likelihood that the upcoming harvest may not sufficiently overcome the depleted quantities of higher-protein wheat.

Interestingly, the harvest futures market carry variables have opposite signs for the spring and winter wheat markets. In the spring wheat market, a higher MGEX carry—which would suggest that there are sufficient amounts of higher protein wheat at time t and that market participants place higher value on next year's crop—decreases the probability of an upcoming high type year. However, in winter wheat markets, a higher carry leads to a higher probability of a high type year. This may indicate that a higher carry in the KCBT market is more suggestive of market participants' expectation of higher yields in the upcoming year, which are inversely correlated with protein levels. Lastly, in both models, higher temperatures during the production period of next year's crop decrease, as expected, the probability of a high year. When temperatures are high, wheat yields are usually lower but protein levels are higher, implying that sufficient high-protein wheat supplies will be available and premiums and discounts are more likely to be low.

Table 4 shows the estimates of the protein pricing model. The spring wheat model seems to provide a better fit to the data better (although both models explain a large portion of the variation across elevators' protein pricing schedules), 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 2). As expected, protein premiums and discounts are, on average, larger in magnitude than for winter wheat. Additionally, during high marketing year types, elevators increase their discounts for lower-protein wheat proportionately 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. However, another interesting (and expected) outcome is that for spring wheat, observing two consecutive high type years leads elevators to raise their premiums for higher protein wheat by approximately 20 cents per bushel. This may explained by the fact that continuous deficits in high protein wheat availability creates additional competition among elevators for any remaining high-quality wheat, and this is manifest in increased price bids.

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 a rational expectation model of elevators' quality-based pricing strategies and empirically estimates the model using a unique elevator-level 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.

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Table 1: 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 2: 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 3: Estimation Results of the Marketing Year Type Forecast Model

Spring Wheat		*Winter Wheat*	
Variable	**Estimate**	**Variable**	**Estimate**
Constant	1.118^{*}	Constant	-0.157
	(0.621)		(0.232)
Normalized Prem–Disc Spread, HRS	0.463^{*}	Normalized Prem–Disc Spread, HRW	0.779^{***}
	(0.253)		(0.268)
Harvest MGEX-KCBT Spread	-0.002^{**}	Harvest MGEX-KCBT Spread	-0.001
	(0.001)		(0.001)
Nearby MGEX-KCBT Spread	0.003^{***}	Nearby MGEX-KCBT Spread	0.003^{***}
	(0.001)		(0.001)
MGEX Harvest Carry	-0.007^{***}	KCBT Harvest Carry	0.003^{**}
	(0.002)		(0.002)
% HRS Exc/Good Quality, MT	-0.247	% HRW Exc/Good Quality, MT	0.111
	(0.226)		(0.133)
% HRW Exc/Good Quality, MT	0.579	% HRW Exc/Good Quality, US	1.072^{***}
	(0.372)		(0.182)
Cumulative Precip	-0.041^{**}	Cumulative Precip	0.043
	(0.019)		(0.028)
Average Temp	-0.027^{***}	Average Temp	-0.011^{**}
	(0.006)		(0.004)
Week Fixed Effects	Yes		Yes
Adjusted R^2	0.129		0.268

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

Table 4: 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.

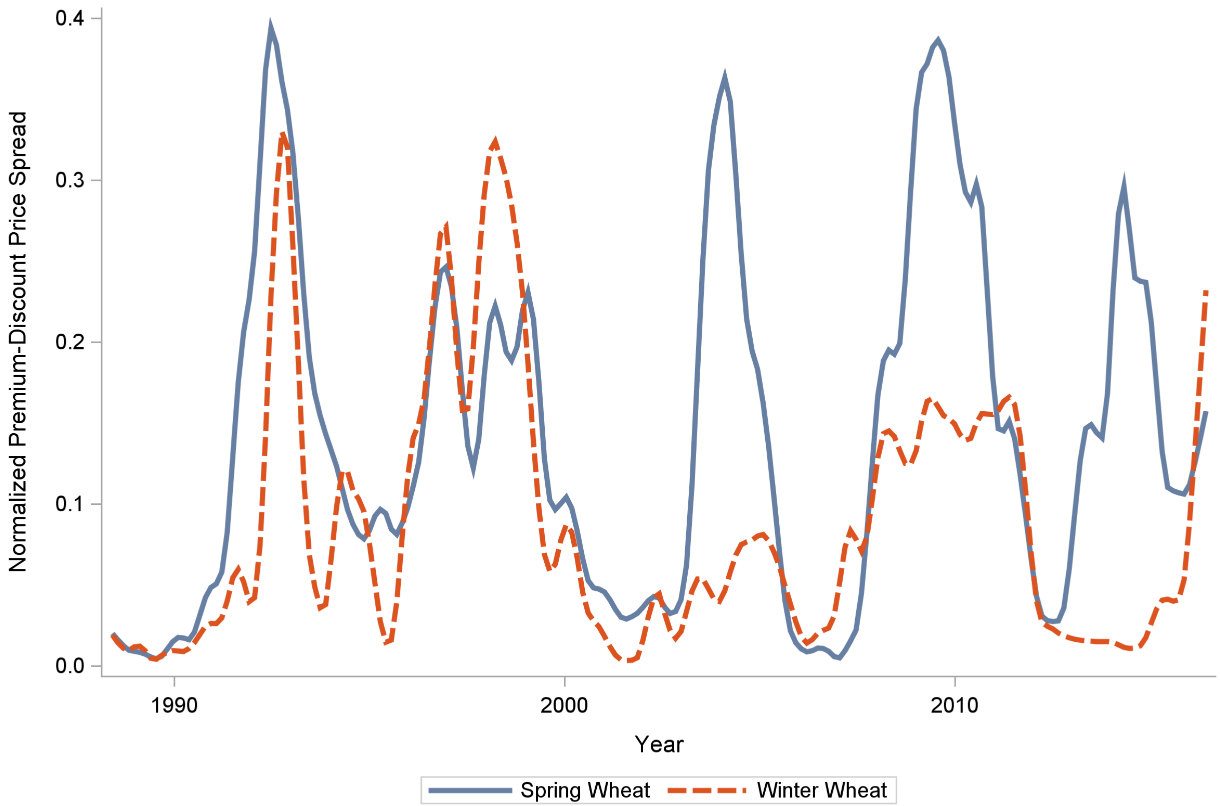
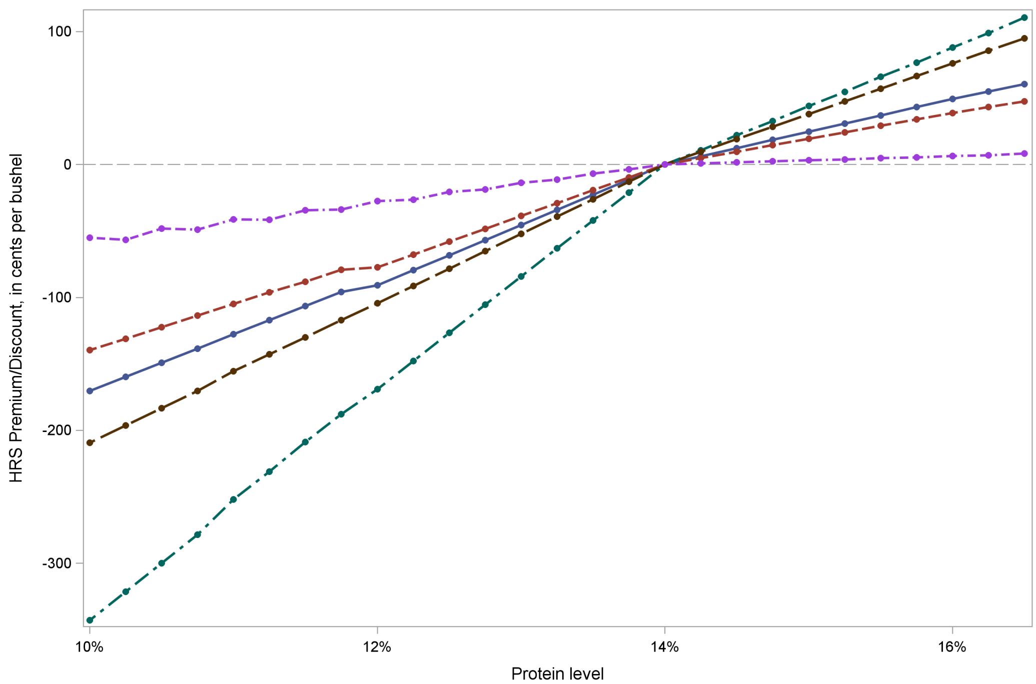


Figure 1: Normalized Price Premium–Discount Spread, 1990–2017

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

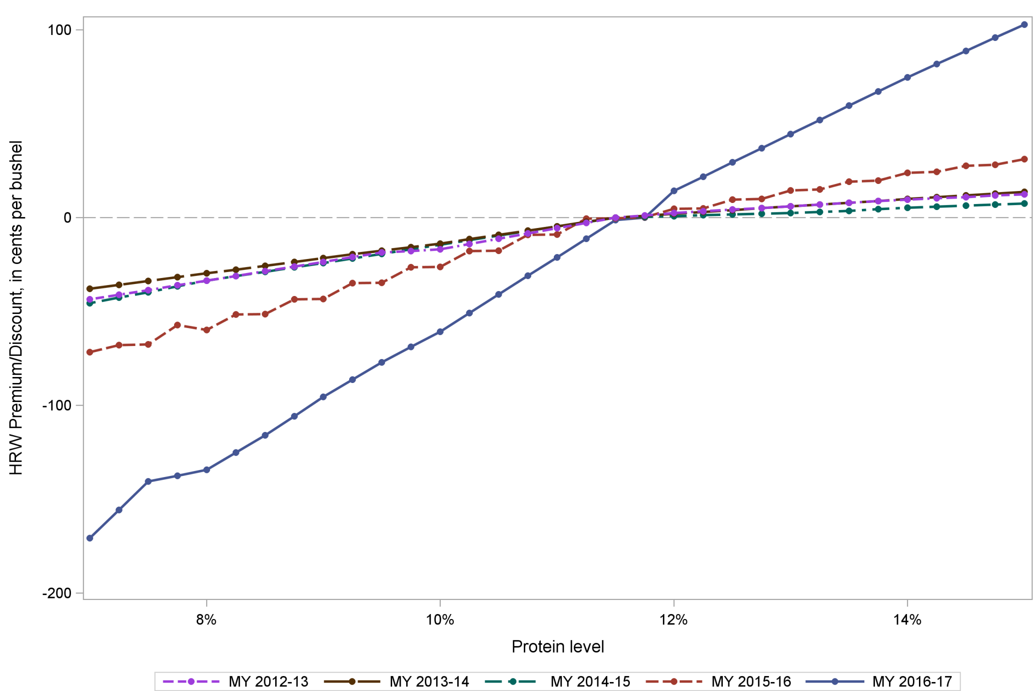
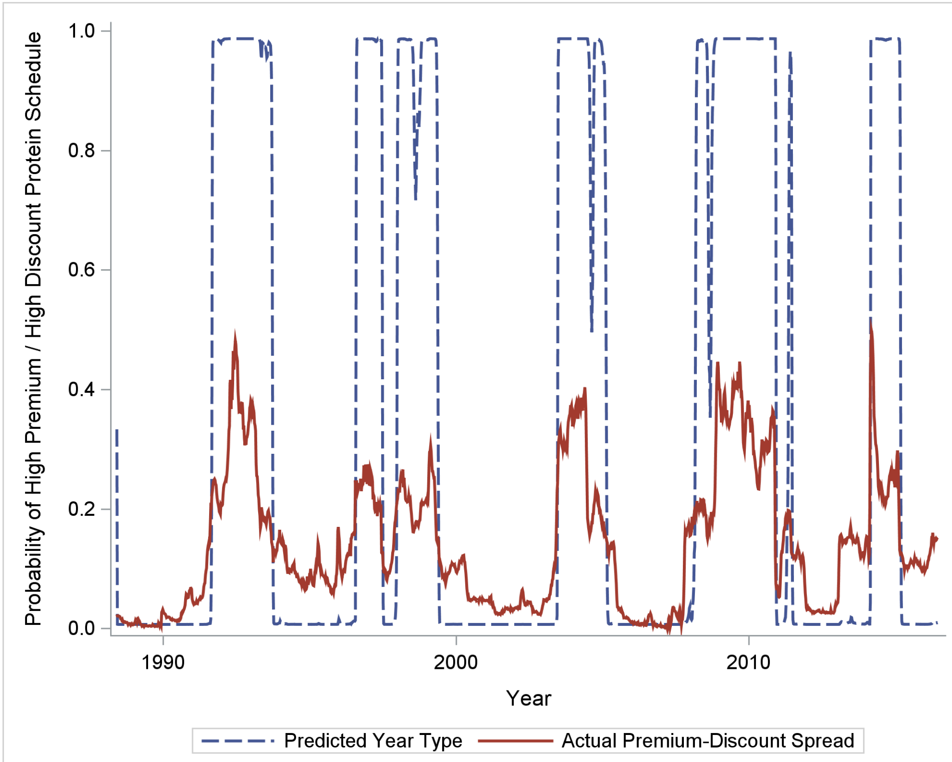


Figure 2: Annual Protein / Discount Schedules, 2012/13–2016/17 Marketing Years

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

(a) Spring Wheat



(b) Winter Wheat

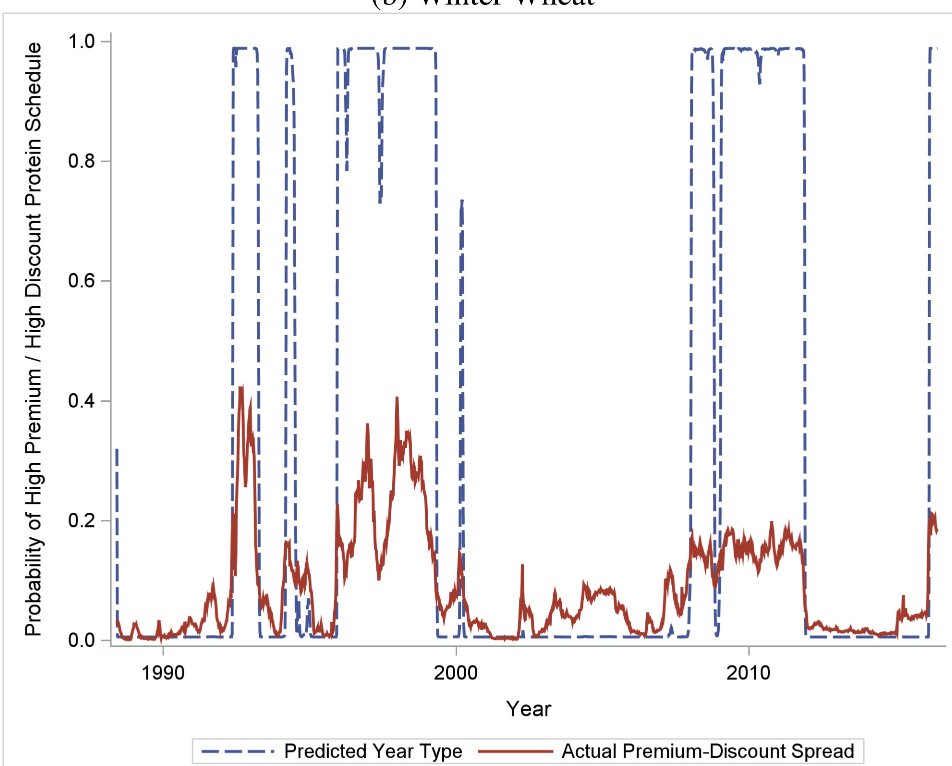


Figure 3: Estimation of the Markov-Chain Dynamic Regime Switching Models