ABSTRACT

WU, SHENAN. Empirical Studies in Price, Risk and Policy. (Under the direction of Barry Goodwin.)

The three essays of this dissertation consider the price relationships, the risk management for agricultural commodities, and the moral hazard in the agricultural insurance.

Essay One analyzes the structural change in corn prices between the United States, China, and other countries. Two events are considered to change the price relationship. The first is China's Temporary Stock Plan in 2008 and the second the decreasing corn exports of the US in 2013 due to the 2012 drought. Linear regression with Bai-Perron tests, cointegration tests, and vector error correction model with Qu-Perron tests are used to identify and estimate the structural change between countries. Empirical results reveal the disappearance of the cointegration relationship between China and the United States after 2008, and the change in adjustment coefficients between the United States and other countries in mid-2013. Impulse response functions are further derived to show a decrease in US corn's market power in the international market after the US exports are decreased.

Essay Two estimates the cross-hedge ratio between grain sorghum spot prices and corn futures prices. Cross-hedging is used when two products are substitutes, and one does not have a futures market. A copula model with GARCH errors is applied to estimate the optimal hedge ratio. Hedging performance is measured by the reduction in the variance of portfolio. Results show that application of a copula model reduces risk more than the conventional method, such as an OLS model and a multivariate GARCH model.

Essay Three examines the moral hazard in the prevented planting insurance. The prevented planting provision is an important part of the Federal Crop Insurance Program. The high level of prevented planting coverage creates the potential for moral hazard during the planting period. The lasso method is applied to determine the exogenous weather variables related to such losses. Conditioning on the selected weather variables, linkages between the loss and market conditions are examined using a logit model. Empirical results suggest that losses are influenced by expected output prices and fertilizer costs. The likelihood of prevented planting losses increases as the expected market price decreases or fertilizer costs increase for corn and soybeans in the Prairie Pothole Region, and grain sorghum and cotton over all states, which indicates moral hazard among these insured producers in the prevented planting coverage.

Empirical Studies in Price, Risk and Policy

by
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DEDICATION

To my loving parents who always support me.

BIOGRAPHY

The author was born in Shanghai, China. He was enrolled in Shanghai Jiao Tong University in 2008 and got his bachelor degree in economics in 2012. He started his master in North Carolina State University in the same year and later decided to pursuit a PhD in NCSU. His advisor is Barry K. Goodwin, a prestigious professor in agricultural economics. His research applies advanced statistical models and focuses on agricultural insurance and risk management.

The author is currently working as a modeling analyst at PenFed Credit Union. He is responsible for building credit risk model with big data and the application of machine learning.

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INTRODUCTION

This dissertation applies econometric and statistical models to the study of agricultural economics. The dissertation topics include agricultural commodities price analysis, risk management and agricultural insurance.

Agriculture is an important sector in the US. In 2016, the agricultural industry contributed about 1 percent of GDP and provided about 2.6 million jobs, approximately 1.4 percent of the US employment. It also plays an important role in trade, as the agricultural sector accounts for about 10 percent of the US exports and has produced a trade surplus since 1959 (Cooke, Melton and Ramos, 2017).

For agricultural producers and traders, price maybe the most important factor in their decision making. In international trade, prices are often related between countries. An increase or decrease of prices in one country often has a similar effect in prices of other countries. This relationship is often known as the law of one price (LOP), which assumes that prices should be close in each country if the market is efficient.

However, the LOP does not always hold, especially when there is a policy or market shock in one country. If the LOP does not hold, it implies that the market is not efficient and there could be opportunity for arbitrage. Price risks for traders also increase, as it becomes harder to predict global prices when the LOP does not hold.

In Essay One, the LOP for corn prices is studied for China, the US and other major corn exporting countries, such as Ukraine and Argentina. Corn is one of the US's major export agricultural commodities and China is the second largest corn consumer, followed by the US. Therefore, it is important to examine how the LOP performs between China, the US and other countries.

Corn prices were volatile between 2007-2008. In early 2008, corn prices went up due to the global food crisis, which was caused by several factors, such as high oil prices, ethanol production and the depreciation of the US dollar. After that, prices took a huge fall when the financial crisis exploded in mid-2008. To stabilize corn prices, the Chinese government issued a policy to buy corn from farmers at a price higher than the market. The policy has lasted for several years and is believed to be one of the reasons why the LOP does not hold between China and other countries. This study should be a good example of how policy changes the LOP relationship. The change of the LOP relationship affects social welfare. When a market is separated from other countries and the price is higher than the global price, it basically hurts buyers and benefits suppliers. Therefore, if the government plans to issue a policy that could change the LOP relationship, the benefits and loss should be carefully evaluated before the policy has been made.

Another notable price gap is found between the US and other countries during mid-2013. In 2013, the US decreased its corn exports due to the 2012 drought. The share of the US exports in the world corn market went from 50 percent in 2012 to only 31 percent in 2013. Meanwhile, there was an environmental policy change with regard to biofuel mandate which decreased US prices. The high production forecast further pushed the price down. This raises an interesting question on how US corn prices are related to prices in other countries after these events.

The methodology I have used in Essay One is the Bai-Perron (2003) and Qu-Perron (2006) tests for structural breaks. These tests are used for estimating the structural break in linear regression models. In this study, I focus on the log relative price ratio and the adjustment coefficients between different countries. The first is related to the existence of the LOP. If the LOP holds, then the price ratio is likely to be consistent across time, otherwise a different ratio will be observed for different time periods. The adjustment coefficients are more related to the degree of adherence to the LOP. The coefficients measure the time it takes for one price to respond to the disequilibrium between two prices. If the coefficients are large, then a stronger price relationship is implied, as the difference between prices in two countries will be eliminated rapidly. Because the US corn export decreased in 2013, I expect the LOP to be weaker in 2013 and the adjustment coefficient to be smaller. As the LOP becomes weaker, it is suggested that traders should predict the global prices based on a variety of prices rather than only using the US prices.

Essay Two studies the relationship between different agricultural commodities. The implication of Essay Two lies in the hedging strategy for commodities traders.

For commodities traders, hedging is a good option to reduce price risks. Hedging strategy is often performed by using a futures contract, but for certain agricultural commodities, there are no futures markets available. To solve this problem, cross-hedging is proposed. In cross-hedging, the price risk of a commodity is hedged by taking a futures position in another related commodity.

Because two different commodity prices are used in the cross-hedging strategy, it is important to find the price relationship that can best reduce risk.

In Essay Two, I try to find the optimal hedge ratio for cross-hedging between sorghum cash prices and corn futures prices. Sorghum is widely used as a substitute for corn in the feed industry and does not have a futures market. For sorghum traders, one way to reduce the sorghum price risks is to hedge the sorghum price through the corn futures market, as the two price are highly related.

The optimal hedge ratio for risk-averse traders with mean-variance preference is derived to be a function of the variance and covariance of two prices. The optimal hedge ratio was at first estimated by ordinary least squares (OLS) regression, and later by the generalized autoregressive conditional heteroskedasticity (GARCH) model to allow for time variation. In recent years, a copula-based GARCH model has been proposed to capture the correlation with more flexible distributions (Patton, 2006). The advantage of a copula model is that it constructs the joint distribution with a copula and has no restrictions on the marginal distributions. By assuming the marginal distribution follow a GARCH model, a copula-based GARCH model preserves the time variation of price variables, but removes the restriction of joint normality or t distribution imposed by multivariate GARCH models. Therefore, a copula-based GARCH model shares the property of a GARCH model with more flexible distributions.

Several copula-based GARCH models are compared with OLS and multivariate GARCH models. Performances are measured by the reduction on variance in the portfolio of sorghum cash prices and corn futures prices. Empirical results show that the Clayton copula model has the best performance in both in-sample and out-of-sample comparisons.

Essay Three focuses on prevented planting (PP) insurance in the crop insurance program. The crop insurance program is a vital part of the agricultural industry. In 2015, the program provided coverage for over 500 crops with a total liability of 102.4 billion (Risk Management Agency, 2016). Prevented planting is defined as the failure to plant an insured crop by a certain date. Prevented planting insurance is intended to provide coverage for pre-planting costs, but has been found to be abused by producers. For example, the Risk Management Agency (RMA) found that some producers grew crop in cropland unfit for planting to claim prevented planting losses. It was also found that prevented planting losses were large when agricultural commodities prices were low, which implies a degree of moral hazard, as producers are likely to be careless in planting when prices are low. Overall, these misbehaviors affect the actuarial performance of the insurance programs and incur additional costs for taxpayers.

Therefore, the purpose of Essay Three is to examine whether there is a moral hazard issue in prevented planting insurance. Most prevented planting claims are caused by extreme weather conditions, so I first condition out the weather effect by using the least absolute shrinkage and selection operator (LASSO) method proposed by Tibshirani (1996). The LASSO method is good for selecting the variables that actually affect the dependent variable. In this case, because there are many weather variables, the LASSO method is applied to select the weather variables that are relevant to the loss. The probability of loss is then estimated by the selected weather variables and variables related to market conditions, such as planting costs and harvest prices. If there is no moral hazard, then the loss should only depend on weather variables. However, empirical results indicate that for many crops, the loss is more likely to occur if planting costs are high or harvest prices are low. This result implies that there is a moral hazard issue in the prevented planting insurance. Moreover, the moral hazard issues are found to be more serious in the Prairie Pothole Region, which consists of the States of Iowa, Minnesota, Montana, North Dakota, and South Dakota. To solve the moral hazard issue, it is suggested that the RMA should decrease the coverage level and set stricter rules for prevented planting claims. Actually, the RMA cut the coverage level of corn in the prevented planting from 60% to 55% in 2017 and eliminated the option for an additional 10% coverage level in 2018 (Clayton, 2017).

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CHAPTER

2

AN EMPIRICAL EVALUATION OF PRICE LINKAGES IN THE INTERNATIONAL CORN MARKET

2.1 Introduction

The law of one price (LOP) is a fundamental assumption in analyzing the price linkage in international trade. The LOP asserts that an efficient market with perfect commodity arbitrage should ensure that prices in different countries are linked through a long-run equilibrium. Under some restriction assumptions, such as fixed exchange rates and zero transportation cost, prices are guaranteed to be internationally equalized (Ardeni, 1989).

The LOP is mainly tested using cointegration tests, and the result does not always support it. Ardeni (1989) compared groups of commodities (wheat, wool, beef, sugar, tea, tin, and zinc) in four countries (Australia, Canada, the United Kingdom, and the US) and the LOP is present only in the wheat and tea markets. The failure can be caused by different commodity characteristics, time period, and transportation costs (Baffes, 1991). Goodwin, Grennes, and Wohlgenant (1991) suggested the use of expectation price to avoid possible arbitrage across spatial markets in a short period. Goodwin (1992) showed that in the wheat market, the LOP is only valid when the transportation cost is added to the model.

The LOP is mainly examined by use of cointegration tests (Ardeni, 1989; Baffes, 1991; Goodwin 1992), which assumes a long-run equilibrium between two price variables. If cointegration tests fail to reject the LOP, the next question occurs is how the equilibrium is maintained in the long run, and especially when a shock occurs. This can be seen as an extension of the LOP problem, and is important in terms of price forecast, risk reduction, and arbitrage for spatial traders.

The prices of agricultural commodities are often nonstationary; one common method for estimating the model is the error correction model proposed by Engle and Granger (1987). The model is based on the cointegration relationship, and the idea behind the model is similar to the LOP: Prices of a homogeneous good should be equalized by an efficient market. The efficiency of the market is measured by the extent to which the shock is passed through markets (McNew and Fackler 1997). In a perfectly efficient market, all prices should respond to the shock simultaneously; otherwise, it takes time for prices in other markets to adjust to the shock in one market. The response time, also known as the adjustment speed, is often influenced by the size of the shock, asymmetric information, transportation costs, and transaction costs in the futures and options market. To take these factors into account, Goodwin and Piggott (2001) used a three-regime error correction model based on the size of the deviation from the equilibrium. They show that in the North Carolina corn and soybean markets, the threshold model implies a faster adjustment behavior than the ordinary error correction model. Serra, Zilberman, and Goodwin (2010) extended the threshold model with a smooth function to solve the discontinuity problem at each regime; the assumption is that adjustment coefficients depend on the deviation from the long-run equilibrium. Small deviations are neglected by the market due to transportation and transaction costs, and prices only respond to shocks that result in large deviations.

Threshold models focus on the deviation from the equilibrium, but when the shock is big, it is possible that the whole price system has been changed. In the international market, this happens if a country levies a heavy tax on imports or simply stops trading. In those situations, the LOP is likely to either disappear or exist, but with different response behavior. In terms of structural change, the threshold error correction model might not work well in capturing breaks and changes in the adjustment speed.

To solve this issue, Bai-Perron (2003) and Qu-Perron (2007) tests are introduced to determine the possible structural breaks in the price system. The Bai-Perron test has been used recently to estimate the break caused by an unexpected event. For instance, Kristofersson and Anderson (2005) used the Bai-Perron test to identify the structural change between fishmeal and soybean meal after the fishery industry shock in 1998. Other related work has been done by Carter and Smith (2007), who tested the price ration of corn and sorghum after contamination of the genetically modified (GM) crop, StarLink. The Qu-Perron test was proposed by Qu and Perron (2007) as an extension of the Bai-Perron test, which allows for multivariate regression.

Candidate events that can change the international corn price system are considered to be

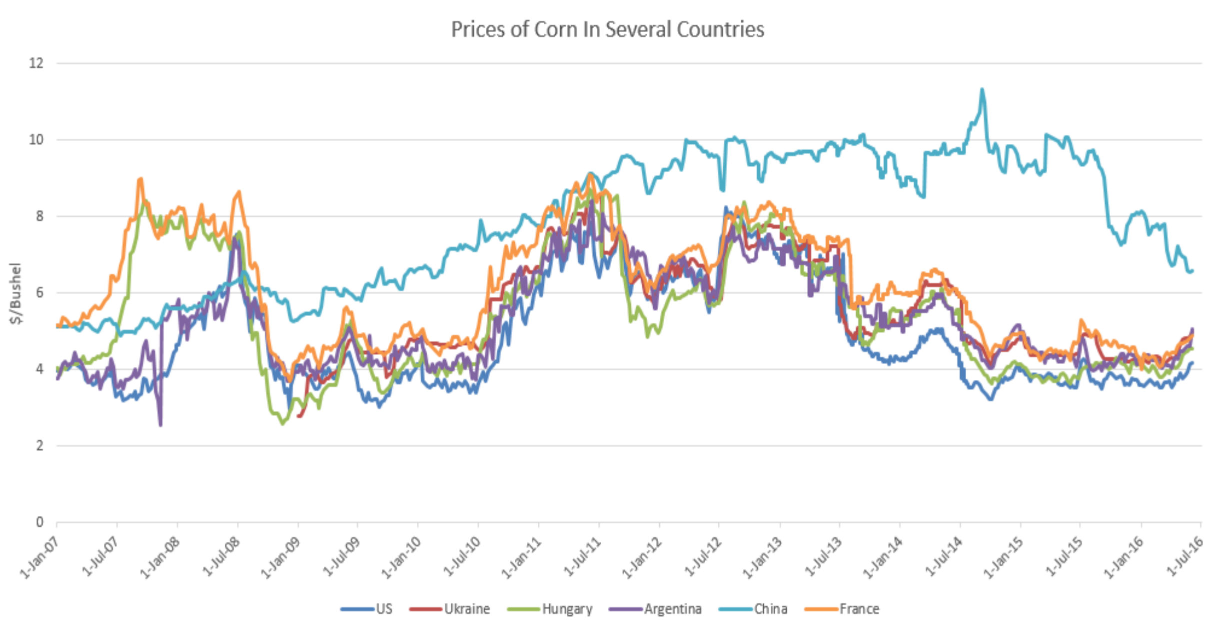

Figure 2.1 Prices of Corn

related to the two largest corn producers and consumers in the world: the US and China. And because the US accounts for more than 50% of the world's corn exports, the US corn prices are used as a benchmark. In Figure 2.1, several countries' corn prices are compared with the US corn price. Ukraine and Argentina are two of the largest corn exporters in the world market, and France represents the price in the European Union. Hungary is a relatively small corn market compared to the rest.

For China, prices deviated from those of the US and other countries. The only similarity that can be observed is the price trend from 2007 to 2009, although the price change was small relative to the US. After that, two prices were unrelated in both values and trend. The huge price gap between China and other countries can lead to arbitrage opportunity. However, because China set an import quota of 7 million tons of corn each year, and any import need to be approved by the government, the arbitrage opportunity is small and China can therefore maintain a higher domestic corn price.

The prices of corn in France and Hungary were high before 2008. For countries other than China, prices were close to the US price between 2008 and 2013. In mid-2013, the US price started to deviate from prices in other countries. However, this deviation became smaller with time, so the deviation was probably caused by a shock in the US corn market and was eventually fixed.

Because France and Hungary are not large corn producers or exporters in the world market, there extremely high prices before 2008 are not studied in this paper. This paper mainly focuses on the corn markets in China and the US. Therefore, two events are considered to possibly explain the price deviations and provide separate price analysis for each country. The first is China's stock policy for domestic corn in 2008, and the second is the fast decreasing exports of the US in 2013 due to the 2012 drought. In the first event, because the price trend disappears, the LOP is examined before and after the event. In the second, prices are likely to be still cointegrated, so both the LOP and price adjustment coefficients were estimated before and after the event.

2.1.1 Policy Change in China

During 2007-2008, world corn markets were notably volatile. Agricultural commodities prices increased dramatically in early 2008 due to the global food crisis and other causes, such as the growing demand in developing countries and high oil prices (Chand, 2008). Later, when the financial crisis occurred, prices took a huge fall.

To stabilize the market and protect farmers, in 2007 the Chinese government issued the Temporary Stock Plan (TSP) policy (Xu, Xi, and Zhang 2010). It worked as a price floor that gave farmers the right to sell corn to the government at a given price beginning in February 2008, when the government planned to buy 8 million tons of corn from the market. Later, with the huge price fall starting in July 2008, the government began to increase its buying volumes. On October 20, 2008, 5 million additional tons of corn were bought by the government. From October 2008 to February 2009, the government bought a total of 40 million tons of corn—one-quarter of the annual production and 40% of the domestic corn market—with an average price of $4.27/bushel. The TSP was abolished and replaced by a subsidy strategy in 2016, due to extremely high inventory and the cost of maintaining the stock. The policy lasted for 8 years, and the volume of corn bought in that period was close to 330 million tons. The government sold about 100 million tons to the market when the price was high to cover the cost, but that left more than 200 million tons in its inventory.

Another policy worth mentioning is China's rejection of US corn in late 2013. On November 29, 2013, China's Entry-Exit Inspection and Quarantine at Shenzhen announced that 60,000 tons of GM corn were rejected because it contained unapproved GM trait MIR162. By 2012, MIR162 was approved for import in areas such as Japan and the European Union, but not in China until year 2014. In the last two months of 2013, China sent back more than 720,000 tons of corn containing MIR162, which accounted for 22.1% of its total corn imports that year. China also started to import corn from Ukraine in June 2013, and the volume of corn imported increased in the following years. In 2014, China imported as much corn from Ukraine as from the US, and in 2015, more than two thirds of China's imported corn came from Ukraine.

To summarize China's corn policy in the international market, China was an exporter before 2008, stopped trading in 2008 and 2009, and started importing in 2010 with a limited quota of 7 million tons each year. Most of the corn imported came from the US before 2013 and from Ukraine after 2014. In general, after the TSP policy in 2008, the quantity imported of corn is small compared to the high stock in China, so the corn price should depend on the domestic market rather than the international market, and the LOP should not hold.

2.1.2 Decreasing US Exports in 2013 due to the 2012 Drought

The 2012 drought was the worst drought in the US since 1895 in terms of precipitation during May-August. The drought may have been caused by the ocean surface temperature together with changes in greenhouse gases (Hoerling et al., 2014). According to the National Ocean and Atmosphere Administration (NOAA), the total damage caused by the drought was 32.4 billion, the largest since 1988. Total production of corn decreased from 12,359 million bushels in 2011 to 10,780 bushels in 2012.

As the world's largest corn producer and exporter, the US is the main supplier for many countries that produce little corn, such as Japan and South Korea; more than 90% of the corn imported by Japan and South Korea is from the US. Being the largest supplier in the international corn market, changes in the US corn price have a great impact on the price in other countries.

The effect of the US corn price on the international market should depend on its corn exports. The 2012 drought led to a decrease in that year's production and a decrease in its exports in 2013. As shown in Figure 2.2, the share of the US corn in the world corn export market was more than 50% before 2012 and fell to 31% in 2013. This shrinkage affected the US market power and its price influence, and gradually recovered as its share started to go back to the level before the drought. Therefore, the analysis focuses on the structural change in 2013 and the different adjustment speeds in the LOP before and after the break.

The remainder of the paper is organized as follows. Section 2 discusses the model used to identify the structural change in the LOP and price relationship. Section 3 presents the data and empirical results, and the implications for policy makers and price prediction are discussed in section 4.

2.2 Models and Tests

2.2.1 Cointegration Test

Cointegration was first suggested by Granger (1981) and formalized by Engle and Granger (1987). A cointegration relationship often exists in two or more prices of substitutes. If a price vector x_t is integrated at $I(1)$ order and there exists a vector α where $\alpha' x_t$ is stationary, then x_t is cointegrated and α is the cointegrating vector.

One way to test cointegration is the unit-root test on the residual of $\alpha' x_t$. Let $y_t = \alpha' x_t$, for series

$$y_t = \rho y_{t-1} + \epsilon_t \quad t = 1, 2, ..., T. \tag{2.1}$$

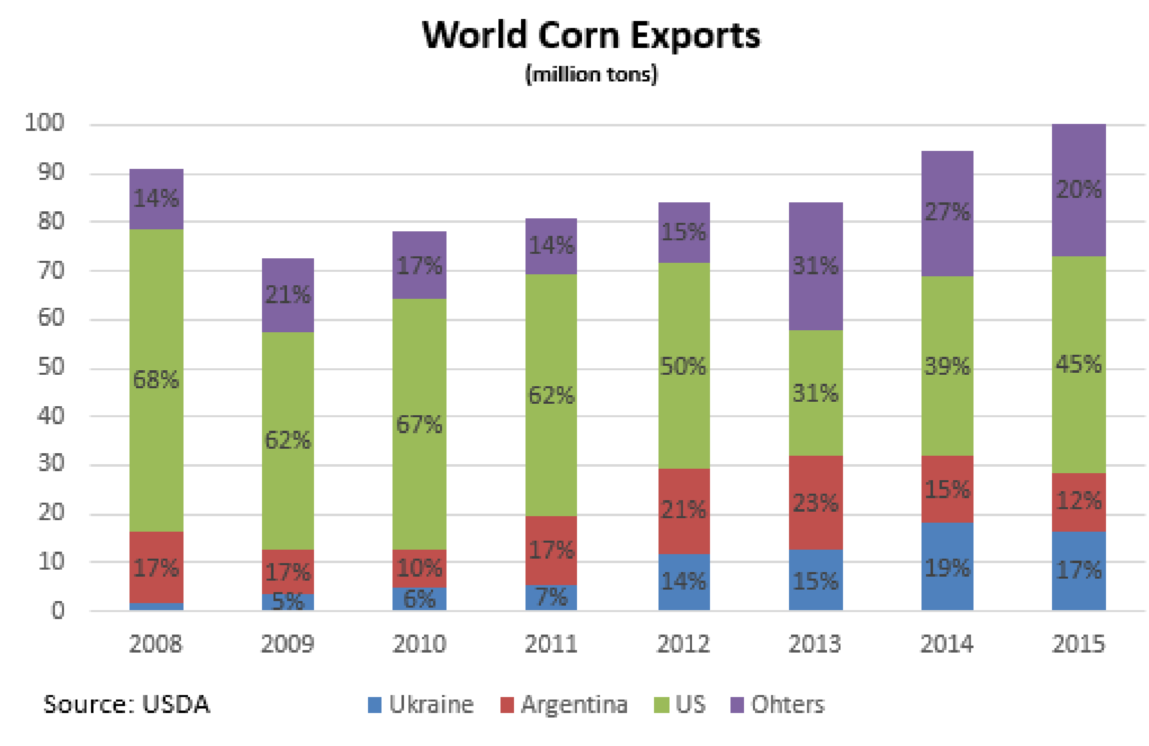

Figure 2.2 World Corn Exports

The augmented Dickey-Fuller test and Phillips-Perron Z test are defined as:

$$\begin{aligned} DF_\rho &= T(\hat{\rho}-1) \\ DF_\tau &= \frac{\hat{\rho}-1}{\hat{\sigma}_\rho} \\ Z_\rho &= DF_\rho - (1/2)T^2\hat{\sigma}^2_\rho(\hat{\lambda}-\hat{\gamma}_0)/s^2 \\ Z_\tau &= (\hat{\gamma}_0/\hat{\lambda})^{1/2}t_\tau - (1/2)T\hat{\sigma}_\rho(\hat{\lambda}-\hat{\gamma}_0)/(s\hat{\lambda}^{1/2}) \end{aligned} \tag{2.2}$$

where $\hat{\sigma}_\rho$ is the estimated variance for the OLS estimator ρ, $\hat{\gamma}_j = \frac{1}{T}\sum_{t=j+1}^{T}\hat{\epsilon}_t\hat{\epsilon_{t-j}}$, $\hat{\lambda} = \sum_{j=0}^{l}K_j[1-j/(l+1)]\hat{\gamma}_j$, where l is the lag, $K_0 = 1$ and $K_j = 2$ for $j > 0$, $s^2 = \frac{1}{T-k}\sum_{t=1}^{T}\hat{\epsilon_t}^2$ is the estimated variance of ϵ_t, and $t_\tau = (\hat{\rho}-1)/\hat{\sigma}_\rho$ is the OLS t-statistic for testing the hypothesis $\rho = 1$.

If cointegrating vector α is known, the residual can easily be calculated. Otherwise, the cointegrating vector α and the corresponding residual can be consistently estimated by the OLS regression of the first price on the rest of the price vectors as $x_{1t} = \alpha'(1, x_{2t}, x_{3t}...x_{pt})'$. More details on the asymptotic distribution of the residual-based tests can be found in Phillips and Ouliaris (1990) and Hamilton (1994).

The residual-based test is easy to adapt, but is not invariant: If a different price is used as the dependent variable in the OLS regression, results may change. Therefore, Johansen and Juselius (1990) propose a full likelihood rank test for the cointegration relationship. Suppose a $p \times 1$ vector x_t follows a VAR(k) model as:

$$x_t = \Pi_1 x_{t-1} + ... + \Pi_k x_{t-k} + \mu + \epsilon_t \tag{2.3}$$

Rewrite equation 2.3 as:

$$\Delta x_t = \Gamma_1\Delta x_{t-1} + ... + \Gamma_{k-1}\Delta x_{t-k+1} + \Pi x_{t-k} + \mu + \epsilon_t \tag{2.4}$$

where

$$\Gamma_i = -(I - \Pi_t - ... - \Pi_i), \quad (i = 1, ..., k-1)$$

and

$$\Pi = -(I - \Pi_1 - ... - \Pi_k). \tag{2.5}$$

If $r = rank(\Pi) = p$, then x_t is stationary. If the rank $0 < r < p$, then x_t is cointegrated at rank r, which means there exists r numbers of linearly independent cointegrating vectors. If $r = 0$, then it means x_{t-k} does not have an effect on x_t. The rank of Π is tested by trace statistics and the eigenvalue of the matrix.

It's possible to fail to reject the null hypothesis with different level of ranks. In such cases, the minimum rank that is not rejected is used as the level of cointegration rank. If x_t is cointegrated, the cointegrating vector is estimated by rewriting Π as $\Pi = \alpha\beta'$ where α is the adjustment coefficient, β is the cointegrating vector, and both are $p \times r$ matrices.

2.2.2 Bai-Perron Test

Bai and Perron (2003) propose several standard tests for multiple structural changes. They estimate the break by minimizing the sum of squared residuals conditional on the breaks. These tests include no break versus a fixed number of breaks, no break versus an unknown number of breaks, and new break versus a model with some breaks.

A univariate linear regression with m breaks (or $m+1$ regimes) is defined as:

$$y_t = x_t'\beta_j + z_t'\delta_j + u_t, \quad t = T_{j-1}, ..., T_j, \tag{2.6}$$

with independent variables x_t $(p \times 1)$ and z_t $(q \times 1)$, and coefficient β being constant across all regimes and δ_j changes in $j = 1, ..., m+1$ regimes. The error term u_t is assumed to be stationary and normally distributed for simplicity. A matrix form of the regression above can be written as:

$$Y = X'\beta + \bar{Z}\delta + U_t \tag{2.7}$$

where $Y = (y_1, ..., y_T)'$, $X = (x_1, ..., x_T)'$, $U = (u_1, ..., u_T)'$, $\delta = (\delta_1', \delta_2', ..., \delta_{m+1}')'$, and $\bar{Z}$ is the matrix which diagonally partitions Z at $(T_1, ..., T_m)$.

For example, $\bar{Z}$ can be a matrix formed by Z_i in each regime as:

$$\bar{Z} = \begin{bmatrix} Z_1 & 0 & ... & 0 \\ 0 & Z_2 & ... & 0 \\ ... & ... & ... & 0 \\ 0 & 0 & 0 & Z_{m+1} \end{bmatrix}$$

with $Z_i = (z_{T_{i-1}+1}, ..., z_{T_i})'$ for each regime i.

The break points are explicitly treated as unknown. Let $T_0 = 0$ and $T_{m+1} = T$; the first break point will be T_1 and the last break point will be T_m. For m breaks points $(T_1, ..., T_m)$, the associated least square of the model $S(T_1, ..., T_m)$ can be written as:

$$(Y - X'\beta - \bar{Z}\delta)'(Y - X'\beta - \bar{Z}\delta) = \sum_{j=1}^{j=m+1} \sum_{t=T_{j-1}+1}^{T_j} (y_t - x_t'\beta - z_t'\delta_j - u_t)^2 \tag{2.8}$$

The optimal set of break points $(\hat{T}_1, ..., \hat{T}_m)$ is estimated by minimizing the associated sum of squared errors (SSE) in equation 2.8 across all possible break points:

$$(\hat{T}_1, ..., \hat{T}_m) = \underset{(T_1,...,T_m)}{\arg\min} S(T_1, ..., T_m) \tag{2.9}$$

If the error term is $i.i.d$, then the F-test for testing the null hypothesis of no change versus the alternative hypothesis of m changes is given by:

$$F(T_1, ..., T_m; q) = \Big(\frac{T-(m+1)q-p}{m}\Big)\frac{\hat{\delta}H'(H(\bar{Z}'M_x\bar{Z})^{-1}H')^{-1}H\hat{\delta}}{SSR_m} \tag{2.10}$$

where $\hat{\delta}$ is the OLS estimator from $(T_1, ..., T_m)$ breaks, H is the matrix such that $(H\hat{\delta})' = (\delta_1' - \delta_2', ..., \delta_k' - \delta_{k+1}')$, and $M_x = I - X(X'X)^{-1}X'$. SSR_m is the sum of squared residuals under the alternative of m breaks. The nominator of the F-test can be treated as the difference in the sum of squared residuals between the null and the alternative. The null is rejected if the difference in the nominator is large, which indicates that breaks are significant. The Sup F-test $SupF(T_1, ..., T_m; q)$ is defined as the maximum of F-test statistics calculated at all possible break points $(T_1, ..., T_m)$.

The unweighted double maximum test $UDmax(M; q)$ is defined as the maximum of $SupF$ $(T_1, ..., T_m; q)$ tests for all possible number of breaks $m = 1, ..., M$. Because for any fixed q, the critical value of Sup $W(T_1, ..., T_m; q)$ decreases as m increases, it becomes easier to reject and may lead to low power. Therefore, a weighted double maximum test is proposed by Bai and Perron (1998). The weighted double maximum test $WD\,max\,W(M; q)$ applies weights to the Sup $F(T_1, ..., T_m; q)$ such that the marginal p-values are equal across the number of breaks m. The weights are set to be $\alpha_1 = 1$ for the first break and $\alpha_m = c(q, \alpha, 1)/c(q, \alpha, m)$ for m greater than one, and $c(q, \alpha, m)$ is the asymptotic critical value of the Sup $F(T_1, ..., T_m; q)$ for a significance level α. The $WD\,max\,W(M; q)$ is then defined as:

$$WD\,max\,W(M; q) = \frac{c(q, \alpha, 1)}{c(q, \alpha, m)} \times \sup_{(T_1,...,T_m)\in T_{all}^m} F(T_1, ..., T_m; q) \tag{2.11}$$

The sequential test $Seq(l+1|l)$ is a test of $l+1$ breaks versus l breaks. The test is defined as:

$$Seq(l+1|l) = \big[S(\hat{T}_1, ..., \hat{T}_l) - \inf_{\tau\in T} S(\hat{T}_1, ..., \hat{T_{i-1}}, \tau, \hat{T}_i, ..., \hat{T}_l)\big]/\hat{\sigma}^2 \tag{2.12}$$

Here, $S(\hat{T}_1, ..., \hat{T}_l)$ is the associated SSE defined in equation 2.8, $(\hat{T}_1, ..., \hat{T}_l)$ is estimated by equation 2.9, and $\hat{\sigma^2}$ is a consistent estimator of the error variance under the null of l breaks. If the new break τ greatly decreases the associated SSE, then the null of l breaks is rejected, and the new $l+1$ breaks are obtained by a global minimization of equation 2.9.

The univariate regression model was later extended to multivariate regression by Qu and Perron

(2007). The model is considered to have a form similar to the univariate model:

$$y_t = (I \otimes z_t')S\beta_j + u_t, \quad t = T_{j-1}, ..., T_j, \tag{2.13}$$

where y_t is an $n \times 1$ vector of dependent variables. The number of regressors is q, and z_t is the set of all regressors $z_t = (z_{1t}, ..., Z_{qt})$. If the number of parameters to be estimated in one regime is p, then S is an $nq \times p$ matrix to specify which regressors appear in the regression. The error term u_t is assumed to be stationary and has joint normal distribution with covariance matrix Σ_j. Similar to minimization of the associated SSE, the breaks are estimated by minimizing the Gaussian likelihood function over $m+1$ regimes:

$$\prod_{j=1}^{m+1} \prod_{t=T_{j-1}+1}^{T_j} f(y_t|x_t; \beta_j, \Sigma_j) \tag{2.14}$$

The $SupF(m;q)$, $UD\,max\,W(M;q)$, $WD\,max\,W(M;q)$ and $Seq(l+1|l)$ tests are constructed in a manner similar to the likelihood ratio test from the Gaussian distribution.

The problem with all of the tests above is that their power can be nonmonotonic. In this paper, the decision regarding the break follows the suggestion in Perron (2006). The first step is to look at the $WDmax$ statistics to decide whether the break exists. If the null of no breaks is rejected, then the sequential test defined in equation 2.12 is applied to test for $l+1$ breaks conditional on l breaks. For example, if $WDmax$ rejects the null, the first break is then tested by the sequential test of one break versus zero breaks $Seq(1|0)$. If $Seq(1|0)$ rejects the null of zero break, then the second and the following breaks are decided by the corresponding sequential tests until the test statistic is not significant.

The reason for this procedure is that simulation (Bai and Perron, 2005) shows that $WDmax$ has the highest power among all tests with unknown breaks, but is low at a fixed number of breaks. So the total number of breaks is tested by the $WDmax$, and each break is tested by the sequential test.

For multivariate regressions, the test statistics proposed by Qu and Perron (2007) are calculated in the same way as the Bai-Perron test in univariate linear regression, but extended to vector regression.

2.2.3 Empirical Models with Structural Break Tests

To test for a structural change in the price relationship, one commonly used method is to examine the relative price. It is straightforward to observe a change in the relative price when only one price changes. For instance, Carter and smith (2007) use the relative price between corn and sorghum to estimate the price change after a StarLink contamination of the food-corn supply. Another good reason to use the relative price is that the price of corn often contains a unit-root, which violates the assumption of the Bai-Perron test. The prices of corn in China, France, and Hungary are measured in the local currency, and therefore the exchange rate may play a role in the relative price. To fully capture possible structural change, models with and without the exchange rate are considered. Here, four linear models are used to test for a maximum break of m between price p_i in country i with the US dollar price and price p_k in other country k:

$$
\begin{array}{ll}
\text{Model One:} & log(p_{it}/p_{kt}^{USD}) = \alpha_j + \epsilon_t \\
\text{Model Two:} & log(p_{it}) = \alpha_j + \beta_j log(p_{kt}^{USD}) + \epsilon_t \\
\text{Model Three:} & log(p_{it}) = \alpha_j + \beta_{1j} log(p_{kt}^{k}) + \beta_2 log(r_{k/usd}) + \epsilon_t \\
\text{Model Four:} & log(p_{it}) = \alpha_j + \beta_{1j} log(p_{kt}^{k}) + \beta_{2j} log(r_{k/usd}) + \epsilon_t
\end{array}
\tag{2.15}
$$

where $j = 1, ..., m+1$ for m breaks. Here, $r_{k/usd}$ is the exchange rate of the foreign currency, p_{kt}^{USD} is the $price$ in country k measured in US dollars, and p_{kt}^{k} is the original price. ϵ_t is assumed to be a stationary random variable that is normally distributed.

The four models are ordered by the degree of restrictions. When the US dollar price is used for other countries, the underlying restriction is that coefficients for the original price p_{kt}^{k} and the exchange rate r_k are the same as $log(p_{kt}^{USD}) = log(p_{kt}^{k}) + log(r_{k/usd})$. In model one, another restriction applied is that the coefficient of the price is one. This restriction is based on the LOP that two prices should be close to each other if transaction costs are low and the market is efficient. Model two loosens the restriction of the coefficient for $log(p_{kt}^{USD})$, but keeps the US dollar price. In model three, the exchange rate is added to the model, but is not allowed to change over regimes. The restriction implies that the exchange rate only has a constant effect on prices and breaks should depend on the price coefficient. The last model has no restrictions on price or exchange rate, which allows a structural change in any variable.

If a break is detected, two outcomes can be observed depending on the cointegration relationship. The first outcome is that the cointegration relationship changes. For example, a change from cointegration to no cointegration implies that the long-run equilibrium no longer exists after the break, and the two markets are being isolated. The second outcome is that prices are still cointegrated, but as OLS estimators change, so does the cointegration vector.

Therefore, after the break is detected, cointegration tests are applied to samples in each period to decide on the type of structural change after the break. This procedure also ensures that the error term ϵ_t is stationary, as required by the Bai-Perron test.

If a cointegration relationship exists between two prices, one possible structural change is the change in the response time of one price to another. Therefore, the vector error correction model (VECM) proposed by Engle and Granger (1987) is applied to estimate the adjustment speed of two prices under the LOP. A pairwise VECM with structural change is defined as:

$$
\begin{cases}
\Delta x_{1,t} = \beta_{1,j} \hat{\mu_{t-1}} + \gamma_{11,j} \Delta x_{1,t-1} + \gamma_{12,j} \Delta x_{2,t-1} + \epsilon_{1t} \\
\Delta x_{2,t} = \beta_{2,j} \hat{\mu_{t-1}} + \gamma_{21,j} \Delta x_{1,t-1} + \gamma_{22,j} \Delta x_{2,t-1} + \epsilon_{2t}
\end{cases}
\tag{2.16}
$$

where $j = 1, 2, .., m$ for m breaks, and $\hat{\mu_{t-1}}$ is the long-term disequilibrium term estimated by the OLS residual of x_{1t} on x_{2t}. If the LOP holds, then a long-run disequilibrium in the OLS residual will be fixed by changes in both prices. The velocity of the adjustment is measured by adjustment coefficients β_1 and β_2, as they represent the response time each price requires to eliminate the disequilibrium term $\hat{\mu_{t-1}}$. Qu-Perron tests are applied to the VECM, as it is suitable for multivariate regression.

2.3 Data and Result

2.3.1 Data

The price of corn in each country is set by nearby future contracts in the futures exchange market. US corn prices are decided by futures contracts from the Chicago Board of Trade. China's prices are obtained from the Dalian Commodity Exchange. France's prices are from the futures exchange market Marché à Terme International de France (MATIF). Hungary's prices are from the Budapest Stock Exchange. Prices for Ukraine and Argentina are the freight on board (FOB) corn export prices in the Black Sea and Argentina.[1] Most prices cover the time period from 2008 to 2016, and some are available from 2000 or 2006. In each model, the longest time period shared by both prices is used. All prices are transformed to log term to reflect the percentage change. Detail for the time period in each country and summary statistics are presented in Table 2.1. The ADF tests for unit root in Table 2.2 shows that prices are nonstationary. Therefore, a relative price ratio or a vector error correction model should be applied to obtain stationary data.

Because the US is the leading exporter in the world market, the relationship between the US and each country is analyzed. For China, the relationship between China and Ukraine is also considered in the model, due to the trade that started in 2013. If two prices are cointegrated, then the VECM and Qu-Perron test for multivariate regression are applied. All tests require at least 5% of the total samples in each period, so for a total data samples T, break points T_j and T_{j-1} would satisfy: $|T_j - T_{j-1}| \geq 0.05\,T$.

2.3.2 Bai-Perron and Cointegration Test for Price Ratio

In the Bai-Perron test, the maximum break is set to be 2 and the error is pre-whitened to solve serial correlationship. As discussed in section 2, the $WDmax$ statistic tests for the existence of structural breaks in the model, and the sequential test $Seq(l+1|l)$ is used to determine each break. For example, if the $WDmax$ is significant and the $Seq(1|0)$ is not, then the first and second breaks are believed not to be significant. In some situations, the $WDmax$ statistics equals $Seq(1|0)$ statistics because

[1] For the US, China, and France, daily prices are available and used in the analysis between these countries. For other countries, weekly prices are used in the model.

the $WDmax$ is estimated as the maximum of all $SupF$ tests and $Seq(1|0)$ is the $SupF$ statistics for one break.

2.3.2.1 China and the US, China and Ukraine

Bai-Perron test results for four models in equation 2.15 are presented in Table 2.3. Results are consistent across four models between China and the US, as two break dates (09/26/2008 and 07/12/2013) are confirmed by at least three models. The first date is right before the time when China started its Temporary Stock Plan. This suggests that information of the stock plan stabilized the price in China's market and caused a structural change in the US-China price relationship. The second break date is observed in July 2013, and is before November 2013 when the US corn was rejected. This result is similar to the corn sorghum prices analysis from Han and Garcia (2017). They find a structural change between corn and sorghum prices in September 2013. They argue that in addition to the rejection event, reasons for the structural change include the decreasing import in June, higher forecast production of corn by the USDA in September and the proposal of biofuels reduction by the Environmental Protection Agency in October. As shown in Figure 2.3, there was no imports from June to September and it suddenly went up to over 700,000 tons and the rejection occurred. It has also been pointed out that the GM ban could be anticipated and lead to the price fall, as the GM corn had not been approved by that time.

For China and Ukraine, two break dates are 05/30/2013 and 07/04/2014. In January 2013, the General Administration of Quality Supervision, Inspection and Quarantine China approved the import of corn from Ukraine. The first estimated break date is consistent with the month when China started to import corn, as China for the first time imported 24.9 tons of corn from Ukraine in May 2013. The total amounts of imports from Ukraine were small in year 2013, but it should give the market a signal that China was willing to import corn from Ukraine.[2] The second break date 07/04/2014 is more related to the expectation of an increase in corn imported from Ukraine. In Figure 2.3, imports of corn from Ukraine grew rapidly in late 2014 and continued to increase in 2015.

To further study the relationship between two prices in each period, cointegration tests are conducted for a full and each period. Results are presented in Table 2.4. If the price stated is in a currency other than US dollars, it is labeled "Cointegration Test with Exchange Rates", as exchange rate is added to the model. If the price is transformed into the US dollar term, then the result is labeled "Cointegration Test with US Dollars."

Cointegration between China and the US is most significant between 09/26/2008 and 07/12/2013. In this period, China was importing corn from the US. The cointegration was also found in the 2007-2008 period before the TSP was made, but it was not significant for some tests. After 2013, when China decreased its corn imports from the US and started to import from Ukraine, the cointegration

[2]China imported 24.9, 62.6 and 45.4 tons of corn from Ukraine in May, July and December in 2013.

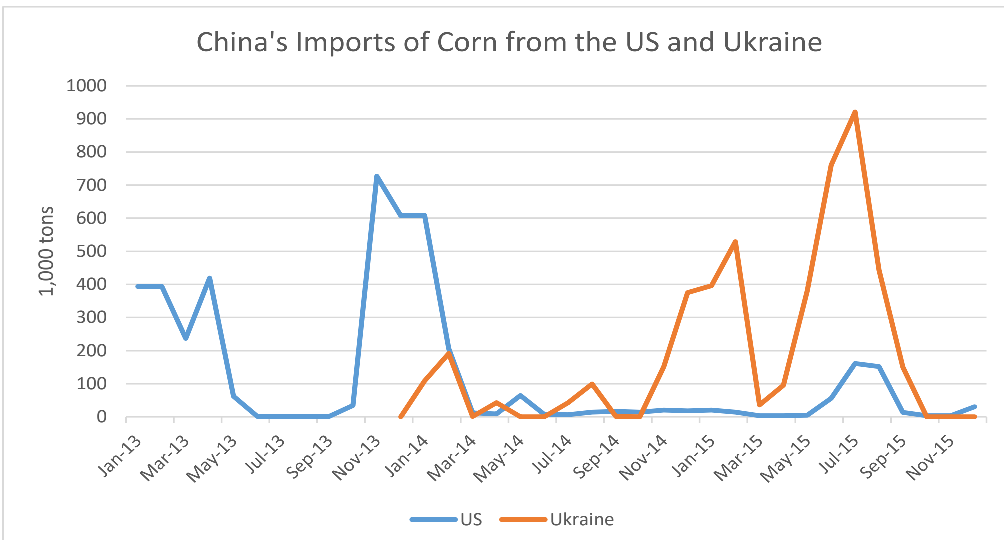

Figure 2.3 China's Imports of Corn

totally disappeared.

For China and Ukraine, although ADF tests suggest the likelihood of a nonstationary OLS residual after 2014, Phillips-Perron and Johansen Rank tests indicate cointegration after 2014, when China increased its imports of corn from Ukraine. Cointegration in 2013 is also confirmed by the test with the model including exchange rates.

Overall, the cointegration relationship is not strong between China and other countries; it is hard to find a situation in which all six test statistics reject the null of no cointegration relationship. However, the Phillips-Perron and Johansen tests indicate that the cointegration relationship is relatively strong for China and the US between 2008 to 2013 and Ukraine between 2014 and 2016. Because the LOP is also measured by the strength of the cointegration relationship, these results suggest that the LOP between China and other countries is consistent with China's import policy.

2.3.2.2 The US and Other Countries

Bai-Perron tests are applied for the price ratio and OLS regression between the US and Ukraine, Argentina, France, and Hungary, and results are summarized in Table 2.5. If the sequential test implies that the first break is significant and the second is not, the significant break is listed as the first break.

The first break between the US and Ukraine, and the US and Argentina is rejected by the $Seq(1|0)$, which suggests no breaks in the model.

For the US and France, several breaks dates are observed. Among them, Jan 2008 occurred three out of four cases, followed by Jun 2007. Break dates in 2010 are not highly significant. Corn prices in France were much higher than US prices before 2008, but the gap between US and France prices started to shrink in 2008 and eventually disappeared in 2009. This was mainly caused by a large increase in US corn prices. Food prices increased dramatically in 2008 due to the depreciation of the U.S. dollar, growth in biofuels production and changes in food demand and supply (Abbott, Hurt and Tyner, 2009). Condon, Klemick and Wolverton (2015) showed that the ethanol production and the expansion of the U.S. Renewable Fuel Standard (RFS) from 2006 to 2008 contributed to the high US corn prices in 2008. Given these factors, 2008 is likely to be a break point for the price structure and 01/23/2008 is selected as the break date.[3]

For the US and Hungary, break date 06/23/2013 is chosen because it occurs two out of four models. This break date is close to the break date found between China and the US. Because China's policy should not affect the price of corn in Hungary, the structural change is likely to be caused by the US itself. The decreasing export in 2013 would weaken the price ratio relationship between two countries. This could also be caused by the price change in the US itself. As mentioned above, the high forecast production in 2013 and EPA's reduction on biofuels mandate decrease the price of

[3] There are three break dates that lie in January 2008. The date 01/23/2008 is selected because model three has fewer restrictions than model one and two.

corn in the US in 2013. Another break date, 04/03/2009, is not chosen because it is not significant in Model One. The overall estimated breaks show less consistency, as break dates change for different models.

The use of price ratio assume that there is a linear relationship between two prices. If a break happens, it should be caused by either a change in the linear relationship itself or a change in the linear coefficient. In the first case, suppose the linear relationship disappears, it implies that two prices are no longer cointegrated and the LOP does not hold. In the second case, two prices are still cointegrated, but with different cointegration vector, which can be caused by a change in the transportation costs.

Therefore, to examine which factor changes, cointegration tests are applied to all pairwise prices in each period of time. As discussed above, break date 01/23/2008 is used for the US and France case and 06/23/2013 is used for the US and Hungary case. Because for the US and Hungary, this break date is only observed in model three and model four which include exchange rates, cointegration tests without the exchange rates are excluded. Test results are presented in Table 2.6. Strong cointegration is observed between the US and Ukraine and the US and Argentina for the full period, which indicates a long-run equilibrium between the US price and other prices. Results in Table 2.6 also indicate that the change in the cointegration relationship is the main reason for the structural change in the price ratio, as the cointegration appears between US and France after 2008. For the US and Hungary, the cointegration become less significant after the break date, which is an evidence that the decreasing US exports weakens the price relationship between two countries.

2.3.3 Vector Error Correction Models

To further analyze possible structural changes in the price of corn between the US and Ukraine, Argentina, and France, a vector error correction model and Qu-Perron test are applied.[4] For France, only data after the break date 01/23/2008 are used, because data before that do not have a cointegration relationship.

Test results are presented in Table 2.7. The estimated break dates are consistent with the results in the previous relative price models between the US and other countries. For example, the break date June 2013 and July 2013 for Ukraine and Argentina has been observed between the US and China, and the US and Hungary. Because the cointegration relationship and cointegration vector does not change between the US and Ukraine and the US and Argentina, the break date is only observed in the VECM. The reason for that is Ukraine and Argentina are also main corn exporting countries and their prices are strongly cointegrated with the US corn prices. Therefore, the decreased exports in the US only changed adjustment speed for the price relationship, not the relationship itself. The second estimated break for Ukraine is 07/27/2014, which is consistent with the break date

[4]Because the cointegration between the US and Hungary is weak after June 2013, it is excluded from the study in this section.

estimated between China and Ukraine. This can be explained by China's increasing imports of corn from Ukraine. The second break date 02/15/2008 for Argentina could be related to the increasing corn prices or the financial crisis, as discussed for the US and France case in the previous model. For France, since the statistic $Seq(1|0)$ is not significant, estimated breaks are ignored and considered insignificant.

VECM is then applied to the full and each period, and results are presented in Table 2.8. Following the notation in equation 2.16 and letting Δx_{1t} denote the US price and Δx_{2t} denote the price for the other country. The residual $\hat{\mu_t}$ is estimated by the OLS regression:

$$x_{1t} = c + \alpha x_{2t} + \mu_t \tag{2.17}$$

If a long-run equilibrium exists, then $\hat{\mu_t}$ should eventually revert to zero .

Empirical results in Table 2.8 are consistent with the LOP assumption, as adjustment coefficients β_1 for the US are all negative and β_2 for the other country are all positive. Given a positive shock to the US price, the disequilibrium term $\hat{\mu_t}$ will become positive; and in order to revert back to zero, the US price should decrease, and the price of the other country should increase.

The absolute value of the adjustment coefficient β reflects the speed of the adjustment. The adjustment coefficient for the US does not change much in each period. On the other hand, large changes are observed in the adjustment speed for Ukraine and Argentina. Half-lifes, represented by the time required for one half of the deviation from the equilibrium to be eliminated, are reported in Table 2.9.[5] Half-lifes for the US range from 10 weeks to 16 weeks and do not change a lot by period, which implies that the time required for the US to eliminate the disequilibrium is quite stable. When no breaks are applied in the VECM, the half-life is much shorter for Ukraine, Argentina and France. This could be that prices in these countries are more influenced by a deviation from the equilibrium and the disequilibrium will be eliminated in a short period. However, if breaks are put into the model, the half-life changes a lot. There is a significant increase in half-lifes for Ukraine and Argentina after 2013. When half-life increases, it indicates that the connection between two prices decreases because it takes longer time for one price to eliminate the disequilibrium. This can be caused by the decreasing export in the US in 2013, as prices of Ukraine and Argentina are less tied to the US price. It is also noted that the half-life for Ukraine in the Jun 2013-July 2014 is extremely large, which raises the question of whether the cointegration relationship exists during that period.

Therefore, the Johansen Rank test is applied to each period to identify whether the cointegration relationship still exists. As expected, the results in Table 2.10 indicate no cointegration between the US and Ukraine during 2013-2014.

[5]Suppose y_t follows an autoregressive of order p and is written as: $y_t = \sum_{j=1}^{p} \phi_j y_{t-j} + \epsilon_t$, the half-life is given by $-ln(2)/(1+\beta)$. This is obtained by the convergence speed of an error correction model $\Delta y_t = \beta y_{t-1} + \sum_{j=1}^{p-1} \phi_j^* \Delta y_{t-j} + \epsilon_t$ where $\beta = \sum_{j=1}^{p} \phi_j - 1$ and $\phi_j^* = -\sum_{k=j+1}^{p} \phi_k$. Because the VECM is used in the paper, the β is estimated directly instead of taking the sum of ϕ_j.

The responses of prices to each break in each period are presented in Figure 2.4. The shock is set to a 1% increase in the price. The response of the US price to its own shock is stable across all periods, which is consistent with the half-lifes. The response of Ukraine's price to the US shock is larger in the first period (before 2013), decreases to about 0.3% between 2013 and 2014, and finally changes to 0.5% after 2013. This suggests that the US has a larger effect on Ukraine's price when it has a greater share of exports in the world corn market. This is also observed by the response of Argentina to the US shock, which is much smaller in regime 3 (after 2013).

The responses of both US and Argentina prices to Argentina price shock are relative small after several weeks. This implies that shocks in Argentina is likely to be eliminated and has little effect on the future prices. One possible explanation is that despite US being the world largest corn exporter, it sometimes imports corn from Argentina when prices in Argentina are low (Newman and Bunge, 2016). When the prices are low in Argentina. the US choose When Moreover, the response of the US price to either Ukraine's or Argentina's price shock is larger after 2013, as shown in period 2 for Ukraine and period 3 for Argentina. This suggests that the effect of the price is related to the relative size of the market share. When the share of Ukraine and Argentina relative to the US increases, the effect of Ukraine's and Argentina's price shocks on the US price increases.

In terms of the LOP, the disequilibrium caused by a price shock often disappears eventually, but the speed of adjustment is not very fast; as Figure 2.4 shows, it often takes more than 12 weeks (about 3 months) for two prices to be close enough to eliminate the disequilibrium. The reason for that might be the asymmetric information and transaction costs in the world market. Because the cointegration relationship between the US and Ukraine disappears in period 2 (2013-2014), the disequilibrium is still large even after 20 weeks.

2.4 Summary and Conclusions

The low of one price is an important assumption in the international trading and can be influence by a policy or a market event. The low of one price is often examined by a cointegration relationship between prices. This paper tests possible structural changes among linkages for corn prices using the relative price ratio and the vector error correction model. The price ratio model is suitable for the structural change in one price and is related to the cointegration relationship. The vector error correction model focus more on the adjustment speed between two prices with regard to the long-run equilibrium. Two events are considered to cause the possible structural change. The first one is China's import policy and its rejection of GM corn from the US. The second one is the decreasing export of the US due to the 2012 drought. Both events are related to the international trade and should have an impact on the low of one price between countries. Bai-Perron tests, cointegration tests, and Qu-Perron tests are applied to identify and test for breaks.

The breaks estimated by the models are consistent with the event. For China, the Bai-Perron

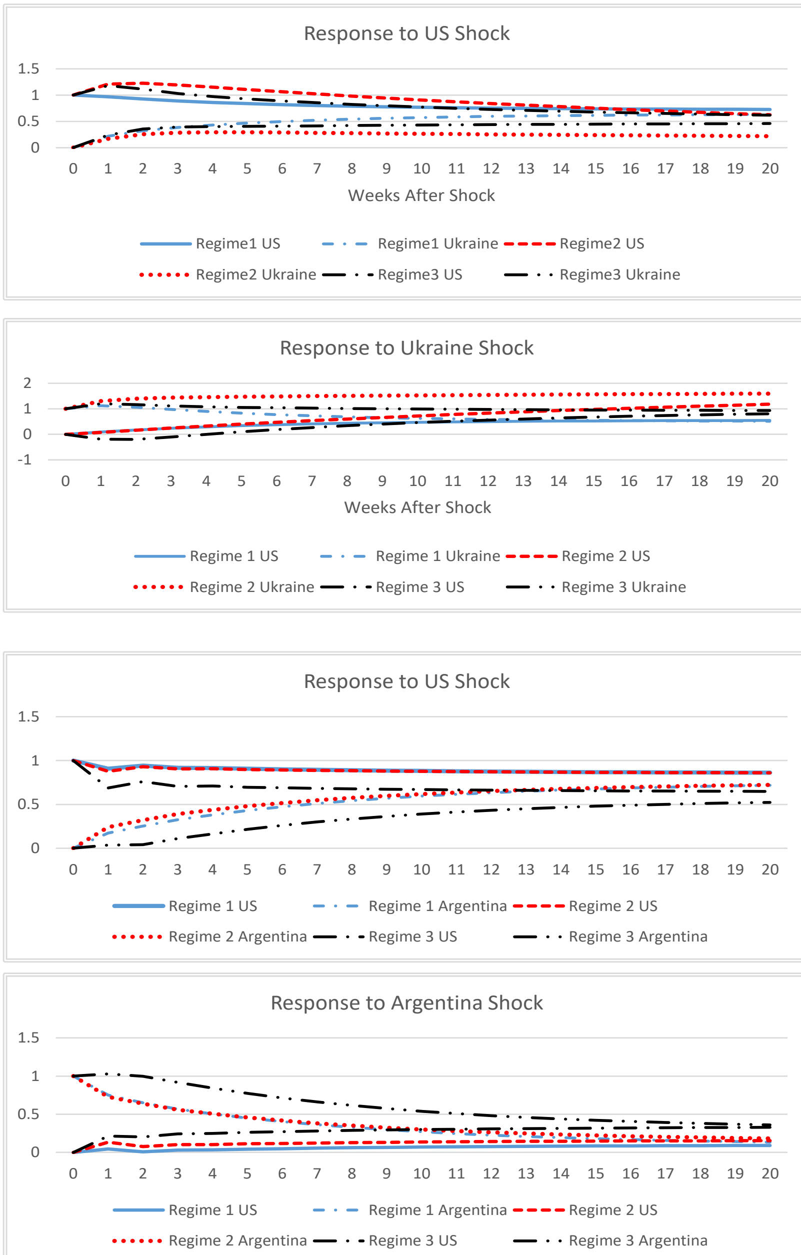

Figure 2.4 Impulse Response in Each Regime

test suggests the break date is the year 2008 when China started to implement the Temporary Stock Plan for corn. This policy led to a separation of China's market from the global market, as there was no strong cointegration relationship between China and other countries. The second break date lies in June 2013, which is before the GM rejection. Several explanation are provided, such as the environmental policy change, anticipation of the rejection and the extreme low import during the June-September period. Also, cointegration relationships between China and the US and China and Ukraine are stronger in the period when China imports corn from each country.

The second event is observed in both the relative price and vector error correction models. The break point lies in mid-2013 and is observed between the US and Hungary for relative price model, and Ukraine and Argentina for the vector error correction model. The cointegration relationship weakens between the US and Hungary after the break date. For Ukraine and Argentina, the vector error correction model implies a longer response time for the prices to the disequilibrium after the break. The response to the price shock suggests that the effect of one price on another is related to the share of corn exports in the world market.

The test results also indicate that a break occurs in early 2008. The break date is observed between the US and France, and the US and Argentina. This structural change is considered to be caused by the global food crisis, financial crisis and the increasing biofuels production.

The paper's implications are twofold. The first is how the policy affects the price relationship. The LOP is one of the fundamental assumptions in international trade, yet it can be violated by domestic policies or market events that are irrelevant to international trade. When China starts to import corn from Ukraine instead of the US, prices of corn in China and Ukraine show stronger cointegration than that between China and the US. An unexpected drought in the US makes the prices in other countries less tied to the US market. Such violation would affect the welfare of importers or exporters, and should be recognized by the policy maker in decision making. For example, if the price of corn in Ukraine is more volatile, then an import of Ukraine corn is likely to transfer this volatility to the importing country's corn market and harm the interests of domestic producer.

The second implication is that even when the LOP holds for two countries, the price relationship between them can be changed by a market event. As shown in the paper, estimated adjustment coefficients are much smaller for Ukraine and Argentina after 2013. In case of an event or a shock, it is suggested that Bai-Perron or Qu-Perron tests should be used to examine whether break has occurred. This is important to international traders who predict the prices based on the assumption of long-run equilibrium. If the US is decreasing its corn export, traders should expect that prices in other exporting countries will be less tied to US prices and it may take longer time for these prices to respond to a shock in the US prices.

Table 2.1 Summary Statistics for Log Prices

	Mean	Std. Dev.	Start From	To
US	1.2544	0.4318	01/02/2000	07/29/2016
China (in CNY)	3.9978	0.1740	01/20/2007	05/30/2016
China (in USD)	2.1129	0.2307	01/20/2007	05/30/2016
Ukraine	1.6957	0.2336	01/02/2009	07/03/2016
Argentina	1.3138	0.4113	01/02/2000	06/03/2016
France (in EUR)	1.8593	0.2386	09/27/2006	05/30/2016
France (in USD)	1.5824	0.2053	09/27/2006	05/30/2016
Hungary (in HUF)	6.9976	0.2694	09/29/2006	06/03/2016
Hungary (in USD)	1.6300	0.2694	09/29/2006	06/03/2016

Table 2.2 ADF Tests for Unit Root

	DF_ρ	p-value	DF_τ	p-value
US	-6.5638	0.3052	-1.7921	0.3845
China (in CNY)	-3.9181	0.5488	-1.7723	0.3944
China (in USDY)	-5.1818	0.4183	-1.9632	0.3029
Ukraine	-10.0760	0.1304	-2.7946	0.0605
Argentina	-6.3454	0.3204	-1.8092	0.3759
France (in EUR)	-6.5768	0.3043	-1.8586	0.3519
France (in USD)	-5.9008	0.3557	-1.7666	0.3973
Hungary (in HUF)	-5.8354	0.3610	-1.8230	0.3692
Hungary (in USD)	-6.0145	0.3465	-1.7492	0.4060

Table 2.3 Bai-Perron Test for Price Ratio between China and US, China and Ukraine

	China and US				
	From 01/26/2007 to 05/27/2016 (No. of Obs:2156)				
	WDmaxF	$Seq(1\|0)$	$Seq(2\|1)$	1st Break (No.)	2nd Break (No.)
Model One	15.87***	15.87***	6.90	10/13/2010 (852)	07/12/2013 (1487)
Model Two	75.52***	75.52***	77.25***	10/06/2008 (382)	07/12/2013 (1487)
Model Three	129.35***	64.74***	84.26***	09/26/2008 (381)	07/12/2013 (1487)
Model Four	83.45***	83.45***	80.43***	09/26/2008 (381)	07/12/2013 (1487)
	China and Ukraine				
	From 01/02/2009 to 06/03/2016 (No. of Obs:460)				
	WDmaxF	$Seq(1\|0)$	$Seq(2\|1)$	1st Break (No.)	2nd Break
Model One	25.34***	6.02	15.88***	05/07/2010 (73)	06/28/2013 (252)
Model Two	51.41***	51.41***	111.90***	06/28/2013 (252)	07/04/2014 (357)
Model Three	98.98***	78.51***	133.09***	06/28/2013 (252)	07/04/2014 (357)
Model Four	1161.52***	1161.52***	120.76***	06/28/2013 (252)	07/04/2014 (357)

***, **, * denotes the significance level of 0.01, 0.05, 0.10.

Table 2.4 Cointegration Tests for Each Regime

	China and US						
	Cointegration Test with Exchange Rates						
Period	ADF Test		Phillips-Perron		H_0	Johansen Rank Test	
	DF_ρ	DF_τ	Z_ρ	Z_τ	rank=r	Max Eigen.	Trace
Full Period	-11.78**	-2.43**	-12.34	-2.49	0	0.0135***	47.0527***
					1	0.0069*	17.9240
					2	.0.0015	3.1090
01/26/2007 to	-13.84***	-2.65***	-15.00	-2.81	0	0.0834***	49.6787***
09/25/2008					1	0.0341	16.5761
					2	0.0089	3.3671
09/26/2008 to	-19.13***	-3.11***	-25.23*	-3.83**	0	0.0173	32.3600*
07/12/2013					1	0.0096	13.0406
					2	0.0021	2.3522
07/15/2013	-9.97**	-2.74***	-9.93	-2.61	0	0.0219	21.0979
05/27/2016					1	0.0096	6.3917

Continued on next page

Table 2.4 (continued).

					2	0.0011	1.8512

Cointegration Test with US Dollar

	ADF Test		Phillips-Perron		H_0	Johansen Rank Test	
	DF_ρ	DF_τ	Z_ρ	Z_τ	rank=r	Max Eigen.	Trace
Full Period	-8.94**	-2.11**	-8.83	-2.10	0	0.0039	11.4604
					1	0.0014	3.1005
2007/1/26 to	-16.71***	-2.90***	-19.46**	-3.18*	0	0.0298	12.8840
09/25/2008					1	0.0036	1.3825
2008/9/26 to	-21.47***	-3.33***	-25.05**	-3.83**	0	0.0154**	18.9277*
07/12/2013					1	0.0016	1.7981
07/15/2013 to	-8.80***	-2.58***	-9.08	-2.53	0	0.0135	11.9094
05/27/2016					1	0.0043	2.8725

China and Ukraine

Cointegration Test with Exchange Rates

Period	ADF Test		Phillips-Perron		H_0	Johansen Rank Test	
	DF_ρ	DF_τ	Z_ρ	Z_τ	rank=r	Max Eigen.	Trace
Full Period	-17.35***	-3.01***	-14.56	-2.77	0	0.0588***	48.6888***
					1	0.0272	20.8512**
					2	0.0177*	8.2049*
01/02/2009 to	-26.43***	-3.86***	-21.36	-3.52*	0	0.0763***	46.2863***
06/23/2013					1	0.0624**	26.3752***
					2	0.0398**	10.1937**
06/28/2013 to	-22.73***	-3.59***	-24.14*	-4.42***	0	0.2223***	39.0003***
06/29/2014					1	0.0741	12.5963
					2	0.0421	4.5154
07/04/2014 to	-7.18*	-1.48	-23.40*	-4.59***	0	0.2464***	41.7004***
06/03/2016					1	0.0901	12.565
					2	0.0272	2.8447

Cointegration Test with US Dollar

	ADF Test tao		Phillips-Perron		H_0	Johansen Rank Test	
	DF_ρ	DF_τ	Z_ρ	Z_τ	rank=r	Max Eigen.	Trace
Full Period	-11.56**	-2.56**	-11.17	-2.52	0	0.0517*	31.8914***

Continued on next page

Table 2.4 (continued).

					1	0.0162	7.5152
01/02/2009 to	-27.02***	-16.65***	-22.72**	-3.60**	0	0.0688**	28.8815***
06/23/2013					1	0.0428**	10.9805***
06/28/2013 to	-0.84	-0.57	-9.21	-2.87	0	0.1204	18.4117*
06/29/2014					1	0.046	4.9406
07/04/2014 to	-7.40*	-1.54	-25.74**	-4.66***	0	0.2099***	24.2691***
06/03/2016					1	0.0253	2.6391

Table 2.5 Bai-Perron Tests for Price Ratios between the US and Other Countries

	WDmaxF	$Seq(1\|0)$	$Seq(2\|1)$	1st Break (No.)	2nd Break (No.)
US and Ukraine					
From 01/02/2009 to 07/03/2016 (No. of Obs: 381)					
Model One	16.4460***	7.5601	10.8489**	12/10/2010 (94)	10/18/2013 (242)
Model Two	18.0810***	9.8299	8.9540	09/10/2010 (83)	10/11/2013 (241)
US and Argentina					
From 01/02/2000 to 06/03/2016 (No. of Obs: 795)					
Model One	7.9963	3.0846	14.4635**	12/17/2010 (545)	07/12/2013 (659)
Model Two	3.8638	3.8639	2.9820	11/10/2006 (344)	12/14/2007 (398)
US and France					
From 09/27/2006 to 05/27/2016 (No. of Obs: 2425)					
Model One	12.5116**	12.5117**	13.6346**	06/22/2007 (183)	01/10/2008 (321)
Model Two	61.8350***	59.5568***	8.2811	01/07/2008 (318)	12/15/2010 (1060)
Model Three	56.7329***	60.5421***	9.9664*	06/21/2007 (182)	01/23/2008 (329)
Model Four	74.8336***	74.8337***	15.8188**	11/20/2008 (538)	10/08/2010 (1013)
US and Hungary					
From 09/29/2006 to 06/03/2016 (No. of Obs: 484)					
Model One	4.2891	4.1560	18.2801***	08/29/2008 (94)	04/03/2009 (122)
Model Two	56.2892***	30.4875***	57.5953***	01/11/2008 (60)	05/01/2009 (123)
Model Three	27.7716***	27.7717***	19.3398***	05/21/2008 (71)	06/23/2013 (336)
Model Four	143.2063***	68.9712***	62.3032***	01/06/2009 (111)	06/16/2013 (335)

Table 2.6 Cointegration Tests for Each Regime between the US and Other Countries

Period	ADF Test		PPerron		H_0	Johansen Rank Test	
	DF_ρ	DF_τ	Z_ρ	Z_τ	rank=r	Max Eigen.	Trace
			US and Ukraine				
Full Period	-47.52***	-5.63***	-68.54***	-6.93***	0	0.1400***	74.0348***
					1	0.0050	2.4044
			US and Argentina				
Full Period	-50.31***	-5.20***	-89.80***	-7.36***	0	0.1384***	65.9964***
					1	0.0063	2.6991
			US and France				
			Cointegration Test with Exchange Rates				
Full Period	-19.83***	-3.35***	-22.28	-3.57	0	0.008	29.9575
					1	0.0025	10.4048
					2	0.0018	4.3726
09/27/2006 to	-14.63***	-2.94***	-15.41	-3.17	0	0.0462	24.2362
01/22/2008					1	0.0241	8.7711
					2	0.0024	0.7802
01/23/2008 to	-49.03***	-5.15***	-56.33***	-5.61***	0	0.0179***	47.7132***
05/27/2016					1	0.0029	9.8671
					2	0.0018	3.6757
			Cointegration Test with US Dollars				
Full Period	-18.44***	-3.23***	-18.16	-3.26	0	0.0064*	18.5467*
					1	0.0012	2.9993
09/27/2006 to	-16.71***	-2.90***	-7.92	-2.31	0	0.0389	13.6851
01/22/2008					1	0.0022	0.7174
01/23/2008 to	-44.02***	-4.91***	-44.23***	-5.05***	0	0.0157***	35.3414***
05/27/2016					1	0.001	2.1688
			US and Hungary				
			Cointegration Test with Exchange Rates				
Full Period	-11.70**	-2.42**	-16.06	-2.90	0	0.0449*	39.1676**
					1	0.0274	16.9827
					2	0.0074	3.5654
09/29/2006 to	-12.28**	-2.59***	-13.46	-2.76	0	0.0974***	45.9109***
06/16/2013					1	0.0277	11.6848
					2	0.0069	2.2999
Period	ADF Test		Phillips-Perron		H_0	Johansen Rank Test	

Continued on next page

Table 2.6 – continued from previous page

	DF_ρ	DF_τ	Z_ρ	Z_τ	rank=r	Max Eigen.	Trace
06/23/2013 to 06/03/2016	-6.14*	-1.75*	-17.89	-3.36	0	0.1334*	36.3388**
					1	0.0706	15.004
					2	0.0271	4.0932
			Cointegration Test with US Dollars				
Full Period	-10.60**	-2.33**	-15.80	-2.89	0	0.0304*	19.4601*
					1	0.0094	4.5483

Table 2.7 Qu-Perron Tests for VECM

		US and Ukraine			
		From 01/23/2009 to 07/03/2016 (No. of Obs: 379)			
Model	WDmaxF	$Seq(1\|0)$	$Seq(2\|1)$	1st Break	2nd Break
VECM	20.151*	20.151*	63.860***	06/26/2013 (228)	07/27/2014 (275)
		US and Argentina			
		From 01/23/2009 to 07/03/2016 (No. of Obs: 793)			
Model	WDmaxF	$Seq(1\|0)$	$Seq(2\|1)$	1st Break	2nd Break
VECM	97.948***	97.948***	76.274***	02/15/2008 (402)	07/05/2013 (656)
		US and France			
		From 01/23/2009 to 07/03/2016 (No. of Obs: 2095)			
Model	WDmaxF	$Seq(1\|0)$	$Seq(2\|1)$	1st Break	2nd Break
VECM	104.436***	9.267	176.990***	11/23/2011 (863)	07/31/2013 (1389)

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Table 2.8 VECM Model for the Full and Each Period

Period	β_1	γ_{11}	γ_{12}	β_2	γ_{21}	γ_{22}
			US and Ukraine			
Full Period	-0.0526**	0.0997*	0.0539	0.0713***	0.1692***	0.2119***
	(0.0205)	(0.0526)	(0.0650)	(0.0149)	(0.0382)	(0.0472)
01/23/2006 to	-0.0635**	0.0318	0.0198	0.0820***	0.1370**	0.2125***
06/19/2013	(0.0273)	(0.0728)	(0.0817)	(0.0204)	(0.0545)	(0.0612)
06/26/2013 to	-0.0413	0.2527***	0.0293	0.0035	0.1616***	0.3047**
07/20/2014	(0.0366)	(0.0872)	(0.2477)	(0.0188)	(0.0447)	(0.1271)
07/27/2014 to	-0.0548	0.2368	-0.2487	0.0290	0.2080***	0.2333**
07/03/2016	(0.0690)	(0.1249)	(0.2052)	(0.0334)	(0.0605)	(0.0994)
			US and Argentina			
Full Period	-0.0550***	0.0073	-0.0089	0.1278***	0.1099**	-0.1092***
	(0.0177)	(0.0393)	(0.0296)	(0.0234)	(0.0519)	(0.0391)
01/23/2006 to	-0.0555**	-0.04943	-0.00829	0.2316***	-0.04244	0.00608
02/08/2008	(0.0234)	(0.0533)	(0.0322)	(0.0398)	(0.0906)	(0.0548)
02/15/2008 to	-0.0541	-0.0218	0.0225	0.0548	0.2784***	-0.3134***
06/28/2013	(0.0361)	(0.0746)	(0.0710)	(0.0354)	(0.0732)	(0.0697)
07/05/2013 to	-0.0601*	0.2596***	-0.1022	0.0254	0.2280***	-0.1333
07/03/2016	(0.0345)	(0.0947)	(0.1036)	(0.0317)	(0.0870)	(0.0952)
			US and France			
Full Period	-0.0550***	0.0073	-0.0089	0.1278***	0.1099**	-0.1092***
	(0.0177)	(0.0393)	(0.0296)	(0.0234)	(0.0519)	(0.0391)

Table 2.9 Half-life in Each Period from the VECM

	Half-Life (Weeks)	Half-Life (Weeks)
US and Ukraine	US	Ukraine
Full Period	13.18	7.94
01/23/2006 to 06/19/2013	10.92	6.90
06/26/2013 to 07/20/2014	16.78	161.67
07/27/2014 to 07/03/2016	12.65	19.51
US and Argentina	US	Argentina
Full Period	12.60	5.41
01/23/2006 to 02/08/2008	12.49	2.98
02/15/2008 to 06/28/2013	12.81	12.61
07/05/2013 to 07/03/2016	11.53	27.20
US and France	US	France
Full Period	12.60	5.00

Table 2.10 Johansen Rank Test for Each Period

US and Ukraine			
Period	H_0	Johansen Rank Test	
	rank=r	Max Eigen.	Trace
01/23/2006 to	0	0.1294***	35.5208***
06/19/2013	1	0.0138	3.2348
06/26/2013 to	0	0.1523	11.0714
07/20/2015	1	0.0319	1.8182
07/27/2014 to	0	0.2791***	33.3024***
07/03/2016	1	0.054	4.8294
US and Argentina			
Period	H_0	Johansen Rank Test	
	rank=r	Max Eigen.	Trace
01/23/2006 to	0	0.1458***	64.1808***
02/08/2008	1	0.0029	1.1561
02/15/2008 to	0	0.1525***	43.5696***
06/28/2013	1	0.0067	1.7056
07/05/2013 to	0	0.2347***	44.1592***
07/03/2016	1	0.0534	7.5124

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CHAPTER

3

COPULA MODEL WITH GARCH ERROR FOR AGRICULTURAL PRICES CORRELATION

3.1 Introduction

Grain sorghum has become a popular crop in the United States in the last several years. The production of grain sorghum has increased from 213 million bushels in 2011 to 597 million bushels in 2015. In 2017, the production was 364 million bushels with an acreage of 5.63 million acres, which is greater than the acreage for oats and barley. Grain sorghum is drought tolerant and grown primarily on dry-land acreage in the so-called Sorghum Belt, which runs from South Dakota to South Texas.[1] In fact, about 75% of grain sorghum is grown in Texas and Kansas.

Sorghum can be used for both human consumption and animal feed. In the United States, grain sorghum is used primarily for animal feed. Grain sorghum contains about 85% of the energy of corn and is considered to be a good substitute for corn in terms of feed value (Rusche, 2015). When compared with the same amount of corn, the feed value of grain sorghum ranges from 85% to 98% based on different livestocks (McCuistion, 2014).

In spite of the popularity of grain sorghum as animal feed, there is no futures markets available for sorghum. The lack of a futures market increases the price risk for sorghum traders. One solution to this is to

[1] That includes the states of South Dakota, Nebraska, Kansas, Oklahoma and Texas

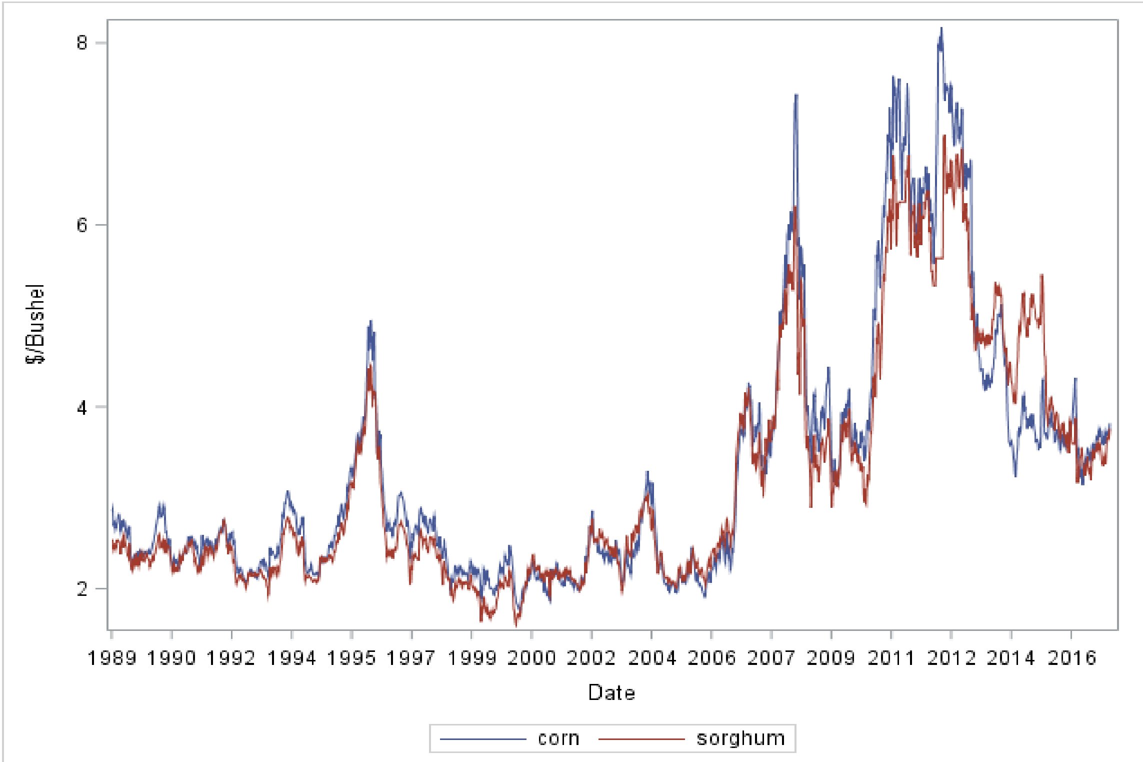

Figure 3.1 Prices of Corn and Sorghum

use the cross-hedging strategy.

Cross-hedging was introduced by Anderson and Danthine (1981) for goods that do not have a functioning futures market. The price risk is hedged by taking a futures position in a related commodity. Because grain sorghum and corn share the same usage in the feed industry and are highly substitutable, prices of corn and sorghum are close to each other. As shown in Figure 3.1, the difference between two prices are small most of times. Therefore, it is common to use the corn futures market to hedge sorghum prices. For instance, a grain sorghum seller who wants to hedge the risk of low sorghum prices can take a short position in the corn futures market, which will compensate for the loss if the price of sorghum falls. The next question—and the most important in the hedging problem—is how to determine the optimal hedge ratio.

The optimal hedge ratio was at first estimated by the ordinary least squares (OLS) regression. Because the OLS estimator suffers from autocorrelation, it was later replaced by the generalized autoregressive conditional heteroskedasticity (GARCH) model. In recent years, the copula model has been proposed to be a good candidate in estimating the hedge ratio for its simplicity and flexibility. This papers applies all three models—OLS, GARCH and copulas—to estimate the hedge ratio and examine their performances. Performances are compared in the degree of reduction in the portfolio variance. Both in-sample and out-of-sample performances are reported. These results should help sorghum traders to decide which model they would like to use and how the model performs in the reduction of the volatility.

The reminder of the paper is organized as follows. Section 2 reviews the literature in the hedging problem.

Section 3 provides a theoretical framework in terms of a trader's utility and the corresponding optimal hedge ratio, as well as the GARCH and copula models used to estimate the ratio. Section 4 presents empirical results for the estimation and hedging performance. Section 5 summarizes the results and the implications of the paper.

3.2 Literature Review

3.2.1 Conventional Hedge Ratio Estimation

The optimal hedge ratio was first estimated by an OLS or GLS regression on the price level or percentage change. In the literature of the agriculture industry, Hayenga and Pietre (1982) used live hog futures to hedge pork prices for wholesale pork producers. Brown and Stewart (1985) used the price difference to decide the hedge ratio in the wheat, corn and soybean markets. Harvey, Ted and Marvin (1986) estimated the optimal hedge ratios using both price differences and price levels in a cross-hedge and showed that the two optimal hedge ratios are significantly different. They argued that regression parameters should be judged by the objective utility function.

3.2.2 Estimation by A GARCH Model

Ordinary price regression suffers from the fact the OLS residuals are often serially correlated. More importantly, the OLS regression implicitly assumes a constant relationship between the spot and the futures prices, which ignores the maturity effect and the change in market conditions (Herbst et al., 1993).[2] To allow for time-varying volatility, Engle (1982) proposed the autoregressive conditional heteroscedasticity (ARCH) model to allow the variance to depend on previous deviations. A more generalized ARCH (GARCH) was proposed by Bollerslev (1986) that allowed the variance to change over the previous estimated variance. Since then, much hedge ratio research has been done using a GARCH model (Baillie and Robert 1991; Myers and Robert 1992).

The univariate GARCH model works well for a single price, but to estimate the optimal hedge ratio between two prices, multivariate models were proposed by Engle and Kroner (1995) to allow the variance and covariance to change over time. In terms of the bivariate GARCH model, Bollerslev (1990) proposed a constant conditional correlation (CCC) GARCH to estimate the correlation of spot and futures prices. Engle and Sheppard (2001) extended the CCC GARCH to the dynamic conditional correlation (DCG) GARCH to allow the correlation to vary over time. The more complicated model is the BEKK model (Baba, Engle, Kraft and Kroner, 1990), which ensures that the variance covariance matrix is positive definite.

Bera, Garcia, and Roh (1997) applied the CCC GARCH, Diagonal VECH GARCH , and BEKK to estimate the optimal hedge ratio in the corn and soybeans markets.[3] Their results suggest that the Diagonal VECH GARCH model has the greatest performance, followed by the OLS estimation and the CCC GARCH model.

[2]The maturity effect implies that the spot and the futures prices converge at maturity and that the price volatility of a futures contract increases as it approaches maturity.

[3]The Diagonal VECH GARCH is a restricted version of the multivariate GARCH where the conditional variance ($h_{11,t}$ and $h_{22,t}$) and covariance ($h_{12,t}$) in the variance covariance matrix H_t only depend on its own lagged squared residuals and lagged conditional variance. More specifically, the conditional variance $h_{11,t}$ only depends on $h_{11,t-1}$ and $\epsilon^2_{1,t-1}$; the conditional variance $h_{22,t}$ only depends on $h_{22,t-1}$ and $\epsilon^2_{2,t-1}$; and the covariance $h_{12,t}$ only depends on $h_{12,t-1}$ $\epsilon_{1,t-1}\epsilon_{2,t-1}$.

The BEKK model works as well as the CCC GARCH model in the in-sample comparison, but much worse in the out-of-sample comparison.

3.2.3 Estimation by A Copula Model

In a multivariate GARCH model, the distribution is often assumed to be joint normal or student's t, both of which have symmetric tail dependence. If the distribution assumption does not hold, then the model cannot be accurately applied. One way to allow for a more flexible joint distribution is to use a copula model. A copula model does not have any assumption on the marginal distributions. This makes the copula a good candidate to capture nonlinear dependency with different marginal distributions. Also, the copula model is able to estimate both symmetric and asymmetric tail dependencies.

Patton (2006) introduced a dynamic copula model that linked the GARCH model and a copula model. The model estimates the marginal distribution by the GARCH model for each price, then applies a copula model to estimate the correlation between the two prices. He used the model to estimate the relationship between different countries' exchange rates and showed that a structural change emerged between the US dollar and the Japanese yen after the Euro was issued. Rodriguez (2007) applied a dynamic copula model with Markov switching parameters to identify the tail dependence during the financial crisis caused by a contagion phenomenon. Wu, Chung and Chang (2010) investigated the correlation between oil price and the exchange rate and demonstrated that a copula-based GARCH model exhibits greater economics benefit of an investor than an OLS and other multivariate GARCH models.

The dynamic copula model has recently been applied in the study of the hedge ratio. Hsu, Tseng and Wang (2008) estimated the hedge ratio by the dynamic Normal, Gumbel and Clayton copula models. They showed that estimates from these copula models have better performance in the reduction of the portfolio variance than the conventional OLS or GARCH models.

In agriculture, Power, Vedenov, Anderson and Klose (2013) proposed a nonparametric copula-based GARCH model to estimate the hedge ratio between cash and futures prices for corn and cattle. They showed that the application of the copula has better performance in terms of tail risk (expected shortfall), but worse in terms of variance reduction than the BEKK model. Zhao and Goodwin (2012) used a dynamic copula model to calculate the hedge ratio of using corn to cross-hedge grain sorghum and wheat to cross-hedge barley. However they did not report the performance of the hedging strategy.

This paper applies methodology similar to that introduced by Zhao and Goodwin (2012) with more detailed analysis of price relationship and hedge effectiveness. Both constant and dynamic copula models are applied to determine the optimal hedge ratio, and hedging performance is compared, both in-sample and out-of sample.

3.3 Model

3.3.1 The Utility Model in the Hedging Problem

For a sorghum trader who wants to hedge the price risk of grain sorghum, he or she can take an opposite position in the corn futures market. The philosophy behind this is to offset losses (gains) in the sorghum market by the gains (losses) from the corn futures market.

The return from a hedging activity depends on the change of sorghum cash prices and corn futures prices from time $t-1$ to t, and the hedge ratio. Let $\Delta s_t = s_t - s_{t-1}$ denote the change of sorghum cash prices and $\Delta f_t = f_t - f_{t-1}$ denote the change of corn futures prices; for each unit of sorghum, if h units of corn is hedged in the futures market, the hedging return x_t on the portfolio is calculated to be:

$$x_t = \Delta s_t + h\Delta f_t \tag{3.1}$$

The objective of a hedging strategy is to maximize a trader's utility given that this trader is risk-averse. Therefore, the optimal hedge units, or the optimal hedge ratio h should depend on a trader's utility function. One of the most popular utility functions in the hedging literature is the mean-variance utility function proposed by Kahl (1983). It derives from the expectation of a concave exponentiation utility function. The mean-variance utility function is defined as:

$$U(x) = E(x) - \frac{\lambda}{2} \cdot Var(x) \tag{3.2}$$

where λ is Arrow-Pratt measure of absolute risk-aversion. More details on the mean-variance utility function can be found in Appendix A.1.

Suppose both prices follow a martingale distribution in which the expectation of the price in the next period equals the present price.[4] The expectation and variance of the return on portfolio x_t at time $(t-1)$ are:

$$\begin{aligned} E_{t-1}(x_t) &= E(s_t) - s_{t-1} + h(f_{t-1} - E(f_t)) \\ Var_{t-1}(x_t) &= \sigma_s^2 + h^2\sigma_f^2 + 2h\sigma_s\sigma_f\rho \end{aligned} \tag{3.3}$$

where σ_s,σ_f and ρ are the standard deviation of two prices and the correlation coefficient respectively.

The optimal hedge ratio h^* is then chosen by maximizing the producer's utility function at time $t-1$:

$$h^* = \arg\min_h \left(E_{t-1}(x_t) - \frac{\lambda}{2} \cdot Var_{t-1}(x_t) \right) \tag{3.4}$$

Taking the first-order condition, the optimal h^* equals:

$$h^* = \frac{f_{t-1} - E(f_t) + \lambda\sigma_s\sigma_f\rho}{\lambda\sigma_f^2} \tag{3.5}$$

From the assumption of martingale distribution, $E(f_t) = f_{t-1}$, the optimal units of the short position are:

$$h^* = \rho\frac{\sigma_s}{\sigma_f} \tag{3.6}$$

The problem then becomes the estimation of the variance and the correlation coefficient of the two prices.

[4]The martingale distribution assumes that the expected value of a random variable equals the presented observed value given all the prior information.

3.3.2 The Multivariate GARCH Model

For a price system, the BEKK model (a multivariate GARCH model named after Baba, Engle, Kraft and Kroner, 1990) is used to estimate the variance and covariance between two prices. It has the advantage of a positive definite variance-covariance matrix, and therefore is considered to be a benchmark for the hedging performance comparison, in addition to the conventional hedge ratio estimator from the OLS regression. The BEKK model assumes that two dependent variables follow a bivariate normal distribution and the variance-covariance matrix depends on the lagged variance-covariance matrix and the lagged squared errors. The bivariate model is given by:

$$Y_t = \beta X_t + \epsilon_t \tag{3.7}$$

where $Y_t = (y_{1t}, y_{2t})'$ is a vector of dependent variable, $\beta = (\beta_{11}, ..., \beta_{1k}; \beta_{21}, ..., \beta_{2k})'$ is the matrix of coefficients and $X_t = (X_{11,t}, ..., X_{1k,t}; X_{21,t}, ..., X_{2k,t})$ is the matrix of independent variables. The errors are assumed to have a bivariate normal distribution

$$\epsilon_t \sim Normal(0, H_t) \tag{3.8}$$

with variance H_t following the equation such that:

$$\begin{aligned} H_t = &\begin{bmatrix} c_{11} & c_{12} \\ c_{12} & c_{22} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}' H_{t-1} \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} + \\ &\begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix}' \begin{bmatrix} \epsilon^2_{1,t-1} & \epsilon_{1,t-1}\epsilon_{2,t-1} \\ \epsilon_{1,t-1}\epsilon_{2,t-1} & \epsilon^2_{2,t-1} \end{bmatrix} \begin{bmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{bmatrix} \end{aligned} \tag{3.9}$$

The second term is an extension of the term p in the univariate GARCH(p, q) model and the third term is the extension to the term q. The diagonal element in the H_t can be written as:

$$\begin{aligned} h_{11,t} =& c_{11} + \alpha^2_{11}\epsilon^2_{1,t-1} + g^2_{11}h_{11,t-1} + \alpha^2_{21}\epsilon^2_{2,t-1} + g^2_{21}h_{22,t-1} \\ &+ 2\alpha_{11}\alpha_{21}\epsilon_{1,t-1}\epsilon_{2,t-1} + 2g_{11}g_{21}h_{12,t-1} \\ h_{12,t} =& c_{12} + \alpha_{11}\alpha_{12}\epsilon^2_{1,t-1} + g_{11}g_{12}h_{11,t-1} + \alpha_{21}\alpha_{22}\epsilon^2_{2,t-1} + g_{21}g_{22}h_{22,t-1} \\ &+ (\alpha_{11}\alpha_{22} + \alpha_{12}\alpha_{21})\epsilon_{1,t-1}\epsilon_{2,t-1} + (g_{11}g_{22} + g_{12}g_{21})h_{12,t-1} \\ h_{22,t} =& c_{22} + \alpha^2_{12}\epsilon^2_{1,t-1} + g^2_{12}h_{11,t-1} + \alpha^2_{22}\epsilon^2_{2,t-1} + g^2_{22}h_{22,t-1} \\ &+ 2\alpha_{12}\alpha_{22}\epsilon_{1,t-1}\epsilon_{2,t-1} + 2g_{12}g_{22}h_{12,t-1} \end{aligned} \tag{3.10}$$

The first three terms are the GARCH(1, 1) model for the univariate model; the other terms show the dependency of the variance of one price on the variance of another price and the covariance.

The price return Δp_t is calculated as 100 multiplied by the log difference of the price p_t to increase the estimation accuracy:

$$\Delta p_t = 100 * (log(p_t) - log(p_{t-1})) \tag{3.11}$$

Prices of agricultural commodities are often integrated of order one, which means prices are nonstationary. Therefore, the augmented Dickey-Fuller (1979) tests are used to examine the unit root for each price. Because grain sorghum is a good substitute for corn, prices are likely to be cointegrated. Cointegration implies that there is a long-run equilibrium between two prices. In time series, variables are defined to be cointegrated if each variable is integrated of order one, but a linear combination of these variables is stationary. For grain sorghum and corn, if both prices have a unit root, the cointegration relation can be examined by the augmented Dickey-Fuller (1979) tests on the OLS residual of one price on the other, as well as the Phillips-Ouliaris (1988) tests and Johansen (1990) rank tests for two prices. Given a cointegration relationship, a vector error correction model (VECM) is applied. For each price, it is assumed to only respond to the disequilibrium term; therefore only the error term is added to the regression model. To be more specific, a bivariate VECM model is defined as:

$$\begin{cases} \Delta s_t = \alpha_s + \beta_s \hat{\mu}_{t-1} + \epsilon_{1t} \\ \Delta f_t = \alpha_f + \beta_f \hat{\mu}_{t-1} + \epsilon_{2t} \end{cases} \tag{3.12}$$

where Δs_t and Δf_t are the log price difference of sorghum and corn prices, respectively; $\hat{\mu}_{t-1}$ is the estimated OLS residual from $s_t = \beta f_t + \mu_t$; and $(\epsilon_{1t}, \epsilon_{2t})$ follows the joint normal distribution defined in equations 8 and 9.

3.3.3 Copula Models with Univariate Normal and T GARCH Errors

The joint distribution of multiple variables can be estimated by a copula function and its own marginal distribution. By Sklar's theorem (1959), the multivariate cumulative distribution function

$$H(x_1, ..., x_k|\Theta) = P(X_1 \leq x_1, ..., X_k \leq x_k|\Theta) \tag{3.13}$$

can be written as

$$H(x_1, ..., x_k|\Theta) = C(F_1(x_1), ..., F_k(x_k)|\Theta) \tag{3.14}$$

where $C(\cdot)$ is a copula distribution function, Θ is the set of model parameters and $F_i = P[X_i \leq x_i|\Theta]$ is the marginal cumulative distribution function (CDF) for variable i.

The probability density function (PDF) can be calculated from the CDF defined in equation 3.14 as:

$$h(x_1, ..., x_k|\Theta) = c(F_1(x_1), ..., F_k(x_k|\Theta) \cdot f_1(x_1|\Theta) \cdot ... \cdot f_k(x_k|\Theta) \tag{3.15}$$

The log-likelihood function is then defined as:

$$LLF(x_1, ..., x_k|\Theta) = ln(c(F_1(x_1), ..., F_k(x_k)|\Theta) + ln(f_1(x_1)|\Theta) + ... + ln(f_k(x_k)|\Theta) \tag{3.16}$$

Suppose a bivariate joint distribution $H(x, y|\Theta)$ has a copula function $C(F_x(x), F_y(y)|\Theta)$ with marginal distributions where $u = F_x(x)$ and $v = F_y(y)$, then the CDF and PDF of the joint distribution can be written as

$$\begin{aligned} H(x, y|\Theta) =& C(F_x(x), F_y(y)|\Theta) = C(u, v|\Theta) \\ h(x, y|\Theta) =& c(u, v|\Theta) \cdot f(x|\Theta) \cdot f(y|\Theta) \end{aligned} \tag{3.17}$$

and its log-likelihood function is

$$LLF(x, y|\Theta) = ln(c(u, v)|\Theta) + ln(f(x)|\Theta) + ln(f(y)|\Theta) \tag{3.18}$$

The likelihood function is usually maximized in two steps to simplify calculation under the full likelihood function. The first step is to estimate the marginal distribution by maximizing $ln(f(x)|\Theta_x)$ and $ln(f(y)|\Theta_y)$ separately. The second step is to estimate the copula function by maximizing the likelihood function $ln(c(u,v)|\hat{\Theta}_x,\hat{\Theta}_y,\Theta_c)$ given the estimates $\hat{\Theta}_x$ and $\hat{\Theta}_y$ in the first step. As Patton (2006) noted, the estimates are consistent and asymptotically normal under standard conditions.

If prices are conitegrated, the marginal distribution of each price can be estimated by a univariate error correction model with a GARCH error term. A univariate error correction model is defined as:

$$\Delta y_t = \alpha + \beta \hat{\mu}_{t-1} + \epsilon_t \tag{3.19}$$

where $\hat{\mu}_{t-1}$ is the estimated OLS residual and the error term ϵ_t follows a normal or t distribution with mean 0 and variance h_t. The variance term h_t in a GARCH (p,q) model follows the equation:

$$h_t = c + \sum_{i=1}^{q} \alpha_i \epsilon_{t-i}^2 + \sum_{j=1}^{p} \gamma_j h_{t-j} \tag{3.20}$$

In the second step, the two estimated error terms ϵ_{1t} and ϵ_{2t} are transformed to u_t and v_t by the inverse normal or t CDF. Copula coefficients are then estimated by the copula likelihood function.

The candidate bivariate copula models include a normal, Student's t, and three Archimedean families of copulas—Clayton, Frank and Gumbel. Among these copulas, normal, student's t and Frank copula have symmetric tail dependence, and the Clayton and Gumbel copulas have asymmetric tail dependence. Tail dependence should affect the linear correlation of two prices under extreme conditions, but is not studied because this paper focuses more on the hedging activity at all times rather than a specific period of time. Because the joint distribution depends on both the copula and marginal distributions, different correlation coefficients can be estimated by selecting either a different copula or different marginal distributions. Therefore, models with different copulas and marginal distributions are examined in the paper and the main purpose is to find the model that can best describe the linear correlation between two or more prices and apply it in the daily hedging activity. The CDF and PDF of all copula models are summarized in Table **??**.

3.3.4 Time-Varying Copula Model

It is possible that parameters in copulas change from time. Therefore, two dynamic copula models defined by Patton (2006) are considered to capture the variation of parameters by time. The first is the Gaussian copula with symmetric tail dependence, and the other is the Gumbel Copula with the asymmetric tail dependence.

In the GARCH model, the variance is allowed to depend on the lagged estimated variance and the lagged squared errors. Similarly, the copula coefficient ρ in the Gaussian copula and θ in the Gumbel copula are set to depend on its lagged value and the lagged conditional covariance.

The coefficient in the dynamic Gaussian copula is defined as:

$$\rho_t = z\left(w_\rho + \beta_\rho \rho_{t-1} + \alpha \frac{1}{q} \sum_{j=1}^{q} F_u^{-1}(u_{t-j}) \cdot F_v^{-1}(v_{t-j}) \right) \tag{3.21}$$

where $F_u^{-1}(\cdot)$ and $F_v^{-1}(\cdot)$ are the inverse CDF of the marginal distribution of u and v, and $z(x) \equiv (1-e^{-x})(1+$

$e^{-x})^{-1} = tanh(x/2)$ is the function that keeps ρ in the range of $(-1, 1)$.

For the dynamic Gumbel copula, the coefficient θ equals:

$$\theta_t = k\left(w_\theta + \beta_\theta \theta_{t-1} + \alpha \frac{1}{q}\sum_{j=1}^{q} F_u^{-1}(u_{t-j}) \cdot F_v^{-1}(v_{t-j})\right) \tag{3.22}$$

where $k(x) \equiv 1 + x^2$ to keep the variable θ in the range of $[1, \infty)$

Here, only the first lag of the coefficient is considered, so the model is similar to the multivariate GARCH model with $p = 1$ and $q = 1$. This should make the comparison more robust as the assumption of the lag dependency is same for different models.

3.4 Empirical Results

Corn prices are measured as the nearby futures from the Chicago Board of Trade (CBOT), and sorghum cash prices are measured from Gulf Coast. The data are obtained from the Commodity Research Bureau (CRB). Weekly prices from January 1989 to June 2017 are used, as daily cash prices often show little or no change. The summary statistics are presented in Table 4.1. For each price, the mean of price difference is close to zero and the standard error is significantly large compared to the mean, which shows high volatility in the price itself.

3.4.1 Results from Cointegration Tests and the BEKK GARCH Model

The ADF tests are applied to each price to check the existence of the unit root. The lag is selected to be one week or one month (4 weeks). The large p-values in table 3.3 indicate that we fail to reject the null of a unit root, which means that prices are nonstationary.

Therefore, cointegration test are applied and results are summarized in Table 3.4. Strong cointegration relations are observed between corn and grain sorghum, since all six tests reject the null hypothesis of no cointegration. This implies that there is a long run equilibrium between corn and sorghum prices.

Due to the cointegration relationship, the BEKK model is estimated based on the vector error correction model defined in equation 3.12, with the variance-covariance matrix defined in equation 9. Results are presented in Table 3.5.

In theory, adjustment coefficients for the sorghum price should be negative to eliminate the disequilibrium caused by corn prices, but the estimate is a positive number, though not statistically significant. This may imply that the return on the sorghum price is unpredictable. For corn futures prices, the adjustment coefficient is large and significant, which indicates that the nearest futures price of corn may depend on the disequilibrium between the sorghum spot price and corn price.

Results from the BEKK model indicate that the variance of each price mostly depends on the lag variance of two prices rather than the lag covariance, as the coefficients $\alpha_{12}, \alpha_{21}, g_{12}, g_{21}$ are relatively small compared to coefficients $\alpha_{11}, \alpha_{22}, g_{11}, g_{22}$. The estimated variance of each price is presented in Figure 3.2. In the figure, several price volatilities hikes are observed. The first is the 2008-2009 period. In this period, prices of agricultural commodities spiked in early 2008 due to the food crisis and later decreased dramatically due to the financial crisis.[5] The second hikes is observed for the sorghum in September. This hike is caused by the data.

[5]According to the International Food Policy Research Institute, the major causes of the 2007-2008 food crisis include

Prices changes for sorghum were zero from June to September in 2012, and these changes accumulated and finally occurred in September, which leads to a large volatility. The last is between the mid-2013, when corn prices were decreased by the high production forecast and the proposal of a reduction in biofuel mandate by the Environmental Protection Agency.

It is complicated to calculate the single effect of each variable, such as lagged variance or covariance, on the conditional covariance term; therefore, the correlation coefficient from the BEKK model is presented in Figure 3.2.

The correlation coefficient is stable most of the time, as it moves up and down from the average correlation coefficient of 0.81. In July 1996, the corn price took a huge fall. The price was decreased by 16% in one week and that probably caused a negative correlation. The low correlation coefficients in July 2011 and July 2012 are caused by zero changes in the sorghum prices in the data. Because sorghum prices changes kept zero for several weeks, the model assumes that corn prices were not related to sorghum prices in these periods. The low correlation coefficient in July 2013 is caused by other factors, as data do show price changes in each week during mid-2013. The low correlation coefficient in mid-2013 was likely caused by the high volatility of each price, especially when unexpected events happened to only one price. For instance, the expectation of China's ban on GM corn from the US increased the volatility of corn prices but had no effect on the sorghum prices, which could leave the two prices unrelated during that time. Other causes for corn price volatility include the high forecast production and the biofuel policy, as mentioned above. Another notable feature is that China started to increase its imports of sorghum from the US in 2013. The total amount of sorghum imported was 0.89 million tons in 2013, 4.15 million tons in 2014, and 8.15 millions in 2015. This increase in the US exports of sorghum should weaken the correlation between the two prices in the US, as the export in 2015 accounted for one third of the sorghum production and prices should partly depend on the demand from China.

3.5 A Copula Model with GARCH Errors

For each price, the variance of the error term is estimated by the univariate GARCH model with the error correction model defined in equation 19. Both normal and t distributions are considered for the error term. Therefore, the marginal distribution of the two prices is assumed to be normal or t. The relation between two variables is then estimated by the copula model.

Results of the normal GARCH and t GARCH models are summarized in Table 3.6. Estimates of the error correction model are a little better than the BEKK model, as the adjustment coefficient for the sorghum price becomes negative, though is still not significant. Results for corn are similar to the BEKK model, as the adjustment coefficients in both models are positive and significant.

In the GARCH model, the GARCH term is larger than the ARCH term, which indicates that the conditional variance depends more on its lagged value than the previous innovation. This should decrease the volatility of the price in the short turn, as the variance depends more on long-term volatility.

The volatility of the two prices is presented in Figures 3.4 and 3.5. Results are consistent with the BEKK model, as high volatility is observed during 2008-2009 and 2011-2013.

"...rising energy prices, the depreciation of the U.S. dollar, low interest rates, and investment portfolio adjustments in favor of commodities" (Headey and Fan, 2010).

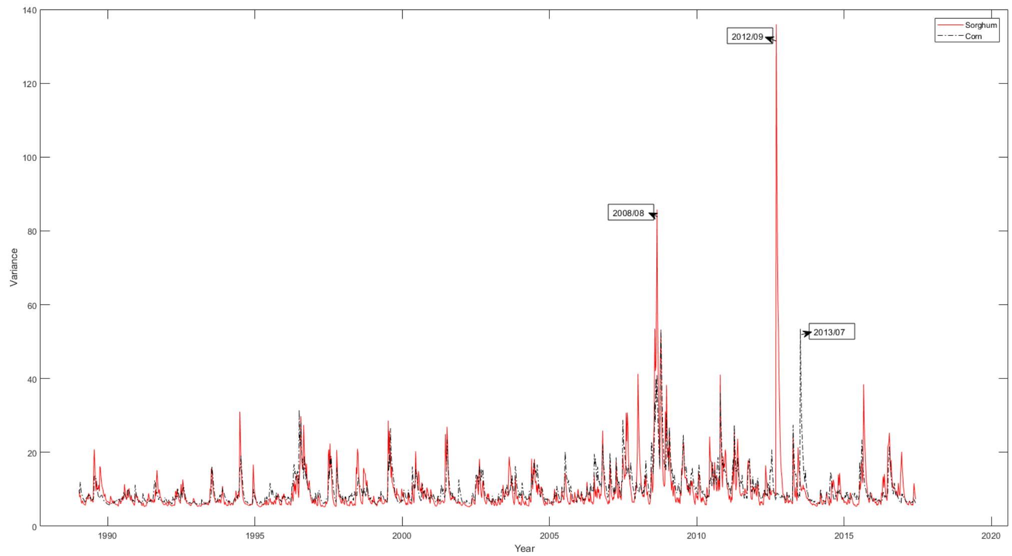

Figure 3.2 Estimated Volatility from the BEKK Model

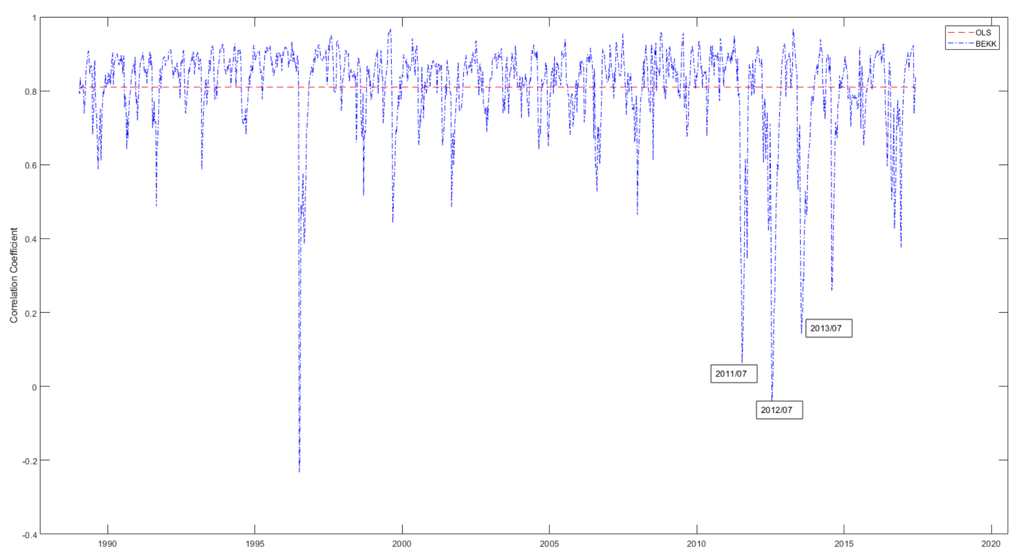

Figure 3.3 Correlation Coefficient from the BEKK Model

To estimate the copula model, each price variable is transformed by the inverse of its marginal CDF. Therefore, the transformed variables are in the range of (0,1) and presented in Figures 3.6 and 3.7. Both figures show a strong correlation between the two transformed variables.

The copula models with the transformed variables are estimated by MLE using the copula density function defined in Table 3.1.[6] The dynamic copula is also estimated by the MLE with the parameters defined in equation 3.21 and equation 3.22. Because the variance-covariance matrixes in the BEKK model are conditional on the variables lagged by one period, the lag term q in the dynamic copula is also set to be one for comparison purpose. Estimated results are presented in Table 3.7 and coefficients are close in the two models, which indicates that the copula parameters does not change much by the marginal distribution. In the dynamic model, both results suggest that the copula parameter mainly depends on the constant term w and the lag innovation of the covariance represented by α. Also, a large covariance tends to decrease the copula parameter. To be more specific, a large covariance (e.g, $\Phi^{-1}(u) \cdot \Phi^{-1}(v)$) is often caused by high volatility in one or two prices, and a smaller copula parameter leads to a lower correlation coefficient between two prices. Therefore, the result suggests that a high volatility in the price decreases the correlation between two prices, which should be true if the abnormal high volatilities of the prices are assumed to be independent. If the high volatility is caused by market conditions or systemic risk, then the model might not work well. For example, during the financial crisis, both prices have high volatility, which leads to a large coefficient in the copula model, but the true correlation is not likely to change.

Estimated dynamic copula parameters ρ and θ are presented in Figures 3.8, 3.9, 3.10 and 3.11. In both models, the copula parameters estimated from the t GARCH is larger than the normal GARCH, which indicates that the correlation is stronger if the marginal distribution follows t distribution. The dynamic normal copula shows little variation in the parameter, as the change in the correlation coefficient ρ is small across time. The θ in the dynamic Gumbel copula has larger fluctuation, which means the parameter is very sensitive to the lagged covariance between two prices. The correlation coefficient corresponding to the Gumbel copula parameter is presented in Figures 3.12 and 3.13. Both figures indicate a lower correlation coefficient in 2011-2013, which is consistent with the BEKK model.

3.6 Hedging Performance

Hedging performance is compared in terms of the variance of the portfolio, defined as:

$$Std(\Delta s_t + \hat{h}_t^* \Delta f_t) \tag{3.23}$$

The optimal OLS hedge ratio is estimated by standard regression: $\Delta s_t = \alpha + h * \Delta f_t + \mu_t$. The hedge ratio in the BEKK model can be easily calculated as the estimated covariance over the variance of the futures price $\hat{h}_t^* = \frac{cov_{t-1}(\Delta s_t, \Delta f_t)}{var_{t-1}(\Delta f_t)}$. The optimal hedge ratio from all other models is calculated from equation 3.6.

In the copula model, the variance of each price is calculated by the normal or t GARCH models. Because the joint distribution combines a copula function and two marginal distributions, the correlation coefficient does not have a closed form expression. Therefore, the correlation is calculated by numerical integration with respect to the joint probability density function (Hsu, Tseng and Wang, 2008). By definition, the correlation

[6]For normal and t copula, the correlation coefficient is estimated by KendallâĂŹs τ instead of the MLE for simplicity.

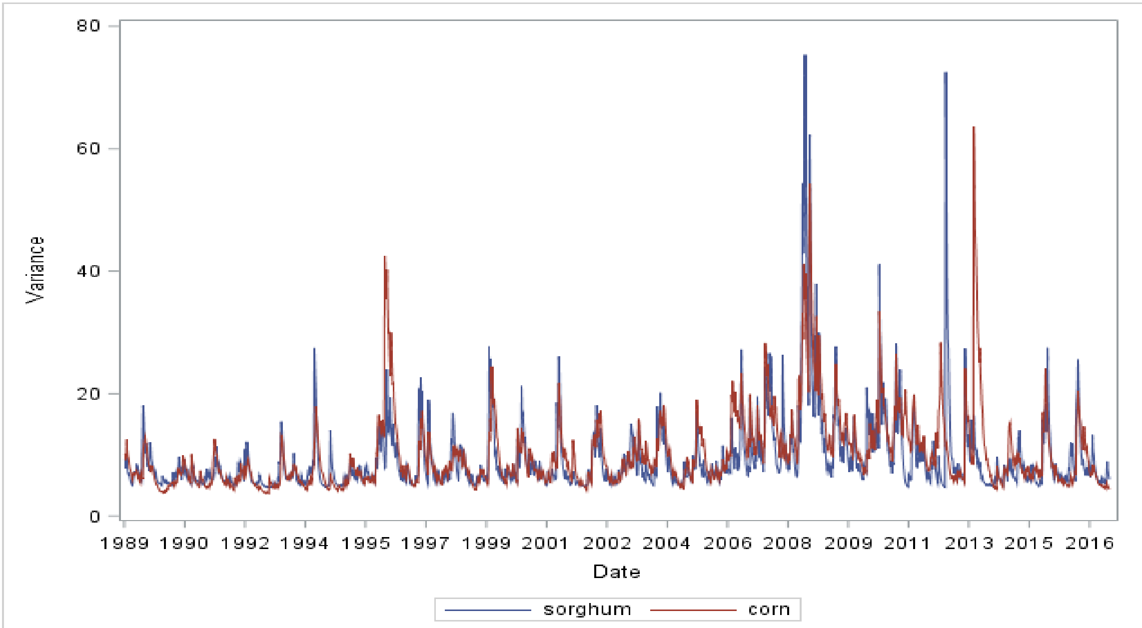

Figure 3.4 Estimated Volatility from the Normal GARCH Model

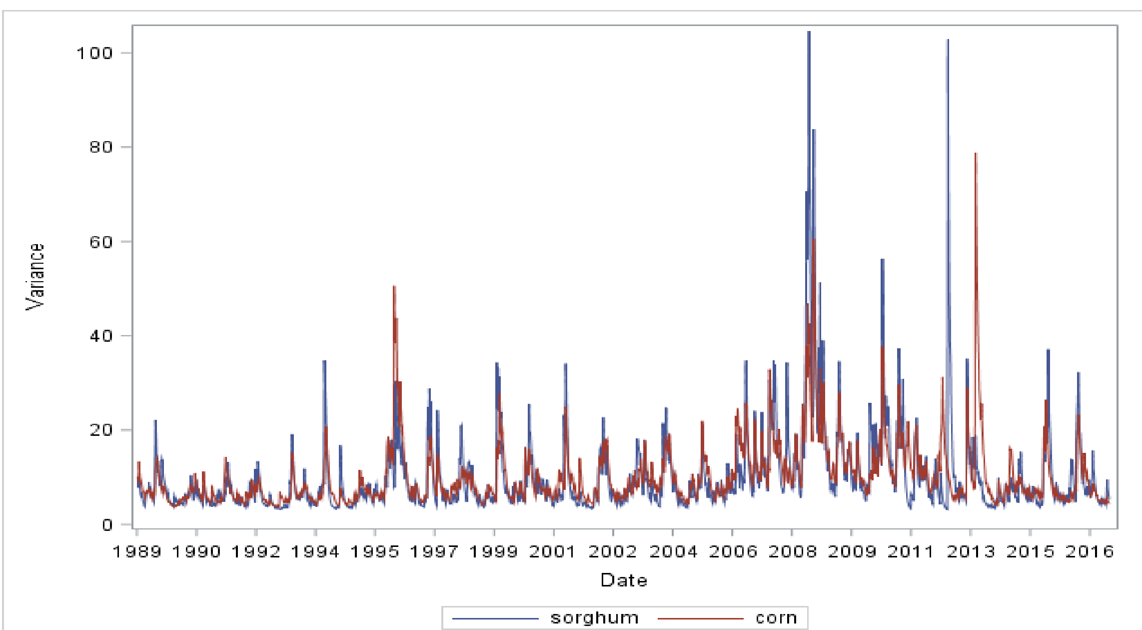

Figure 3.5 Estimated Volatility from the t GARCH Model

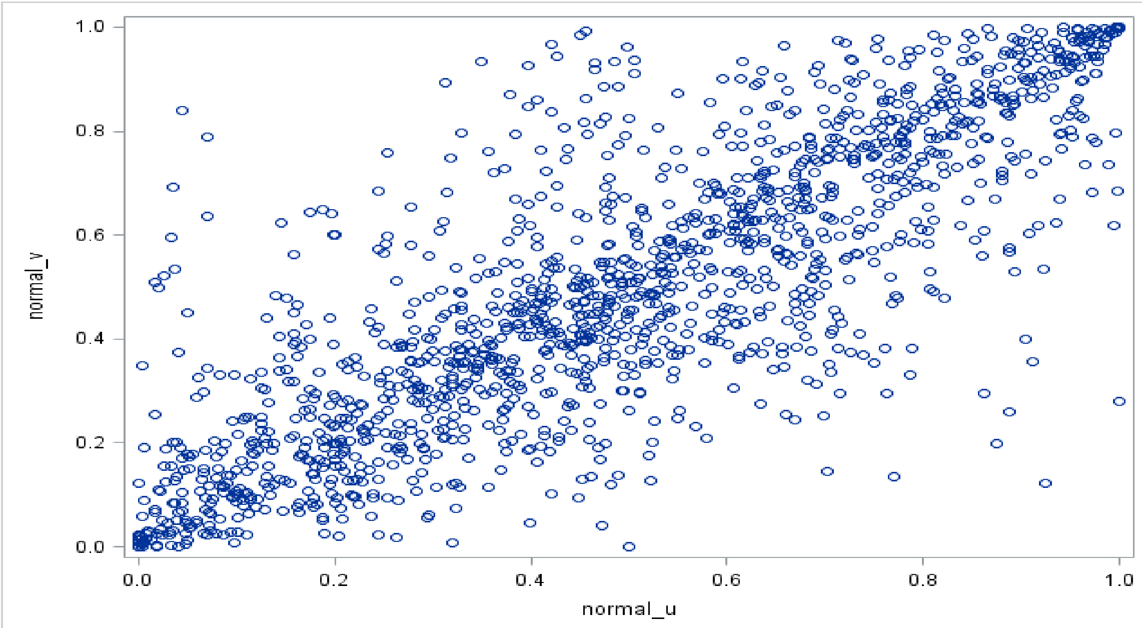

Figure 3.6 u and v from the Normal GARCH Model

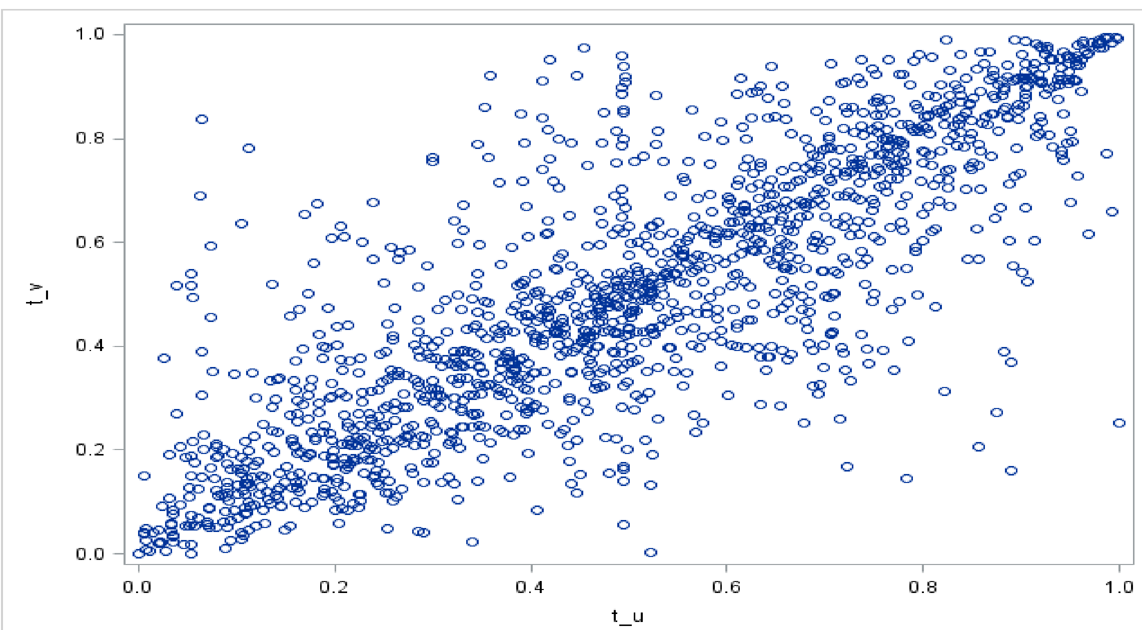

Figure 3.7 u and v from the t GARCH Model

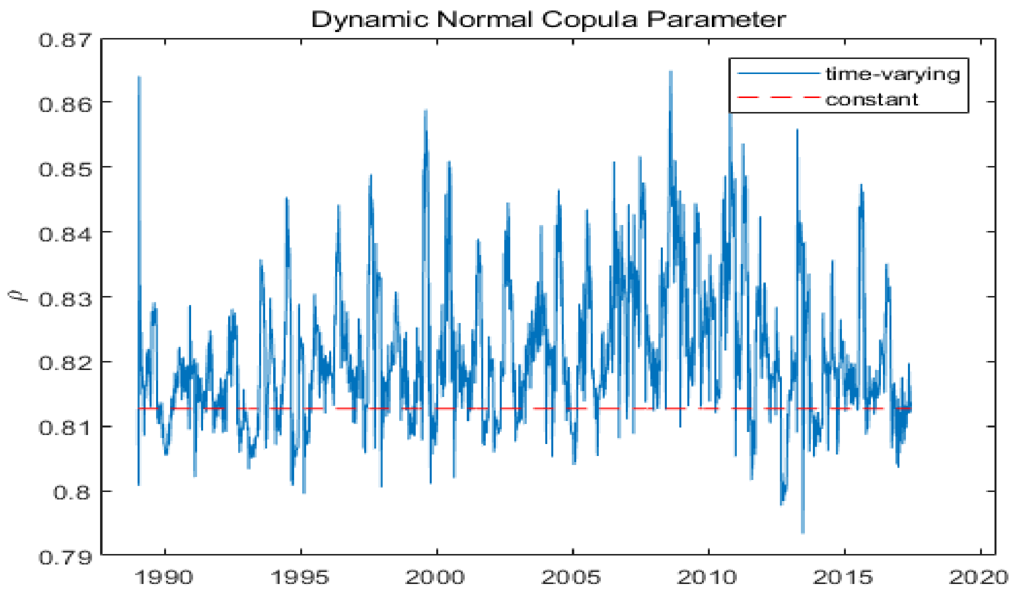

Figure 3.8 Dynamic Normal Copula from the Normal GARCH Model

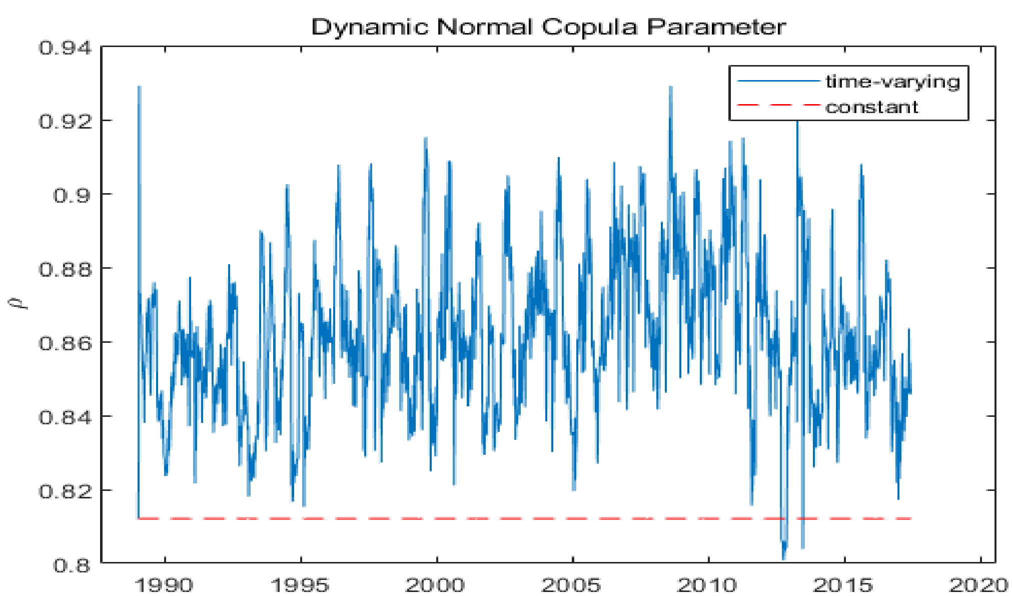

Figure 3.9 Dynamic Normal Copula from the t GARCH Model

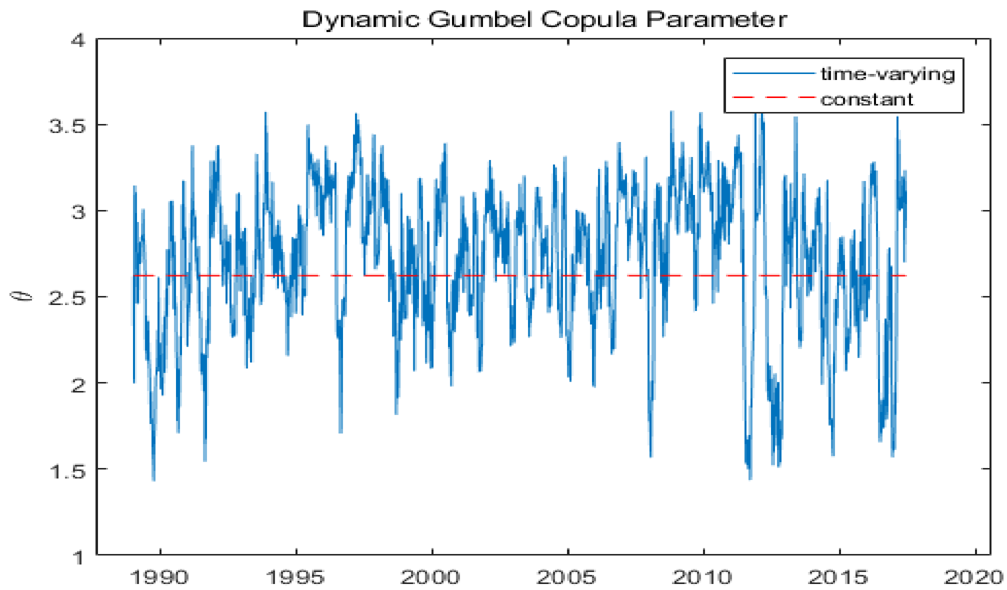

Figure 3.10 Dynamic Gumbel Copula from the Normal GARCH Model

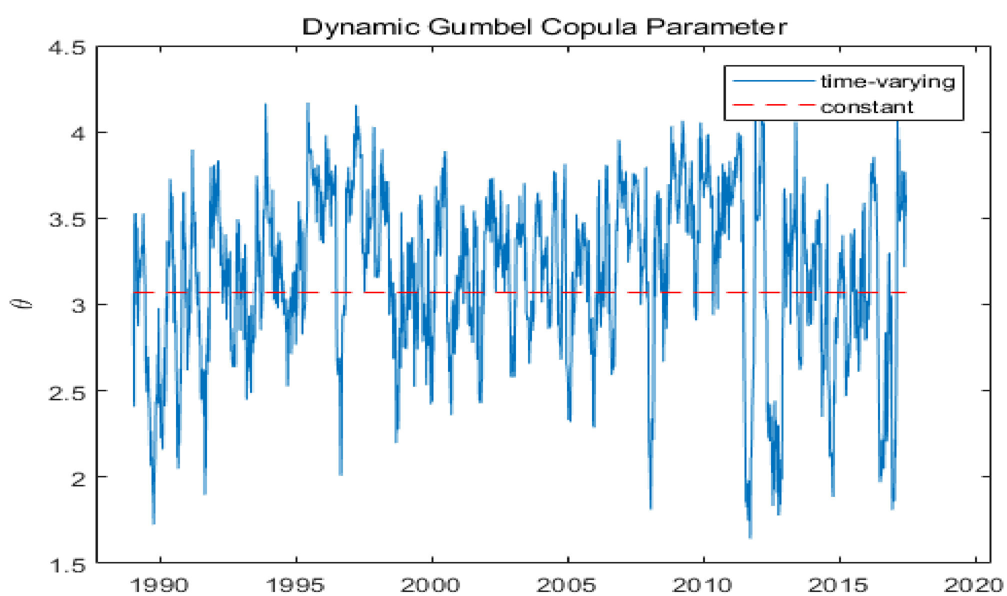

Figure 3.11 Dynamic Gumbel Copula from t GARCH Model

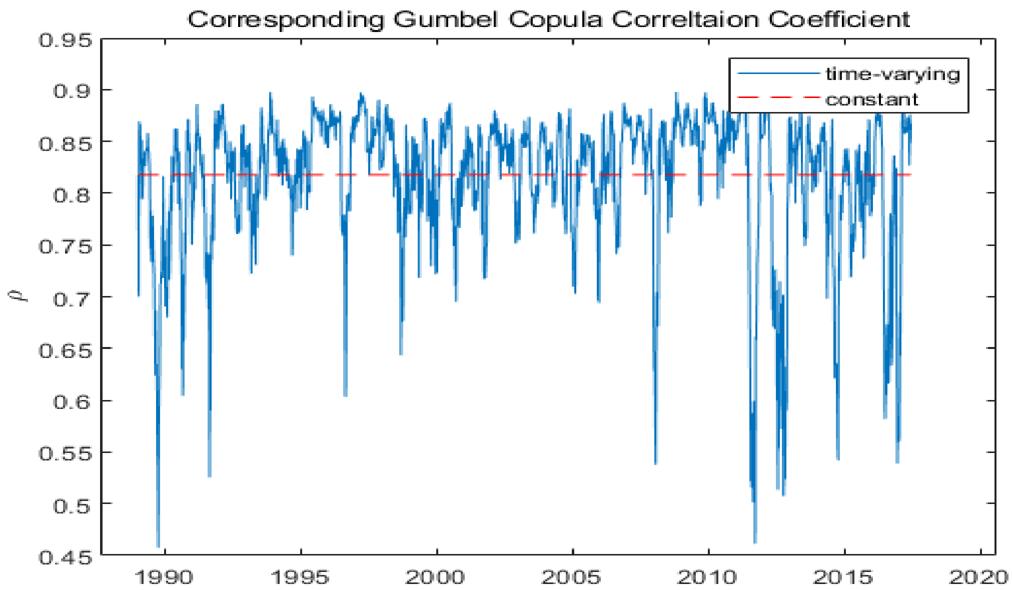

Figure 3.12 Dynamic Gumbel Copula from the Normal GARCH Model

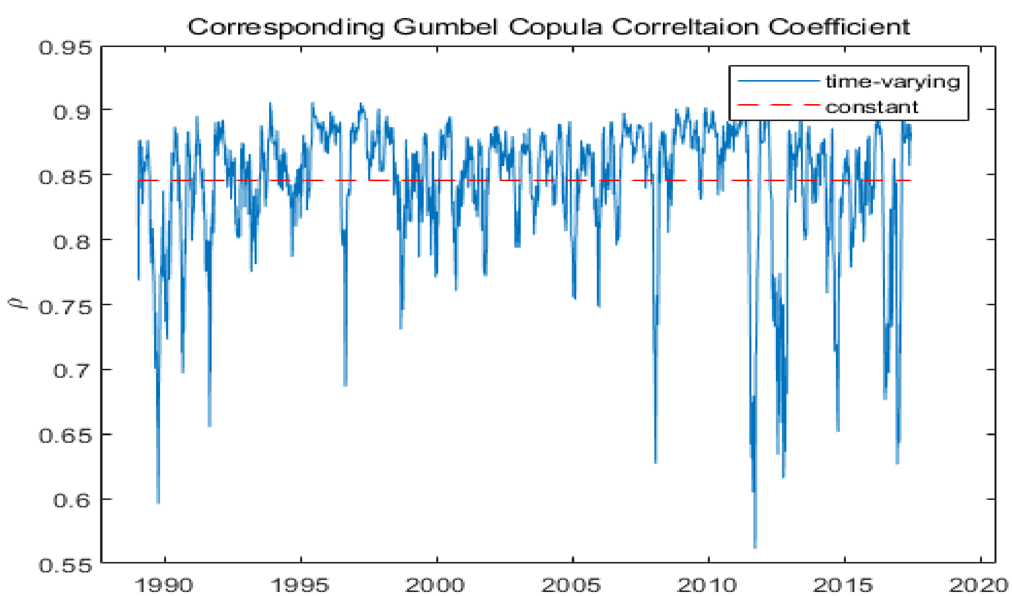

Figure 3.13 Dynamic Gumbel Copula from t GARCH Model

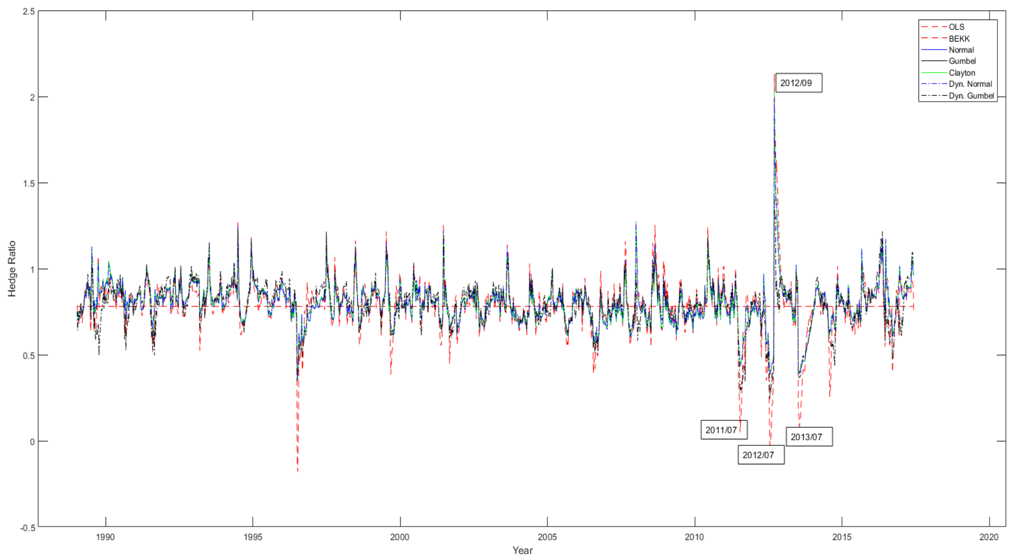

Figure 3.14 Hedge Ratio From Normal GARCH Errors

coefficient between two variables with joint probability distribution $h_t(x1, x2|\Phi)$ at time t can be calculated as:

$$\rho_t = \frac{Cov_t(x_1, x_2)}{\sqrt{\sigma_{x_{1t}}\sigma_{x_{2t}}}} = \frac{\int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x_1 x_2 h_t(x_1, x_2|\Phi) d x_1 d x_2}{\sqrt{\sigma_{x_{1t}}\sigma_{x_{2t}}}} \tag{3.24}$$

The joint probability density function is achieved by the product of a copula function and two marginal distributions as defined in equation 3.17. The denominators, $\sigma_{x_{1t}}$ and σ_{x2t}, are the standard deviation calculated from the marginal distribution (e.g, normal GARCH and t GARCH).

Hedging ratios for different models are presented in Figure 3.14 and 3.15. Most hedging ratios are smaller than one, as corn prices are often a little higher than sorghum prices. Hedging ratios from the BEKK are more volatile than copula models, as the variance and covariance matrixes depend on more variables than in copula models. Hedging ratios from different copula models are close to each other. Extreme hedging ratios are observed during the period when the correlation coefficient are low. As mentioned above, the abnormal hedging ratio in mid-2011 and mid-2012 are caused by the several consecutive zero difference data. The low hedging ratio in mid-2013 is caused by unexpected events and policies regarding both crops.

3.6.1 In-sample Comparison of Hedging Performance

This section provides the results of the hedging performance using all samples in the data. The hedging performance is calculated on the basis of one week, two weeks, one month, and three months to reflect both short-term and long-term behavior.[7] Results are summarized in Table 3.8. The hedge ratio estimated by

[7]The optimal hedging ratio for one month or three months could be different unless the one-period price changes are serially independent and stationary (Chen et.al, 2004).

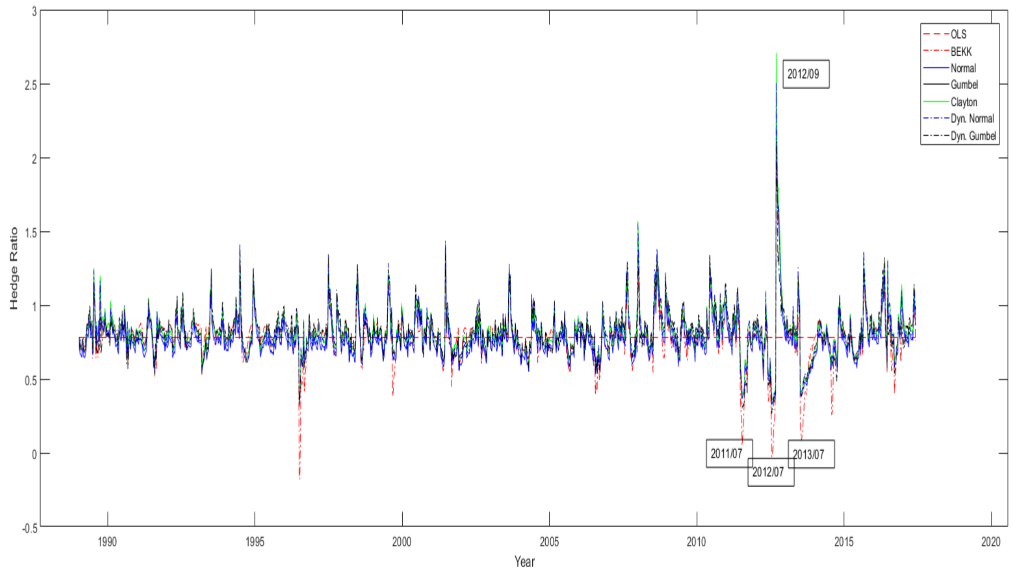

Figure 3.15 Hedge Ratio From t GARCH Errors

OLS regression outperforms most of the models, except for the Clayton copula, which has the best hedging performance across all models. For a one-week performance, the Clayton copula reduces the standard deviation more than the OLS model by 0.0023, or approximately 4.4%. For three months, the difference is 0.0115, or approximately 5.33%.

Compared to other copulas, the Clayton copula has greater lower tail dependence than upper tail dependence, which indicates a larger probability for two variables to be in the left tail than the right.[8] Assuming the log price difference follows a normal or t distribution, area in the left tail implies huge decreases in the prices. Therefore, the Clayton copula assumes that large decreases in both prices are more likely to occur than large increases in both prices. On the contrary, normal, t and Frank copulas have symmetric tail dependence and the Gumbel has larger upper tail dependence than left tail. Therefore, if the true correlation has the characteristic that decreases in prices are more related to each other than increases, the Clayton copula is likely to capture this characteristic and present better results.

It is surprising to observe that dynamic copula models often perform worse than the nondynamic ones. One possible explanation is that the dynamic model does not capture the true correlation when there is a systemic risk, or the true correlation is more stable and the estimated correlation coefficient is too sensitive to the price volatility.

[8] If random variables X and Y follow the copula distribution function C with marginal distribution F_x and F_y, lower tail dependence is defined as: $\lambda_L = \lim_{u\to 0^+} Pr(F_x < u|F_y < u) = \lim_{u\to 0^+} \frac{C(u,u)}{u}$. Upper tail dependence is defined as: $\lambda_U = \lim_{u\to 1^-} Pr(F_x > u|F_y > u) = \lim_{u\to 1^-} \frac{1-2u+C(u,u)}{1-u}$.

3.6.2 Out-of-sample Comparison of Hedging Performance

In-sample models are often criticized for the overfitting issue, especially in the forecast area, and a model with good in-sample performance does not necessarily demonstrate good out-of-sample performance. Therefore, an out-of-sample comparison is conducted in this section. The out-of-sample comparison removes the last 100 observations from the data, or approximately two years. For each observation being removed, the hedge ratio is estimated using all previous data. This method ensures that each out-of-sample estimation uses all of the available information. More specifically, data from 07/15/2015 to 06/06/2017 are first taken out from the whole dataset. The hedge ratio for 07/15/2015 is estimated using all the data before it (from 01/01/1989 to 07/08/2015). For the next observation on 07/22/2015, the estimation adds the data for 07/15/2015 to the model. By continuously updating the dataset in the model, 100, 99, 97 and 89 hedging outcomes are computed for one week, two weeks, one month, and three months.

Standard deviations of the return on these out-of-sample data are presented in Table 3.9. The out-of-sample comparison still favors the Clayton copula, as it shows the minimum standard deviation of all the models. Unlike in the in-sample comparison, the OLS hedging estimator is worse than most of the models. The second-best hedging estimator is the BEKK model, which is also considered to be a benchmark in the comparison. Compared to the BEKK model, the Clayton copula reduced the standard deviation more by 0.001, or approximately 2.30%, in one week of hedging and 0.0018, or approximately 1.61%, in three months of hedging. The performance of the dynamic copula model is still worse or equal to the nondynamic copula model, which suggests that it does not capture the correlation well across time.

3.7 Conclusion

Grain Sorghum is an important animal feed in the livestock industry and considered to be good substitute for corn. Because there is no futures market for grain sorghum, it is a good option for sorghum traders to hedge the price risk by corn futures, as two prices are highly related. The most important question in this hedging problem is to find the optimal hedge ratio for the traders.

The optimal hedge ratio derives from the popular mean-variance utility function and is decided by the variance and correlation coefficient between grain sorghum spot prices and corn futures prices. The traditional estimation methods include the OLS and multivariate GARCH models, where the joint distribution is often assumed to be normal. This paper applies a copula model to estimate the variance and correlation coefficient between two prices. Application of a copula model allows a more flexible joint distribution for the two prices. The marginal distribution of each price is assumed to be normal or t, and is estimated by the GARCH model. A dynamic property is also added to the copula model to allow for time variation of the copula parameter. After that, the correlation coefficient is computed by numeric integration over the full probability density function of the joint distribution. Finally, the hedge ratio is calculated with the variance from the marginal distribution and the correlation coefficient from the joint distribution.

Hedging performance is compared based on the reduction in the variance of the portfolio for both in-sample and out-of-sample cases. The conventional OLS and multivariate GARCH hedging estimators are used as benchmarks. Most copula models have better performances than the OLS estimator but worse than the multivariate GARCH model in the out-of-sample comparison. Among all the models, the Clayton copula has the best performance for both in-sample and out-of-sample comparisons. It is surprised to find that performance of a dynamic copula model is often similar to the nondynamic ones, especially for the dynamic Gumbel copula where the estimated parameter has a relative large variation. It is possible that the dynamic model does not capture the true variables that affect the conditional copula parameter, as only the lagged covariance and lagged copula parameter are used in the model.

The contribution of the paper lies in the hedging concept. It provides sorghum traders a new method to estimate the hedge ratio. The estimation from the Clayton copula can reduce the variance of the portfolio more than the OLS and multivariate GARCH models. For example, if a grain sorghum trader wants to buy sorghum in one week and hedge the price risk of sorghum using corn futures, the out-of-sample performance indicates that the standard deviation for the portfolio is 4.54% for the conventional OLS estimator and 4.25% for the Clayton copula. Suppose the trader is risk-averse and has the mean-variance utility, a decrease in the variance of the portfolio should increase his or her utility. By applying the Clayton copula, the risk of the portfolio is mostly decreased and the producer's utility is maximized.

The copula models with GARCH errors used in this paper can also be applied in other hedging studies, as the flexibility of a copula model is likely to improve the hedging performance. Although some copula models do not perform better compared to the OLS or multivariate GARCH models, the copula model still shows promise in providing a better hedge ratio estimator in the hedging problem and should be noticed in the risk management.

Table 3.1 Bivariate Copula Model

Type	$C(u,v,\theta)$	$c(u,v,\theta)$	$Paramters$
Normal	$\Phi(\Phi^{-1}(u),\Phi^{-1}(u),\rho)$	$\frac{\phi(\Phi^{-1}(u),\Phi^{-1}(v),\rho)}{\phi(u)\phi(v)}$	$\rho\in(-1,1)$
Student's t	$T_v(T_v^{-1}(u),T_v^{-1}(v),\rho)$	$\frac{t_2(T_v^{-1}(u),T_v^{-1}(v),\rho)}{t_v(T_v^{-1}(u))t_v(T_v^{-1}(v))}$	$\rho\in(-1,1)$ $v>2$
Clayton	$w^{-1/\theta}$ $w=u^{-\theta}+^{-\theta}-1$	$(\theta+1)(uv)^{-(\theta-1)}w^{-1/\theta-2}$	$\theta\in(0,+\infty)$
Frank	$\log[1+\frac{w_u w_v}{e^{-\theta}-1}]$ $w_u=e^{-\theta u}-1$ $w_v=e^{-\theta v}-1$	$\frac{-\theta(e^{-\theta}-1)e^{-\theta(u+v)}}{(e^{-\theta}-1+w_u w_v)^2}$	$\theta\in(-\infty,\infty)\setminus\{0\}$
Gumbel	$e^{-w^{1/\theta}}$ $w=(-\log u)^{\theta}+(-\log v)^{\theta}$	$\frac{C(u,v,\theta)(w^{1/\theta}+\theta-1)}{uv\cdot w^{(2-1/\theta)}(\log u\log v)^{1-\theta}}$	$\theta\in[1,\infty)$

Table 3.2 Summary Statistics for Prices

	# of Obs.	Mean	Std. Err	Min	Max
Corn Price	1496	3.3174	1.4296	1.7590	8.1755
Corn Price (Log)	1496	1.1244	0.3687	0.5647	2.1011
Corn Price Return (Log)	1495	0.0195	3.1415	-22.4528	13.4527
Sorghum Price	1496	3.1979	1.2902	1.6010	6.9850
Sorghum Price (Log)	1496	1.0927	0.3605	0.4706	1.9438
Sorghum Price Return (Log)	1495	0.0264	3.0631	-14.6556	20.8449

Table 3.3 ADF Test for Unit Root

	Lags	DF_ρ	p-value	DF_τ	p-value
Sorghum	1	-0.4011	0.5920	-0.3289	0.5669
	4	-0.3041	0.6138	-0.2644	0.5912
Corn	1	-0.4848	0.5735	-0.4008	0.5390
	4	-0.5037	0.5694	-0.3989	0.5398

Table 3.4 Cointegration Test Results

Corn and Grain Sorghum						
ADF Test		Phillips-Perron		H_0	Johansen Rank Test	
DF_ρ	DF_τ	Z_ρ	Z_τ	rank=r	Max Eigen.	Trace
-43.62***	-4.70***	-38.73***	-4.45***	0	0.0147***	25.2512***
				1	0.0020	3.0489

Wheat and Barley						
ADF Test		Phillips-Perron		H_0	Johansen Rank Test	
DF_ρ	DF_τ	Z_ρ	Z_τ	rank=r	Max Eigen.	Trace
-59.51***	-5.36***	-49.14***	-4.89***	0	0.0421***	61.2839***
				1	0.0023	3.0692

Table 3.5 VECM with BEKK GARCH Results

VECM Estimats			
Variables	Estimate	Std. Error	P-Value
α_s	0.0225	0.0723	0.7554
β_s	0.8800	0.9134	0.3355
α_f	0.0544	0.0756	0.4716
β_f	3.7986	0.9210	0.0001
BEKK GARCH Model Estimates			
Parameter	Estimate	Std. Error	P-Value
c_{11}	2.1613	0.4179	0.0001
c_{12}	1.7761	0.4206	0.0001
c_{22}	1.4505	0.3952	0.0003
α_{11}	0.5268	0.0559	0.0001
α_{21}	-0.1324	0.0582	0.0231
α_{12}	0.0774	0.0553	0.1618
α_{22}	0.2879	0.0452	0.0001
g_{11}	0.8639	0.0277	0.0001
g_{21}	-0.1123	0.0418	0.0073
g_{12}	0.0356	0.0236	0.1315
g_{22}	0.8281	0.0273	0.0001

Table 3.6 Error Correction Model with GARCH Model

Normal Garch		T Garch	
Sorghum		Sorghum	
VECM Estimation		VECM Estimation	
Variables	Estimate	Variables	Estimate
Intercept	0.0998	Intercept	0.0365
	(0.0740)		(0.0625)
lag_r	-1.3175*	lag_r	-0.1084
	(0.7592)		(0.7112)
GARCH Estimation		GARCH Estimation	
Variables	Estimate	Variables	Estimate
ARCH0	1.4064***	ARCH0	0.9405***
	(0.1774)		(0.2289)
ARCH1	0.1632***	ARCH1	0.2308***
	(0.0225)		(0.0410)
GARCH1	0.6861***	GARCH1	0.6890***
	(0.0336)		(0.0453)
		Inverse of t DF	0.1763***
			(0.0213)
Corn		Corn	
VECM Estimation		VECM Estimation	
Variables	Estimate	Variables	Estimate
Intercept	0.0796	Intercept	0.0485
	(0.0692)		(0.0670)
lag_r	2.7006***	lag_r	1.5715***
	(0.7402)		(0.7540)
GARCH Estimation		GARCH Estimation	
Variables	Estimate	Variables	Estimate
ARCH0	0.4851***	ARCH0	0.6804***
	(0.0888)		(0.2054)
ARCH1	0.1147***	ARCH1	0.1458***
	(0.0152)		(0.0303)
GARCH1	0.8415***	GARCH1	0.7925***
	(0.0162)		(0.0381)
		Inverse of t DF	0.1633***
			(0.0226)

Table 3.7 Copula Estimation Results From the GARCH Model

	Normal GARCH Estimate	*t* GARCH Estimate
Normal Copula		
ρ	0.8148	0.8122
t Copula		
ρ	0.8349	0.8409
DF of Freedom	3.0963***	2.907***
	-(0.3522)	(0.3136)
Clayton		
θ	2.1712***	2.2084***
	-(0.0776)	(0.0787)
Gumbel		
θ	2.5863***	3.0705***
	(0.0564)	(0.0577)
Frank		
θ	9.0515***	9.3132***
	(0.2606)	(0.2670)
Dynamic Normal		
w	4.9999	5.0000***
	(4.7169)	(0.2192)
β	0.1972	0.7211
	(9.1613)	(1.0861)
α	-3.4400	-3.2451***
	(3.6150)	(0.2456)
Dynamic Gumbel		
w	2.4075***	2.4578
	(0.4009)	(3.6047)
β	-0.2034	-0.1449
	(1.9910)	(14.3655)
α	-5.0000***	-4.9999*
	(0.6075)	(1.3071)

Table 3.8 In-sample Hedging Performance

	One Week	Two Weeks	One Month	Three Months
OLS	0.0524	0.0802	0.1179	0.2170
BEKK	0.0533	0.0811	0.1197	0.2284
Marginal Distribution: Normal Garch				
Normal	0.0529	0.0806	0.1180	0.2176
Student	0.0539	0.0820	0.1201	0.2217
Clayton	0.0501	0.0763	0.1117	0.2055
Gumbel	0.0530	0.0808	0.1183	0.2182
Frank	0.0580	0.0882	0.1293	0.2393
Dynamic Normal	0.0533	0.0811	0.1188	0.2194
Dynamic Gumbel	0.0531	0.0809	0.1185	0.2186
Marginal Distribution: T Garch				
Normal	0.0524	0.0802	0.1179	0.2170
Student	0.0552	0.0840	0.1230	0.2270
Clayton	0.0521	0.0792	0.1159	0.2135
Gumbel	0.0547	0.0833	0.1219	0.2250
Frank	0.0533	0.0812	0.1188	0.2190
Dynamic Normal	0.0549	0.0834	0.1222	0.2258
Dynamic Gumbel	0.0548	0.0834	0.1222	0.2254

Table 3.9 Out-of-sample Hedging Performance

Out of Sample				
	One Week	Two Weeks	One Month	Three Months
OLS	0.0454	0.0705	0.0955	0.1178
BEKK	0.0435	0.0668	0.0891	0.1119
Marginal Distribution: Normal Garch				
Normal	0.0445	0.0680	0.0915	0.1168
Student	0.0451	0.0689	0.0928	0.1189
Clayton	0.0425	0.0650	0.0875	0.1101
Gumbel	0.0446	0.0681	0.0917	0.1170
Frank	0.0480	0.0731	0.0986	0.1283
Dynamic Normal	0.0447	0.0682	0.0918	0.1172
Dynamic Gumbel	0.0443	0.0678	0.0915	0.1165
Marginal Distribution: t Garch				
Normal	0.0438	0.0667	0.0893	0.1127
Student	0.0453	0.0688	0.0922	0.1173
Clayton	0.0431	0.0657	0.0880	0.1105
Gumbel	0.0449	0.0684	0.0915	0.1162
Frank	0.0440	0.0670	0.0897	0.1132
Dynamic Normal	0.0449	0.0682	0.0914	0.1158
Dynamic Gumbel	0.0448	0.0682	0.0915	0.1162

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CHAPTER

4

MORAL HAZARD IN THE PREVENTED PLANTING

4.1 Introduction

The US Federal Crop Insurance Program (FCIP) has continued to grow in prominence. Subsidized crop insurance is now the major instrument used to support US farmers, and accounts for the largest share of spending (outside of nutritional assistance) under the 2014 Farm Bill. Outlays for the program are projected to be $41 billion for 2014-2018 (Johnson and Monke, 2013). The program has expanded to cover a wide range of perils. In 2015, 543 crops and 297 million acres were covered, with a total liability of $102.4 billion (Risk Management Agency, 2016). An important aspect of the program—Prevented Planting (PP) provisions—is often ignored.

Prevented planting was added to the basic crop insurance provisions by the 1994 Crop Insurance Reform Act. The Risk Management Agency (RMA) defines PP as the failure to plant an insured crop by the final planting date due to an insured cause of loss: drought, cold wet weather, excess moisture, hail, and freezing.[1] The PP provision is available for corn, soybeans, grain sorghum, barley, wheat, cotton, and other common US crops.

Prevented planting indemnity payments depend on the PP coverage factor, per-acre production guarantee for timely planted acreage, projected price, and number of eligible PP acres. In 2017, the RMA reduced the PP coverage factor for corn from 60% to 55%; other coverage factors remained at 60% for soybeans, grain

[1]The final planting date is the date by which an insurable crop must initially be planted in order to be insured for the full amount of insurance (OIG, 2013).

sorghum, barley, and wheat, and 50% for cotton. The producer is also allowed to buy an additional 5% or 10% under the PP coverage terms.[2] The per-acre production guarantee is the insurance a producer has if the crop is planted before the final planting date, such as yield or revenue protection. To be eligible for the payments, at least 20 acres or 20 percent of the insured crop must be prevented from planting.

PP indemnity payments are calculated as follows:
Suppose a soybean producer selects a 60% PP coverage factor and 75% coverage level for revenue protection, with a projected price of \$3/bushel and actual production history (APH) of 100 bushels/acre.[3] If the insured producer has 20 acres prevented from planting, then the PP indemnity payment is $60\% \cdot 75\% \cdot 3 \cdot 100 \cdot 20 = \$2,700$.

4.1.1 Issues Related to Prevented Planting

The objective of the PP provision is to cover the costs of pre-planting activities if the insured producer is prevented from planting. However, it has been suggested (RMA Office of Inspector General, 2013) that the RMA's PP coverage level exceeds the actual costs of pre-planting activities. Ratios of PP indemnity payments to pre-planting costs were estimated to be more than 1.5 for corn and cotton, and between 1 and 1.5 for wheat and soybeans (Agralytica, 2013). The report by the RMA Office of Inspector General (OIG, 2013) also found that PP payment rates (per acre) substantially exceeded concomitant Conservation Reserve Program payments for similar land. Such high levels of PP coverage create the potential for moral hazard, as producers intentionally fail to plant to get indemnity payments. For instance, some producers are found by the RMA to grow crops in cropland unfit for planting rather than being enrolled in a United States Department of Agriculture (USDA) conservation program.

Another issue related to the abuse of PP coverage is that the RMA has not issued detailed guidance for determining whether affected acres are qualified for PP claims. Therefore, Approved Insurance Providers do not always note the lack of documentation and support for PP claims.[4] After reviewing 192 policy files, the OIG report (2013) concluded that "as a result, over \$43 million in prevented payments were not fully supported, and acres that are regularly too wet for crop production may regain or continue to have eligibility for prevented planting coverage."

The abuse of PP coverage causes great concern for the actuarial structure of the FCIP, because PP indemnity payments often account for a significant share of total indemnity payments. In the last decade, \$61.2 billion in total indemnities were paid to insured producers; of these \$10.1 billion were PP indemnity payments. The overall share of total PP indemnity payments exceeded 20% in crop years 2010, 2011 and 2015. In all other crop years, the share exceeded 10% with the exception of 2012. In 2012, the total indemnity payments doubled due to the tremendous drought in that year, but the PP indemnity payments were only about 10% of the year 2011.[5] For corn, soybeans, and wheat, shares of PP indemnity payments are even higher in most years.

Evaluation of the planted acreage and PP claims reveals that only 0.01% of prevented planting land was

[2]The PP coverage factor reflects the pre-planting input costs for producers. Similar to the coverage level, the PP coverage factor is used to determine PP indemnity payments based on yield or revenue protection.

[3]Actual production history is used by the RMA to determine a producer's guaranteed yield, calculated as the average production of a producer in a 10-year period.

[4]Approved Insurance Providers are responsible for reviewing and determining indemnity payments to the insured producer.

[5]The reason for the low PP indemnity payments is that PP claims caused by cold wet weather and excessive moisture, which often account for 90% of the total PP indemnity payments, decreased dramatically due to the 2012 drought.

actually replanted to a second crop (OIG, 2013). Producers have several incentives not to plant a second crop. First, a second planting decreases the first crop's PP indemnity payments, unless the producer qualifies for double cropping[6]. If a second crop is planted before the final planting date of the first crop, the PP payment is not applicable; otherwise, the payment is reduced to 35%. Second, producers who plant a second crop are often penalized by reductions in coverage. In particular, late-planted crops (i.e., planted after a final planting date) have their coverage reduced by 1% per day. Moreover, the Agricultural Risk Protection Act of 2000 requires the RMA to assign the producer a recorded yield equal to 60% of the producer's APH for the first crop if a second crop is planted. Before the Act, approximately 36% of all prevented planting acres were planted to a second crop (OIG, 2013). The objective of these strict policies for second crop planting is to prevent producers from claiming PP when the land is good for planting. However, the nearly zero second crop planting rate indicates that many producers did not intend to plant the crop, but rather were seeking prevented planting payments.

According to the report by the OIG of RMA (OIG, 2013), the Prairie Pothole Region (PPR) has experienced high levels of prevented planting activity. This area consists of the States of Iowa, Minnesota, Montana, North Dakota, and South Dakota. The PPR accounts for more than 50% of the PP indemnity payments for corn and sorghum, and 90% of the payments for barley and spring wheat. The PPR is suspected of fraud and moral hazard, as PP indemnity payments per acre are much higher than the conservation program payments per acre. For example, RMA issued a concern about PP claims for wet land in the PPR in 2012, when the weather was extremely dry, and should not have prohibited wet land from being planted.

4.1.2 Fraud and Moral Hazard

Fraud related to PP provisions is studied by comparing the PP cause of loss in the acreage to its surrounding areas (Rejesus et al., 2003; Jin, Rejesus, and Little, 2005;). In these studies, producers who buy additional PP coverage factors are more likely to be flagged as fraudulent. Although fraud may be a problem for PP provisions, it seems unlikely that it would be common, given that fraud brings high risk and penalties. Instead, moral hazard is more likely and is often seen in insurance programs.

In agricultural insurance, moral hazard was first discussed by Chambers in 1989 and examined, within the Multiple Peril Crop Insurance (MPCI) framework, by evaluating the use of chemicals and estimating the difference between real and expected indemnities (Chambers, 1989; Horowitz and Lichtenberg 1993; Smith and Goodwin, 1996; Coble, Knight, Pope and Jeffery, 1996). To prevent moral hazard, area yield insurance has been proposed and provided by RMA (Miranda, 1991; Chambers and Quiggin, 2002). However, area-based insurance does not work for PP coverage, because PP coverage does not involve planting activity and the cause of loss might be specific to each producer.

Moral hazard exists in PP coverage if producers are able to choose between being prevented from planting or timely planting. The opportunity costs of prevented planting are mainly determined by expected harvest revenue. The benefits are the PP payment and savings in input costs during the growing period. In reality, labor costs are often private information to producers, but expected harvest revenue and fertilizer costs can be partly observed in the market. Two important factors in the decision process are projected harvest price and fertilizer costs. Given an extreme weather event, the risk in not claiming PP is that planting incurs additional costs, and expected yield might be low. However, if the projected harvest price is high, then planting usually

[6]Double cropping: producing two or more crops for harvest on the same acreage in the same crop year.

leads to a higher profit, as guaranteed payments for timely planting can exceed the sum of planting costs and PP indemnity payments. Therefore, a high projected price should reduce the incentive for PP claims. In reality, the share of PP indemnity payments often has a negative relation with the projected price. For example, PP indemnity payments were low in 2012, when prices for agricultural commodities were high. This relationship proves that some insured producers are able to choose between planting and being prevented from planting, which can lead to moral hazard.

The objective of this study, therefore, is to determine whether PP losses are endogenous to market conditions, such as projected harvest price and fertilizer costs. The literature on PP insurance frequently studies fraud and the characteristics of producers with PP claims (Rejesus et al., 2003; Rejesus, Escalantec, and Lovell, 2005; Jin, Rejesus and Little, 2005). These studies focus only on producers with PP claims, which means that results are conditional on the event of PP losses and lack generality among all insured producers. This study is the first to analyze the behavior of all insured producers in PP insurance with respect to market conditions.

The novelty also lies in the methodology of estimating the probability of loss. PP losses are strongly related to weather conditions, as 95% of the PP claims are caused by extreme weather such as drought and excessive wetness. The relation between weather and the probability of loss in crop insurance has been widely studied in the literature of weather derivatives and weather index insurance (Martin, Barnett, and Coble, 2001; Turvey, 2001; Vedenov and Barnett, 2004; Woodard and Garcia, 2008). Unfortunately, there is no single model that can be used to predict the yield or probability of loss due to weather conditions (Vedenov and Barnett, 2004). This problem is solved, however, by the development of econometrics in high-dimensional models: significant weather indexes that affect the probability of loss are selected by using the least absolute shrinkage and selection operator (LASSO) method from more than 250 variables. Conditioning on the selected weather indexes, estimates of the relation between the probability of loss and market conditions are more accurate and robust.

The remainder of the article is organized as follows. Section 2 discusses the model and data used to identify the moral hazard. Section 3 presents empirical results. In section 4, the implications for taxpayer subsidies are reviewed and potential impacts on budgetary outlays are discussed.

4.2 Model and Data

The probability of PP loss is estimated by a binomial logistic regression. The RMA does not provides farm-level insurance data unless a loss occurs, so insurance data with no loss are not available at farm level. Therefore, loss data are aggregated to county-level by crop year and combined with county-level insurance data. The insurance data cover the crop year from 2002 to 2016. PP coverage factors are unobserved for producers who do not claim PP, so the average coverage level for timely planting is used. Winter wheat and cotton are not grown in the PPR, and are therefore excluded from the comparison. Definitions of explanatory variables and summary statistics are presented in Table 4.1.

The model, candidate weather variables, and estimations of expected harvest price and fertilizer costs are discussed in the following sections.

4.2.1 LASSO for Logistic Regression

For county i, if the probability of one insured acre being prevented from planting is p_i, then the probability of county i having n_i insured acres, with y_i acres being prevented from planting, is:

$$f(n_i, y_i) = \binom{y_i}{n_i} p_i^{y_i} (1-p_i)^{n_i - y_i} \tag{4.1}$$

Linear logistic regression models the probability p_i by:

$$log(\frac{p_i}{1-p_i}) = \boldsymbol{\beta}'\boldsymbol{x_i} \tag{4.2}$$

where $\boldsymbol{\beta}$ is the coefficient vectors and $\boldsymbol{X_i}$ is the vector of independent variables of county i.

Dropping the constant term $\binom{y_i}{n_i}$, the sum of log-likelihood function then becomes:

$$L(\boldsymbol{\beta}; \boldsymbol{n}, \boldsymbol{y}, \boldsymbol{x}) = \sum_{i=1}^{K} \{y_i log(p_i) + (n_i - y_i) log(1-p_i)\} \tag{4.3}$$

Given the complexity of the relationship between weather and the probability of loss, the LASSO method is used to select important weather variables that affect the probability of loss.

The LASSO method (Tibshirani, 1996) has recently become a popular method in model selection. Variables are selected from the minimization of the objective function:

$$\hat{\boldsymbol{\beta}} = \arg\min_{\beta} ||\boldsymbol{Y} - \boldsymbol{X}\boldsymbol{\beta}||_2^2 + \lambda |\sum_{j=1}^{p} \beta_j| \tag{4.4}$$

where $||\boldsymbol{u}||_2^2 = \sqrt{\sum_{i=1}^{i=n} u_i^2}$, and λ is the regularization parameter.

The linear regression model works well if the error distribution is Gaussian. However, if the response variable is discrete, then a generalized linear model with the LASSO is more appropriate (Hastie, Tibshirani, and Wainwright, 2015). Here, the response variable follows a binomial distribution, and the LASSO selects variables from the negative log-likehood function with l_1 regularization:

$$\hat{\boldsymbol{\beta}} = \arg\min_{\beta} (-L(\boldsymbol{\beta}; \boldsymbol{n}, \boldsymbol{y}, \boldsymbol{x})) + \lambda |\sum_{j=1}^{p} \beta_j| \tag{4.5}$$

where $L(\boldsymbol{\beta}; \boldsymbol{n}, \boldsymbol{y}, \boldsymbol{x})$ is the log-likelihood function defined in equation 4.3.

Replacing p_i with the link function in equation 4.2, objective function 4.5 is convex and can be solved by algorithms such as the quasi-Newton method:

$$\hat{\boldsymbol{\beta}} = \arg\min_{\beta} - \sum_{i=1}^{K} \{y_i \boldsymbol{\beta}'\boldsymbol{x_i} + (n_i - y_i) log(1 + e^{\boldsymbol{\beta}'\boldsymbol{x_i}})\} + \lambda |\sum_{j=1}^{p} \beta_j| \tag{4.6}$$

4.2.2 Candidate Weather Variables

The probability of PP loss conditional on weather is equal to the probability of a yield at the left tail of its distribution: $P(Y < y|weather)$, where y is a small number. Temperature and precipitation are the most popular variables for predicting yield (Schlenker and Roberts, 2006; Vedenov and Barnett, 2004;), and are included in the candidate variables. To supplement the effects of temperature and precipitation, monthly aggregate heating degree days (HDD), cooling degree days (CDD) and cumulative precipitation are used.[7] The cumulative precipitation in month i is calculated as the sum of the precipitation in previous months, starting at the beginning of the planting season. The square and cube of cumulative precipitation are included to reflect the polynomial relationship. All of the above weather data are obtained from the National Oceanic and Atmospheric Administration.

If the weather is good for planting, then a minor change in the weather should have little effect on the probability of loss. Nevertheless, an increase in precipitation during extremely wet weather could contribute a lot to losses. It is therefore assumed that the probability of loss also depends on extreme weather conditions that are hard to identify based on the original weather data. To solve this problem, extreme weather indicators are introduced.

Extreme weather indicators are measured by the deviation from the average level of the weather condition. Monthly average temperature, precipitation, HDD, and CDD are standardized at the county level by its mean and standard deviation: $\tilde{x} = \frac{x-\mu_x}{\sigma_x}$. For each variable, the mean and variance are calculated using weather data from 1895 to 2016. Extreme weather indicators are defined as:

$$\begin{aligned} w_{ijt} &= \begin{cases} 0 & \text{if } |\tilde{x}_{ijt}| < 1) \\ 1 & \text{otherwise.} \end{cases} \\ w2_{ijt} &= \tilde{x}_{ijt} * I(\tilde{x}_{ijt} < -1) \\ w3_{ijt} &= \tilde{x}_{ijt} * I(\tilde{x}_{ijt} > 1) \end{aligned} \tag{4.7}$$

where w_{ijt}, $w2_{ijt}$ and $w3_{ijt}$ are the extreme weather indicators generated from weather index i of county j in month t, and $I(\cdot)$ is the indicator function. Weather indexes that lie outside one standard deviation are assumed to indicate abnormal weather. Different thresholds have been considered, and one standard deviation is chosen to retain most of the information in $w2$ and $w3$ indicators as larger thresholds often end up with very little data in the extreme weather group. Here, w_{ijt} is the dummy variable on whether the weather condition is normal or abnormal, and $w2_{ijt}$ and $w3_{ijt}$ capture the degree of the unusual weather condition on both sides. For example, let $i = 1$ for temperature, $i = 2$ for precipitation, $i = 3$ for HDD, and $i = 4$ for CDD. Then a drought in county j in month t can be reflected in extreme high temperature $w3_{1jt}$, low precipitation $w2_{2jt}$, and high CDD $w3_{4jt}$.

Weather indexes generated by the National Climatic Data Center (NCDC) are also added to the model. These eight indexes are useful, as they measure moisture, drought and wetness and the probability of precipitation. Names of indexes and their implications are summarized in Table 4.2. All indexes are continuous variables, but reflect different levels of drought and wetness; therefore a transformation is used to categorize these indexes into groups while preserving some degree of continuity. Two dummy variables and two

[7] Daily HDD is calculated as the average temperature on that day subtracted from 65°F. CDD is calculated as the average temperature minus 65°F. Monthly aggregate HDD and CDD are the sum of daily HDD and CDD in a month.

continuous variables are defined as:

$$
\begin{aligned}
h_{ijt} &= \begin{cases} 1 & \text{if } z_{ijt} \text{ is in category ``Near Normal"} \\ 0 & \text{otherwise.} \end{cases} \\
h2_{ijt} &= \begin{cases} z_{ijt} & \text{if } z_{ijt} \text{ is in category ``Mild to moderate Drought" and ``Severe Drought."} \\ 0 & \text{otherwise.} \end{cases} \\
h3_{ijt} &= \begin{cases} z_{ijt} & \text{if } z_{ijt} \text{ is in category ``Mild to moderate Wetness" and ``Severe Wetness."} \\ 0 & \text{otherwise.} \end{cases} \\
h4_{ijt} &= \begin{cases} 1 & \text{if } z_{ijt} \text{ is in category ``Extreme Wetness/Drought."} \\ 0 & \text{otherwise.} \end{cases}
\end{aligned}
\tag{4.8}
$$

where z_{ijt} is index i of county j in month t from the original data. From the previous assumption—that only extreme weather affects the probability of loss—indexes in "Near Normal" category should not affect the probability of loss, and indexes in "Extreme" category should always have a large effect. The unknown effect of the indexes lies in the categories of "Mild to moderate" and "Severe", where the degree of extreme weather is determined by the index; therefore, continuous variables are used to predict the probability of loss.

The planting period often lasts for two or three months. To cover the whole planting period and provide more weather information, weather variables for six months are included in the model. The reason for not using 12-month weather data is that weather conditions after the final planting date should not affect the producer's decision regarding claiming PP. The latest final planting dates are June for corn, soybeans, grain sorghum, cotton, spring barley, and spring wheat, and December for winter barley and winter wheat. Therefore, weather data from January to June are used for corn, soybeans, grain sorghum, cotton, spring barley, and spring wheat, and data from July to December for winter barley and winter wheat.

In summary, the numbers of weather variables over the six months are $4 \cdot 6 = 24$ for original weather data on temperature, precipitation, HDD, and CDD; $3 \cdot 6 - 1 = 17$ for the linear, square, and cube of cumulative precipitation; $3 \cdot 4 \cdot 6 = 72$ for three extreme weather indicators generated from original weather data; and $4 \cdot 8 \cdot 6 = 192$ for four indicators transformed from eight weather indexes.[8] With a total of 305 weather indicators included in model selection, weather effects should be conditioned out in the analysis of the PP loss.

4.2.3 Market Condition Estimates

Input and output market conditions are considered to be represented by fertilizer costs and the expected harvest price. Fertilizer costs are measured by monthly fertilizer cost indexes from the USDA. However, cost indexes are not available after 2013, so indexes after 2013 are estimated by the following OLS regression:

$$Cost_t = \beta_0 + \beta_1 * DAP_t + \beta_2 * KCL_t + \beta_3 * UREA + \beta_4 * Diesel + \beta_5 * CPI \tag{4.9}$$

[8]The number of indexes for original weather data should subtract one, because the first month of the cumulative precipitation in the linear term is equal to the monthly precipitation.

where the regressors are prices of diammonium phosphate (DAP), potassium chloride (KCL), urea, and diesel and the consumer price index (CPI). These prices are used by the RMA to determine input costs for margin protection (RMA, 2017).[9] Spot prices of DAP at US Gulf, KCL at Vancouver, urea at Black Sea, and diesel at New York Harbor are used and the CPI data are obtained from the Federal Reserve Bank of ST. Louis. Weekly data from 2002 to 2012 are used to estimate the price coefficients, and OLS results are summarized in Table 4.3. The R-square is 0.9652, and all price coefficients are positive; this is reasonable, as any increase in these prices increases the input costs. Cost indexes after 2013 are then estimated using price data from 2013 to 2016.

The expected harvest price is estimated in ways similar to the projected price identified by the RMA. The RMA calculates the projected price as an average of daily settlement prices for the harvest year and month's futures contract in the price discovery period. The price discovery period usually lasts for a month, so a monthly average settlement prices are used. February prices for December contracts at the Chicago Board of Trade (CBOT) are used for corn and grain sorghum.[10] February prices for November contracts at the CBOT are used for soybeans. February prices for December contracts at the Intercontinental Exchange are used for cotton. For wheat and barley prices, selections of month and futures markets are guided by the RMA's price discovery period and the commodities exchange.[11]

The price in each state should also depend on state characteristics. Therefore, an adjustment is made to reflect the perceived price for local producers. The USDA provides the index of price received by producers at the state level, so the expected harvest price P_i in state i is adjusted by the difference between the price received index in state i and state j, where the relevant commodity exchange is located:

$$P_i = P_p + P_{ri} - P_{rj} \tag{4.10}$$

Here, P_p is the average settlement price, P_{ri} is the index of price received in state i during the price discovery month, and P_{rj} is the index of price received in the state where the commodities exchange is located. For example, if the futures contract is from the CBOT in Illinois, then P_{rj} is the index of price received in Illinois.

A change in the expected harvest price this year is also expected to change the producer's behavior; an increase in the harvest price from last year should lead to more careful preparation for planting activity this year. Therefore, the price ratio is included in the model as the log change in the expected harvest price from last year:

$$P_{ratio} = log(P_t/P_{t-1}) \tag{4.11}$$

Usually, log price is preferred because it reflects proportional change. Therefore, log input price and log expected harvest price are used as default. The linear, square and cube of both prices are included in the model as candidate variables.

4.3 Empirical Results

The main purpose of this paper is to examine the effect of price on the PP claims. Therefore, five variables—log expected harvest price, log input price, price ratio, average coverage level, and acres/unit—are forced to be

[9] Margin protection provides coverage against an unexpected decrease in operating margin.

[10] The price of grain sorghum is equal to that of corn, as grain sorghum is a good substitute for corn.

[11] The month is selected as the month of the beginning date in the RMA's price discovery period.

included in the logistic LASSO model as selected. To condition out the effect of weather and other factors that can possibly affect the probability of PP loss, all other variables—year, state, farm resource regions, price factors, and weather indicators—are chosen to be candidates and selected from the LASSO model.

Before the minimization, all independent variables $\boldsymbol{X}$ are standardized to have 0 mean ($\frac{1}{N}\sum_{i=1}^{N} x_{ij} = 0$) and unit variance ($\frac{1}{N}\sum_{i=1}^{N} x_{ij}^2 = 1$). The regularization parameter λ in equation 4.5 is set to be $\lambda = \rho^i$ for the ith step, and ρ is arbitrarily set to 0.7. The base value ρ doesn't matter as long as λ converges to a small number after several steps. Twenty-five steps have been considered, and Nesterov's (2013) method is applied to solve the minimization problem for its optimal converge rate for the first-order black box optimization. Data are divided into training and validation data. Seventy-five percent of the data are randomly chosen for training data and the rest are used for validation data. For each λ and its corresponding estimated coefficients, the BIC of the validation data is computed. The optimal λ is then selected from the smallest BIC of the validation data. The numbers of selected variables, λ, and BIC are reported in Appendix A.2.

It is difficult to estimate standard errors in the LASSO model, as the limit distribution of the LASSO estimator is complicated (Knight and Fu, 2000). Bootstrap (Tibshirani, 1996) and bayesian LASSO (Kyung et.al 2010) methods are computationally hard to apply in the logistic LASSO case, as the estimation involves an outer loop iterating on the parameters and an inner loop to update. Therefore, coefficients of the selected variables and their standard errors are computed by a standard binomial logistic regression with unpenalized maximum likelihood estimators (MLE). The use of post-LASSO estimators have two advantages.[12] First, in the OLS estimation, post-LASSO estimators often provide better, or at least equal, performance than the LASSO estimators in terms of bias and rate of convergence (Belloni and Chernozhukov, 2013). Because the minimization in the logistic LASSO model applies a second-order Taylor expansion of the likelihood function, which is similar to the OLS estimator, it is likely to improve the estimation by the post-LASSO procedure. Second, without the penalty term in the LASSO, it is easier to identify the total effect of each variable in the model. Results of main parameters are presented in Table 4.4 and full results of the LASSO and other variables are listed in Appendix A.

If moral hazard does not exist, then producers should be forced to be prevented from planting only by extreme weather, and the variables in Table 4.4 should have little effect on the probability of PP loss. However, all of the estimators in Table 4.4 are significant at the 0.01 level, which provides evidence of moral hazard that market conditions contribute to the PP loss.

When expected planting revenues are low or input costs are high, insured producers are encouraged to not prepare well for planting in order to claim PP to save fertilizer costs. Therefore, the likelihood of PP loss should be negatively related to the expected harvest price and price ratio, and positively related to input costs.

It should be noted that changes in the expected harvest price also influence the price ratio, because the price ratio includes the term $log(P_t)$. Therefore, the total effects of the harvest price are the sum of the harvest price and price ratio. On the other hand, the effect of the input price depends solely on the coefficient of the log input price. The results in Table 4.4 suggest that in most cases—except for wheat and barley—the likelihood of PP loss increases if the expected harvest price decreases or the input price increases.

Moral hazard is assumed to exist if the sums of the coefficients of harvest price and price ratio are negative, and the coefficient of the input price is positive. Using this standard, moral hazard is detected in corn, soybeans, grain sorghum, spring barley, and cotton producers.

[12]Post-LASSO estimators are estimators from OLS regression with the selected variables from the LASSO.

The moral hazard problem is more severe in the PPR, as the absolute value of price coefficients become larger. For example, the coefficient of harvest price decreases from −2.76 for corn producers in all states, to −5.18 for producers in the PPR, and the coefficient of input price also increases from 0.30 to 4.77. Similar results can be found for soybeans, grain sorghum, and spring barley. This finding proves that producers in the PPR are more likely to claim PP than producers in other regions when the overall benefit of PP is large.

The average coverage level in the model reflects the producer's risk preference. It should be noted that a higher coverage level increase both PP indemnity payments and guarantee payments for timely planting.[13] The effect of coverage level on the producer's decision process relies on the probability of loss for planting. If the PP coverage factor is 60% and the probability of loss for planting is 60%, then the coverage level has no impact on the producer's choice. In general, the probability of loss for planting is often less than the coverage factor; therefore, an increase in the coverage level often increases more on PP indemnity payments and should increase the probability of PP loss. Results confirm that coverage level has a positive effect on the probability of PP loss for all crops except soybeans.

The variable acres/unit is used to measure the size of farms in the county. Large-size farms are supposed to have less prevented planting activity, because they often have better equipment in the case of extreme weather. Also, larger acres/unit implies more corporate farms in the region, and corporate farms are shown to be less likely to submit a PP claim (Rejesus, Escalante, and Lovell, 2005). In the results, larger acres/unit decreases the probability of loss for corn (all states), grain sorghum (PPR), barley, winter wheat, and cotton and increases the probability of loss for other crops. No consistent pattern exists for the effect of farm size on the probability of loss; it could be caused by the abuse of PP by corporate farms. If large-size farms are involved in the abuse of PP, then the coefficient would be changed from negative to positive.

4.4 Conclusions and Implication

The large share of prevented planting indemnity payments in the crop insurance program raises questions of whether high prevented planting coverage levels lead to moral hazard. Most prevented planting claims are caused by extreme weather, so the LASSO method is applied to condition out weather effects. After conditioning out exogenous weather conditions, the relation between market conditions and the probability of prevented planting loss is examined for corn, soybeans, grain sorghum, barley, wheat, and cotton in the US. The report by the Risk Management Agency is also concerned with high indemnity payments in the Prairie Pothole Region. Therefore, the relation between market conditions and losses are also studied in this specific region.

Empirical results suggest that market conditions have large impacts on the probability of prevented planting loss, and prevented planting claims are not fully caused by extreme weather. Producers are found to claim more prevented planting losses when the input costs for normally planting are high and the harvest revenues are low. More specifically, lower harvest prices or higher fertilizer costs increase the probability of PP loss for corn, grain sorghum, spring barley, and cotton across the states. This problem is more serious in the Prairie Pothole Region, which has been accused of a large degree of moral hazard by the Risk Management Agency.

[13] PP indemnity payments can be calculated as PP coverage level multiplied by the guarantee payment for timely planting.

Because prevented planting insurance program is provided as a basic part of the Federal Crop Insurance Program, the existence of moral hazard in the prevented planting insurance affects the actuarial structure of the whole program and incurs additional costs for taxpayers. To measure the cost of possible moral hazard behavior in the prevented planting insurance, effects of the price factors on the probability are estimated. The major concern regarding moral hazard is how market conditions may lead to higher losses or indemnity payments; therefore, the probability of loss and the corresponding indemnity payments are estimated if the expected harvest price is decreased by 1% or the input price is increased by 1%. Both events should increase the probability of loss and the indemnity payments. The probability of loss is estimated at the mean value, and total indemnity payments are estimated as the proportional of the probability of loss.[14] For each change in the price, the probability after the change and the change in total indemnities are reported in Table 4.5. The most significant change in indemnities occurs for corn and soybeans in the Prairie Pothole Region: a 1% decrease in the expected harvest price will increase the annual prevented planting indemnity payments by 12.31 million for corn and 5.52 million for soybeans in the Prairie Pothole Region. Similarly, a 1% increase in input costs will increase the annual prevented planting indemnity payments by 52.21 million for corn and 10.55 million for soybeans. For other crops, such as grain sorghum, cotton, and spring barley, the change is small—but still incurs additional indemnity payments for prevented planting insurance.

In 2017, the RMA reduced the prevented planting coverage factor for corn from 60% to 55%. In 2017, the proportion of the prevented planting indemnity payments of corn in the total corn indemnity payments went from 17.04% to 14.95% in 2016. It is hard to conclude that this reduction is solely caused by the reduction in the coverage level, but the same reduction could be considered for grain sorghum, cotton, and spring barley, as results show evidence of moral hazard among these producers. In December 2017, the RMA announced to eliminate the option to purchase an additional 10% prevented planting coverage for the 2018 crop year and future crop year (Clayton, 2017). The RMA did not mention the reason for this elimination, but this could be a sign that the RMA found serious moral hazard issues among producers who bought additional coverage. In this paper, we find that prevented planting insurance for corn and soybeans in the PPR suffers a large degree of moral hazard, and may lead to huge indemnity payments, given certain market conditions. Therefore, claims for prevented planting should be reviewed more carefully, as insured producers in the Prairie Pothole Region are more likely to seek prevented planting payments when the benefits of prevented planting exceed timely planting.

[14] Total indemnity payments can be calculated as $Total\,Acres * Probability\,of\,Loss/Acre * Indemnities/Acre$. Here, indemnities per acre are assumed to be at the mean values, and do not change with the harvest price.

Table 4.1 Variable Definitions and Summary Statistics

Variable	Definition
Year	Crop year
State FIPSs	FIPSs Code for each state
Region	Farm resources region
Total Acres	Total insured acres in the county
Acres Loss	Total acres with PP losses in the county
Harvest Price	Expected havest price (log term)
Input Price	Estimated fertilizer costs (log term)
Price Ratio	log ratio change in the expected havest price from last year
Coverage Level	Average coverage level (sum of covered acres/total insured acres)
Acres/Unit	Total insured acres/Total units (log term)

	Corn		Corn (PPR)		Soybeans	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Year	2009.54	4.05	2009.53	4.03	2009.58	4.05
State FIPSs	30	14	30	10	29	13
Region	3.61	2.42	1.99	1.24	3.48	2.47
Total Acres	37652	48826	83126	65769	38141	45978
Acres Loss	654	3276	1826	6931	524	2497
Harvest Price	1.38	0.32	1.32	0.33	2.19	0.32
Input Price	5.46	0.34	5.46	0.33	5.47	0.33
Price Ratio	0.03	0.22	0.03	0.22	0.00	0.27
Coverage Level	0.68	0.08	0.71	0.07	0.69	0.07
Acres/Unit	4.43	0.62	4.63	0.46	4.36	0.55

	Soybeans (PPR)		Grain Sorghum		Grain Sorghum (PPR)	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Year	2009.55	4.05	2009.69	4.09	2009.47	4.16
State FIPSs	29	10	31	14	45	4
Region	1.70	0.90	4.36	2.34	2.60	0.80
Total Acres	88291	64099	6960	15552	2934	6739
Acres Loss	1556	5073	119	839	138	567
Harvest Price	2.16	0.31	1.40	0.31	1.28	0.33
Input Price	5.46	0.33	5.47	0.33	5.45	0.34
Price Ratio	-0.01	0.27	0.03	0.22	0.03	0.23
Coverage Level	0.73	0.04	0.64	0.07	0.63	0.06
Acres/Unit	4.55	0.42	3.99	0.79	4.06	0.90

Continued on Next Page

Table 4.1 (continued).

Variable	Spring Barley Mean	Spring Barley Std. Dev	Spring Barley (PPR) Mean	Spring Barley (PPR) Std. Dev	Fall Barley Mean	Fall Barley Std. Dev
Year	2009.53	4.14	2009.10	4.12	2009.38	4.22
State FIPSs	34	14	33056	6039	31	13
Region	4.15	2.23	3.27	1.97	4.47	2.47
Total Acres	5501	13326	11180	19479	9805	17099
Acres Loss	222	1653	531	2648	410	2249
Harvest Price	5.97	0.35	1.33	0.38	5.95	0.36
Input Price	5.48	0.29	5.47	0.30	5.46	0.30
Price Ratio	0.03	0.31	0.03	0.27	0.03	0.36
Coverage Level	0.65	0.07	0.67	0.05	0.67	0.07
Acres/Unit	4.02	0.91	4.23	0.75	4.34	0.79

Variable	Fall Barley (PPR) Mean	Fall Barley (PPR) Std. Dev	Spring Wheat Mean	Spring Wheat Std. Dev	Spring Wheat (PPR) Mean	Spring Wheat (PPR) Std. Dev
Year	2009	4	2010	4	2010	4
State FIPSs	33184	5916	34	11	35296	7745
Region	3.29	1.96	3.65	2.35	2.86	1.79
Total Acres	11282	19539	68993	92683	72494	95343
Acres Loss	536	2660	2465	13256	2951	14590
Harvest Price	1.33	0.38	1.78	0.37	1.75	0.35
Input Price	5.47	0.30	5.47	0.34	5.47	0.34
Price Ratio	0.03	0.28	-0.01	0.30	-0.02	0.30
Coverage Level	0.67	0.05	0.69	0.05	0.69	0.04
Acres/Unit	4.24	0.74	4.61	0.67	4.52	0.66

Variable	Winter Wheat Mean	Winter Wheat Std. Dev	Cotton Mean	Cotton Std. Dev
Year	2009.45	3.92	2009.58	4.03
State FIPSs	30	14	30	18
Region	3.88	2.45	6.20	1.81
Total Acres	17895	39081	23301	43339
Acres Loss	383	1879	337	2231
Harvest Price	1.76	0.36	-0.30	0.25
Input Price	0.03	0.33	5.47	0.33

Continued on Next Page

Table 4.1 (continued).

Price Ratio	0.01	0.08	0.03	0.30
Coverage Level	0.66	0.07	0.64	0.06
Acres/Unit	4.14	0.69	4.62	0.68

Table 4.2 Weather Indexes Summary*

Palmer Hydrological Drought Index (PHDI)
Palmer Drought Severity Index (PDSI)
Modified Palmer Drought Severity Index (PMDI)
Palmer "Z" Index (ZNDX)

Approximate Cumulative Frequency** (%)	Range* PHDI, PDSI, PMDI	Range Z	Category
>96	>4	>3.5	Extreme Wetness
90-95	(3,4]	(2.5,3.5]	Severe Wetness
73-89	(1.5,3]	(1,2.5]	Mild to Moderate Wetness
28-72	[-1.5,1.5]	[-1.25,1]	Near Normal
11-27	[-3,-1.5)	[-1.99,-1.25)	Mild to Moderate Drought
5-10	[-4,-3)	[-2,2.75)	Severe Drought
<4	<-4	<-2.75	Extreme Drought

Standardized Precipitation Index (SPxx)
Probablility of observing a given amount of precipitation in xx month
Available SPxx are SP01, SP02, SP06, and SP09

Range	Category	Range	Category
<-3	Extreme Drought	>3	Extreme Wetness
$[-3,-2)$	Moderate Drought	(2,3]	Severe Wetness
$[-2,-1)$	Mild Drought	(-1,-2]	Mild Wetness
$[-1,0]$	Normal	(0,1]	Normal

*The range and the corresponding category are introduced in the NCDC's weather division documentation.

**Frequency of the indexes is calculated through all months and weather divisions.

Table 4.3 OLS Regression of Fertilizer Indexes

Variable	Estimators	Standard Errors	P-values
Intercept	-93.51508	36.60831	0.0118
DAP	0.09218	0.01623	< .0001
PCL	0.21836	0.01527	< .0001
UREA	0.07881	0.03244	0.0165
Diesel	16.73314	6.19579	0.0078
CPI	0.74519	0.24132	0.0025
		R-Square	0.9652

Table 4.4 Main Results from Logistic Regression*

	Intercept	Coverage	Harvest Price	Input Price	Price Ratio	Acres /Unit
Corn (ALL)	495.8704	1.8506	-2.7613	0.3003	1.661	-0.2566
	(1.9981)	(0.0089)	(0.0192)	(0.0158)	(0.0124)	(0.0009)
Corn (PPR)	-29.5394	4.8368	-5.1815	4.7725	1.0942	0.2183
	(0.0509)	(0.0182)	(0.0114)	(0.0113)	(0.0053)	(0.0017)
Soybeans	496.23	-4.5747	5.5584	-2.2376	-1.3128	0.0897
(ALL)	(2.4785)	(0.0115)	(0.0327)	(0.0149)	(0.0087)	(0.0010)
Soybeans	-14.0405	-4.5857	-1.8027	1.4225	-0.1592	0.6752
(PPR)	(0.0546)	(0.0273)	(0.0181)	(0.0140)	(0.0075)	(0.0019)
Grain	-12.7323	0.6589	-0.7011	1.0287	0.4073	0.5239
Sorghum (ALL)	(0.0652)	(0.0274)	(0.0175)	(0.0149)	(0.009)	(0.0021)
Grain	-23.2451	5.0302	-4.059	4.0758	-0.0989	-0.1546
Sorghum (PPR)	(0.2785)	(0.1402)	(0.0533)	(0.0563)	(0.0269)	(0.0092)
Spring	-16.8773	11.2182	-0.7969	0.8394	0.2174	-0.3148
Barley (ALL)	(0.0911)	(0.0403)	(0.0153)	(0.0184)	(0.0116)	(0.0032)
Spring	-25.9612	15.9222	-2.1117	1.6508	0.3191	-0.1608
Barley (PPR)	(0.0944)	(0.0562)	(0.0169)	(0.0177)	(0.0107)	(0.0041)
Fall	-7.4839	12.4092	-0.4347	-0.6102	1.3147	-0.3959
Barley (ALL)	(0.0686)	(0.041)	(0.0127)	(0.0143)	(0.0082)	(0.0033)
Fall	-1.5878	15.7104	1.6355	-3.0465	3.4193	-0.2766
Barley (PPR)	(0.1094)	(0.055)	(0.0202)	(0.0214)	(0.0115)	(0.0041)
Spring	-5.0613	10.2785	0.9797	-2.6339	-0.4636	0.2497
Wheat (ALL)	(0.0368)	(0.0193)	(0.0086)	(0.0082)	(0.0037)	(0.0017)
Spring	-10.146	12.98	0.0492	-1.4933	-0.0382	0.3337
Wheat (PPR)	(0.0425)	(0.0236)	(0.0095)	(0.0094)	(0.0044)	(0.0019)
Winter	-15.8857	3.6159	1.216	0.4394	0.6591	-0.1488
Wheat (ALL)	(0.0389)	(0.0116)	(0.0131)	(0.0094)	(0.0075)	(0.0012)
Cotton (ALL)	-21.9057	7.8701	-0.3138	0.2852	-0.7178	-0.006
	(0.0787)	(0.0164)	(0.0081)	(0.0048)	(0.0056)	(0.0015)

*All estimated coefficients are significant at the 0.01 level

Table 4.5 Probability and Indemnities Response for Changes in Price Factors

	Corn	Corn	Soybeans	Soybeans	Sorghum
	ALL	PPR		PPR	ALL
Probability at Mean Value	0.4240%	0.3899%	0.4136%	0.3021%	0.9807%
Annual Indemnities	309.53*	175.81	137.07	73.35	7.04
1% Decrease in Harvest Price					
Estimated Probability	0.4055%	0.4172%	0.3664%	0.3140%	0.9901%
Change in Annual Indemnities	-13.51	12.31	-15.64	2.89	0.07
1% Increase in Input Costs					
Estimated Probability	0.4297%	0.5054%	0.3662%	0.3264%	1.0368%
Change in Annual Indemnities	4.13	52.12	-15.71	5.90	0.40
	Sorghum PPR	Spring Barley All	Spring Barley PPR	Fall Barley All	Fall Barley PPR
Probability at Mean Value	3.8799%	0.4788%	0.9793%	0.7364%	0.8829%
Annual Indemnities	0.41	11.03	9.55	10.78	9.55
1% Decrease in Harvest Price					
Estimated Probability	4.0786%	0.4839%	1.0068%	0.7404%	0.8631%
Change in Annual Indemnities	0.02	0.12	0.27	0.06	-0.21
1% Increase in Input Costs					
Estimated Probability	4.7978%	0.5012%	1.0708%	0.7125%	0.7485%
Change in Annual Indemnities	0.10	0.52	0.89	-0.35	-1.45
	Spring Wheat All	Spring Wheat PPR	Winter Wheat	Cotton	
Probability at Mean Value	0.6191%	0.5326%	1.3837%	0.3948%	
Annual Indemnities	96.26	93.66	42.13	21.95	
1% Decrease in Harvest Price					
Estimated Probability	0.6086%	0.5321%	1.3544%	0.3945%	
Change in Annual Indemnities	-1.64	-0.08	-0.89	-0.02	
1% Increase in Input Costs					
Estimated Probability	0.5366%	0.4910%	1.4170%	0.4010%	
Change in Annual Indemnities	-12.84	-7.30	1.02	0.34	

*The unit of annual indemnities is $1,000,000.

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CHAPTER

5

CONCLUSION

The three essays in the dissertation are concerned with price, risk management and policy. Although the topics in the three essays are separated, there is a connection between price and policy, and price and risk management.

Essay One shows that China's policy has separated its market from the world market and the law of one price in international corn trade does not hold. As China's domestic corn prices are higher than the global prices, this policy hurts the corn buyers in China and benefits the suppliers, which shows a good example of how policy affects the price.

On the other hand, price also affects the performance of a policy. In Essay Three, the moral hazard issue is examined in the prevented planting insurance. The results shows that higher planting costs or lower harvest prices increase the probability of loss, as producers are more likely to claim loss when the planting costs are high or the planting revenue are low. Empirical results also imply more serious moral hazard issues in the Prairie Pothole Region. Therefore, it is suggested that the RMA set stricter rules and review more carefully on the prevented planting claims in the Prairie Pothole Region.

In agricultural industry, policies are often made to protect farmers, or producers at the cost of taxpayers and buyers. This often causes a distortion in the market and should be carefully evaluated before a policy has been made. Also, because agricultural policies are mostly subsidized by the government, it is important to eliminate the possible misuse of the policy in reality. In Essay Three, moral hazard is found in the subsidized crop insurance program, which incurs additional costs to the program and should be taken seriously by the policy makers.

In general, agricultural commodities prices are sometimes very volatile and can be influenced by many factors other than policies. Therefore, it is important to understand how price change and are predicted. The prediction of price in the trade often depends on prices in other countries based on the law of one price (LOP) assumption. In Essay One, I show that the degree of the LOP changes as the market conditions change. As the US corn exports decreased in 2013, the price relationship between the US and other countries became weaker. So instead of using US corn prices as the benchmark prices, it is recommended that traders should predict prices based on more information, such as the corn prices in other export countries.

If traders are risk-averse and want to avoid the risk of volatile prices, hedging may be very good option. To reduce the price risks for commodities with no futures markets, the cross-hedging strategy is developed in Essay Two. A copula-based GARCH model is proposed to estimate the optimal hedge ratio between sorghum cash prices and corn futures prices. It turns out that the Clayton copula model has better performance in the reduction on the variance of the portfolio than the conventional OLS and multivariate GARCH models. This finding provides sorghum traders a new model to calculate the optimal hedge ratio and helps them to further decrease the price risks.

This dissertation also makes contributions to the application of econometrics models. Essay one applies Qu-Perron tests to examine the structural changes in the vector error correction model, which is an expansion of the widely used Bai-Perron structural break tests for single equation. The estimated breaks are consistent with the policy changes and market events, which justifies the model in the analysis of possible shocks. Essay two applies a dynamic copula-based GARCH model in the estimation of hedge ratio. The better performance from the Clayton copula shows promise of the copula-based model in the hedging literature. Essay three uses the newly developed least absolute shrinkage and selection operator (LASSO) method to solve a complicated problem in deciding the relationship between losses and weather conditions. This application of the LASSO should also be useful in determining the weather derivatives, as most studies only choose a limited number of weather variables in the analysis.

APPENDICES

APPENDIX

A

COPULA MODEL WITH GARCH ERROR FOR AGRICULTURAL PRICES CORRELATION

A.1 Derivation of the Mean-Variance Utility

Suppose an individual has the exponential utility function of the portfolio of assets x, which is given by:

$$U(x) = -e^{(-\lambda x)}, \quad \lambda > 0. \tag{A.1}$$

This exponential utility function is concave in x, as the first-order derivative is positive and second-order derivative is negative:

$$U'(x) = \lambda e^{(-\lambda x)} > 0 \quad U''(x) = -\lambda^2 e^{(-\lambda x)} < 0. \tag{A.2}$$

The parameter λ in the utility function is the Arrow-Pratt measure of absolute risk-aversion, which can shown by the equation:

$$r_A = -\frac{U''(x)}{U'(x)} = \lambda \tag{A.3}$$

If the portfolio x follows a normal distribution with mean μ and variance σ^2, and let $\phi(\mu,\sigma^2)$ denote the probability density function of x, the expected utility of the return can be written as:

$$\begin{aligned} E(x) &= \int_{-\infty}^{\infty} \phi(x)U(x)dx = \frac{1}{\sqrt{(2\pi)}\sigma} \int_{-\infty}^{\infty} -e^{(-\lambda x)} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dx \\ &= \frac{1}{\sqrt{(2\pi)}\sigma} \int_{-\infty}^{\infty} -e^{-(\lambda x + \frac{(x-\mu)^2}{2\sigma^2})} dx \end{aligned} \tag{A.4}$$

The exponential term can be rewritten as:

$$\lambda x + \frac{(x-\mu)^2}{2\sigma^2} = \frac{(x-(\mu-\lambda\sigma))^2}{2\sigma^2} + \lambda(\mu - \frac{\lambda\sigma^2}{2}) \tag{A.5}$$

Therefore, equation 28 can be rewritten as:

$$E(x) = -e^{-\lambda(\mu-\frac{\lambda\sigma^2}{2})} \frac{1}{\sqrt{(2\pi)}\sigma} \int_{-\infty}^{\infty} e^{-\frac{(x-(\mu-\lambda\sigma))^2}{2\sigma^2}} dx \tag{A.6}$$

Note that the probability density function of a normal distribution with mean $\mu - \lambda\sigma$ and variance σ^2 has the same form as the last two terms in equation A.6. Because the probability density function has the property as:

$$\frac{1}{\sqrt{(2\pi)}\sigma} \int_{-\infty}^{\infty} e^{-\frac{(x-(\mu-\lambda\sigma))^2}{2\sigma^2}} dx = 1 \tag{A.7}$$

The expected utility then becomes:

$$E(x) = -e^{-\lambda(\mu-\frac{\lambda\sigma^2}{2})} \tag{A.8}$$

Therefore, to maximize the expected utility is equal to maximize the term $(\mu - \frac{\lambda\sigma^2}{2})$. That is, to maximize the expected exponential utility function defined in equation 25 is the same as to maximize the mean-variance utility function defined as:

$$U_{MV} = E(x) - \frac{\lambda}{2} Var(x) \tag{A.9}$$

APPENDIX

B

MORAL HAZARD IN THE PREVENTED PLANTING

B.1 Lasso Selection and Full Results

The optimal λ is selected from the minimum of the BIC of the validation dataset. The total number of candidate variables is 384, and the number of variables selected often increases as the dataset size increases. The BIC has been divided by the sample size to fit the table. Results are presented in Table B.1, and the optimal number of effects and BIC are in bold text.

The variables selected and full results of the logistic regression are presented in Table B.2. Notations for extreme weather indicators are consistent with the definitions in equation 4.7 and 4.8. Cumulative precipitation is labeled as $pcpn^p\_cum\_month_i$, where $p = 1, 2, 3$ denotes the linear, square, and cube terms respectively. State variables are labeled as $state\ i$ where i is the state FIPS code.

Table B.1 Selection of Lambda

		Corn (ALL)		Corn (PPR)		Soybeans (ALL)	
Step	λ	No. of Effect	BIC	No. of Effect	BIC	No. of Effect	BIC
0	1	6	47993820	6	20334596	6	28445095
1	0.7	11	45108376	7	18002228	10	25812716
2	0.49	16	40129059	11	15808464	14	23158415
3	0.343	22	36164780	15	13810941	20	21081518
4	0.2401	30	33092572	20	11760339	22	19114115
5	0.1681	38	30772610	23	10430831	25	18001721
6	0.1176	49	29105968	31	9365582	33	16905518
7	0.0824	64	27888583	43	8555278	44	15982794
8	0.0576	83	26804128	54	8058326	57	15228398
9	0.0404	99	25973470	63	7725279	76	14631005
10	0.0282	121	25375643	74	7629958	95	14226080
11	0.0198	138	24927820	81	7565435	114	14005900
12	0.0138	163	24534414	**88**	**7509392***	137	13808098
13	0.0097	190	24141118	97	7583708	159	13711969
14	0.0068	221	23884900	110	7592020	181	13629946
15	0.0047	233	23768024	126	7613349	207	13597247
16	0.0033	259	23571711	149	7737642	234	13566920
17	0.0023	284	23467218	165	7884895	**249**	**13557883***
18	0.0016	**299**	**23387080***	173	8011916	263	13618052
19	0.0011	318	23467058	189	8168205	282	13741395
20	0.0008	331	23520273	206	8332588	292	13818387
21	0.0006	338	23598684	210	8471078	309	13876970
22	0.0004	349	23690844	230	8645682	320	13955018
23	0.0003	347	23804665	250	8848774	335	14029262
24	0.0002	352	23892841	260	9037042	340	14083065
25	0.0001	357	23962250	272	9211670	345	14133532
		Soybeans (PPR)		Grain Sorghum (ALL)		Grain Sorghum (PPR)	
Step	λ	No. of	BIC	No. of	BIC	No. of	BIC

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Table B.1 (continued).

		Effect		Effect		Effect	
0	1	6	11106054	6	4117765	6	199995
1	0.7	8	10049571	18	3684120	8	175718
2	0.49	9	9445985	20	3390972	9	164684
3	0.343	15	8783905	30	3173054	**10**	**158292***
4	0.2401	21	7860822	41	3052948	14	162967
5	0.1681	26	7025832	47	2993249	16	168085
6	0.1176	27	6498522	**60**	**2988142***	17	171463
7	0.0824	29	6135696	72	3016755	20	174791
8	0.0576	39	5826383	88	3072550	25	179941
9	0.0404	42	5601395	110	3160737	30	182935
10	0.0282	57	5450777	120	3231381	32	192159
11	0.0198	77	5351936	139	3311417	41	205144
12	0.0138	93	5232782	155	3394519	42	223560
13	0.0097	**108**	**5177972***	177	3547098	44	245493
14	0.0068	129	5256928	200	3708218	44	266768
15	0.0047	134	5390944	220	3819343	45	285474
16	0.0033	140	5656611	241	3874430	47	306397
17	0.0023	152	5770066	247	4014551	50	329021
18	0.0016	168	5992290	264	4143653	52	347627
19	0.0011	180	6278875	276	4366241	52	366154
20	0.0008	204	6656125	291	4605181	55	379673
21	0.0006	217	7139085	307	4773270	62	395499
22	0.0004	225	7606098	312	4966594	61	415805
23	0.0003	238	7773301	325	5054687	63	437479
24	0.0002	256	7969562	339	5037144	66	456311
25	0.0001	266	8545336	343	5027026	66	476186

		Spring Barley (ALL)		Spring Barley (PPR)		Fall Barley (ALL)	
Step	λ	No. of Effect	BIC	No. of Effect	BIC	No. of Effect	BIC
0	1	6	3021095	6	2105792	6	2850727
1	0.7	8	2375617	10	1704812	8	2272839
2	0.49	10	2065593	14	1315981	12	1968880
3	0.343	11	1828755	14	1050265	14	1751102

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Table B.1 (continued).

4	0.2401	11	1696523	14	908518	16	1557493
5	0.1681	15	1599782	15	821515	19	1432599
6	0.1176	21	1453371	23	747302	22	1330889
7	0.0824	25	1314587	27	693853	33	1261701
8	0.0576	32	1226826	31	662747	45	1183359
9	0.0404	39	1193635	**33**	**660702***	45	1143894
10	0.0282	49	1186039	42	676354	**51**	**1129599***
11	0.0198	60	1186519	51	689088	74	1134864
12	0.0138	**71**	**1168403***	56	698789	88	1153170
13	0.0097	87	1169737	64	729280	100	1181877
14	0.0068	103	1193059	78	764150	113	1198684
15	0.0047	120	1251526	91	793756	128	1222282
16	0.0033	130	1339308	99	815574	149	1275361
17	0.0023	153	1407462	106	852896	156	1344094
18	0.0016	172	1475506	117	853198	172	1394878
19	0.0011	189	1542084	121	852953	179	1450474
20	0.0008	203	1632052	132	854450	197	1511249
21	0.0006	219	1716994	136	864835	211	1586686
22	0.0004	231	1788040	159	872337	223	1725086
23	0.0003	247	1927352	172	896369	226	1921913
24	0.0002	265	2119622	187	937342	236	2212315
25	0.0001	283	2345345	191	990791	249	2614560

		Fall Barley (PPR)		Spring Wheat (ALL)		Spring Wheat (PPR)	
Step	λ	No. of Effect	BIC	No. of Effect	BIC	No. of Effect	BIC
0	1	6	2095723	6	21598619	6	19980611
1	0.7	9	1769400	9	18422927	11	15888681
2	0.49	10	1504813	11	14232791	12	13182024
3	0.343	11	1365069	12	11805722	14	11557591
4	0.2401	16	1234906	16	10222893	16	10591725
5	0.1681	18	1139541	17	9287103	19	10045203
6	0.1176	18	1073469	18	8739973	22	9453520
7	0.0824	21	969657	24	8365557	26	9124781
8	0.0576	34	894086	30	7982598	40	8836363

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Table B.1 (continued).

9	0.0404	**39**	**855861***	33	7723458	48	8402031
10	0.0282	47	856612	39	7526000	56	8092925
11	0.0198	54	877494	46	7368699	62	7819189
12	0.0138	60	910119	55	7275234	74	7823020
13	0.0097	68	973254	**72**	**7273958***	**88**	**7797286***
14	0.0068	78	1035102	90	7363099	102	7834463
15	0.0047	90	1025752	109	7590616	110	7800734
16	0.0033	98	1045585	113	7731483	118	7875871
17	0.0023	109	1206656	135	7921387	133	8018991
18	0.0016	123	1473750	149	8365013	145	8053426
19	0.0011	136	1687202	157	9043818	169	8405569
20	0.0008	145	1783869	171	10072350	181	8772857
21	0.0006	155	1928588	199	11608734	191	8972219
22	0.0004	170	2112715	203	12585027	198	9157037
23	0.0003	183	2470480	224	13729095	211	9356605
24	0.0002	202	2964317	235	15211113	222	10041752
25	0.0001	205	3536969	240	15960608	239	10771039

		Winter Wheat		Cotton	
Step	λ	No. of Effect	BIC	No. of Effect	BIC
0	1	6	30377455	6	6487061
1	0.7	7	24505653	8	6052426
2	0.49	9	19982440	8	6003648
3	0.343	13	16260868	11	5893592
4	0.2401	13	14313171	14	5398711
5	0.1681	16	13174204	17	5150952
6	0.1176	21	12413846	19	4747142
7	0.0824	31	11766247	23	4475922
8	0.0576	37	11323235	33	4319917
9	0.0404	50	10779644	**47**	**4238888***
10	0.0282	72	10263417	63	4260992
11	0.0198	90	9876028	76	4310607
12	0.0138	109	9627363	89	4380588
13	0.0097	129	9387707	108	4450111
14	0.0068	155	9224714	116	4556888

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Table B.1 (continued).

15	0.0047	178	9165033	129	4707358
16	0.0033	**189**	**9092403***	143	4907831
17	0.0023	196	9107948	161	5123896
18	0.0016	222	9147453	172	5272152
19	0.0011	247	9202007	182	5573982
20	0.0008	276	9277670	204	5893060
21	0.0006	286	9373644	211	6257780
22	0.0004	304	9448776	217	6662955
23	0.0003	321	9566474	242	7044013
24	0.0002	329	9712847	254	7270137
25	0.0001	336	9839494	270	7524102

* denotes the minimum BIC of λ in the validation dataset.

Table B.2 Full Logistic Results from Lasso Selected Variables

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
Corn (ALL)			**Soybeans (ALL)**		
Intercept	506.2351	3.0939	Intercept	496.2247	2.4785
Coverage Level	1.8853	0.0089	Coverage Level	-4.5747	0.0115
Price Ratio	2.5583	0.0126	Harvest Price	5.5584	0.0327
Input Price	1.5096	0.0157	Price Ratio	-1.3128	0.0087
Acres/Unit	-0.2586	0.0009	Input Price	-2.2376	0.0149
Linear Price	-1.3831	0.0077	Acres/Unit	0.0897	0.0010
Cubic Price	0.0046	0.0001	Cubic Price	-0.0011	0.0000
cddc_Jan	0.0307	0.0012	cddc_Jan	0.0341	0.0002
cddc_Mar	0.2384	0.0010	cddc_Feb	0.0253	0.0002
cddc_May	-0.0048	0.0000	cddc_Mar	0.2481	0.0012
cddc_Jun	0.0094	0.0000	cddc_May	-0.0024	0.0000
hddc_Jan	-0.0159	0.0012	cddc_Jun	0.0053	0.0000
hddc_Feb	-0.0052	0.0002	hddc_Jan	0.0019	0.0000
hddc_Mar	-0.2362	0.0010	hddc_Mar	-0.2494	0.0012
hddc_Apr	0.0057	0.0000	hddc_Jun	0.0094	0.0000
hddc_Jun	0.0012	0.0000	pcpn_Jan	0.0997	0.0024
pcpn_Feb	0.2530	0.0012	pcpn_Feb	0.3520	0.0017
pcpn_Apr	0.0021	0.0007	pcpn_Mar	-0.2369	0.0010
pcpn_Jun	-0.4295	0.0016	pcpn_Apr	-0.0053	0.0010
tmpc_Jan	-0.5531	0.0368	pcpn_May	0.1673	0.0009
tmpc_Feb	-0.1387	0.0051	pcpn_Jun	0.0811	0.0011
tmpc_Mar	-7.2469	0.0302	tmpc_Mar	-7.6576	0.0382
tmpc_May	-0.1062	0.0005	tmpc_May	-0.0812	0.0006
$pcpn^2$_cum_Jan	-0.0126	0.0002	$pcpn^2$_cum_Jan	-0.0070	0.0005
$pcpn^2$_cum_May	-0.0082	0.0001	$pcpn^2$_cum_Feb	-0.0339	0.0001
$pcpn^2$_cum_Jun	0.0170	0.0001	$pcpn^2$_cum_Jun	0.0030	0.0000
$pcpn^3$_cum_Jan	0.0051	0.0000	$pcpn^3$_cum_Jan	0.0029	0.0000
$pcpn^3$_cum_Feb	-0.0017	0.0000	$pcpn^3$_cum_Mar	0.0003	0.0000
$pcpn^3$_cum_Mar	0.0002	0.0000	$pcpn^3$_cum_Apr	0.0000	0.0000
$pcpn^3$_cum_Apr	0.0000	0.0000	$pcpn^3$_cum_May	-0.0001	0.0000
$pcpn^3$_cum_May	0.0000	0.0000	w_cddc_Jan	-0.1249	0.0061
$pcpn^3$_cum_Jun	-0.0002	0.0000	w_cddc_Feb	-0.3837	0.0043
w_cddc_Jan	-0.7222	0.0068	w_cddc_Mar	-0.1765	0.0048
w_cddc_Feb	0.0658	0.0093	w_cddc_Apr	-0.7473	0.0035

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
w_cddc_Mar	0.2163	0.0035	w_cddc_May	-0.0700	0.0046
w_cddc_Apr	-0.3946	0.0032	w_cddc_Jun	0.1531	0.0022
w_cddc_May	-0.6649	0.0036	w2_cddc_Jan	0.4882	0.0118
w_cddc_Jun	0.2775	0.0060	w2_cddc_Mar	-0.5973	0.0061
w2_cddc_Jan	-0.7809	0.0115	w2_cddc_Apr	-0.3022	0.0058
w2_cddc_Feb	0.5389	0.0107	w2_cddc_May	-0.3636	0.0055
w2_cddc_Mar	-0.1866	0.0054	w2_cddc_Jun	-0.7675	0.0041
w2_cddc_Apr	0.0730	0.0058	w3_cddc_Jan	-0.0061	0.0015
w2_cddc_May	-0.6588	0.0046	w3_cddc_Mar	0.0276	0.0017
w2_cddc_Jun	0.0381	0.0046	w3_cddc_Apr	0.3152	0.0016
w3_cddc_Jan	0.0841	0.0009	w3_cddc_May	-0.4330	0.0037
w3_cddc_Feb	0.0501	0.0048	w_hddc_Mar	-0.5748	0.0022
w3_cddc_Mar	-0.2925	0.0012	w_hddc_Apr	1.4332	0.0035
w3_cddc_Apr	0.2274	0.0014	w_hddc_Jun	-1.6176	0.0078
w3_cddc_Jun	-1.0452	0.0053	w2_hddc_Jan	-0.7058	0.0261
w_hddc_Feb	1.1671	0.0045	w2_hddc_Feb	-0.2823	0.0235
w_hddc_Mar	-0.1612	0.0050	w2_hddc_May	0.3303	0.0035
w_hddc_Apr	1.0062	0.0038	w2_hddc_Jun	-0.7652	0.0070
w_hddc_May	-0.5301	0.0037	w3_hddc_Jan	0.9684	0.0050
w_hddc_Jun	-2.8791	0.0071	w3_hddc_Mar	0.6153	0.0025
w2_hddc_Jan	-0.5149	0.0344	w3_hddc_May	-0.5399	0.0029
w2_hddc_Feb	0.9558	0.0365	w3_hddc_Jun	0.2972	0.0042
w2_hddc_Mar	-0.7137	0.0032	w_tmpc_Jan	-0.3484	0.0052
w2_hddc_Apr	-0.6145	0.0075	w_tmpc_Mar	0.1354	0.0024
w2_hddc_Jun	-2.0692	0.0062	w_tmpc_Apr	0.3202	0.0030
w3_hddc_Jan	1.6621	0.0069	w_tmpc_May	0.6283	0.0060
w3_hddc_Mar	0.7352	0.0036	w_tmpc_Jun	0.6531	0.0029
w3_hddc_Apr	1.0771	0.0108	w2_tmpc_Jan	0.1627	0.0047
w3_hddc_May	-0.2305	0.0042	w2_tmpc_Apr	-0.6812	0.0052
w3_hddc_Jun	1.8002	0.0038	w2_tmpc_May	1.5274	0.0074
w_tmpc_Mar	0.2233	0.0034	w3_tmpc_Jan	0.3483	0.0049
w_tmpc_May	0.6571	0.0040	w3_tmpc_Feb	0.1187	0.0020
w_tmpc_Jun	0.9464	0.0043	w3_tmpc_Apr	-0.1567	0.0025
w2_tmpc_Jan	0.6378	0.0021	w3_tmpc_May	-0.2506	0.0055
w2_tmpc_Feb	-0.0302	0.0024	w3_tmpc_Jun	-0.7619	0.0037
w2_tmpc_Mar	0.5274	0.0028	w_pcpn_Jan	-1.6708	0.0058

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
w2_tmpc_Apr	-0.3492	0.0040	w_pcpn_Feb	0.6383	0.0020
w2_tmpc_May	1.9434	0.0053	w2_pcpn_Apr	0.7010	0.0023
w3_tmpc_Jan	-0.4815	0.0031	w3_pcpn_Jan	0.5563	0.0265
w3_tmpc_Feb	0.5615	0.0035	w3_pcpn_Feb	-1.2539	0.0236
w3_tmpc_Mar	0.0024	0.0022	w3_pcpn_Apr	-0.5214	0.0031
w3_tmpc_May	-0.3509	0.0019	w3_pcpn_May	0.9612	0.0045
w_pcpn_Jan	-2.0076	0.0058	h_pdsi_Jan	0.1015	0.0032
w_pcpn_Mar	-0.6075	0.0039	h_pdsi_Feb	-0.0471	0.0029
w_pcpn_May	0.2204	0.0035	h_pdsi_May	-0.3623	0.0025
w_pcpn_Jun	0.3113	0.0064	h_pdsi_Jun	0.8299	0.0027
w2_pcpn_Jan	0.5433	0.0085	h2_pdsi_Feb	0.1694	0.0017
w2_pcpn_Feb	0.4381	0.0032	h2_pdsi_Apr	0.2470	0.0030
w2_pcpn_Apr	2.2151	0.0105	h3_pdsi_Jan	0.2088	0.0016
w3_pcpn_Jan	0.9369	0.0345	h3_pdsi_Feb	0.0319	0.0013
w3_pcpn_Feb	-0.4578	0.0363	h3_pdsi_May	-0.0512	0.0005
w3_pcpn_Apr	-0.9607	0.0067	h3_pdsi_Jun	0.3020	0.0010
w3_pcpn_May	0.9218	0.0039	h4_pdsi_Mar	-0.9146	0.0094
w3_pcpn_Jun	0.6988	0.0064	h_phdi_Jan	0.0723	0.0020
h_pdsi_Jan	0.4073	0.0036	h_phdi_Mar	-0.1120	0.0014
h_pdsi_Feb	0.0098	0.0027	h_phdi_Apr	-0.1709	0.0018
h_pdsi_Mar	-0.1318	0.0030	h_phdi_May	0.2764	0.0022
h_pdsi_Apr	-0.3302	0.0024	h_phdi_Jun	-0.4796	0.0021
h_pdsi_May	0.7705	0.0043	h2_phdi_Mar	0.0917	0.0012
h_pdsi_Jun	0.6574	0.0045	h3_phdi_Apr	-0.0985	0.0009
h2_pdsi_Feb	-0.1777	0.0018	h4_phdi_Jan	1.6204	0.0061
h2_pdsi_Mar	0.0668	0.0025	h4_phdi_Mar	0.9718	0.0094
h2_pdsi_May	-0.1522	0.0030	h4_phdi_Apr	0.0099	0.0067
h2_pdsi_Jun	-0.6771	0.0039	h_pmdi_Jan	0.1679	0.0022
h3_pdsi_Jan	0.6979	0.0026	h_pmdi_Feb	0.0730	0.0020
h3_pdsi_Mar	-0.3552	0.0031	h_pmdi_Apr	0.0195	0.0019
h3_pdsi_May	0.4824	0.0031	h_pmdi_May	0.0645	0.0019
h3_pdsi_Jun	0.5390	0.0027	h2_pmdi_Jan	-0.0708	0.0014
h4_pdsi_Jan	0.8650	0.0051	h2_pmdi_Apr	-0.2133	0.0030
h4_pdsi_Apr	-0.7415	0.0044	h2_pmdi_May	0.1188	0.0016
h4_pdsi_May	2.6911	0.0118	h2_pmdi_Jun	-0.1554	0.0016
h4_pdsi_Jun	14.9919	0.0115	h3_pmdi_Jan	-0.1114	0.0012

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
h_phdi_Jan	0.0325	0.0019	h3_pmdi_Feb	-0.1263	0.0011
h_phdi_Feb	0.2605	0.0020	h4_pmdi_Jan	-0.9508	0.0060
h_phdi_Mar	0.2834	0.0020	h4_pmdi_Feb	-0.6887	0.0052
h_phdi_Apr	-0.0404	0.0019	h4_pmdi_Apr	0.0225	0.0064
h_phdi_May	0.2012	0.0022	h4_pmdi_Jun	0.7470	0.0039
h_phdi_Jun	-0.1909	0.0021	h_zmdi_Jan	0.2009	0.0016
h2_phdi_Jan	-0.5348	0.0021	h_zmdi_Feb	0.0799	0.0012
h2_phdi_Jun	0.2423	0.0030	h_zmdi_Mar	0.0089	0.0013
h3_phdi_Jan	-0.5305	0.0020	h_zmdi_Apr	0.1717	0.0013
h3_phdi_Feb	0.1248	0.0010	h_zmdi_May	-0.0105	0.0015
h3_phdi_Mar	0.4324	0.0028	h2_zmdi_Jan	-0.1265	0.0007
h3_phdi_Apr	-0.3020	0.0013	h2_zmdi_Feb	0.0980	0.0010
h3_phdi_May	0.0575	0.0017	h2_zmdi_Mar	-0.0511	0.0007
h4_phdi_Jun	-12.9421	0.0000	h2_zmdi_Apr	-0.1393	0.0007
h_pmdi_Jan	0.0638	0.0018	h2_zmdi_Jun	0.2302	0.0009
h_pmdi_Feb	0.0551	0.0021	h3_zmdi_Jan	0.1552	0.0006
h_pmdi_Mar	-0.3446	0.0021	h3_zmdi_Mar	0.0334	0.0004
h_pmdi_Apr	-0.1286	0.0020	h3_zmdi_Apr	0.0838	0.0005
h_pmdi_May	-0.2640	0.0027	h3_zmdi_May	0.0250	0.0004
h_pmdi_Jun	0.2467	0.0024	h3_zmdi_Jun	0.0342	0.0003
h2_pmdi_Jan	0.2873	0.0017	h4_zmdi_Jan	-0.3052	0.0026
h2_pmdi_Feb	0.2698	0.0016	h4_zmdi_Feb	-0.0105	0.0028
h2_pmdi_Mar	0.0035	0.0022	h4_zmdi_Mar	0.2845	0.0020
h2_pmdi_Apr	0.3386	0.0012	h4_zmdi_Apr	0.0939	0.0018
h2_pmdi_May	-0.2079	0.0024	h4_zmdi_May	0.2367	0.0019
h2_pmdi_Jun	0.0676	0.0026	h_sp01_Jan	-0.5898	0.0021
h3_pmdi_Jan	0.0639	0.0008	h_sp01_Feb	0.2763	0.0028
h3_pmdi_Feb	-0.0511	0.0011	h_sp01_May	0.7928	0.0077
h3_pmdi_Mar	-0.2565	0.0011	h2_sp01_Feb	-0.3610	0.0024
h3_pmdi_Apr	0.1151	0.0010	h2_sp01_Mar	0.5683	0.0020
h3_pmdi_May	-0.1382	0.0017	h2_sp01_Apr	0.6339	0.0038
h3_pmdi_Jun	-0.1512	0.0016	h2_sp01_May	-1.2384	0.0078
h4_pmdi_Feb	0.2045	0.0044	h2_sp01_Jun	0.4360	0.0027
h4_pmdi_Mar	-0.4690	0.0048	h3_sp01_Jan	-0.6435	0.0051
h4_pmdi_May	-1.0410	0.0092	h3_sp01_Mar	0.0097	0.0021
h4_pmdi_Jun	-0.4905	0.0081	h3_sp01_May	0.4189	0.0074

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
h_zmdi_Jan	0.2255	0.0014	h3_sp01_Jun	0.3600	0.0050
h_zmdi_Feb	0.3166	0.0013	h4_sp01_Jan	-1.2613	0.0199
h_zmdi_Mar	-0.1523	0.0011	h4_sp01_Feb	-0.5918	0.0211
h_zmdi_Apr	0.0581	0.0012	h4_sp01_Apr	-0.4237	0.0077
h_zmdi_May	-0.3138	0.0012	h4_sp01_May	0.3359	0.0256
h_zmdi_Jun	0.0559	0.0012	h4_sp01_Jun	0.2442	0.0465
h2_zmdi_Jan	-0.0536	0.0006	h_sp02_Jan	0.0751	0.0016
h2_zmdi_Feb	-0.0617	0.0008	h_sp02_Feb	-0.1026	0.0024
h2_zmdi_Mar	-0.0583	0.0005	h_sp02_Mar	0.0998	0.0022
h2_zmdi_Apr	-0.1208	0.0006	h_sp02_Apr	0.3092	0.0022
h2_zmdi_May	-0.0144	0.0007	h2_sp02_Jan	0.1300	0.0025
h2_zmdi_Jun	0.1652	0.0006	h2_sp02_Feb	0.2889	0.0030
h3_zmdi_Jan	0.1938	0.0005	h2_sp02_Mar	-0.3424	0.0022
h3_zmdi_Feb	0.1208	0.0004	h2_sp02_Apr	-0.2952	0.0031
h3_zmdi_Mar	-0.0233	0.0003	h2_sp02_May	-0.6511	0.0027
h3_zmdi_Apr	0.0228	0.0004	h2_sp02_Jun	-0.5663	0.0027
h3_zmdi_May	-0.0072	0.0003	h3_sp02_Jan	0.1186	0.0022
h3_zmdi_Jun	0.0163	0.0003	h3_sp02_Feb	-0.0662	0.0022
h4_zmdi_Jan	-0.5920	0.0023	h3_sp02_Mar	0.2808	0.0024
h4_zmdi_Feb	0.0256	0.0024	h3_sp02_Apr	0.3577	0.0022
h4_zmdi_Mar	0.5115	0.0019	h3_sp02_Jun	0.1673	0.0014
h4_zmdi_Apr	-0.1693	0.0016	h4_sp02_Mar	-2.2527	0.0396
h4_zmdi_Jun	-0.3416	0.0018	h4_sp02_May	0.7196	0.0055
h_sp01_Feb	-0.3098	0.0024	h_sp06_Jan	-0.3074	0.0013
h_sp01_Mar	-0.1577	0.0026	h_sp06_Feb	0.1399	0.0014
h_sp01_Apr	-0.1345	0.0034	h_sp06_Mar	-0.1902	0.0014
h_sp01_May	0.2317	0.0033	h_sp06_Apr	-0.0669	0.0015
h_sp01_Jun	-0.1722	0.0049	h_sp06_Jun	0.1267	0.0017
h2_sp01_Jan	-0.5969	0.0015	h2_sp06_Jan	0.3617	0.0031
h2_sp01_Apr	0.4092	0.0044	h2_sp06_Feb	0.2594	0.0028
h2_sp01_May	-1.0196	0.0044	h2_sp06_Mar	0.2235	0.0022
h2_sp01_Jun	1.1811	0.0026	h2_sp06_Apr	0.0992	0.0028
h3_sp01_Jan	0.0337	0.0033	h2_sp06_May	0.2516	0.0034
h3_sp01_Feb	-0.9171	0.0047	h3_sp06_Feb	0.2013	0.0015
h3_sp01_Mar	-0.3784	0.0026	h3_sp06_Apr	-0.1577	0.0014
h3_sp01_Apr	0.0834	0.0030	h3_sp06_May	-0.1878	0.0012

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
h3_sp01_Jun	-0.6357	0.0027	h3_sp06_Jun	0.2915	0.0012
h4_sp01_Jan	1.0311	0.0192	h4_sp06_Jan	-1.1915	0.0283
h4_sp01_Feb	1.0262	0.0102	h4_sp06_May	-0.2032	0.0106
h4_sp01_Mar	-0.8050	0.0075	h4_sp06_Jun	-0.2713	0.0106
h4_sp01_Apr	-0.1035	0.0095	h_sp09_Jan	-0.0607	0.0014
h4_sp01_Jun	-3.8035	0.0617	h_sp09_Feb	0.0288	0.0015
h_sp02_Feb	-0.2286	0.0020	h_sp09_Mar	0.3971	0.0015
h_sp02_Apr	0.1993	0.0020	h_sp09_Apr	0.1300	0.0017
h_sp02_May	0.3149	0.0021	h_sp09_May	-0.1615	0.0017
h_sp02_Jun	0.2348	0.0013	h_sp09_Jun	-0.3003	0.0016
h2_sp02_Jan	0.1681	0.0017	h2_sp09_Jan	-0.3373	0.0023
h2_sp02_Feb	0.4769	0.0024	h2_sp09_Feb	-0.8465	0.0024
h2_sp02_Mar	-0.1159	0.0015	h2_sp09_Apr	0.2444	0.0028
h2_sp02_Apr	0.0054	0.0029	h2_sp09_May	-0.1250	0.0038
h2_sp02_May	-0.9345	0.0027	h2_sp09_Jun	0.0706	0.0037
h3_sp02_Jan	0.1759	0.0015	h3_sp09_Jan	-0.0281	0.0013
h3_sp02_Feb	0.0368	0.0018	h3_sp09_Feb	0.0408	0.0014
h3_sp02_Apr	-0.1249	0.0020	h3_sp09_Mar	-0.1808	0.0012
h3_sp02_May	0.4099	0.0020	h3_sp09_Apr	-0.0708	0.0013
h3_sp02_Jun	0.4512	0.0015	h3_sp09_May	-0.0259	0.0014
h4_sp02_Mar	-1.3787	0.0174	h3_sp09_Jun	-0.2289	0.0011
h4_sp02_Apr	-0.6216	0.0120	h4_sp09_Jan	-0.9397	0.0147
h4_sp02_May	1.6731	0.0057	h4_sp09_Feb	-0.7634	0.0043
h4_sp02_Jun	0.4544	0.0089	h4_sp09_Mar	1.0308	0.0104
h_sp06_Jan	-0.3123	0.0011	h4_sp09_Apr	-1.7666	0.0191
h_sp06_Feb	0.1265	0.0012	h4_sp09_May	-0.0654	0.0153
h_sp06_Mar	-0.1465	0.0013	h4_sp09_Jun	-0.7051	0.0056
h_sp06_Apr	-0.2659	0.0013	Year2005	1.0820	0.0047
h_sp06_May	0.0805	0.0015	Year2007	0.7335	0.0040
h2_sp06_Jan	0.0245	0.0023	Year2009	-0.6748	0.0074
h2_sp06_Feb	0.0876	0.0024	Year2010	-1.1943	0.0061
h2_sp06_Mar	0.2910	0.0020	Year2011	0.0814	0.0039
h2_sp06_Apr	-0.2514	0.0025	Year2012	-1.1294	0.0118
h2_sp06_May	0.1269	0.0031	Year2013	1.6285	0.0058
h2_sp06_Jun	-0.1937	0.0024	Year2014	-0.8922	0.0073
h3_sp06_Jan	0.0198	0.0013	Year2015	0.4004	0.0066

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
h3_sp06_Feb	0.0198	0.0012	Year2016	-0.1863	0.0065
h3_sp06_Mar	-0.0448	0.0012	Region1	0.9659	0.0023
h3_sp06_Apr	-0.1283	0.0012	Region2	0.7748	0.0020
h3_sp06_May	-0.3677	0.0014	Region3	0.7591	0.0047
h3_sp06_Jun	0.1981	0.0010	Region4	0.5193	0.0032
h4_sp06_Jan	-2.7611	0.0332	Region6	-0.4394	0.0069
h4_sp06_Feb	-1.9079	0.0273	Region8	-0.2493	0.0044
h4_sp06_Mar	1.1206	0.0295	state2	0.8303	0.0051
h4_sp06_May	-0.5360	0.0067	state4	1.1779	0.0227
h4_sp06_Jun	0.7494	0.0067	state6	0.1918	0.0106
h_sp09_Jan	-0.2183	0.0012	state8	-2.5656	0.0306
h_sp09_Feb	0.1080	0.0013	state9	-0.6002	0.0086
h_sp09_Mar	0.1724	0.0013	state12	-0.0990	0.0026
h_sp09_Apr	0.3014	0.0015	state13	-1.2515	0.0030
h_sp09_May	0.1474	0.0014	state14	-1.0463	0.0057
h_sp09_Jun	-0.3993	0.0013	state15	0.1435	0.0041
h2_sp09_Jan	-0.3067	0.0020	state16	1.3372	0.0059
h2_sp09_Feb	-0.1557	0.0021	state18	-0.0880	0.0062
h2_sp09_Mar	0.3145	0.0018	state20	-0.2528	0.0044
h2_sp09_Apr	0.1182	0.0022	state21	-0.1917	0.0038
h2_sp09_May	0.0814	0.0028	state22	0.7387	0.0059
h3_sp09_Jan	-0.0043	0.0011	state23	0.5591	0.0023
h3_sp09_Feb	-0.3194	0.0012	state25	-1.8273	0.0049
h3_sp09_Mar	0.0359	0.0011	state29	1.5788	0.0054
h3_sp09_Apr	0.0801	0.0012	state31	0.6161	0.0043
h3_sp09_May	0.1062	0.0012	state32	0.1730	0.0030
h3_sp09_Jun	-0.3598	0.0010	state33	-0.4658	0.0061
h4_sp09_Jan	-0.0352	0.0098	state35	-0.1734	0.0069
h4_sp09_Feb	-1.0176	0.0035	state36	0.6592	0.0047
h4_sp09_Mar	1.6485	0.0068	state37	0.8621	0.0039
h4_sp09_Apr	-1.4603	0.0122	state38	-0.2180	0.0060
h4_sp09_May	-0.3688	0.0106	state39	0.9486	0.0070
h4_sp09_Jun	-1.6151	0.0049	state41	0.3860	0.0306
Year2004	-0.7974	0.0033	state42	0.2505	0.0059
Year2005	-0.6889	0.0052	state46	-0.4551	0.0044
Year2006	-1.6682	0.0077			

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
Year2007	-2.2438	0.0059	Soybeans (PPR)		
Year2008	-0.2851	0.0034	Intercept	-14.0405	0.0546
Year2009	0.6006	0.0062	Coverage Level	-4.5857	0.0273
Year2010	-0.5000	0.0042	Harvest Price	-1.8027	0.0181
Year2013	2.3282	0.0050	Price Ratio	-0.1592	0.0075
Year2014	1.3347	0.0057	Input Price	1.4225	0.0140
Year2015	1.3146	0.0045	Acres/Unit	0.6752	0.0019
Year2016	-1.1393	0.0047	hddc_Feb	-0.0002	0.0000
Region1	0.9405	0.0020	hddc_Apr	0.0024	0.0000
Region2	0.8471	0.0017	hddc_May	0.0067	0.0000
Region3	1.0941	0.0028	pcpn_May	0.1794	0.0015
Region4	0.4922	0.0029	$pcpn^3$_cum_Jun	0.0001	0.0000
Region5	1.4348	0.0048	w_cddc_Mar	-1.0412	0.0064
Region6	2.1185	0.0054	w_cddc_May	-0.0544	0.0044
Region7	-0.3206	0.0107	w3_cddc_Jun	0.9266	0.0180
Region8	1.4330	0.0063	w_hddc_Jan	0.2579	0.0041
state1	1.4912	0.0134	w_hddc_Feb	0.3906	0.0043
state2	0.8744	0.0067	w_hddc_Apr	0.8221	0.0036
state3	0.4856	0.0091	w_hddc_Jun	-1.3385	0.0076
state4	1.9849	0.0038	w2_hddc_Mar	-0.2781	0.0024
state5	-2.1673	0.0368	w3_hddc_Feb	1.0032	0.0047
state6	-2.3566	0.0152	w3_hddc_May	-1.3311	0.0136
state9	-4.0602	0.0229	w_tmpc_Mar	-0.1314	0.0025
state10	-0.4404	0.0102	w_tmpc_Jun	0.3927	0.0027
state11	-0.1570	0.0027	w2_tmpc_Feb	0.0286	0.0046
state12	0.1204	0.0030	w2_tmpc_Apr	-0.4718	0.0054
state13	-0.7362	0.0026	w_pcpn_Jan	0.0000	0.0000
state14	-0.3486	0.0039	w_pcpn_Feb	0.0000	0.0000
state15	0.0376	0.0042	w_pcpn_Jun	0.5232	0.0106
state16	0.6967	0.0069	w2_pcpn_Jan	1.7398	0.0254
state17	-3.4417	0.1226	w2_pcpn_Mar	0.2229	0.0027
state18	-1.6133	0.0081	w2_pcpn_May	-1.5036	0.0148
state19	-3.2012	0.0336	w3_pcpn_Jun	-0.9974	0.0198
state22	1.4277	0.0069	h_pdsi_May	-0.4396	0.0027
state23	1.2251	0.0029	h_pdsi_Jun	0.4847	0.0038
state25	-0.8885	0.0031	h2_pdsi_Jan	0.1509	0.0021

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
state27	-1.7993	0.0187	h2_pdsi_Feb	0.2921	0.0021
state28	-0.4990	0.0218	h2_pdsi_Jun	0.3542	0.0029
state29	1.2227	0.0038	h3_pdsi_Mar	0.2348	0.0011
state30	-1.1816	0.0083	h_phdi_Jan	0.1853	0.0031
state31	1.7198	0.0024	h_phdi_Apr	-0.0049	0.0031
state32	0.6330	0.0030	h_phdi_Jun	-0.5006	0.0035
state33	1.1109	0.0057	h4_phdi_Jan	0.2632	0.0028
state34	2.7143	0.0142	h_pmdi_Feb	-0.3490	0.0029
state35	0.1857	0.0056	h_pmdi_Mar	0.3106	0.0025
state36	0.6529	0.0060	h_pmdi_Apr	0.2980	0.0026
state37	1.3479	0.0022	h2_pmdi_Apr	-0.3164	0.0021
state38	-0.7521	0.0071	h4_pmdi_Apr	0.2806	0.0042
state39	1.7277	0.0055	h4_pmdi_May	-0.4021	0.0029
state40	2.2276	0.0176	h_zmdi_Feb	-0.3210	0.0023
state41	-0.3378	0.0095	h_zmdi_Mar	0.0891	0.0020
state42	-1.6149	0.0087	h_zmdi_Apr	-0.1321	0.0024
state43	-5.3282	0.2501	h_zmdi_May	-0.6509	0.0024
state44	-2.8964	0.0249	h2_zmdi_Jan	-0.1928	0.0015
state46	-0.2673	0.0024	h2_zmdi_Feb	0.2775	0.0027
			h2_zmdi_Apr	-0.1901	0.0015
Corn (PPR)			h2_zmdi_May	-0.0029	0.0015
Intercept	-29.5394	0.0509	h2_zmdi_Jun	0.3017	0.0018
Coverage Level	4.8368	0.0182	h3_zmdi_Jan	0.0252	0.0006
Harvest Price	-5.1815	0.0114	h3_zmdi_Apr	0.0553	0.0007
Price Ratio	1.0942	0.0053	h3_zmdi_Jun	0.0287	0.0004
Input Price	4.7725	0.0113	h4_zmdi_Jan	-0.5131	0.0034
Acres/Unit	0.2183	0.0017	h4_zmdi_Mar	-0.2059	0.0031
hddc_Mar	0.0002	0.0000	h4_zmdi_Apr	0.0791	0.0029
hddc_May	0.0053	0.0000	h4_zmdi_May	0.4264	0.0031
pcpn_Jan	0.1591	0.0030	h_sp01_Jan	-0.1282	0.0026
pcpn_May	0.1299	0.0011	h_sp01_Feb	-0.0373	0.0028
tmpc_Feb	-0.0722	0.0002	h_sp01_May	0.3068	0.0027
$pcpn^3$_cum_May	0.0000	0.0000	h2_sp01_Jan	-0.5995	0.0029
$pcpn^3$_cum_Jun	0.0001	0.0000	h2_sp01_Feb	-0.2967	0.0037
w2_cddc_May	-0.1861	0.0085	h2_sp01_Mar	-0.4672	0.0023
w_hddc_Mar	-0.2417	0.0018	h2_sp01_Apr	0.4102	0.0053

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
w_hddc_Jun	-0.5651	0.0030	h2_sp01_May	-0.1290	0.0046
w3_hddc_Jan	815.6212	20.6455	h4_sp01_Jan	1.1793	0.0231
w3_hddc_Feb	0.7559	0.0026	h4_sp01_May	0.9435	0.0241
w3_hddc_Apr	-0.0063	0.0018	h_sp02_Feb	0.1765	0.0018
w3_hddc_May	-0.3832	0.0034	h_sp02_Mar	-0.1004	0.0018
w_tmpc_Jan	-0.7937	0.0033	h_sp02_Jun	-0.0374	0.0024
w_tmpc_Mar	0.3336	0.0018	h2_sp02_Jan	0.3930	0.0047
w_tmpc_May	0.1573	0.0022	h3_sp02_Jan	0.4268	0.0034
w_tmpc_Jun	0.5494	0.0021	h3_sp02_Jun	-0.0796	0.0019
w2_tmpc_May	0.7229	0.0048	h_sp06_Jan	-0.0458	0.0021
w3_tmpc_Feb	0.0448	0.0017	h_sp06_Apr	0.2186	0.0028
w2_pcpn_Jan	818.4436	20.6672	h2_sp06_Jan	-0.1300	0.0063
h_pdsi_Feb	0.0227	0.0035	h2_sp06_Mar	0.3439	0.0034
h_pdsi_Mar	-0.3523	0.0028	h2_sp06_Apr	0.5036	0.0046
h_pdsi_Apr	-0.4419	0.0028	h2_sp06_May	0.8615	0.0071
h2_pdsi_Feb	0.0188	0.0052	h2_sp06_Jun	-0.5134	0.0051
h4_pdsi_May	-0.4204	0.0034	h3_sp06_Jan	0.1013	0.0022
h_phdi_Jan	0.1286	0.0034	h3_sp06_Mar	0.5064	0.0020
h_phdi_Jun	0.1490	0.0025	h3_sp06_Apr	0.0519	0.0028
h4_phdi_Jan	0.0402	0.0025	h_sp09_Feb	-0.5161	0.0024
h4_phdi_Mar	0.0177	0.0041	h_sp09_Jun	-0.0913	0.0019
h4_phdi_Apr	-0.3944	0.0032	h2_sp09_Jan	0.5808	0.0041
h_pmdi_Jan	0.0091	0.0033	h2_sp09_Feb	-0.7838	0.0037
h_pmdi_Apr	0.0110	0.0024	h2_sp09_Mar	0.3378	0.0035
h2_pmdi_Feb	0.1506	0.0050	h3_sp09_Apr	-0.2255	0.0025
h2_pmdi_Mar	0.1448	0.0018	h3_sp09_May	0.0521	0.0016
h3_pmdi_May	-0.0343	0.0007	h4_sp09_Mar	0.7331	0.0089
h4_pmdi_Feb	0.6039	0.0038	h4_sp09_Apr	-2.9066	0.0254
h_zmdi_Feb	0.1661	0.0025	h4_sp09_Jun	-0.5389	0.0073
h_zmdi_Mar	0.1563	0.0017	Year2007	1.0013	0.0081
h_zmdi_May	-0.6302	0.0019	Year2013	-0.2666	0.0086
h2_zmdi_Jun	0.3216	0.0014	Year2016	-1.4561	0.0078
h3_zmdi_Feb	0.1063	0.0006	Region1	0.9661	0.0034
h3_zmdi_Apr	0.0149	0.0004	Region2	0.4338	0.0021
h3_zmdi_Jun	0.0230	0.0003	state13	-0.6899	0.0041
h4_zmdi_Jan	-0.9721	0.0026	state31	1.0854	0.0025

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
h4_zmdi_May	1.1639	0.0025	state37	1.7379	0.0028
h_sp01_Jan	-0.7920	0.0030			
h_sp01_Apr	-0.5423	0.0034			
h2_sp01_Feb	-0.2407	0.0014	**Sorghum (ALL)**		
h3_sp01_Apr	-0.0766	0.0029	Intercept	-12.7323	0.0652
h_sp02_Jan	-0.2795	0.0017	Coverage Level	0.6589	0.0274
h_sp02_Mar	0.1369	0.0015	Harvest Price	-0.7011	0.0175
h_sp02_Jun	0.4707	0.0021	Price Ratio	0.4073	0.0090
h2_sp02_May	-0.2421	0.0044	Input Price	1.0287	0.0149
h3_sp02_Feb	-0.2009	0.0020	Acres/Unit	0.5239	0.0021
h3_sp02_May	0.0874	0.0014	cddc_Mar	-0.0052	0.0000
h3_sp02_Jun	0.3747	0.0020	pcpn_Jan	-0.0188	0.0014
h_sp06_Mar	-0.2483	0.0016	pcpn_Mar	0.1799	0.0010
h_sp06_Apr	0.1736	0.0019	$pcpn^2$_cum_May	-0.0020	0.0000
h_sp06_Jun	-0.2478	0.0020	$pcpn^2$_cum_Jun	0.0032	0.0000
h2_sp06_Jan	0.3773	0.0055	w_cddc_Mar	-0.1748	0.0038
h2_sp06_Apr	0.6456	0.0035	w_tmpc_May	-0.0187	0.0036
h2_sp06_May	0.9260	0.0057	w_tmpc_Jun	0.1197	0.0032
h3_sp06_Mar	0.0866	0.0018	w2_pcpn_Jan	0.7677	0.0064
h4_sp06_May	1.0650	0.0066	w2_pcpn_Mar	-0.6041	0.0055
h_sp09_Jan	-0.5345	0.0016	w2_pcpn_Apr	0.4149	0.0028
h2_sp09_Mar	1.1539	0.0028	h_pdsi_Jan	-0.5734	0.0043
h2_sp09_Apr	0.4971	0.0035	h_pdsi_May	-0.0249	0.0033
h3_sp09_Feb	-0.1016	0.0016	h2_pdsi_Jun	-0.0565	0.0011
h3_sp09_Mar	0.0995	0.0017	h3_pdsi_Jun	-0.0181	0.0011
h3_sp09_Apr	-0.4513	0.0020	h_phdi_Jan	0.2091	0.0041
h3_sp09_Jun	-0.4264	0.0014	h_phdi_Mar	-0.4452	0.0043
h4_sp09_Feb	-0.3757	0.0039	h_pmdi_Mar	0.0945	0.0038
h4_sp09_Apr	-2.9924	0.0155	h_pmdi_Apr	0.7368	0.0032
h4_sp09_Jun	-1.9743	0.0060	h_zmdi_May	-0.5914	0.0037
Year2007	-0.3071	0.0051	h2_zmdi_Feb	0.1507	0.0020
Year2016	-0.5204	0.0052	h3_zmdi_Jan	0.2224	0.0013
Region1	0.5714	0.0028	h3_zmdi_Jun	0.0747	0.0009
Region2	0.7314	0.0019	h_sp01_Feb	0.5654	0.0039
state13	-0.7085	0.0034	h2_sp01_Feb	-0.1710	0.0044
state31	1.7604	0.0024	h2_sp01_May	-0.1714	0.0028

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
state37	1.8555	0.0024	h4_sp01_Feb	0.3516	0.0145
			h4_sp01_Apr	0.4400	0.0110
Sorghum (PPR)			h4_sp01_May	1.4553	0.0086
Intercept	-23.2451	0.2785	h_sp02_Apr	-0.2026	0.0031
Coverage Level	5.0302	0.1402	h2_sp02_Jan	0.2856	0.0040
Harvest Price	-4.0590	0.0533	h2_sp02_Apr	-0.5282	0.0029
Price Ratio	-0.0989	0.0269	h3_sp02_Jan	-0.2005	0.0033
Input Price	4.0758	0.0563	h4_sp02_May	-1.8836	0.0160
Acres/Unit	-0.1546	0.0092	h4_sp02_Jun	2.0373	0.0109
w_tmpc_Jan	1.0700	0.0178	h_sp06_Jan	-0.4469	0.0033
h3_sp06_Jun	0.2055	0.0083	h_sp06_Feb	0.3074	0.0034
h3_sp09_May	1.1222	0.0078	h2_sp06_Jan	0.2527	0.0053
Year2010	1.2190	0.0127	h2_sp06_Mar	-0.1531	0.0036
			h3_sp06_Jun	0.2987	0.0035
Spring Barley (ALL)			h_sp09_Mar	-0.1545	0.0034
Intercept	-16.8773	0.0911	h_sp09_Apr	-0.6883	0.0035
Coverage Level	11.2182	0.0403	h_sp09_May	0.1923	0.0037
Harvest Price	-0.7969	0.0153	h2_sp09_Apr	0.3956	0.0030
Price Ratio	0.2174	0.0116	h2_sp09_May	-1.0367	0.0035
Input Price	0.8394	0.0184	h2_sp09_Jun	-0.3286	0.0035
Acres/Unit	-0.3148	0.0032	h4_sp09_Mar	-17.7323	404.8866
hddc_Mar	0.0021	0.0000	Region2	1.1875	0.0067
hddc_May	0.0026	0.0000	Region3	-0.4099	0.0047
tmpc_Jan	-0.0257	0.0004	state2	0.6011	0.0056
$pcpn^2$_cum_Mar	0.0026	0.0000	state4	2.1009	0.0051
w_cddc_Apr	0.4646	0.0063	state14	-0.2323	0.0049
w3_cddc_Feb	-0.1085	0.0042	state16	-1.1128	0.0078
w3_cddc_Jun	0.1128	0.0022	state33	1.5871	0.0048
w_hddc_Jun	-0.1180	0.0058			
w_tmpc_Jan	-0.1381	0.0049	**Spring Barley (PPR)**		
w2_pcpn_Apr	-0.3789	0.0032	Intercept	-25.9612	0.0944
w3_pcpn_Jan	0.5281	0.0039	Coverage Level	15.9222	0.0562
h_pdsi_Jun	0.4956	0.0059	Harvest Price	-2.1117	0.0169
h2_pdsi_Feb	-0.1228	0.0021	Price Ratio	0.3191	0.0107
h3_pdsi_Jun	-0.0061	0.0014	Input Price	1.6508	0.0177
h4_pdsi_Mar	-0.1706	0.0318	Acres/Unit	-0.1608	0.0041

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
h_phdi_May	-0.2959	0.0067	cddc_Jan	-0.0901	0.0013
h3_phdi_Jan	0.1728	0.0018	hddc_Mar	0.0038	0.0000
h_pmdi_May	0.4828	0.0067	pcpn_May	0.1542	0.0017
h2_pmdi_Jun	0.0471	0.0025	w_cddc_Apr	-0.2172	0.0068
h3_pmdi_Apr	-0.0826	0.0016	w3_hddc_Mar	0.3670	0.0060
h4_pmdi_Jan	0.4994	0.0069	w_tmpc_Apr	0.0356	0.0047
h4_pmdi_Mar	1.0909	0.0318	w_pcpn_Apr	0.2007	0.0054
h_zmdi_Apr	-0.2566	0.0039	w2_pcpn_May	-0.6100	0.0039
h_zmdi_Jun	-0.3494	0.0041	h_pdsi_Feb	0.0453	0.0056
h2_zmdi_Apr	0.0275	0.0015	h_pdsi_Mar	-0.0265	0.0046
h3_zmdi_Jan	-0.0109	0.0013	h2_pdsi_Apr	0.1696	0.0031
h3_zmdi_Feb	-0.0571	0.0011	h4_pdsi_Jan	0.4644	0.0050
h3_zmdi_Mar	0.0192	0.0010	h4_phdi_Mar	0.3644	0.0059
h3_zmdi_Apr	-0.0337	0.0013	h_zmdi_May	0.1000	0.0045
h3_zmdi_Jun	0.0375	0.0008	h2_zmdi_Jan	0.2683	0.0035
h4_zmdi_Mar	0.2013	0.0056	h2_zmdi_Apr	-0.1472	0.0024
h_sp01_Apr	-0.1246	0.0041	h4_zmdi_Jan	0.6653	0.0064
h_sp01_May	-0.6641	0.0042	h3_sp01_Mar	-0.2129	0.0023
h2_sp01_May	0.1697	0.0070	h3_sp01_Jun	0.2529	0.0032
h_sp02_Apr	-0.1895	0.0037	h2_sp02_Mar	-0.0774	0.0038
h2_sp02_Jan	0.1367	0.0068	h3_sp02_Jan	0.5070	0.0026
h2_sp02_Mar	-0.3784	0.0040	h3_sp06_Apr	0.2351	0.0050
h3_sp02_Jan	0.3433	0.0047	h3_sp06_May	0.1552	0.0028
h3_sp02_Mar	0.0242	0.0027	h_sp09_Jan	-0.0090	0.0043
h3_sp02_Jun	0.1427	0.0054	h3_sp09_Apr	0.0903	0.0051
h_sp06_Jun	-0.0821	0.0046	h3_sp09_May	0.4226	0.0034
h2_sp06_Mar	0.3471	0.0059	Year2011	0.4269	0.0097
h2_sp06_Apr	0.2275	0.0059			
h3_sp06_Jun	-0.1437	0.0050			
h4_sp06_Feb	-0.5815	0.0648	**Fall Barley (ALL)**		
h4_sp06_May	0.4603	0.0139	Intercept	-7.4839	0.0686
h_sp09_Jun	0.1247	0.0048	Coverage Level	12.4092	0.0410
h2_sp09_Jan	0.6285	0.0075	Harvest Price	-0.4347	0.0127
h3_sp09_Jan	0.2289	0.0044	Price Ratio	1.3147	0.0082
h3_sp09_May	0.4936	0.0030	Input Price	-0.6102	0.0143
h3_sp09_Jun	0.0216	0.0045	Acres/Unit	-0.3959	0.0033

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
Year2006	-1.2920	0.0132	cddc_Sep	0.0169	0.0002
Year2007	0.1490	0.0144	cddc_Nov	-1.4514	32.9033
Year2008	-0.9120	0.0132	hddc_Jul	0.0152	0.0001
Year2010	-0.1036	0.0104	hddc_Dec	0.0019	0.0000
Year2011	0.2953	0.0113	tmpc_Nov	-0.1035	0.0005
Year2015	-0.9265	0.0100	w_hddc_Sep	-0.1023	0.0038
state1	5.7474	0.0168	w_tmpc_Jul	-0.2238	0.0104
state3	2.8249	0.0178	w2_tmpc_Nov	-0.5803	0.0047
state4	1.1970	0.0087	w_pcpn_Sep	0.0000	0.0000
state24	-0.7734	0.0063	h_pdsi_Aug	0.3416	0.0063
state26	7.8073	0.0941	h2_pdsi_Oct	-0.5170	0.0019
state31	0.2396	0.0052	h3_pdsi_Jul	0.0044	0.0013
state40	1.3525	0.0280	h_phdi_Jul	-0.1254	0.0043
state44	-1.0794	0.0155	h_phdi_Aug	-0.2067	0.0068
			h2_phdi_Sep	0.3568	0.0022
Fall Barley (PPR)			h2_phdi_Dec	0.0021	0.0021
Intercept	-1.5878	0.1094	h4_phdi_Nov	0.4027	0.0057
Coverage Level	15.7104	0.0550	h3_pmdi_Sep	0.0502	0.0013
Harvest Price	1.6355	0.0202	h4_pmdi_Oct	0.4518	0.0064
Price Ratio	3.4193	0.0115	h_zmdi_Jul	-0.2370	0.0033
Input Price	-3.0465	0.0214	h_zmdi_Nov	-0.0961	0.0041
Acres/Unit	-0.2766	0.0041	h2_zmdi_Oct	0.1180	0.0020
hddc_Jan	0.0119	0.0001	h3_zmdi_Aug	-0.0183	0.0008
hddc_May	0.0026	0.0000	h3_zmdi_Sep	0.0033	0.0008
tmpc_May	0.0000	0.0000	h3_zmdi_Nov	0.1653	0.0013
tmpc_Jun	-0.1115	0.0004	h4_zmdi_Sep	0.1787	0.0070
w_tmpc_Mar	-0.0557	0.0052	h4_zmdi_Nov	0.6875	0.0052
w2_tmpc_Apr	0.3806	0.0110	h_sp01_Jul	0.4396	0.0097
w2_tmpc_May	-0.2490	0.0057	h_sp01_Sep	-0.4464	0.0065
w2_pcpn_Feb	-0.2545	0.0062	h3_sp01_Sep	-0.4723	0.0050
h2_phdi_Jun	0.0130	0.0024	h_sp02_Dec	0.0348	0.0036
h3_phdi_Jun	0.0889	0.0016	h2_sp02_Nov	-0.4872	0.0065
h4_phdi_Mar	0.0072	0.0083	h3_sp02_Jul	-0.1239	0.0071
h3_pmdi_Apr	-0.0230	0.0015	h2_sp06_Oct	0.2028	0.0057
h4_pmdi_Mar	0.1666	0.0086	h2_sp09_Oct	-0.3594	0.0051
h_zmdi_Jan	-0.1360	0.0035	Year2004	-0.0950	0.0075

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
h2_zmdi_Feb	-0.0945	0.0015	Year2005	0.3749	0.0077
h2_zmdi_Jun	0.2636	0.0060	Year2006	-1.3281	0.0108
h3_zmdi_Feb	-0.0560	0.0009	Year2008	-0.4886	0.0106
h3_zmdi_May	0.1724	0.0010	Year2009	0.0354	0.0090
h3_zmdi_Jun	-0.0104	0.0009	Year2011	1.0654	0.0084
h4_zmdi_Mar	-0.0437	0.0079	Year2015	-1.8569	0.0092
h4_zmdi_Apr	0.6842	0.0069	state3	4.7785	0.0176
h4_zmdi_May	0.3143	0.0092	state24	-0.7139	0.0050
h4_zmdi_Jun	0.0561	0.0071	state31	0.1743	0.0044
h_sp01_Jan	0.4684	0.0047			
h3_sp01_Jun	0.2813	0.0022	**Winter Wheat**		
h2_sp06_Mar	0.4555	0.0056	Intercept	-15.8857	0.0389
h_sp09_Jan	-0.1737	0.0042	Coverage Level	3.6159	0.0116
h2_sp09_Mar	-0.2143	0.0052	Harvest Price	1.2160	0.0131
h3_sp09_Feb	0.0526	0.0038	Price Ratio	0.6591	0.0075
Year2005	1.3022	0.0138	Input Price	0.4394	0.0094
Year2008	-1.3533	0.0129	Acres/Unit	-0.1488	0.0012
Year2011	0.0387	0.0117	price3	-0.0007	0.0000
Year2013	1.9352	0.0137	cddc_Oct	0.0057	0.0000
			cddc_Dec	0.0004	0.0002
Spring Wheat (ALL)			hddc_Oct	0.0078	0.0000
Intercept	-5.0613	0.0368	pcpn_Aug	0.1315	0.0008
Coverage Level	10.2785	0.0193	pcpn_Oct	0.0753	0.0006
Harvest Price	0.9797	0.0086	pcpn_Sep	0.3560	0.0007
Price Ratio	-0.4636	0.0037	pcpn_Nov	0.3505	0.0007
Input Price	-2.6339	0.0082	pcpn_cum_Oct	-0.0339	0.0005
Acres/Unit	0.2497	0.0017	pcpn_cum_Dec	0.0551	0.0004
hddc_Feb	0.0005	0.0000	$pcpn^2$_cum_Sep	0.0037	0.0000
hddc_Mar	0.0011	0.0000	$pcpn^3$_cum_Jul	-0.0001	0.0000
hddc_Apr	0.0027	0.0000	$pcpn^3$_cum_Aug	-0.0002	0.0000
hddc_May	0.0020	0.0000	$pcpn^3$_cum_Nov	0.0000	0.0000
pcpn_Jun	0.1223	0.0009	$pcpn^3$_cum_Dec	0.0000	0.0000
pcpn_cum_Jun	-0.0234	0.0004	w_cddc_Jul	-0.1972	0.0038
w2_cddc_May	-0.2444	0.0034	w_cddc_Nov	0.4160	0.0050
w_hddc_Jun	0.1143	0.0023	w_cddc_Dec	-0.0982	0.0054
w2_tmpc_Feb	-0.0784	0.0021	w2_cddc_Jul	-0.4421	0.0028

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
w3_tmpc_Jan	0.0776	0.0021	w2_cddc_Aug	0.1569	0.0023
w2_pcpn_Mar	0.0282	0.0020	w2_cddc_Sep	-0.0572	0.0028
h_pdsi_Mar	-0.4676	0.0025	w2_cddc_Nov	-0.3553	0.0066
h2_pdsi_Mar	0.2777	0.0017	w2_cddc_Dec	2.7246	0.0155
h3_pdsi_Apr	-0.1847	0.0007	w3_cddc_Aug	-0.2331	0.0015
h3_phdi_May	-0.2376	0.0013	w3_cddc_Sep	-0.7853	0.0026
h4_phdi_Feb	-0.5212	0.0056	w3_cddc_Nov	0.0055	0.0022
h_pmdi_Jan	0.0787	0.0024	w3_cddc_Dec	0.1157	0.0010
h_pmdi_Jun	0.4542	0.0020	w_hddc_Jul	-0.1140	0.0036
h2_pmdi_Jan	0.0913	0.0017	w_hddc_Aug	0.5906	0.0035
h3_pmdi_May	0.3493	0.0013	w_hddc_Oct	0.9946	0.0100
h4_pmdi_Feb	0.9769	0.0057	w_hddc_Sep	1.0718	0.0065
h_zmdi_Mar	-0.1146	0.0020	w_hddc_Nov	-0.3426	0.0021
h_zmdi_Apr	0.0681	0.0014	w_hddc_Dec	1.0508	0.0428
h2_zmdi_May	0.0610	0.0015	w2_hddc_Jul	-0.3162	0.0040
h3_zmdi_Feb	-0.1282	0.0004	w2_hddc_Oct	1.0831	0.0083
h3_zmdi_Mar	0.0175	0.0004	w2_hddc_Sep	-0.2870	0.0049
h3_zmdi_May	0.0881	0.0003	w3_hddc_Jul	0.1640	0.0008
h3_zmdi_Jun	0.0135	0.0002	w3_hddc_Aug	-0.1560	0.0019
h4_zmdi_Feb	0.3370	0.0027	w3_hddc_Oct	-0.3955	0.0084
h4_zmdi_Mar	0.1968	0.0026	w_tmpc_Oct	-0.0912	0.0032
h4_zmdi_May	0.6533	0.0023	w_tmpc_Dec	-0.5545	0.0041
h_sp01_Jan	-0.0072	0.0021	w2_tmpc_Jul	-0.0515	0.0027
h_sp01_Mar	0.3870	0.0028	w2_tmpc_Aug	0.7096	0.0067
h_sp01_May	-0.6480	0.0016	w2_tmpc_Nov	-0.0013	0.0025
h3_sp01_Mar	-0.0367	0.0031	w3_tmpc_Aug	-0.3805	0.0019
h_sp02_Mar	-0.2103	0.0017	w3_tmpc_Sep	-0.2476	0.0018
h_sp02_Apr	-0.2734	0.0017	w3_tmpc_Nov	-0.0226	0.0018
h2_sp02_Jan	0.5779	0.0033	w_pcpn_Sep	-0.1422	0.0063
h2_sp02_Feb	0.3249	0.0018	w_pcpn_Dec	-0.9704	0.0429
h2_sp02_Apr	0.4011	0.0040	w2_pcpn_Oct	0.4135	0.0043
h2_sp02_May	-0.1007	0.0031	w2_pcpn_Sep	0.7286	0.0035
h3_sp02_Jan	0.3592	0.0022	w2_pcpn_Nov	-0.5602	0.0031
h3_sp02_Feb	-0.3609	0.0017	w3_pcpn_Jul	0.3454	0.0028
h3_sp02_Mar	-0.4529	0.0024	h_pdsi_Nov	-0.2386	0.0035
h4_sp02_May	2.5393	0.0072	h_pdsi_Dec	-0.0697	0.0029

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
h_sp06_Feb	0.2903	0.0019	h3_pdsi_Dec	0.2851	0.0017
h_sp06_May	0.4056	0.0021	h4_pdsi_Jul	-0.2070	0.0050
h3_sp06_Feb	0.4406	0.0017	h_phdi_Jul	-0.0512	0.0024
h3_sp06_Mar	0.7151	0.0015	h_phdi_Oct	0.0833	0.0023
h3_sp06_May	0.2667	0.0016	h_phdi_Sep	0.2509	0.0021
h3_sp06_Jun	0.2490	0.0014	h_phdi_Nov	0.3765	0.0031
h_sp09_Mar	-0.0678	0.0017	h_phdi_Dec	0.1156	0.0032
h2_sp09_Mar	0.0593	0.0033	h2_phdi_Nov	-0.3907	0.0024
h3_sp09_Apr	0.1916	0.0019	h3_phdi_Jul	0.0925	0.0012
h3_sp09_May	0.2749	0.0014	h3_phdi_Nov	-0.0998	0.0016
h4_sp09_Jun	0.0000	0.0000	h4_phdi_Nov	0.3189	0.0042
Year2005	-0.3651	0.0043	h_pmdi_Aug	0.2010	0.0025
Year2010	0.0627	0.0032	h_pmdi_Oct	-0.0374	0.0033
Year2012	1.4571	0.0048	h_pmdi_Dec	-0.1331	0.0028
Year2013	0.3803	0.0043	h2_pmdi_Jul	-0.0151	0.0012
Region1	1.5612	0.0054	h2_pmdi_Oct	-0.0966	0.0014
Region6	-0.2631	0.0051	h2_pmdi_Nov	0.4081	0.0022
Region7	0.5843	0.0042	h3_pmdi_Aug	0.1672	0.0012
state24	-1.1063	0.0028	h3_pmdi_Oct	0.0276	0.0014
state31	0.2263	0.0017	h3_pmdi_Nov	0.1915	0.0012
state44	-2.2653	0.0073	h3_pmdi_Dec	-0.2853	0.0016
			h4_pmdi_Aug	0.8858	0.0047
Spring Wheat (PPR)			h4_pmdi_Oct	0.6252	0.0055
Intercept	-10.1460	0.0425	h4_pmdi_Sep	0.1623	0.0029
Coverage Level	12.9800	0.0236	h_zmdi_Jul	0.2112	0.0015
Harvest Price	0.0492	0.0095	h_zmdi_Aug	-0.2431	0.0018
Price Ratio	-0.0382	0.0044	h_zmdi_Sep	0.2851	0.0021
Input Price	-1.4933	0.0094	h_zmdi_Nov	0.2829	0.0019
Acres/Unit	0.3337	0.0019	h_zmdi_Dec	0.0701	0.0017
cddc_Jan	-0.1714	0.0009	h2_zmdi_Sep	-0.1463	0.0012
cddc_Jun	-0.0052	0.0000	h2_zmdi_Nov	0.0305	0.0009
hddc_Mar	0.0027	0.0000	h3_zmdi_Aug	-0.1338	0.0008
hddc_Apr	0.0028	0.0000	h3_zmdi_Oct	0.1635	0.0006
pcpn_Mar	-0.1413	0.0024	h3_zmdi_Sep	0.1776	0.0006
w_cddc_May	-0.0548	0.0044	h3_zmdi_Nov	0.0635	0.0007
w3_cddc_Mar	0.0284	0.0014	h4_zmdi_Jul	-0.5378	0.0022

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
w3_cddc_May	-0.1436	0.0071	h4_zmdi_Oct	-0.4374	0.0024
w_hddc_Mar	13.2047	0.0024	h4_zmdi_Sep	0.5774	0.0027
w2_hddc_Jan	-0.2871	0.0021	h4_zmdi_Nov	-0.2587	0.0025
w3_hddc_Mar	-0.7786	0.0034	h4_zmdi_Dec	0.0604	0.0028
w_tmpc_Jan	0.3439	0.0058	h_sp01_Oct	-0.2113	0.0031
w_tmpc_Feb	0.2869	0.0027	h_sp01_Sep	-0.3792	0.0025
w_tmpc_Apr	0.0376	0.0023	h2_sp01_Aug	-0.1666	0.0054
w_tmpc_May	0.5267	0.0035	h2_sp01_Sep	0.7951	0.0043
w2_tmpc_Jun	0.3072	0.0040	h2_sp01_Dec	0.5336	0.0037
w_pcpn_Mar	-12.8880	0.0000	h3_sp01_Dec	0.5078	0.0032
w2_pcpn_May	-0.4328	0.0022	h4_sp01_Aug	0.3886	0.0179
h_pdsi_Mar	-0.9110	0.0029	h4_sp01_Oct	-0.5218	0.0059
h2_pdsi_Feb	-0.0114	0.0027	h4_sp01_Sep	-1.5295	0.0117
h2_pdsi_Apr	0.3004	0.0016	h4_sp01_Dec	-2.1899	0.0199
h3_pdsi_Feb	-0.1154	0.0007	h_sp02_Jul	0.0724	0.0018
h3_pdsi_Apr	-0.1196	0.0009	h_sp02_Aug	0.0402	0.0019
h_phdi_Jan	-0.2135	0.0027	h_sp02_Dec	-0.4583	0.0021
h_phdi_Apr	-0.8119	0.0030	h2_sp02_Jul	-0.2218	0.0028
h_phdi_May	0.0106	0.0029	h2_sp02_Oct	0.0408	0.0015
h2_phdi_Mar	0.3390	0.0024	h2_sp02_Sep	-0.1377	0.0046
h2_phdi_Jun	0.0327	0.0020	h2_sp02_Nov	-0.3258	0.0043
h_pmdi_Mar	0.6485	0.0027	h3_sp02_Aug	0.0528	0.0025
h2_pmdi_Jan	0.2558	0.0024	h3_sp02_Oct	0.1654	0.0016
h3_pmdi_May	0.0566	0.0007	h3_sp02_Nov	0.1423	0.0019
h3_pmdi_Jun	-0.0186	0.0005	h3_sp02_Dec	-0.3479	0.0018
h4_pmdi_Mar	0.1973	0.0027	h4_sp02_Jul	-0.5393	0.0357
h_zmdi_Apr	0.2251	0.0016	h4_sp02_Sep	-1.1089	0.0100
h_zmdi_Jun	0.0740	0.0021	h4_sp02_Nov	0.2896	0.0098
h2_zmdi_May	0.2068	0.0019	h_sp06_Aug	-0.3272	0.0019
h2_zmdi_Jun	0.3524	0.0018	h_sp06_Oct	0.1065	0.0019
h3_zmdi_Jan	-0.0917	0.0005	h_sp06_Dec	-0.2252	0.0019
h3_zmdi_Mar	0.0277	0.0004	h2_sp06_Aug	-0.1488	0.0030
h3_zmdi_May	0.0927	0.0004	h2_sp06_Sep	0.2354	0.0054
h3_zmdi_Jun	0.0124	0.0004	h3_sp06_Oct	-0.0256	0.0015
h4_zmdi_May	0.4055	0.0023	h3_sp06_Nov	-0.2193	0.0015
h_sp01_Jan	0.3747	0.0058	h3_sp06_Dec	-0.1840	0.0016

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
h_sp01_Jun	-0.2036	0.0033	h4_sp06_Sep	-1.1047	0.0072
h2_sp01_Feb	0.2033	0.0018	h4_sp06_Dec	-0.5480	0.0103
h2_sp01_Apr	0.0506	0.0032	h_sp09_Jul	-0.0157	0.0019
h3_sp01_May	0.0267	0.0031	h_sp09_Sep	0.2189	0.0027
h_sp02_Jan	-0.1414	0.0031	h2_sp09_Oct	0.3077	0.0033
h_sp02_Feb	-0.0831	0.0020	h2_sp09_Sep	-0.6875	0.0052
h_sp02_Apr	-0.5891	0.0019	h2_sp09_Nov	-0.5892	0.0044
h_sp02_Jun	0.1154	0.0022	h2_sp09_Dec	-0.7898	0.0040
h2_sp02_Jan	1.0075	0.0049	h3_sp09_Jul	0.1591	0.0016
h2_sp02_Apr	0.8908	0.0043	h3_sp09_Aug	-0.3068	0.0019
h2_sp02_May	-0.1303	0.0048	h3_sp09_Sep	0.1425	0.0021
h3_sp02_Jan	0.4866	0.0032	h3_sp09_Nov	-0.0615	0.0015
h3_sp02_Feb	-0.5479	0.0026	h4_sp09_Oct	0.2125	0.0101
h3_sp02_Mar	-0.6568	0.0018	h4_sp09_Sep	-0.2169	0.0086
h3_sp02_Jun	0.1109	0.0027	h4_sp09_Dec	0.9556	0.0056
h4_sp02_May	1.4927	0.0094	Year2005	1.5616	0.0048
h_sp06_Jan	-0.2782	0.0023	Year2008	-1.3342	0.0079
h_sp06_Mar	0.1026	0.0017	Year2009	0.4366	0.0072
h2_sp06_Jan	-0.7570	0.0072	Year2010	1.8094	0.0045
h2_sp06_Feb	0.0823	0.0038	Year2011	-0.7154	0.0073
h2_sp06_May	-0.2255	0.0086	Year2012	-0.7119	0.0072
h3_sp06_Jan	-0.3543	0.0025	Year2013	-0.8545	0.0066
h3_sp06_Mar	0.9033	0.0021	Year2014	0.2412	0.0044
h3_sp06_May	0.2729	0.0024	Region1	0.8670	0.0036
h3_sp06_Jun	0.0940	0.0023	Region2	-2.0923	0.0085
h4_sp06_May	0.0376	0.0098	Region3	-1.1702	0.0047
h_sp09_Apr	0.2611	0.0024	Region4	-0.4845	0.0033
h_sp09_Jun	0.1391	0.0023	Region6	-0.1069	0.0064
h2_sp09_Jun	0.8102	0.0080	Region7	0.3663	0.0078
h3_sp09_Jan	0.2651	0.0023	Region8	0.7166	0.0036
h3_sp09_Mar	-0.2043	0.0018	state2	1.2661	0.0034
h3_sp09_May	0.1967	0.0019	state3	3.2621	0.0092
h4_sp09_Jun	0.0000	0.0000	state4	1.9422	0.0072
Year2012	0.5411	0.0107	state6	-0.8228	0.0133
Year2014	-0.5247	0.0030	state9	0.0993	0.0058
Year2016	-0.7680	0.0061	state11	1.0231	0.0032

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
state21	-1.0480	0.0038	state14	0.8254	0.0051
state24	-1.3179	0.0045	state15	-0.2489	0.0042
state31	-0.3453	0.0029	state16	-0.8346	0.0049
			state17	-18.9806	217.8322
Cotton			state18	-0.7835	0.0081
Intercept	-21.9057	0.0787	state23	0.8309	0.0033
Coverage Level	7.8701	0.0164	state25	0.3800	0.0079
Harvest Price	-0.3138	0.0081	state26	6.9279	0.0127
Price Ratio	-0.7178	0.0056	state27	-0.5761	0.0180
Input Price	0.2852	0.0048	state29	0.9237	0.0056
Acres/Unit	-0.0060	0.0015	state30	0.1227	0.0043
cddc_Feb	0.0234	0.0001	state32	0.4830	0.0036
cddc_Mar	-0.0135	0.0000	state33	0.5399	0.0050
hddc_Apr	0.0115	0.0001	state34	-2.6845	0.0133
tmpc_Apr	0.1301	0.0011	state35	-1.1066	0.0084
pcpn^3_cum_May	0.0000	0.0000	state38	-0.3748	0.0045
w_cddc_Feb	-0.0341	0.0037	state39	1.2080	0.0051
w2_cddc_Jan	0.0099	0.0070	state40	-0.1930	0.0112
w2_cddc_May	-0.1079	0.0038	state42	-0.3259	0.0064
w3_hddc_Jun	-0.7291	0.0039	state46	-1.6599	0.0105
w_tmpc_Jan	-0.1873	0.0023			
w2_tmpc_Feb	0.0843	0.0040			
w3_tmpc_May	-0.1749	0.0032			
h2_pdsi_Feb	0.0431	0.0012			
h3_pdsi_Jun	-0.1483	0.0011			
h4_pdsi_May	-0.3002	0.0049			
h4_pdsi_Jun	0.4302	0.0048			
h4_phdi_Jun	0.0000	0.0000			
h4_pmdi_Jan	1.1537	0.0039			
h4_pmdi_May	0.0000	0.0000			
h2_zmdi_Jan	0.0408	0.0010			
h_sp01_May	-0.1368	0.0035			
h3_sp01_May	0.7052	0.0044			
h4_sp01_May	2.9148	0.0109			
h_sp02_Jun	0.1712	0.0026			
h2_sp02_Feb	0.3199	0.0041			

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Table B.2 (continued.)

Variable	Estimate	Std. Err	Variable	Estimate	Std. Err
h3_sp02_Mar	0.2839	0.0017			
h3_sp02_Apr	0.2941	0.0021			
h4_sp02_Jun	1.1260	0.0182			
h_sp06_Mar	-0.1204	0.0026			
h2_sp06_Feb	0.2297	0.0040			
h3_sp06_Feb	0.3602	0.0042			
h3_sp06_May	0.1036	0.0028			
h3_sp09_Feb	0.4672	0.0045			
h3_sp09_May	0.1897	0.0027			
h3_sp09_Jun	0.4368	0.0028			
Year2005	-2.2794	0.0071			
Year2015	1.2487	0.0030			
Region3	-1.2703	0.0053			
Region6	1.4474	0.0045			
Region8	2.3543	0.0039			
state1	1.9317	0.0043			