Moral Hazard and Subsidized Crop Insurance

Shenan Wu,
Barry K. Goodwin,
and Keith Coble*

September 18, 2019

Abstract

Along with adverse selection, moral hazard is one of the major hurdles that private and public insurance plans must contend with. Moral hazard occurs if risks are endogenous to a producer's behavior and if the insurer is unable to properly monitor the insured. We review the role of moral hazard in the US crop insurance program. We conduct an empirical analysis of one important aspect of the US crop insurance program—Prevented Planting. This provision provides indemnity payments if conditions are not suitable for planting. The program has been the subject of considerable controversy, especially during 2019, when the rate of claims is expected to be especially high. Because loss adjustors may encounter difficulties in assessing the weather conditions associated with prevented planting claims, the program is susceptible to moral hazard. We consider the extent to which prevented planting claims may be endogenous to prices. We find significant evidence of moral hazard. The likelihood of prevented planting claims increases as the expected market price decreases or as fertilizer costs increase for corn and soybeans in the Prairie Pothole Region and for grain sorghum and cotton in all states.

Key Words: Crop Insurance, Prevented Planting, Moral Hazard, LASSO estimation, Logistic Regression

JEL Codes: Q18, Q14

* Wu is Senior Data Scientist at PenFed Credit Union. Goodwin is William Neal Reynolds Distinguished Professor in the Department of Agricultural Economics and Graduate Alumni Distinguished Professor in the Department of Economics at North Carolina State University. Coble is W. L. Giles Distinguished Professor in the Department of Agricultural Economics at Mississippi State Univeristy. Goodwin's research was supported by the NC Agricultural Research Service and the US Forest Service. Direct correspondence to Goodwin at Box 8109, North Carolina State University, Raleigh, NC, 27695, E-mail: barry_goodwin@ncsu.edu.

1 Introduction

The US federal crop insurance program continues 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 2018 Farm Bill. According to the Congressional Budget Office (CBO, 2019), the outlays for the program are projected to be $41 billion during 2019-2023. The program has expanded to cover a wide range of perils. In 2015, the program covered 324 million acres with a total liability of $109.6 billion (Risk Management Agency, 2019). Along with adverse selection, moral hazard is a significant issue in the US crop insurance program. Moral hazard occurs if insured agents change their behavior in a way that alters their risks and insurers are unable to properly monitor and price such changes in risk. An important, but often ignored feature of coverage in the federal program lies in the Prevented Planting (PP) provisions, which pay indemnities in the event a producer is prevented from planting due to covered hazards. In 2019, the Farm Service Agency reported that over 19.4 million acres were prevented from planting, with 73% of that total being in 12 midwestern states that experienced heavy rainfall and flooding (FSA, 2019). We discuss the role of moral hazard in the US program and examine the extent to which agents that have coverage for PP change the likelihood of collecting PP payments when input or output prices change. We demonstrate that PP claims are indeed endogenous to changes in input and output prices and thereby confirm the presence of moral hazard.

Prevented planting was brought into the basic provisions of the crop insurance program by the 1994 Crop Insurance Reform Act. The Risk Management Agency (RMA) defines PP as a failure to plant an insured crop by the final planting date due to an insured cause of loss.[1] The insured causes of loss include drought, cold wet weather, excess moisture, hail, and freeze conditions. The PP provision is available for corn, soybeans, grain sorghum, barley, wheat, cotton, and other primary commodity crops in the US. Under the program,

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

growers of insured crops that cannot be planted due to these insured hazards will receive 50-60% of the total insured value of the crop. The payments are intended to compensate the pre-planting costs that growers incurred.

Prevented planting indemnity payments depend on the PP coverage factor, the per-acre production guarantee for timely-planted acreage, the projected price, and the number of eligible PP acres. In 2017, RMA reduced the PP coverage factor for corn from 60% to 55%. The coverage factors remained 60% for soybeans, grain sorghum, barley, and wheat, and 50% for cotton. RMA continued to make adjustments to the PP factors for other crops in 2018 and 2019. The producer is also allowed to buy an additional 5% or 10% on the PP coverage factor.[2] The per-acre production guarantee is the insurance a producer has if the crop is planted before the final planting date under farm-level yield or revenue coverage. To be eligible for the payments, at least 20 acres or 20 percent of the insured crop must be prevented from planting.

It is useful to review an example of how PP coverage actually operates. Consider a corn producer who selects the 60% PP coverage factor and the 75% coverage level for revenue protection with a projected price of \$3/bushel and an actual production history (APH) of 100 bushels/acre.[3] If the insured producer has 20 acres that were prevented from planting, then the PP indemnity payment is $60\% \cdot 75\% \cdot 3 \cdot 100 \cdot 20 = \$2700$.

2 Moral Hazard and Prevented Planting

Moral hazard in crop insurance programs may arise through a number of mechanisms and conditions. In every case, insured agents undertake actions that change the probability of loss relative to what the losses might be if the agent were uninsured. This may involve changes in production practices that include input selection and usage, cultivation and managerial

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

[3]Actual production history is used by the RMA to determine the yield guarantee associated with the insurance coverage. It is calculated as the average per-acre yield of a unit over a 10-year period.

practices, and the choice of crops. Smith and Goodwin (1996) found that insured wheat growers tended to use less fertilizer and chemical inputs as compared to similarly situated non-insured producers. Coble, Knight, Pope and Williams (1996) focused on expected indemnities in poor production years to identify moral hazard. Area-wide index insurance has been proposed as an instrument to manage moral hazard (see Miranda, 1991; and Chambers and Quiggin, 2002). Yu and Sumner (2018) found that subsidized crop insurance has a significant impact on crop choices. This occurs through a shift toward riskier crops. Fadhliani, Luckstead, and Wailes (2019) examine crop insurance demand by riskaverse Indonesian rice farmers. Their empirical analysis showed that crop insurance purchases result in a decline in expected yield through reductions in input use and that higher subsidy rates amplify the reduction in input use and yield.

Kim and Kim (2018) analyzed the existence of moral hazard in the prevented planting provisions. They found that producers who has chosen PP indemnities over late planting tended to have higher coverage levels. They termed this effect as 'ex-post moral hazard.' Roll (2019) examine the effect of crop and livestock insurance on input use and yield. Their empirical analysis focused on the Norwegian salmon farming industry. Their results indicated that insurance had an enhancing effect on production and efficiency and changed the utilized input mix, with farmers that are more highly insured using more feed and less capital.

Climate change and its impacts on crop insurance programs has also been considered. Tack, Coble, and Barnett (2018) found that a one-degree Celsius increase in temperature would increase 90% coverage level premiums by 39% on average. Tack and Ubilava (2015) found that extreme weather oscillations alter cotton yield distributions in the Southeastern United States. These impacts imply significant effects on crop insurance premium rates.

The objective of the Prevented Planting provision is to cover the costs associated with pre-planting activities in the event that the insured producer is prevented from planting. A recent Office of the Inspector General (OIG) report argued that RMA had set the coverage for PP at a level that exceeds the actual costs of pre-planting activities (OIG, 2013). Ratios of PP indemnity payments to pre-planting costs were estimated to be over 1.5 for corn and cotton, and between 1 and 1.5 for wheat and soybeans (Agralytica, 2013). The report by OIG also found that prevented planting payment rates (per-acre) substantially exceeded the concomitant Conservation Reserve Program rental payments for similar land.[4] Such high levels of PP coverage create the potential for moral hazard as producers may take advantage of the PP provisions by growing crops on land that is not suitable for planting rather than enrolling such land in a conservation program.

Another issue that relates to the potential for abuse in PP coverage pertains to difficulties in determining when acreage is qualified for PP claims. Approved Insurance Providers (AIPs) do not always note the lack of documentation and support for PP claims.[5] After reviewing 192 policy files, the OIG report concluded that "over $43 million in prevented planting 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."

Abuse of PP coverage raises concerns regarding the actuarial performance of the Federal Crop Insurance Program because PP indemnity payments often account for a significant share of the total indemnity payments. In the last decade, $61.2 billion in total indemnities were paid to the insured producers and among them $10.1 billion were in the form of PP indemnity payments. The overall share of total PP indemnity payments exceeded 20% in the crop year 2010, 2011 and 2015. In other crop years, the share exceeded 10% except for 2012. In 2012, the share of PP indemnity payments was extremely low due to low PP indemnity payments and very large total indemnity payments.[6] For corn, soybeans, and wheat, shares of PP indemnity payments are especially high in most years. In 2019, large PP claims are anticipated as nearly 20 million acres are estimated to have been prevented from planting due to excessive moisture.

[4]The Conservation Reserve Program (CRP) is a land retirement program administered by the Farm Service Agency (FSA). In exchange for a yearly rental payment, farmers enrolled in the program agree to remove environmentally sensitive land from agricultural production and plant species that will improve environmental quality. CRP contracts are 10-15 years in length.

[5]The AIPs are responsible for reviewing and determining the indemnity payments to the insured producer.

[6]In 2012, PP indemnity payments were about 10% of the total for 2011 and the total indemnity payments doubled relative to 2011.

An evaluation of the planted acreage and PP claims undertaken by the OIG (2013) revealed that only 0.01% of prevented planting land was actually replanted to a second crop. Producers have incentives not to plant a second crop for several reasons. First, a second planting decreases the first crop's PP indemnity payments unless the producer qualifies for double cropping. If a second crop is planted before the final planting date of the first crop, then the PP payment is not applicable, otherwise the payment is reduced to 35% of liability. Second, producers that plant a second crop are often penalized by reductions in coverage. In particular, late planted crops (planted after a final planting date) have their coverage reduced by 1% per day after the final planting date set by the RMA. Moreover, the Agricultural Risk Protection Act of 2000 required 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 percent 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 acreage is suitable for planting. However, the near complete absence of second crop planting indicates that many producers did not intend to plant the crop but rather were seeking prevented planting payments which, as noted, typically exceeded actual pre-planting costs.

According to the report by the OIG (2013), the Prairie Pothole Region (PPR) has experienced especially high levels of PP claims. The PPR is an area consisting of parts of Iowa, Minnesota, Montana, North Dakota, and South Dakota. The PPR accounts for over 50% of the PP indemnity payments for corn and sorghum and 90% of the payments for barley and spring wheat. Producers in the PPR have been suspected of practicing fraud and moral hazard because the PP indemnity payments per acre are much higher than the conservation program payments. For example, RMA issued a concern for the PP claims for wetlands in the PPR in 2012, when the weather was extremely dry and should not have prohibited timely planting.

Concerns regarding fraud and abuse in the PP program were examined by Jin, Rejesus and Little (2005) and Rejesus et al. (2003). These authors compared PP indemnities to claims in surrounding areas . These studies indicated that producers who buy additional PP coverage are more likely to be flagged as suspicious by the RMA. One avenue for examining claims for suspicious behavior lies in an assessment of market factors that serve as incentives to actually plant and harvest a crop. This is but one form of moral hazard that has been noted as a problem in most existing multiple peril crop insurance programs. Such coverage is currently offered by the RMA but has experienced relatively low enrollment when compared to individual coverage.

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 the expected harvest revenues. The benefit is the PP payment and savings in variable production costs such as for labor and fertilizer during the growing period. Labor costs are generally not observable but expected harvest revenue and fertilizer costs can be at least partially observed. Two important factors in the decision making are the projected harvest price and fertilizer costs. Given an extreme weather event, the cost of not claiming PP is that planting incurs additional costs, and the expected yield might be low and may not be fully compensated by the basic provisions of crop insurance. However, if the projected harvest price is high, then planting usually leads to more profits as the guaranteed payments for timely planting can be expected to exceed the sum of planting costs and PP indemnity payments. Therefore, if claims are endogenous to market prices, as might be suspected in a moral hazard situation, a high projected price should reduce incentives for PP claims. Likewise, if variable planting costs are particularly high, producers may have lower incentives to plant the crop if they have PP coverage.

The objective of this study is to determine whether PP losses are endogenous to market conditions that are represented by the projected harvest price and fertilizer costs. The existing literature examining PP coverage is often devoted solely to fraudulent claims and the characteristics of producers having PP claims (Rejesus, Escalantec, and Lovell, 2005; Jin, Rejesus and Little, 2005; and Rejesus et al., 2003). These studies only focus on the group of producers that have PP claims, thus making more general inferences about all producers difficult. To our knowledge, this study is the first to analyze the behavior of all insured producers in PP insurance with respect to market conditions.

Our approach is also novel 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 conditions such as drought and excessive moisture. The relationship between weather and the probability of loss in the crop insurance has been widely studied in the literature on weather derivatives and weather index insurance (Martin, Barnett and Coble, 2001; Turvey, 2001; Vedenov and Barnett, 2004; and Woodard and Garcia, 2008). Unfortunately, there is no single set of weather variables (which differ in both calendar time and in the specific metric used to evaluate weather) from among the extensive set of available weather data that can be used to predict the yield or probability of loss associated with weather (Vedenov and Barnett, 2004). This problem has recently been addressed through the development of high dimensional econometric models. These models use penalized regression methods to select the specific set of weather variables that best predict weather-based losses. We utilize the least absolute shrinkage and selection operator (LASSO) method to select a subset of explanatory weather factors from a collection of over 250 variables. Once PP claims are conditioned on the optimal weather variables, we examine the extent to which projected market prices and fertilizer costs affect prevented planting claims. If such market factors are statistically significant when claims are conditioned on weather conditions, moral hazard is indicated. Moral hazard would suggest that higher commodity prices and lower fertilizer costs should lead to fewer and smaller PP claims.

3 Empirical Methods and Analysis

The probability of PP loss is estimated by applying a binomial logistic regression model. Because of confidentiality restrictions, RMA does not provide farm-level experience data and thus our empirical analysis is based upon the county-level, aggregated summary of business data. In particular, we consider annual observations on relevant insurance experience at the county and crop level of aggregation. We use the online 'cause of loss' data to identify losses that are associated with prevented planting. Definitions of the explanatory variables and summary statistics are presented in table 1.

For a single 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 can be expressed as[7]

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

We apply a linear logistic regression model to evaluate the probability p_i by

$$log(\frac{p_i}{1-p_i}) = \boldsymbol{\beta}'\boldsymbol{x_i} \tag{2}$$

where $\boldsymbol{\beta}$ is a vector of coefficients and $\boldsymbol{X_i}$ is a vector of explanatory variables for county i.

Dropping the constant term $\binom{y_i}{n_i}$, yields the following sum of the log-likelihood function values

$$L(\boldsymbol{\beta}; \boldsymbol{n}, \boldsymbol{y}, \boldsymbol{x}) = \sum_{i=1}^{K} \left\{ y_i log(p_i) + (n_i - y_i) log(1-p_i) \right\} \tag{3}$$

Given the complexity of the relationship between weather and the probability of loss and the extensive variety of weather variables available, we use the LASSO method to select the most important weather variables that affect the probability of loss. The LASSO method was introduced by Tibshirani (1996) and has recently become a popular method for model selection and specification. Variables are selected by minimizing the following objective function

$$\hat{\boldsymbol{\beta}} = \arg\min_{\beta} ||\boldsymbol{Y} - \boldsymbol{X\beta}||_2^2 + \lambda|\sum_{j=1}^{p} \beta_j| \tag{4}$$

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

The linear regression model is appropriate for prediction and inference if the error distribution is Gaussian. However, if the response variable is discrete, then a generalized linear

[7] Note that, for ease of exposition, we suppress subscripts that correspond to year t and crop j.

model specified by the LASSO method is more appropriate (Hastie, Tibshirani and Wainwright, 2015). In our case, the response variable follows a binomial distribution, and LASSO selects variables from the negative log-likehood function with l_1 regularization:

$$\hat{\boldsymbol{\beta}} = \arg\min_{\beta}(-L(\boldsymbol{\beta}; \boldsymbol{n}, \boldsymbol{y}, \boldsymbol{x})) + \lambda|\sum_{j=1}^{p}\beta_j| \tag{5}$$

where $L(\boldsymbol{\beta}; \boldsymbol{n}, \boldsymbol{y}, \boldsymbol{x})$ is the log-likelihood function defined in equation 3. Replacing p_i with the link function in equation 2, the objective function 5 is convex and can be solved by standard nonlinear estimation algorithms such as the quasi-Newton methods

$$\hat{\boldsymbol{\beta}} = \arg\min_{\beta} -\sum_{i=1}^{K}\{y_i\boldsymbol{\beta}'\boldsymbol{x_i} + (n_i - y_i)log(1 + e^{\boldsymbol{\beta}'\boldsymbol{x_i}})\} + \lambda|\sum_{j=1}^{p}\beta_j| \tag{6}$$

Our empirical model relates the probability of a PP loss to a range of weather variables. Temperature and precipitation are the most popular variables used to predict crop yields (Schlenker and Roberts, 2006; Vedenov and Barnett, 2004), and therefore are included in the set of candidate weather variables. To supplement the effects of temperature and precipitation, monthly aggregate heating degree days (HDD), cooling degree days (CDD) and the cumulative precipitation are included in the candidate set of potential predictors.[8] The cumulative precipitation in month i is calculated as the sum of the precipitation in previous months starting at the beginning period of the planting season. Square and cubic transformations of cumulative precipitation are included to reflect the nonlinear relationship. The entire set of weather data, which also included various drought indexes, were obtained from the National Climate Data Center of the National Oceanic and Atmospheric Administration (NOAA).

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 the precipitation in extremely wet weather might significantly contribute to losses. To capture such impacts, we identify a class of variables that represent extreme weather conditions. Extreme weather indicators are measured by the deviation from the average level of the weather variable. Monthly average

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

temperature, precipitation, HDD and CDD are standardized at the county level by using means and standard deviations $\tilde{x} = \frac{x-\mu_x}{\sigma_x}$. Data series from 1895 to 2016 are used to identify normal and abnormal weather conditions. The extreme weather indicators are defined as

$$
\begin{aligned}
w_{ijt} &= \begin{cases} 0 & \text{if } |\tilde{x}_{ijt}| < 1) \\ 1 & \text{otherwise.} \end{cases} \\
w2_{ijt} &= \tilde{x}_{ijt} * I(\tilde{x}_{ijt} < -1) \\
w3_{ijt} &= \tilde{x}_{ijt} * I(\tilde{x}_{ijt} > 1)
\end{aligned} \tag{7}
$$

where w_{ijt}, $w2_{ijt}$ and $w3_{ijt}$ are the extreme weather indicators generated from weather index i for 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 were considered and a one standard deviation value was chosen as optimal. w_{ijt} is a dummy variable indicating whether a weather condition is normal or abnormal, and $w2_{ijt}$ and $w3_{ijt}$ capture the degree of the unusual weather conditions that are either too low or too high. For example, let $i = 1$ for temperature, $i = 2$ for precipitation, $i = 3$ for HDD and $i = 4$ for CDD. A drought in county j in month t will 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 into the model. These eight indexes are useful as they measure moisture and precipitation. The specific indexes are defined and summarized in table 2. All indexes are continuous variables but each reflects a different measure of drought and wetness. We utilize a transformation to categorize these indexes into groups while still preserving a degree of continuity.

Two dummy variables and two continuous variables are defined as

$$h_{ijt} = \begin{cases} 1 & \text{if } z_{ijt} \text{ is in category "Near Normal".} \\ 0 & \text{otherwise.} \end{cases}$$
$$h2_{ijt} = \begin{cases} z_{ijt} & \text{if } z_{ijt} \text{ is in category "Mild to moderate Drought" and "Severe Drought".} \\ 0 & \text{otherwise.} \end{cases}$$
$$h3_{ijt} = \begin{cases} z_{ijt} & \text{if } z_{ijt} \text{ is in category "Mild to moderate Wetness" and "Severe Wetness".} \\ 0 & \text{otherwise.} \end{cases}$$
$$h4_{ijt} = \begin{cases} 1 & \text{if } z_{ijt} \text{ is in category "Extreme Wetness/Drought".} \\ 0 & \text{otherwise.} \end{cases} \tag{8}$$

where z_{ijt} is the 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 the "Near Normal" category should not affect the probability of loss, and indexes in the "Extreme" category should have a large effect. The unknown effect of the indexes lies in the category of "Mild to moderate" and "Severe" where the degree of extreme weather is determined by the index. Therefore, continuous variables rather than discrete indicators are used to predict the probability of loss for weather in these categories.

The normal planting period may span two or more months. To ensure that all potentially relevant weather variables are considered, we include monthly weather variables over a six month period preceding the start of the normal planting period. Weather conditions after the final planting date should not affect a producer's decision on claiming PP. The latest final planting dates are in June for corn, soybeans, grain sorghum, cotton, spring barley and spring wheat, and in 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 are used for winter barley and winter wheat.

In summary, the numbers of weather variables in six months are $4 \cdot 6 = 24$ for original weather data on temperature, precipitation, HDD and CDD, $3 \cdot 6 - 1 = 17$ for linear, square and cubic transformations of cumulative precipitation, $3 \cdot 4 \cdot 6 = 72$ for three extreme weather indicators generated from the original weather data, and $4 \cdot 8 \cdot 6 = 192$ for four indicators generated from eight weather indexes.This yields a total of 305 weather indicators that are included in the LASSO model selection and then used to condition weather effects.

Market conditions are represented using fertilizer costs and the expected harvest price. Fertilizer costs are measured by the monthly fertilizer cost indexes obtained from the USDA. However, the cost indexes are not available after 2013, so indexes after 2013 are estimated using the following OLS regression

$$Cost_t = \beta_0 + \beta_1 * DAP_t + \beta_2 * KCL_t + \beta_3 * UREA + \beta_4 * Diesel + \beta_5 * CPI \tag{9}$$

where the regressors are prices of Diammonium Phosphate (DAP), Potassium Chloride (KCL), urea, diesel and the consumer price index (CPI). These prices are used by RMA to determine the input costs for margin protection insurance (RMA, 2017).[9] Spot prices of DAP at the US Gulf, KCL at Vancouver, urea at the Black Sea, and diesel at New York are used and the CPI data are obtained from Federal Reserve Bank of ST.Louis. Weekly data from 2002 to 2012 are used to estimate the price coefficients and the OLS results are summarized in table 3. The R-Square is 0.9652 and all the price coefficients are positive as expected since any increase in these prices increases the input costs. The cost indexes after 2013 are then estimated using the price data from 2013 to 2016.

The expected harvest price is estimated using an approach analogous to how RMA defines a projected price for revenue coverage. RMA calculates the projected price as an average of daily settlement prices for the harvest period futures contract over the price discovery period. The price discovery period usually lasts for a month, so a monthly average settlement price is used. February prices for the December contract at the Chicago Board of Trade (CBOT) are used for corn and grain sorghum. February prices for the November contract at the CBOT

[9] Margin protection provides coverage against an unexpected decrease in the operating margin between revenues and costs.

are used for soybeans. February prices for the December contract at the Intercontinental Exchange are used for cotton. For wheat and barley prices, the chosen month and futures markets are guided by RMA's price discovery period and commodities exchange provisions.

The price in each state should also depend on the state basis. Therefore, an adjustment is made to reflect the perceived price for local producers. USDA provides the prices 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 in state i and state j where the relevant commodity exchange is located

$$P_i = P_p + P_{ri} - P_{rj} \tag{10}$$

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 price received in the state where the commodities exchange is located. For example, if the futures contract is from 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 influence a producer's behavior. An increase in the harvest price from last year should lead to a more careful preparation for the planting activity this year. Therefore, the price ratio of current year to previous year prices is included in the model as the log change in the expected harvest price relative to the previous year:

$$P_{ratio} = log(P_t/P_{t-1}) \tag{11}$$

We utilize the following regressors in addition to the aforementioned collection of weather variables—the log of the expected harvest price, the log of the fertilizer price, the log of the price ratio, the average crop insurance coverage level and a measure of the crop insurance unit size (acres/unit). These variables are included in all models and are not subject to the LASSO selection method. In addition to the weather variables, we include a time trend, a state indicator, and a farm resource region indicator in the set of potential regressors to be chosen by LASSO. 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 5 is set to be $\lambda = \rho^i$ for ith step and ρ is arbitrarily set to 0.7. The initial base value of ρ does not affect the estimates as long as λ converges to a small number after several iterations. Twenty-five steps are used in the optimization and Nesterov's (2013) method is applied to solve the minimization problem for its optimal convergance rate for the first-order optimization. The data are divided into training and validation data sets. Seventy-five percent of the data are randomly chosen for training and the remainder are used for validation. For each λ and its corresponding estimated coefficients, the Bayesian Information Criterion (BIC) of the validation data is computed. The optimal λ is then selected from the smallest BIC for the validation data.

It is difficult to estimate standard errors in the LASSO model, so the selected variables and their standard errors are computed by a standard binomial logistic regression with unpenalized maximum likelihood estimators (MLE). In the estimation, post-LASSO estimators often provide better or at least equal performance relative to the LASSO estimators in terms of bias (Belloni and Chernozhukov, 2013).[10] It is possible to improve the estimation using the post-LASSO procedures because the minimization method applies a second-order Taylor series expansion of the likelihood function, which is analogous to least squares regression.

If moral hazard does not exist, then producers' planting decisions should be only be influenced by weather. In such a case, the variables in table 4 should have little impact on the probability of PP loss. Our results indicate that all of the parameter estimates in table 4 are statistically significant at the 0.01 or smaller level. This suggests the presence of moral hazard in prevented planting claims. Producers' planting decisions appear to be influenced by market conditions. We expect that the likelihood of PP claims should be higher when the expected planting revenues are low or input costs are high.It is also the case that changes in the expected harvest price are also reflected in the price ratio. Therefore, the total effects of the harvest price are given by the sum of the harvest price effect and the effect of the price ratio. Conversely, the effect of the input price solely depends on the coefficient of the logarithmic input price. The results in table 4 suggest that, in all cases except for wheat and barley, the likelihood of PP claims increases if the expected harvest price decreases

[10]Post-LASSO estimators are taken from the standard regression estimates using the selected variables from the LASSO.

or the input price increases. Moral hazard is indicated if both (or either of) the sum of the coefficients of harvest price and the price ratio effects are negative and the coefficient of input price is positive. Using this criteria, moral hazard is indicated for corn, soybeans, grain sorghum, spring barley and cotton. In accordance with widespread observations, moral hazard is more severe in the Prairie Pothole Region (PPR) as the magnitude of the price coefficients is much larger for this region. For example, the coefficient of harvest price increases in magnitude from -2.76 for corn producers in all states to -5.18 for producers in the PPR. Likewise, the coefficient for input prices also increases from 0.30 to 4.77. Similar results are found for soybeans, grain sorghum and spring barley. This finding suggests that producers in the Prairie Pothole Region are more likely to have PP claims than are producers in other regions.

The average coverage level in the model may reflect producers' risk preferences as well as perceptions of yield and price risk for the relevant crops and areas. It should be noted that a higher coverage level increase both the PP indemnity payments and the insurance guarantee associated with timely planting.[11] The effect of coverage level on producers' decision-making influences 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 producer's choice. In general, the probability of loss for planting is often less than the coverage level. Therefore, an increase in the coverage level often increases the potential PP indemnity payments and thus should increase the probability of PP indemnity payments. Results confirm that coverage level has this positive effect on the probability of PP claims for all crops except soybeans.

The variable acres/unit is used to measure the average size of the insurance unit in the county and may also indicate the scale of farms in the county. Larger farms may have less prevented planting activity because they often have better equipment and superior managerial skills to address extreme weather. Larger units may also reflect corporate farm structures. Rejesus, Escalante, and Lovell (2005) found that corporate farms were less likely to submit

[11] PP indemnity payments can be calculated as the PP coverage level multiplied by the guarantee associated with timely planting.

a PP claim. Finally, increases in the subsidy rate for enterprise units in 2011 caused a significant shift in participation toward more highly aggregated enterprise units. Such units typically have lower overall risk due to the effect of aggregating across all units operated by a farm in a county. Enterprise units also realize lower premium rates to reflect this aggregation effect. Our results indicate that a larger average unit decreases the probability of loss for corn (in all states), grain sorghum (in the PPR), barley, winter wheat and cotton and increases the probability of loss for other crops. Thus, there is not a consistent pattern for the effect of unit size on the probability of loss.

The existence of moral hazard in PP coverage affects the actuarial performance of the entire federal crop insurance program and results in additional costs for taxpayers. We examine the extent to which market conditions lead to higher indemnity payments. In particular, we consider how a 1% increase in input prices or a 1% decrease in output prices change the probability of loss and the corresponding PP indemnity payments.[12] For each change in the price, the probability after the change and the change in the total indemnities are reported in table 5. The most significant change in the indemnities are for corn and soybeans in the PPR. A 1% decrease in the expected harvest price will increase the annual indemnity payments by \$12.31 million for corn and \$5.52 million for soybeans in the PPR. A 1% increase in input costs will increase the annual 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 changes are smaller but still indicate higher indemnity payments for the PP insurance.

4 Concluding Remarks

Very large PP indemnity payments in the crop insurance program raise important questions about the role of moral hazard. PP claims should be driven solely by extreme weather

[12] The probability of loss is estimated at the mean and the total indemnity payments are estimated as the proportion indicated by the probability of loss. Total indemnity payments can be calculated as $Total\ Acres * Probability\ of\ Loss/Acre * Indemnities/Acre$. Here, the indemnities per acre variable is evaluated at the mean value and is not affected by the harvest price.

events. We condition the effects of market conditions (reflected in input and output prices) on a variety of weather indicators. The most important weather factors for each crop and region are chosen using LASSO regression methods. We find that the opportunity costs of submitting PP claims are strongly related to market conditions and are not solely driven by weather conditions, thereby indicating moral hazard. The problems of moral hazard appear to be especially acute in the Prairie Pothole Region of the midwest. Price impacts on PP claims and overall PP claims are typically substantially higher in this region.

In 2017, RMA reduced the PP coverage factor for corn from 60% to 55%. Our results suggest that the same reduction should be considered for grain sorghum, cotton and spring barley as our results provide evidence of moral hazard among producers of these crops. PP claims for corn and soybeans in the Prairie Pothole Region appear to be influenced by a large degree of moral hazard which can result in excessive PP indemnity payments under certain market conditions. Therefore, claims for PP should be reviewed more carefully in the PPR. The PP indemnity payments in 2019 are expected to be very large due to excessive moisture in important growing regions, making these issues of particular relevance in the current policy environment. The extent to which such large indemnity payments in 2019 will reflect moral hazard is unclear since many growing regions experienced weather extremes which resulted in a significant amount of acreage that justifiably could not be planted. Under such circumstances, a substantial level of valid claims for PP is anticipated. Data for 2019 PP payments are not yet available but are expected to be substantial. The PP provisions present significant challenges to loss adjustors and AIPs, who may be limited in their abilities to accurately assess past weather conditions at any given location.

References

Agralytica. (2013). "Evaluation of Prevented Planting Program." *Agralytica Consulting.*

Belloni, A., and Chernozhukov, V. (2013). "Least squares after model selection in high-dimensional sparse models." *Bernoulli*, 19(2), 521-547.

Congressional Budget Office (CBO) (2019) "USDA's Mandatory Farm Programs–CBO's May 2019 Baseline." Available online at https://www.cbo.gov/system/files/2019-05/51317-2019-05-usda_0.pdf (accessed September 11, 2019).

Chambers, R. G. (1989). "Insurability and moral hazard in agricultural insurance markets." *American Journal of Agricultural Economics.* 71(3), 604-616.

Coble, K. H., Knight, T. O., Pope, R. D., and Williams, J. R. (1997). "An expected-indemnity approach to the measurement of moral hazard in crop insurance." *American Journal of Agricultural Economics.* 79(1), 216-226.

Fadhliani, Z., Luckstead, J., and Wailes, E. J. (2019). "The impacts of multiperil crop insurance on Indonesian rice farmers and production." *Agricultural Economics*, 50(1), 15-26.

Farm Service Agency (2019). "Report: Farmers Prevented from Planting Crops on More than 19 Million Acres," August 12, 2019, online: https://www.fsa.usda.gov/news-room/news-releases/2019/report-farmers-prevented-from-planting-crops-on-more-than-19-million-acres (accessed September 10, 2019).

Hastie, T., Tibshirani, R., and Wainwright, M. (2015). "Statistical learning with sparsity: the lasso and generalizations." *CRC press.*

Horowitz, J. K., and Lichtenberg, E. (1993). "Insurance, moral hazard, and chemical use in agriculture." *American Journal of Agricultural Economics.* 75(4), 926-935.

Jin, Y., Rejesus, R. M., and Little, B. B. (2005). "Binary choice models for rare events data: a crop insurance fraud application." *Applied Economics*. 37(7), 841-848.

Ker, A. P., and Coble, K. (2003). "Modeling conditional yield densities." *American Journal of Agricultural Economics*. 85(2), 291-304.

Kim, T., and Kim, M. K. (2018). "Expost moral hazard in prevented planting." *Agricultural Economics*, 49(6), 671-680.

Martin, S. W., Barnett, B. J., and Coble, K. H. (2001). "Developing and pricing precipitation insurance." *Journal of Agricultural and Resource Economics*. 261-274.

Miranda, M. J. (1991). Area-yield crop insurance reconsidered. American Journal of Agricultural Economics, 73(2), 233-242.

Nesterov, Y. (2013). "Gradient Methods for Minimizing Composite Objective Function." *Mathematical Programming* 140:125161.

Office of Inspector General (OIG). (2013). "RMA: Controls Over Prevented Planting".

Quiggin, J. C., Karagiannis, G., and Stanton, J. (1993). "Crop insurance and crop production: An empirical study of moral hazard and adverse selection." *Australian Journal of Agricultural and Resource Economics*. 37(2), 95-113.

Rejesus, R. M., Escalante, C. L., and Lovell, A. C. (2005). "Share tenancy, ownership structure, and prevented planting claims in crop insurance." *American journal of agricultural economics*. 87(1), 180-193.

Rejesus, R. M., Lovell, A. C., Little, B. B., and Cross, M. H. (2003). "Determinants of anomalous prevented planting claims: theory and evidence from crop insurance." *Agricultural and Resource Economics Review*. 32(2), 244-258.

Risk Management Agency (RMA). (2017). "Margin Protection for Federal Crop Insurance".

Roll, K. H. (2019). “Moral hazard: the effect of insurance on risk and efficiency.” *Agricultural Economics*, 50(3), 367-375.

Schlenker, Wolfram, and Michael J. Roberts. ”Nonlinear effects of weather on corn yields.” *Applied Economic Perspectives and Policy.* 28, no. 3 (2006): 391-398.

Smith, V. H., and Goodwin, B. K. (1996). “Crop insurance, moral hazard, and agricultural chemical use.” *American Journal of Agricultural Economics.* 78(2), 428-438.

Tack, J., Coble, K., and Barnett, B. (2018). “Warming temperatures will likely induce higher premium rates and government outlays for the US crop insurance program.” *Agricultural Economics*, 49(5), 635-647.

Tack, J. B., and Ubilava, D. (2015). “Climate and agricultural risk: measuring the effect of ENSO on US crop insurance.” *Agricultural Economics*, 46(2), 245-257.

Tibshirani, R. (1996). “Regression shrinkage and selection via the lasso.” *Journal of the Royal Statistical Society.* Series B (Methodological), 267-288.

Turvey, C. G. (2001). “Weather derivatives for specific event risks in agriculture.” *Review of Agricultural Economics.* 23(2), 333-351.

Vedenov, D. V., and Barnett, B. J. (2004). “Efficiency of weather derivatives as primary crop insurance instruments.” *Journal of Agricultural and Resource Economics.* 387-403.

Yu, J., and Sumner, D. A. (2018). “Effects of subsidized crop insurance on crop choices.” *Agricultural Economics*, 49(4), 533-545.

Woodard, J. D., and Garcia, P. (2008). “Basis risk and weather hedging effectiveness.” *Agricultural Finance Review.* 68(1), 99-117.

Table 1: Variable Definitions and Summary Statistics

Variable	Definition
Year	Crop year
State Fips	Fips 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 Fips	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 Fips	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

Continued on Next Page

Table 1 – Continued From Previous Page

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

	Spring Barley		Spring Barley (PPR)		Fall Barley	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Year	2009.53	4.14	2009.10	4.12	2009.38	4.22
State Fips	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

	Fall Barley (PPR)		Spring Wheat		Spring Wheat (PPR)	
Variable	Mean	Std. Dev	Mean	Std. Dev	Mean	Std. Dev
Year	2009	4	2010	4	2010	4
State Fips	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

	Winter Wheat		Cotton	
Variable	Mean	Std. Dev	Mean	Std. Dev
Year	2009.45	3.92	2009.58	4.03
State Fips	30	14	30	18
Region	3.88	2.45	6.20	1.81
Total Acres	17895	39081	23301	43339

Continued on Next Page

Table 1 – Continued From Previous Page

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
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 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)
The probablility of observing a given amount of precipitation in xx month
Available SPxx are SP01, SP02, SP06 ,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 divions

Table 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: 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 0.01 level

Table 5: Probability and Indemnities Response for Changes in Price Factors

	Corn ALL	Corn PPR	Soybeans	Soybeans PPR	Sorghum 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.