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IMPACT OF RMA’S PROJECTED PRICE ON PREVENT PLANTING CLAIMS

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Abbreviations

PP	Prevent Planting
LP	Late Planting
APH	Actual Production History
RP	Revenue Protection
YP	Yield Protection
RP-HPE	Revenue Protection with Harvest Price Exclusion

Abstract

This research studies the presence of ex-post moral hazard in the prevent planting provision from the crop insurance program in cotton, corn, and soybeans for the Plains Region and Southeast Regions of the U.S. Three fixed effect models are developed using the proportion of prevent plant acres as the dependent variable, as well as weather, input price, expected harvest price and a break-even point for the independent variables. In addition, a fourth fixed effect (FE) model is introduced using the logit transformation and the same variables as in previous models. The results show the number of PP claims has been driven not solely by weather conditions but by other market-related variables such as expected harvest price and input price, for cotton and soybeans. It is concluded that the proportion of prevented plant acres is endogenous to changes in the input price, expected harvest price, and break-even point, in the case of cotton and soybeans, confirming the presence of moral hazard in these two crops. In contrast, the results show no conclusive evidence that suggests moral hazard in corn.

Chapter 1. Introduction

After the Great Depression and the Dust Bowl in the 1930s, the U.S. Congress authorized the creation of the Federal Crop Insurance Corporation (FCIC), in order to carry out programs that would help with the recovery of agriculture. The Act of 1980, helped expand crop insurance to many other crops and regions of the U.S. and the 1994 Act made participation in the program mandatory for farmers to be eligible for some other farm program benefits. Ever since its creation the program has grown and continues to grow prominently (RMA).

Consequently, crop insurance has become a part of the suite of agricultural risk management tools that farmers use for hedging against possible undesirable outcomes, such as losses in production or a drop-in crop prices, among other events. Under this category of tools, we can also find futures contracts, forward contracts and spread sales (Velandia et al., 2015).

Moreover, with the objective of reducing ad hoc disaster assistance payments, previously delivered through ad hoc disaster bills, in the early 1994 the FCIC introduced the Prevent Planting (PP) provision into the crop insurance program. This became a common component of crop insurance through the Federal Crop Insurance Reform and Department of Agriculture Reorganization Act of 1994 (U.S. Congress, 1994).

Currently, this provision can be found under the Revenue Protection (RP), Revenue Protection with the Harvest Price Exclusion (RP-HPE) and Yield Protection (YP), insurance plans. Out of which the most popular plan is the Revenue Protection (RP) (Schnitkey et al., 2020).

Today, subsidized crop insurance has become the main instrument to support U.S. farmers, accounting for the biggest share of spending under the 2018 Farm Bill, without considering nutritional assistance, as presented in Figure 1. In 2020 alone, the program managed more than $114 billion of insurance liability and had an operating budget of $67.1 million in 2021 (RMA, 2021). The projected outlays for the program are expected to be $41 billion during 2019–2023, according to the Congressional Budget Office (CBO, 2019). Based on the projected outlays, crop insurance expenditure is expected to continue growing as presented Figure 2. As the program has grown in importance and as annual outlays have increased, as with any insurance program, interest in the actuarial soundness of the program and the existence of moral hazard and adverse selection incentives has also risen.

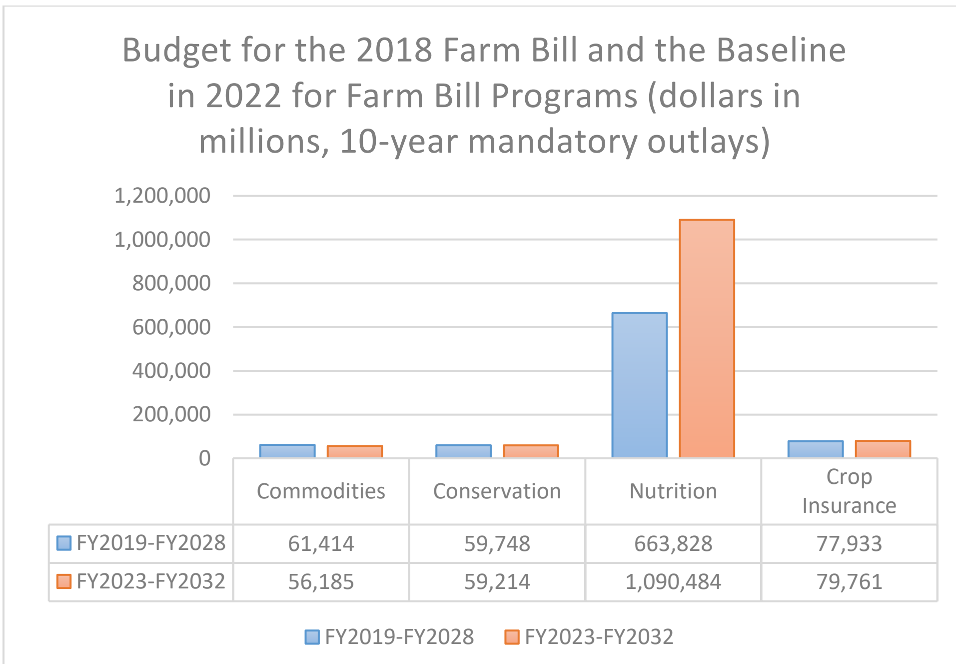


Figure 1. 2018 farm bill and projected outlay for the four greatest expenses.
Note: Nutrition (primarily SNAP), Commodities, Crop Insurance, and Conservation, account for 99% of the 2018 farm bill's mandatory spending.
Sources: CRS using CRS Report R45425, Budget Issues That Shaped the 2018 Farm Bill; CBO Baseline (May 2022), at https://www.cbo.gov/about/products/baseline-projections-selected programs, for the five largest titles; and amounts in law for programs in other titles.

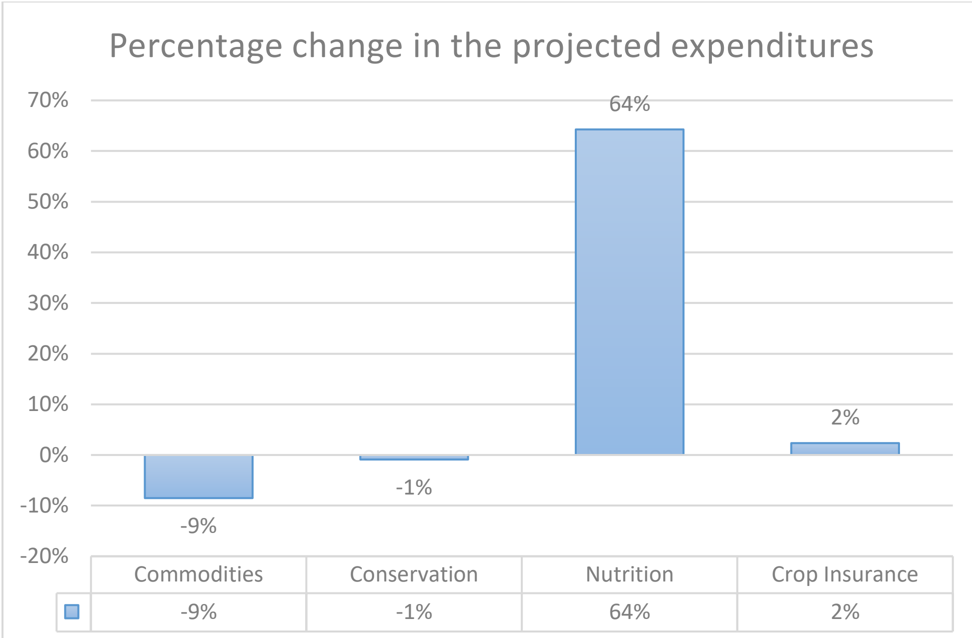


Figure 2. Change in the projected expenditures for the 5-year and 10-year budget projections.
Notes: Crop insurance has the second greatest increase in expenditures after nutrition.

While many studies have deeply considered the existence and potential corrections for moral hazard in the crop insurance program, few have focused on moral hazard in prevented planting (PP). Prevented planting is a provision included in the crop insurance defined as "failure to plant an insured crop by the final planting date, or within any applicable late planting (LP) period", resulting from severe weather events, like drought or excess of moisture (2020 Prevented Planting Standards Handbook).

Since the introduction of the PP provision, there has been a steady increase in prevent planting claims. Kim and Kim (2018) performed calculations from RMA cause of loss data showing that prevented planting payments accounted on average for 9% of the total indemnity from 1998 to 2008. However, from 2009 to 2013 prevented planting payments represented a total of 17% of the total indemnities. Such an increase in prevented planting payments may be the result of increased prevalence of extreme weather events in the observed timeframe. However, as participation in the crop insurance program has increased, concerns over proper use of the program increase as well. Moreover, a presence of moral hazard in PP claims behavior would mean the insurance premium subsidies paid to farmers are having an undesirable effect on production since it would be incentivizing farmers to not plant on fields that would have otherwise been planted in the year of the claim. An outcome that is against the goal of the USDA's Strategic Plan FY 2014–2018, Goal 3, which promotes agricultural production and the improvement of food security. In short, an effect of moral hazard caused by prevented planting is the increase of federal crop insurance expenditures by overcompensating producers and incentivizing the abandonment of profitable production (Boyer and Smith, 2019).

1.1. Moral hazard, asymmetric information and principal- agent problems

Moral hazard in crop insurance is a subset of a class of issues known as principal agent problems. A principal-agent problem occurs when one of the parties (the agent), works in favor of another party (the principal) in return of incentives. The work may inflict costs for the agent, which can cause the agent to ignore the best interest of the principal, thereby creating a conflict of interest. Asymmetric information which can also be referred to as information failure, typically refers to the case where one participant in a transaction possesses private information not known to the other participant(s). Of course, the difference in information can create a scenario where one of the participants has an advantage over the other. Consequently, asymmetric information is a primary component of principal-agent problems of which adverse selection (cases of hidden individual traits generally referred to as types) and moral hazard (cases of hidden or unknown actions) are problems commonly found within insurance.

In insurance, hidden actions of moral hazard refer to the way the agent's actions affect the distribution of covered events. Hence, the individual who performs the action (the agent), takes on more risk because another (the principal) bears the cost of that risk, and the agent's actions are hidden from the principal. The agent in this case is the insured individual and the principal is the insurer. Moral hazard has the effect of increasing the cost of offering insurance since it has the effect of increasing the cost and/or the severity of claims. Effectively, asymmetric information problems such as moral hazard is a form of market failure in insurance markets (Roberts, Key and O'Donoghue 2006).

Crafting effective solutions to moral hazard problems in insurance, and crop insurance specifically, requires an understanding of the complex patterns that may give rise to this behavior. The literature subdivides moral hazard issues into two types depending on the timing of actions relative to the event leading to a claim. Ex-ante refers to a change in behavior of the insured before losses occur, e.g. if a farmer changes his/her input use, because they have crop insurance, compared to a farmer without it (Rees and Wambach, 2008). This behavior can increase the frequency and potentially the severity of claims. Ex- post refers to a change in behavior of the insured after losses have occurred, e.g. a farmer may decide to reduce pesticide application in a year with high pest pressure. Ex-post moral hazard tends to increase the cost of an insured event that has occurred (Zweifel and Eisen 268-291). Specific to this study, the prevented planting provision of crop insurance is susceptible to both types of moral hazard. For example, ex-ante moral hazard would occur if the cost factors, used to determine the amount of a prevented planting payment, are set too high. In this case a farmer may conceivably incorporate fields that are more susceptible to insured planting challenges, e.g. frequent floods, etc. On the other hand, ex-post moral hazard would occur if late planting was possible, but a farmer abandons a field and accepts a prevent plant payment when harvest prices seem unfavorable. Each of these scenarios has the effect of increasing the cost of providing crop insurance, additionally, affects total production in years where prevented planting claims are made. As prevented planting claims increase over time, the need to understand and mitigate potential moral hazard incentives also increases in importance. While several steps have been taken to reduce ex-ante moral hazard in prevented planting over the years, such as adjustments in the PP cost factors (USDA-RMA, 2018) and the introduction of the 1 in 4 rule (RMA, 2021), less has been done from a policy perspective to address the potential for ex-post moral hazard in the provision. This study therefore serves to identify and better understand the mechanisms that lead to ex-post moral hazard in the provision of Prevent Planting.

1.2. Choosing prevented planting or late planting and moral hazard incentives

Prevented planting coverage is available for YP, RP or RP-HPE crop insurance plans purchased at the buy-up level. A farmer who is prevented from planting the lesser of 20 acres or 20% of his insured acres (Frankenfield, 2018) before the final planting date can accept a prevented planting (PP) payment or instead, late plant (LP), with a coverage level, reduced by the number of days after the final planting date. Prevented planting payments comprise of several components which include the prevented planting coverage factor (given as a percentage of the crop insurance guarantee and is based on an estimate of the pre-planting costs for a specific crop), the insurance coverage level or coverage rate (from 50% up to 85%), the projected price or guarantee price, the per-acre production guarantee or production history (APH which is an estimate of the average per acre crop yield for the previous 4-10 years), and the number of acres prevented from planting.

As an example, if a soybean producer is protected against lost production with revenue protection (RP) with a 60% PP coverage factor (which is 55% for corn and 60% for soybean), an 80% insurance coverage under the RP insurance plan, have a projected price of $10/bushel, APH of 90 bushel/ acre, and is prevented from planting more than 20 acres, the indemnity payment s/he would receive would be equal to 0.60*0.8*10*90= $432/acre. The decision to accept a prevented planting payment has to be balanced with the decision to late plant, the same which will carry a reduced crop insurance guarantee and an increased risk of reduced harvest yields.

1.3. Economic framework

The economic framework is borrowed from Kim and Kim (2018) in order to establish the decision process of whether to accept prevented planting vs choosing to late plant (LP). A risk averse and profit maximizing farmer will have a profit function as in equation (1) if s/he chooses to make a prevented planting claim.

$$\pi_{pp} = \Theta_{pp} * \Theta * p_g * \ q_{\,APH} - c_1 - pm - c_{cv} \qquad (1)$$

Where π_{pp} is the profit received for the PP claim, Θ_{pp} is the PP coverage factor (55% for corn and 60% for soybean), Θ is the insurance coverage, p_g is the projected price or guarantee price in $/bushel, $q_{\,APH}$ is the production history (APH) in bushel/acre, c_1 is the input cost for planting the first crop, pm is the crop insurance premium paid in $/acre, c_{cv} is the cost for planting a cover crop in $/acre; which is a condition to claim the PP.

On the other hand, if the farmer opts to Late Plant a second crop, the coverage level will be reduced by 1% per day, starting from the last day of the planting period. Consequently, the farmer's profit when late planting is reflected in the equation (2) as follows:

$$\tilde{\pi}_{Lp} = \left[(\tilde{p} * \tilde{q} - c_1 - pm - c_2 + \max\left\{0, in_j\ \right\}\right], \text{ j= yp, rp} \quad (2)$$

Where $\tilde{\pi}_{Lp}$ is the estimated profit received for late planting (LP) a second crop, $\tilde{p}$ is the uncertain crop price in $/bushel, $\tilde{q}$ is the uncertain yield in bushels/acre, c_1 is the cost for planting the first crop, pm is the crop insurance premium paid in $/acre, c_2 is the cost for planting a second crop, and max $\left\{0, indemnity\ payment_j\ \right\}$ is the indemnity the farmer expects depending on the type of crop insurance j= yield protection (yp), revenue protection (rp). (Kim and Kim, 2018).

For a farmer deciding whether to accept a PP payment or to LP, s/he will be indifferent when the profit for the PP claim π_{pp} equals the sum of the expected profit for LP $\tilde{\pi}_{Lp}$ and the risk premium RPr based on the farmer's risk preferences as in equation (3).

$$\pi_{pp} = \tilde{\pi}_{Lp} + RPr \quad (3)$$

Given that $\tilde{\pi}_{Lp}$ decreases as input costs increase or as the projected price decreases, a farmer's incentive to accept (PP) increases as expected costs increase or as expected prices decrease.

1.4. Problem identification

Based on the exploratory research, there is little information up to date with respect to the presence of moral hazard in the PP program for three crops selected. The growth of the program and number of PP claims, create the question of whether this growth is related to normal causes such as a wider adoption of the program and extreme weather patterns, or if it the result of the presence of moral hazard. The farmer's decision making-process, as described in the introduction, is necessary to understand how the provision may have some flaws that might be incentivizing the increase on PP claims.

1.5. Significance of study

Several studies have investigated the existence of moral hazard related to prevented planting. Following these studies, changes have been made to the national regulation of the prevented planting provision to account for moral hazard incentives, such as the change made in 2017 by the RMA in the payment structure, reducing the coverage factor for corn, in order to balance indemnities with the estimated pre-planting costs and reduce ex-ante moral hazard incentives. However, as shown in studies such as Kim and Kim (2018) and Wu et al (2020) for example, moral hazard incentives, specifically ex-post moral hazard incentives, likely still exist. Furthermore, while work has been done demonstrating the potential existence of ex-post moral hazard in prevented planting claims, much is still to be known about the mechanism through which such ex-post moral hazard incentives arise. Such an understanding allows the RMA more precision in anticipating indemnity payment patterns as well as insights for updates to the program to improve its performance. This study accounts for weather variables, but most importantly for market factors like input cost and crop price expectation. Additionally, dissimilar to some work done in the past, we use the RMA projected price with a state level basis correction, as opposed to the previous year's harvest price, as a more realistic measure of the farmer's expected harvest price. We also account for the potentially asymmetric response of PP acreage to changes in the expected price. Results from this study update our understanding of moral hazard incentives in PP.

1.6. Objectives

The general objective of the study is to test for the presence of ex-post moral hazard in cotton, corn, and soybeans for the Plains Region and Southeast Regions. The specific objectives of the study are:

1. Review the most important variables introduced in previous models to identify ex-post moral hazard in prevent planting.
2. Develop a base model according to the literature review.
3. Conduct a model specification test.
4. Improve the base model by introducing the break-even cost bound.

5. Analyze how expected prices below the break-even cost influence the number of PP claims.

1.7. General procedures

A background of the base model, as well as improvements to the model, and the research procedures use in this study are presented in Chapter 2. Moreover, the analysis of the results is presented in Chapter 3. Finally, a summary and conclusions are presented in the last section in Chapter 4.

1.8. Literature review

There have been studies suggesting the provision under the crop insurance program is susceptible to moral hazard. In fact, several studies have investigated and demonstrated the existence of moral hazard related to post planting changes in behavior.

Velandia et al. (2015) analyze farmer's decision to participate in crop insurance based on some factors such as owned acres, off-farm income, education, age, and business risk. They developed a multivariate and multinomial probit model, finding that producers consider the interaction between the different risk management tools, taking the correlation between the tools in their final decision process, to select their portfolio of risk management instruments.

On the other hand, Babcock (2015) examines how the coverage choice can be better explained using prospect theory rather than expected utility maximization. Their results demonstrate that farmers would choose a lower coverage level than the predicted with expected utility maximization. They note that premiums could be fair in aggregated levels but not at the individual level.

Moreover, Connor and Katchova (2020) examine how crop insurance and moral hazard can affect variability and drought susceptibility on corn and soybean yields likely because of lower quality lands being incorporated brought into production once insured. They find that when crop participation increases by 1 percentage point, drought susceptibility also increases by 1.2%.

In addition, Chen and Miranda (2007) found out that unfavorable weather increases crop abandonment among corn producers in North Central, Central Plains and Southeast regions and among upland cotton producers in all Southern regions. Subsequently, they found a decline of futures prices during the growing season will also increase crop abandonment in most regions with the exception for corn in Southern, Plains and upland cotton in Southeast.

Rejesus, Escalante, and Lovell (2005) determined that crop insurance incentivize farmers to choose prevent plating (PP), with indemnity payments that exceeded the cost invested in the crop. Their results showed that the decision to submit the prevent plant (PP) claim is based on opportunity cost principles resulting in ex-ante moral hazard incentives. This study and a similar study by Rejesus et al (2003) led to updates in PP coverage factors to reduce incentives for ex-ante moral hazard. More recent work has looked at the existence of ex-post moral hazard in prevented planting claims. Ex-post moral hazard in PP is typically associated with increases in PP claims once an insurable event has occurred. Thus, farmers may have incentive to accept a PP claim even when late planting is possible. According to the report by USDA-OIG (2013) only 0.1% of producers who receive the prevent planting payment, plant a second crop during the late planting period.

Kim and Kim (2018) examine how crop insurance affects the farmer's choice to prevent plant or late plant, based upon crop prices and the expected yield at harvest time. Using data from the Corn Belt Region, they assume a risk-averse farmer and determine that the farmer will choose to late planting if s/he expects higher prices and yield. Concluding, there is ex-post moral hazard, and crop insurance increases the likelihood of preventing planting claims over production during the late planting period.

Likewise, Wu, Goodwin, and Coble (2019) examine how prevent planting claims increase as the market price for the crop decreases or as the cost of input increases. Indeed, their results showed that most corn producers would be better off by abandoning profitable production and taking the prevented planting (PP) indemnity, for most of the days during the late planting period. These results lead to believe that claims may be endogenous to prices.

Furthermore, Boyer and Smith (2019) study how coverage factors may influence the final decision to plant during the late planting period. Using data on corn and soybean from two field experiments in Tennessee, they found out that after a certain date, profit-maximizing producers would rather abandon production, taking the prevent planting (PP) payment instead of late planting (LP).

Additionally, Boyer and Smith (2019) found that the increase in coverage level reduces the number of days during the late plating period when planting would be optimal. Thus, higher coverage levels increase the incentive to abandon production. In fact, reducing the coverage factor, extends the number of days during the late planting period where panting is more profitable. Furthermore, the USDA-RMA has already implemented a change in 2017.

1.9. Conceptual framework

Based on the previous literature, it is concluded that the best approach to identify the presence of ex-post moral hazard is by starting with a simple economic model, following by the econometric model and then by the base model constructed accordingly with the literature review and finally improving the model. A description of the research process is described in Figure 3 below.

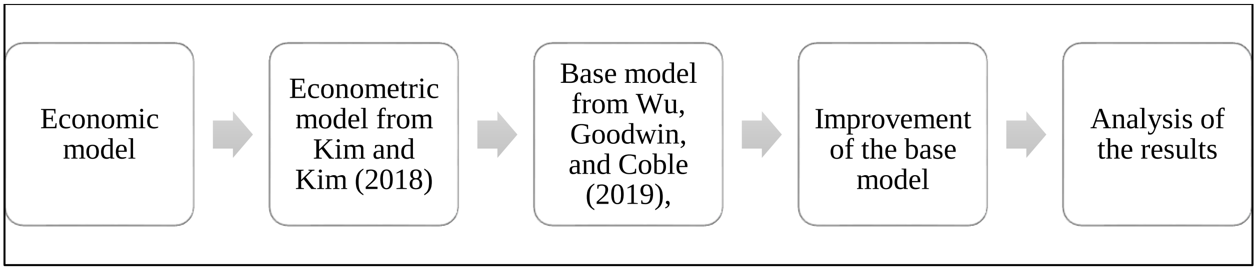


Figure 3. Conceptual framework for research development.

Chapter 2. Methods and Data

2.1. Economic model

To investigate the presence of moral hazard in the prevent planting provision, on cotton, corn, and soybeans, the study uses literature review to establish that the amount of PP claims is a function of several factors which are identified next in equation (4):

$$PP\ claims = f(Prec, temp, exp\ harv\ pr, inpt, dsuit) \qquad (4)$$

Where the PP claims is a function of the precipitation $prec$, temperature $temp$, expected harvest price $exp\ harv\ pr$, input prices $inpt$, days suitable for planting $dsuit$.

Furthermore, the papers from Wu, Goodwin, and Coble (2019), and Kim and Kim (2018) served as a starting point for the model specification.

2.2. Econometric model

Following the econometric model from Kim and Kim (2018), the base model is derived and adapted by introducing several variables, among which one of them is the lower bound price considered to be the equilibrium price. The model is described in the equation (5) presented below:

$$y_{it} = \beta_0 + \sum_{K=1}^{k} X_{itk}\,\beta_k + \varepsilon_{it} \quad (5)$$

Where, y_{it} is the proportion of acres prevented from being planted in county i and time t, the term X_{itk} describes all the explanatory variables, such as input price, expected harvest price and precipitation also for each county i and time t, and ε_{it} alludes to the error term in county i and time t. Moreover, with this model we can identify the change in each variable and the effects in the amount of PP claims. The presence of moral hazard would suggest that with higher crop prices, and lower input prices, the amount of PP claims should be smaller, maintaining all the other variables constant. Likewise, excess of precipitation or extreme temperatures would also increase the likelihood of PP claims, which could be attributable to natural causes. It is necessary to clarify, that even though natural causes could be involved in the increase in PP claims, weather changes should be assessed further to adjust the PP provisions to account for those changes.

2.3. Data

Firstly, a description of the type of data and sources from where the data was obtained is provided. Secondly, tables showing the correlation of the data are presented. Thirdly, a description about the variables used in the model is presented. Furthermore, a distinction is made between the weather variables, which are indispensable for the correct analysis of the model, and the non-weather-related variables, which are introduced to identify the presence of moral hazard, in the crops.

Description of the data

A panel data is gathered and joined together for the study, with a time horizon starting from 2011 to 2020, based on the quality and availability of the data at the time of the research. Furthermore, the research focuses on two regions in the U.S. These are the Plains region, which is constituted by Kansas, Nebraska, North Dakota, South Dakota and Oklahoma, as well as the Southeast region, which includes Alabama, Georgia, North Carolina, South Carolina and Tennessee.

Weather data was obtained from the PRISM Climate Group, which stands for "parameter-elevation regressions on independent slopes model", based at Oregon State University and supported by the RMA. The spatial climate dataset was download and used at the county level with daily observations.

Additionally, the Cause of Loss Historical Data provided by the RMA, was firstly used to obtained the information with respect to type of crop, insurance plan, type of loss, county and year. However, after running the first analysis using the cause of loss ratio as the dependent variable from our model and looking closely to the data, missing information and errors were found.

Consequently, it was decided to use a different dataset to avoid reporting issues and get better results. Furthermore, the data later used was the Crop Acreage Data Report provided by Farm Service Agency (FSA). This institution requires all producers to submit an annual report concerning cropland use on their farms if they participate in certain programs, making this firsthand information trustworthy. From the report, the proportion of prevented planted acres is calculated and added to the model as the dependent variable.

From the Crop Acreage Data Report, 3 of the most important crops are selected for the analysis which are corn, soybean, and cotton. These crops are selected for their importance and abundancy in most of the regions of the U.S.

Weather variables

The model integrates several weather variables, which are fundamental for the model since in theory weather should be the only factor driving the number of PP claims. Accordingly, variables that account for precipitation, extreme precipitation and frost are created to introduce into the model.

The National Agricultural Statistics Service (NASS) conducts numerous surveys annually, one of which is the number of days suitable for field work. Moreover, this data was included in the model, the same which identifies the number of days where the weather and field conditions are optimal, for farming operations. This variable is included as a different type of weather variable which can be insightful to understand how extreme the weather has to be, in order to prevent farmers from working. The introduction of this variable into the model allows to capture the effects of weather events such as snow, frost and rainfall all of which do not allow the equipment's to operate on the field and delay planting.

On the other hand, the cumulative precipitation, defined as the precipitation capture in the soil at a particular time, was calculated using the winter precipitation or pre-planting season (January to May) precipitation combined with the in-season precipitation. This simple calculation was made by summing the monthly precipitation from each count i at t time.

$$Cmp = \sum_{i=1}^{i} X_{it} \;(6)$$

In addition, the excess of moisture defined as abnormal values of precipitation is calculated. Consequently, every value above the sum of the average precipitation, plus the standard deviation is considered to be an excess. Therefore, the excess of moisture ExM is calculated as the difference between the monthly precipitation $Pr_{\,it}$ and the mean precipitation $\overline{Pr}_{\,it}$ + the respective standard deviation of the precipitation $6_{Pr_{\,it}}$.

$$ExM = \; Pr_{\,it} - \left(\overline{Pr}_{\,it} + \; 6_{Pr_{\,it}}\right) (7)$$

Non-Weather variables

Additionally, the model also integrates several non-weather-related variables, whose purpose is to identify the effect in the number of PP claims, thereby, identifying the presence of moral hazard in the provision. Accordingly, variables that account for expected harvest price and input prices, are created and introduce into the model.

The expected harvest price is calculated using a process analogous to the projected price from the Price Discovery produced by the RMA, which is calculated as the average of the daily settlement prices during the price discovery period. The price discovery period last for a month, making the price discovery a monthly average settlement price.

Consequently, February future (before planting season starts) prices for the December contract at the Chicago Board of Trade (CBOT) were used for corn, February prices for the November contract at the CBOT were used for soybean, and February prices for the December contract at the Intercontinental Exchange were used for cotton.

Since prices per state should also depend on a state basis an adjustment is made. The adjustment helps localize the price of the commodity to ensure an accurate number regarding the expected harvest price that farmer's will assume in their planting decision.

Consequently, the adjustment factor P_{af} is calculated by taking the index price received P_{ri} during the discovery month in state i and subtracting the index price of the commodity in state j where the exchange is located P_{rj}.

$$P_{af} = P_{ri} - P_{rj} \ (8)$$

For example, as corn futures contract is traded at the CBOT located in Illinois, the P_{rj} would be the index price in Illinois. Furthermore, to obtain the adjusted expected harvest price P_a the monthly average settlement price P_p for the discovery period are summed with the adjustment factor P_{af}.

$$P_a = P_p + P_{af} \ \ (9)$$

Finally, the adjusted expected harvest price is converted into a logarithmic form for interpretation purposes. The logarithm of the adjusted expected harvest price is included in the model to better assess the farmer's response to high or low expected prices in their final decision to file the PP claim or LP a second crop instead.

$$Log\, P_a = log\, \left(P_p + P_{af}\right) (10)$$

The price ratio is calculated by dividing the current adjusted expected harvest price P_t in t time by the lagged adjusted expected harvest price P_{t-1}, which is the harvest price received the previous year. Then the variables are converted to a logarithmic form. The expected harvest price is used and not the actual price received, since the farmers decision is based on expectations of the price, which is uncertain during the pre-planting season. This variable is included as this ratio is the rate of change in prices. It is expected that a change in the present price relative to last year's price, will affect farmer's decisions.

$$Log\ P_{ratio} = \log\left(\frac{P_t}{P_{t-1}}\right) \quad (11)$$

To obtain the cost of inputs, the monthly fertilizer cost index from the USDA was used. However, information after 2018 is was not available, therefore, missing information was completed using the following Ordinary least squares (OLS) regression:

$$\text{Cost}_t = \beta0 + \beta1 * \text{DAP}_t + \beta2 * \text{KCL}_t + \beta3 * \text{UREA} + \beta4 * \text{Diesel} + \beta5 * \text{CPI} \quad (12)$$

Just like Wu, Goodwin, and Coble (2019), spot prices for diammonium phosphate (DAP) at the US Gulf, potassium chloride (KCL) at Vancouver, urea at the Black Sea, diesel at New York, and the consumer price index (CPI) from the Federal Reserve Bank of Saint Louis, were used to calculate the missing information from 2018 to 2020.

Finally, the dependent variable is calculated by dividing the total of prevent planted acres $PP\ acres_{it}$ in a giving county i at a giving time t by the total planted acres $PL\ acres_{it}$ from the FSA report, to create the proportion of prevent planting $PrpPP$, which is a non- negative dependent variable.

$$PrpPP = \frac{PP\ acres_{it}}{PL\ acres_{it}} \quad (13)$$

2.4. Fixed effects model

Using the variables describe previously, three fixed effect models are developed and estimated. In order to control for the unobserved time invariant effects or for any individual-specific attribute that do not vary across time, all the models presented are run as fixed effect models as expressed in the equation (14):

$$y_{it} - \bar{y}_i = \beta_0 + \beta\,(x_{it} - \bar{x}_i) + (\varepsilon_{it} - \bar{\varepsilon}_i) \quad (14)$$

Where observation y at i county and t time is subtracted by the county average. For example, variables such as county, state, the type of crop and year do not change over time or change at a constant rate over time for the case of "year", which means these variables have fixed effects or the effect they produce is constant.

The fixed effect model is used, since the heterogeneity of the sample used is not random but fixed. In fact, based on the literature there are patterns that are state specific, meaning the heterogeneity is individual specific and not random. In order to prove this theory, a Hausman test is conducted as shown below.

Table 1. Hausman test results for the base model

	Cotton	**Corn**	**Soybeans**
Chi2	72.21	231.69	66.13
Prob>chi2	0.0000	0.0000	0.0000
Degrees of freedom	7	7	7

Notes: Ho: Random effects are appropriate vs Ha: Fixed effects are appropriate.

The Hausman Test or model misspecification test is used on the panel data to choose between the fixed effects model or the random effects model. The null hypothesis specifies that the preferred model is random effects. However, the alternative hypothesis specifies that is preferred to use is the fixed effects model. Given the results, it is concluded the effects are not random but fixed, and the best model to use is the fixed effects model.

For this reason, panel ids were created grouping the data by county, state, and crop. Later the command xset from the statistical software package STATA was used to define the data as a panel, using the panel ID and Year. Subsequently, the command xtreg was used to run all the models, which specifies each model to have fixed effects.

Additionally, to identify that the used of the quadratic form from the variable "year" was a better fit for the model than just "year", a comparison between both models is made. The Akaike information criterion (AIC) and the Bayesian information criterion (BIC) are used to select the best model. Furthermore, it is determined that the model with the lowest AIC and BIC is the one using the quadratic form of the variable year, meaning that it fits the model better.

Consequently, the base model or first model is described next in the equation (15):

$$PrpPP_{it} = \beta_0 - \beta_1 \, Log \, P_a + \beta_2 \, Log \, P_{ratio} - \beta_3 \, Index - \beta_4 \, Dsuit + \beta_5 \, Cmp + \beta_6 \, ExM + \beta_7 \, t + \beta_8 \, (t * t) \quad (15)$$

Where, $PrpPP_{it}$ is the proportion of prevented plant acres at i county at t time, B_0 is our constant or intercept, $Log\ P_a$ is the logarithm of the adjusted expected harvest price, $Log\ P_{ratio}$ is the logarithm of the price ratio, $Index$ is the cost of the inputs, $Dsuit$ is the days suitable for farming operations, Cmp is the cumulative precipitation, ExM is the excess of moisture, t is the year, and $t * t$ is the interaction term between years.

Furthermore, for the second model, a dummy or categorical variable that establishes a lower bound price representing the equilibrium price is introduced. This variable is of great importance to understand famer's decision to prevent plant or late plant. It is estimated that expected harvest prices below the bound would likely increase the willingness to prevent plant. In other words, if the farmer is expecting a lower price that does not cover their planting cost, s/he will opt to prevent plant if possible.

This lower bound denominated "delta" is the long- run average cost (LRAC) and is derived from the long run average price (LRAP), assuming that farmers are profit maximizers. According to microeconomic theory in order to maximize profit, Marginal Revenue (MR) must be equal to Marginal Cost (MC). Thus, the equality is transformed as follows:

$$MR = MC$$

$$\frac{d\ (p)}{d(q)} = \frac{d\ (TC)}{d(q)} \rightarrow \frac{d\ (p)}{d(q)} = \frac{d\ (VC + FC)}{d(q)} \rightarrow \frac{d\ (p)}{d(q)} = \frac{d\ (VC)}{d(q)} \rightarrow AP = AVC \rightarrow LRAP = LRAC$$

Where Marginal Revenue (MR) equals the first derivative of price (P) with respect to quantity (q) and Marginal Cost (MC) equals the first derivative of total cost (TC) with respect to quantity (q). Normally in the short-run, total cost (TC) is equal to fixed cost (FC) plus variable cost (VC), but in the long run fixed cost are considered to be zero. Subsequently, converting the equation produces an equality between the Long Run Average Price (LRAP) and the Long Run Average Cost (LRAC). Hence, the new variable delta δ is calculated using the next equation (16)

$$\delta = (Log\, P_{ai} - \overline{Log\, P_a}\,) = \begin{cases} 1, & if\ \delta < 0 \\ 0, & if\ \delta > 0 \end{cases} \quad (16)$$

Where $Log\, P_{a_i}$ is the log of the adjusted expected harvest price, and $\overline{Log\, P_a}$ is the Long Run Average Cost (LRAC), calculated as the 10 year mean of the log of the adjusted expected harvest price. Thus, a price difference lower than zero would be equal to 1 and a price difference greater than zero would be equal to 0. Consequently, the second model is described next in the equation 17:

$$PrpPP_{it} = \beta_0 + \beta_1\, \delta + \beta_2\, Log\, P_{ratio} - \beta_3\, Index - \beta_4\, Dsuit + \beta_5\, Cmp + \beta_6\, ExM + \beta_7\, t + \beta_8\, (t * t) \quad (17)$$

Where, $Log\, P_a$ the logarithm of the adjusted expected harvest price is subtracted, and substitute for the new variable δ define as “Low Price Indicator.”

For the third model the dummy variable delta defined as “Low Price” is transformed into a continuous variable by multiplying delta by the log of the adjusted expected harvest price, as seem in equation (18).

$$Continuous\ Low\ Price = (\delta *\ Log\, P_a) \quad (18)$$

Consequently, the third model is described next in the equation (19):

$$PrpPP_{it} = \beta_0 - \beta_1\, Log\, P_a + \beta_2\, \delta_c + \beta_3\, Log\, P_{ratio} - \beta_4\, Index - \beta_5\, Dsuit + \beta_6\, Cmp + \beta_7\, ExM + \beta_8\, t + \beta_9\, (t * t) \quad (19)$$

Where, $Log\, P_a$ the logarithm of the adjusted expected harvest price is once again included, and delta δ is substitute for its continuous version δ_c define as “Continuous Low Price”.

2.5. Logit transformation

Even though the used of the fixed effects model has been tested as a better fit against the random model. The very nature of the data and the dependent variable used in the model, the same which is a proportion, raise the question if the model used is the best. In order to handle the data with a bounded nature, and fix any irrational prediction for extreme values of the regressors, a logit transformation is proposed as suggested in the Stata Journal (Baum, 2008). This transformation can be expressed in equation (20) below:

$$\mathrm{y} = \frac{1}{1 + \exp(-\mathrm{X}\beta)} \quad (20)$$

Consequently, the transformation creates the response variable y^* as expressed in equation (21) below:

$$\mathrm{y}^* = \log\left(\frac{y}{1-y}\right) \quad (21)$$

However, the interpretation of the results would change, and it would be defined as the change in log of odds. In other words, the change in the likelihood of an event occurring. For example, the odds of claiming the prevent plant payment.

Chapter 3. Results

3.1. Summary statistics

A summary of statistics for all the variables included in the model is presented below in Table 2. The number of observations range from 30,326 to 33,764 depending on the variable. Furthermore, it was found that the average proportion of prevent planting claims was .0241037, which will range from 0 to 1, since is a proportion, with a maximum of .994117. The adjusted expected harvest price defined as “High price” had an average price of 1.714837/bushel with a maximum of $2.616666/bushel. The average low adjusted expected harvest price, which in other words is the average prices below the breakeven cost line, was $.9783272/bushel, with a maximum of $2.347558/bushel. The average projected price ratio was .0408262 and a maximum of .6135295. The average number of days suitable for farming operations was 65.21 days with a maximum of 174.9. The average input cost was $78.8248/acre, with a maximum of $101.4/acre. The average pre-season precipitation was 329.1304 millimeters, with a maximum of 1080.82. Finally, the average excess of moisture in the soil was 77.79782 millimeters, with a maximum of 1080.82 millimeters.

Table 2. Summary statistics from all the variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
Proportion of Prevent Planting	33,764	0.0263753	0.0911609	0	0.994117
High Price	30,346	1.69894	0.7585859	-.597837	2.616666
Continuous Low Price	30,346	0.9783272	0.962438	-.597837	2.347558

(table cont’d.)

Variable	Obs.	Mean	Std. Dev.	Min	Max
Projected Price Ratio	30,326	.0408262	0.1185566	-.3024478	0.6135295
Days suitable for farming operations	32,729	65.21653	22.12648	8.5	174.9
Cost Index	33,764	78.8248	18.63446	46.87901	101.4
Pre-season Precipitation	33,716	329.1304	133.5573	0	1080.82
Excess Moisture	33,764	77.79782	185.3216	0	1080.82
Year	33,764	2015.5	2.872326	2011	2020

3.2. Data correlation

Table 3. shows the inverse relationship between the expected prices and the number of PP claims for cotton, which is the basis for the research and the selection of the variables.

Table 3. Correlation between PP claims and expected harvest price for cotton

	Average PP claims per state	Average expected harvest price per state
Average PP claims per state	1.000	-
Average expected harvest price per state	-0.0356	1.000

Notes: The correlation between price and number of PP claims is inverse.

Table 4. shows the inverse relationship between the expected prices and the number of PP claims for corn, which is the basis for the research and the selection of the variables.

Table 4. Correlation between PP claims and expected harvest price for corn

	Average PP claims per state	Average expected harvest price per state
Average PP claims per state	1.000	-

Average expected harvest price per state	-0.7133	1.000

Notes: The correlation between price and number of PP claims is inverse.

Table 5. shows the inverse relationship between the expected prices and the number of PP claims for soybeans, which is the basis for the research and the selection of the variables.

Table 5. Correlation between PP claims and expected harvest price for soybeans

	Average PP claims per state	Average expected harvest price per state
Average PP claims per state	1.000	-
Average expected harvest price per state	-0.5150	1.000

Notes: The correlation between price and number of PP claims is inverse.

3.3. Fixed effects base model

Table 6 displays the results for the first or base model, with fixed effects, and robust standard errors. The proportion of prevent plant acres $PrpPP$ is the dependent variable against which all independent variables are regressed. Furthermore, in their majority the results follow the expected coefficient signs for the statistically significant variables. Note that robust standard errors are used to correct for heteroscedasticity. Because robust standard errors can provide a more accurate measure for the true standard error of a regression coefficient.

The first variable "High Price" is negative for cotton, which confirms the inverse relationship between the adjusted expected harvest price and the amount of PP claims. In contrast this variable is positive and statistically significant for corn and soybeans. Based on the results it would seems as if the farmer's expected harvest price influences their decision to PP claim only when planting cotton. Moreover, the results show that in the case of cotton, each 1% increase in the adjusted expected harvest price, would reduce the proportion of prevent planting acres by 0.151 acres, holding everything else constant. On the other hand, in the case of corn and soybeans the increase in price would actually increase the likelihood of PP claim by 0.0607 and 0.0282 acres, respectively.

Table 6. Fixed effects base model results

Variable	Description	Cotton	Corn	Soybeans
High Price	$Log\ P_a$ Adjusted expected harvest price	-0.151*** (0.0430)	0.0607*** (0.0116)	0.0282** (0.0133)
Projected Price Ratio	$Log\ P_{ratio}$ Adj. expected harvest price/ lagged expected harvest price	0.0681*** (0.0204)	0.0127** (0.00598)	0.0378** (0.0147)
Cost Index	Input costs	0.000784 (0.000590)	-0.000230 (0.000171)	0.000596** (0.000266)
Days suitable for farming operations	Number of days optimal for working	-0.000426*** (0.0000940)	-0.00151*** (0.000119)	-0.00119*** (0.000118)
Preseason Precipitation	Cumulative precipitation from January to May	0.0000413* (0.0000226)	0.0000597*** (0.0000115)	0.0000465*** (0.0000102)
Excess Moisture	Difference between precipitation and the average precipitation plus the standard variation	0.0000689*** (0.0000163)	0.0000226*** (0.00000637)	0.0000387*** (0.00000693)

Notes: Numbers in parenthesis are the standard errors; significance levels are 1% (***), 5% (**), 10% (*). Proportion of prevent plant acres is used as the dependent variable
(table cont'd.)

Variable	Description	Cotton	Corn	Soybeans
Year		-14.61***	-2.374***	-0.164
		(4.075)	(0.617)	(0.467)
Year Squared		0.00362***	0.000590***	0.0000421
		(0.00101)	(0.000153)	(0.000116)
Constant		14717.0***	2389.4***	160.3
		(4105.2)	(622.1)	(470.5)
Observations		2787	3045	14785
No. of counties		300	331	1500
R-squared (overall)		0.0798	0.0648	0.0574
Adj. R-squared		.112689	.0924532	.0844767
F-Statistics		10.77	67.43	64.14
Prob > F		0.0000	0.0000	0.0000

Notes: Numbers in parenthesis are the standard errors; significance levels are 1% (***), 5% (**), 10% (*). Proportion of prevent plant acres is used as the dependent variable.

The second variable "Projected Price Ratio" is positive and statistically significant for cotton, corn and soybean. This variable captures the change in the expected price with respect to last year, explaining that if last year's harvest price was greater than the current year, the farmer will be inclined to PP. Hence, the positive sign which determines that the greater the change in harvest price with respect to last year's, the greater the proportion of prevent planting claims relative to the planted acres. In the case of cotton this would mean that each 1% increase in the projected price ratio, would increase the proportion of prevent planting acres by 0.0681 acres. Similarly, in the case of corn this would mean that each 1% increase in the projected price ratio, would increase the proportion of prevent planting acres by 0.0127 acres. Likewise, in the case of soybean this would mean that each 1% increase in the projected price ratio, would increase the proportion of prevent planting acres by 0.0378 acres.

The third variable "Cost Index", is positive and statistically significant for soybeans. In contrast, it is statistically insignificant for cotton and corn. Furthermore, this would mean that the increase in input cost for soybeans would increase the proportion of prevent planting, just as expected. In the case of soybeans, the increase of $1/acre of input cost, would increase the proportion of prevent planting acres by 0.000596 acres.

The fourth variable "Days Suitable for Farming Operations", is negative and statistically significant for all three crops. This variable intuitively explains the inverse relationship between the amount of days optimal for working on the field and the success of the crop or PP claim. In the case of cotton the results show that the increase of 1 day suitable for planting, would reduce the proportion of prevent planting acres by 0.000426 acres. Alternatively, in the case of corn, the increase of 1 day suitable for planting, would reduce the proportion of prevent planting acres by 0.00151 acres. Similarly, in the case of soybean, the increase of 1 day suitable for planting, would reduce the proportion of prevent planting acres by 0.00119 acres.

The fifth variable "Pre-season Precipitation", is positive and statistically significant for all three crops, as expected. Since weather conditions or in this case precipitation is the greatest cause of loss for PP claims. In the case of cotton, the results show that the increase of 1 millimeter of rain, would increase the proportion of prevent planting acres by 0.0000413 acres. Likewise, in the case of corn, the results show that the increase of 1 millimeter of rain, would increase the proportion of prevent planting acres by 0.0000597 acres. Similarly, for soybean, the results show that the increase of 1 millimeter of rain, would increase the proportion of prevent planting acres by 0.0000465 acres.

The sixth variable "Excess Moisture", is also positive and statistically significant for all three crops, just as expected since the excess of moisture in the soil is the main cause of loss for PP claims in the Plains region and Southeast region. In the case of cotton, the results show that the increase of 1 millimeter of rain above the monthly average, would increase the proportion of prevent planting acres by 0.0000689 acres. Likewise, in the case of corn, the results show that the increase of 1 millimeter of rain above the monthly average, would increase the proportion of prevent planting acres by 0.0000226 acres. Similarly, in the case of soybean, the results show that the increase of 1 millimeter of rain above the monthly average, would increase the proportion of prevent planting acres by 0.0000387 acres.

The seventh variable “Year” resulted to be negative and statistically significant for cotton and corn. This would mean that each year that passes by reduces the amount of PP claims. However, this result seems to be just a small part of a wider picture. Consequently, the eight variable “Year Squared” is also introduced in the model. This variable which in contrast is positive and also statistically significant for cotton and corn, allows to see the bigger picture. Concluding that as matter of fact year over year the number of PP claims are getting reduced, but also over time the number of claims keep growing. In other words, the number of PP claims is increasing at decreasing rate.

This means in the case of cotton, that with every 1 year that passes, the proportion of prevent planting acres decreases by 14.61 acres relative to the previous year. In contrast, every 1 year that passes, also increase the total proportion of prevent planting acres by 0.00362 acres.

Likewise, in the case of corn this would mean, that with every 1 year that passes, the proportion of prevent planting acres decreases by 2.374 acres relative to the previous year. In contrast, every 1 year that passes, also increase the total proportion of prevent planting acres by 0.00590 acres.

It is inferred from these results that from the 3 crops, cotton is the most prominent in showing the presence of moral hazard, followed by soybean. In contrast, corn appears to be free of moral hazard for this data.

3.4. Fixed effects with dummy variable

Table 7 is calculated with the new added variable delta defined as “Lower Price Indicator” and without the variable “High Price”. Consequently, Table 7 displays the results for the second model, with fixed effects and robust standard errors. Just as before the proportion of prevent plant acres $PrpPP$ is the dependent variable against which all independent variables are regressed.

Table 7. Fixed effects with dummy variable results

Variable	Description	Cotton	Corn	Soybeans
Low Price	$\delta * Log\ P_a$ Delta* Log Adjusted expected harvest price	0.0228*** (0.00792)	-0.00360 (0.00320)	0.00875*** (0.00323)
Projected Price Ratio	$Log\ P_{ratio}$ Adj. expected harvest price/ lagged expected harvest price	0.00350 (0.0197)	0.00789 (0.00630)	0.0245* (0.0136)
Cost Index	Input costs	0.000207 (0.000479)	-0.0000625 (0.000163)	0.000974*** (0.000215)
Days suitable for farming operations	Number of days optimal for working	-0.000563*** (0.000107)	-0.00147*** (0.000116)	-0.00121*** (0.000118)
Preseason Precipitation	Cumulative precipitation from January to May	0.0000517** (0.0000226)	0.0000634*** (0.0000113)	0.0000522*** (0.0000105)

Notes: Numbers in parenthesis are the standard errors; significance levels are 1% (***), 5% (**), 10% (*). Proportion of prevent plant acres is used as the dependent variable.
(table cont’d.)

Variable	Description	Cotton	Corn	Soybeans
Excess Moisture	Difference between precipitation and the average precipitation plus the standard variation	0.0000610*** (0.0000161)	0.0000271*** (0.00000624)	0.0000378*** (0.00000687)
Year		-9.854*** (2.720)	-4.253*** (0.460)	-2.385*** (0.573)
Year Squared		0.00245*** (0.000675)	0.00106*** (0.000114)	0.000593*** (0.000142)
Constant		9927.9*** (2740.9)	4283.7*** (463.6)	2398.2*** (577.7)
Observations		2787	3045	11936
No. of counties		300	331	1199
R-squared (overall)		0.0613	0.0711	0.0570
Adj. R-squared		.102044	.090550	.0844809
F-Statistics		11.02	66.67	60.44
Prob > F		0.0000	0.0000	0.0000

Notes: Numbers in parenthesis are the standard errors; significance levels are 1% (***), 5% (**), 10% (*). Proportion of prevent plant acres is used as the dependent variable.

The new added variable “Lower Price Indicator” is positive and statistically significant for both cotton and soybeans. Nevertheless, corn becomes statistically insignificant with respect to the first fixed effect model. It is worth noting that the signs got switched from negative when using “High Price”, to positive using “Lower Price Indicator” as a lower bound for cotton.

The result show that in the case of cotton, each 1% increase in the adjusted expected harvest price below the equilibrium price, would increase the proportion of prevent planting acres by 0.0228 acres. In other words, the increase in “Lower Price” is to the downside, or basically a decrease in the adjusted expected harvest price, which increase the number of PP claims. Likewise, for soybeans this would mean that each 1% increase in the adjusted expected harvest price below the equilibrium price, would increase the proportion of prevent planting acres by 0.00875 acres.

In contrast, with the previous model, the second variable “Projected Price Ratio” becomes statistically insignificant for cotton, becomes insignificant for corn, cotton and reduces the significance for soybeans. Furthermore, in the case of soybeans the results show that each 1% increase in the projected price ratio, would increase the proportion of prevent planting acres by 0.0245 acres.

The third variable “Cost Index”, remains insignificant for cotton and corn, but becomes more significant for soybeans from 5% level to a 1% level. The results show that in the case of soybeans, the increase of $1/acre of input cost, would increase the proportion of prevent planting acres by 0.000974 acres.

The fourth variable “Days Suitable for Farming Operations” remains negative and statistically significant for all of the three crops. In the case of cotton the results show, the increase of 1 day suitable for planting, would reduce the proportion of prevent planting acres by 0.000563 acres. Alternatively, in the case of corn, the increase of 1 day suitable for planting, would reduce the proportion of prevent planting acres by 0.00147 acres. Similarly, in the case of soybean, the increase of 1 day suitable for planting, would reduce the proportion of prevent planting acres by 0.00121 acres.

The fifth variable “Pre-season Precipitation”, remains with the same coefficient signs, improving the statistical significance for corn, from 10% to 5% level. In the case of cotton, this would mean that the increase of 1 millimeter of rain, would increase the proportion of prevent planting acres by 0.0000517 acres, which is more than before. Likewise, in the case of corn, this would mean that the increase of 1 millimeter of rain, would increase the proportion of prevent planting acres by 0.0000634 acres, which is a bit more than before. Similarly, for soybean, this would mean that the increase of 1 millimeter of rain, would increase the proportion of prevent planting acres by 0.0000522 acres, which is more than before.

Furthermore, the sixth variable “Excess Moisture”, remains with the same positive coefficient signs and significance level. In the case of cotton, the results show that the increase of 1 millimeter of rain above the monthly average, would increase the proportion of prevent planting acres by 0.0000610 acres. Likewise, in the case of corn, this would mean that the increase of 1 millimeter of rain above the monthly average, would increase the proportion of prevent planting acres by 0.0000271 acres. Similarly, in the case of soybean, this would mean that the increase of 1 millimeter of rain above the monthly average, would increase the proportion of prevent planting acres by 0.0000378 acres.

Furthermore, the seventh variable “Year” and the eight variable “Year Squared” maintain their coefficient signs and significance level as for cotton and corn, but they also become significant for soybean. Consequently, the results show that in the case of cotton, with every 1 year that passes, the proportion of prevent planting acres decreases by 9.854 acres relative to the previous year. In contrast, every 1 year that passes, also increase the total proportion of prevent planting acres by 0.00245 acres.

Likewise, in the case of corn the results show that with every 1 year that passes, the proportion of prevent planting acres decreases by 4.253 acres relative to the previous year. In contrast, every 1 year that passes, also increase the total proportion of prevent planting acres by 0.00106 acres. Similarly, in the case of soybeans the results show that with every 1 year that passes, the proportion of prevent planting acres decreases by 2.385 acres relative to the previous year. In contrast, every 1 year that passes, also increase the total proportion of prevent planting acres by 0.000593 acres.

It is proven that overall, the addition of the dummy variable delta defined as "Lower Price" helps with the accuracy of the model.

3.5. Fixed effects with continuous variable

Table 8 is calculated with the new continuous variable defined as "Continuous Lower Price" and the variable "High Price" is again introduced into the model. Therefore, Table 8 displays the results for the third model, with fixed effects and robust standard errors. Like before the proportion of prevent plant acres $PrpPP$ is the dependent variable against which all independent variables are regressed.

Table 8. Fixed effects with continuous variable results

Variable	**Description**	**Cotton**	**Corn**	**Soybeans**
High Price	$Log\ P_a$ Adjusted expected harvest price	-0.136*** (0.0450)	0.0788*** (0.0135)	0.0742*** (0.0181)
Continuous Low Price	$\delta * Log\ P_a$ Delta* Log Adjusted expected harvest price	-0.0179 (0.0200)	0.00618*** (0.00236)	0.0102*** (0.00196)
Projected Price Ratio	$Log\ P_{ratio}$ Adj. expected harvest price/ lagged expected harvest price	0.0658*** (0.0207)	0.00662 (0.00630)	-0.00544 (0.0198)
Cost Index	Input costs	0.000964 (0.000637)	-0.000259 (0.000174)	0.000578** (0.000267)
Days suitable for farming operations	Number of days optimal for working	-0.000434*** (0.0000924)	-0.00150*** (0.000119)	-0.00121*** (0.000120)

Notes: Numbers in parenthesis are the standard errors; significance levels are 1% (***), 5% (**), 10% (*). Proportion of prevent plant acres is used as the dependent variable.
(table cont'd.)

Variable	Description	Cotton	Corn	Soybeans
Preseason Precipitation	Cumulative precipitation from January to May	0.0000435* (0.0000228)	0.0000582*** (0.0000115)	0.0000436*** (0.0000103)
Excess Moisture	Difference of precipitation and the average precipitation plus the standard variation	0.0000682*** (0.0000163)	0.0000229*** (0.00000638)	0.0000392*** (0.00000696)
Year		-14.70*** (4.133)	-2.499*** (0.628)	-1.443** (0.563)
Year Squared		0.00365*** (0.00103)	0.000621*** (0.000156)	0.000359** (0.000140)
Constant		14807.2*** (4163.6)	2516.1*** (632.8)	1450.1** (567.2)
Observations		2787	3045	14785
No. of counties		300	1400	1199
R-squared (overall)		0.0793	0.0611	0.0570
Adj. R-squared		0.09743	0.09184	0.0837
F-Statistics		10.02	59.93	58.90
Prob > F		0.0000	0.0000	0.0000

Notes: Numbers in parenthesis are the standard errors; significance levels are 1% (***), 5% (**), 10% (*). Proportion of prevent plant acres is used as the dependent variable.

The first variable “High price” is significant for all three crops, with a negative coefficient for cotton and a positive coefficient for corn and soybeans. Therefore, the results show that in the case of cotton, each 1% increase in the adjusted expected harvest price, would reduce the proportion of prevent planting acres by 0.136 acres.

The second modified variable “Continuous Low Price” maintains the same positive coefficient signs for corn and soybeans, becoming insignificant for cotton. Furthermore, the results show that in the case of corn, each 1% increase in the adjusted expected harvest price below the equilibrium price, would increase the proportion of prevent planting acres by 0.00618 acres. Similarly, for soybeans the results show that each 1% increase in the adjusted expected harvest price below the equilibrium price, would increase the proportion of prevent planting acres by 0.00102 acres.

The third variable “Projected Price Ratio” becomes only significant for cotton. In the case of cotton, the results show that each 1% increase in the projected price ratio, would increase the proportion of prevent planting acres by 0.0658 acres.

The fourth variable “Cost Index”, remains to be only significant for soybeans. The results show that in the case of soybeans, the increase of $1/acre of input cost, would increase the proportion of prevent planting acres by 0.000578 acres.

Likewise, the fifth variable “Days Suitable for Farming Operations” remains with the same negative coefficient signs and significance, for all three crops. The results show that in the case of cotton, the increase of 1 day suitable for planting, would reduce the proportion of prevent planting acres by 0.000434 acres. Likewise, in the case of corn, the increase of 1 day suitable for planting, would reduce the proportion of prevent planting acres by 0.00150 acres. Similarly, in the case of soybean, the increase of 1 day suitable for planting, would reduce the proportion of prevent planting acres by 0.00121 acres.

The sixth variable “Pre-season Precipitation” also maintains the same layout as the second fixed effect model. Meaning the three coefficients are positive and significant. The results show that in the case of cotton, the increase of 1 millimeter of rain, would increase the proportion of prevent planting acres by 0.0000435 acres, which is more than before. Similarly, in the case of corn, the increase of 1 millimeter of rain, would increase the proportion of prevent planting acres by 0.0000582 acres, which is more than before. Likewise, in the case of soybeans, the increase of 1 millimeter of rain, would increase the proportion of prevent planting acres by 0.0000436 acres, which is more than before.

The seventh variable “Excess Moisture” maintains the same layout as the second fixed effect model, where all three crops are significant with positive coefficients. The results in the case of corn show that the increase of 1 millimeter of rain above the monthly average, would increase the proportion of prevent planting acres by 0.0000682 acres. Similarly, in the case of corn, the results show that the increase of 1 millimeter of rain above the monthly average, would increase the proportion of prevent planting acres by 0.0000229 acres. Likewise, in the case of soybean, the results show that the increase of 1 millimeter of rain above the monthly average, would increase the proportion of prevent planting acres by 0.0000392 acres.

Furthermore, the eight variable “Year”, the ninth variable “Year Squared” and the tenth variable “Constant” are significant for all three crops with the same coefficient signs as before. Consequently, the results show that in the case of cotton, with every 1 year that passes, the proportion of prevent planting acres decreases by 14.70 acres relative to the previous year. In contrast, every 1 year that passes, also increase the total proportion of prevent planting acres by 0.00365 acres. Similarly, the results show that in the case of soybeans, with every 1 year that passes, the proportion of prevent planting acres decreases by 2.499 acres relative to the previous year. In contrast, every 1 year that passes, also increase the total proportion of prevent planting acres by 0.000621 acres. Likewise, the results show that in the case of soybeans, with every 1 year that passes, the proportion of prevent planting acres decreases by 1.443 acres relative to the previous year. In contrast, every 1 year that passes, also increase the total proportion of prevent planting acres by 0.000359 acres.

3.6. Logit fixed effects model

Table 9 displays the results for the model using the logit transformation, with fixed effects, and robust standard errors. The change in log of odds $PrpPP$ is the dependent variable against which all independent variables are regressed. Furthermore, in their majority the results follow the expected coefficient signs for the statistically significant variables. Note that robust standard errors are used to correct for heteroscedasticity. Because robust standard errors can provide a more accurate measure for the true standard error of a regression coefficient.

Table 9. Fixed effect vs Logit Fixed effects

Variable	**Cotton**		**Corn**		**Soybeans**	
	Fixed	**Logit**	**Fixed**	**Logit**	**Fixed**	**Logit**
High Price	-0.136***	-7.330***	0.0788***	2.617***	0.0742***	1.454**
	(0.0450)	(1.396)	(0.0135)	(0.538)	(0.0181)	(0.566)
Continuous Low Price	-0.0179	-0.00967	0.00618***	0.105	0.0102***	0.402***
	(0.0200)	(1.087)	(0.00236)	(0.0919)	(0.00196)	(0.0951)
Projected Price Ratio	0.0658***	4.100***	0.00662	0.155	-0.00544	-0.182
	(0.0207)	(0.960)	(0.00630)	(0.266)	(0.0198)	(0.691)
Cost Index	0.000964	0.0452*	-0.000259	-0.0217***	0.000578**	0.0464***
	(0.000637)	(0.0232)	(0.000174)	(0.00814)	(0.000267)	(0.0103)
Days suitable for farming operations	-0.000434***	-0.00531	-0.00150***	-0.0856***	-0.00121***	-0.0728***
	(0.0000924)	(0.00614)	(0.000119)	(0.00409)	(0.000120)	(0.00532)
Preseason Precipitation	0.0000435*	0.00313***	0.0000582***	0.00435***	0.0000436***	0.00282***
	(0.0000228)	(0.00101)	(0.0000115)	(0.000527)	(0.0000103)	(0.000500)
Excess Moisture	0.0000682***	0.000480	0.0000229***	-0.0000276	0.0000392***	0.000454**
	(0.0000163)	(0.000466)	(0.00000638)	(0.000189)	(0.00000696)	(0.000187)
Year	-14.70***	-420.5***	-2.499***	-42.23	-1.443**	-177.9***
	(4.133)	(65.65)	(0.628)	(25.84)	(0.563)	(36.77)
Year Squared	0.00365***	0.104***	0.000621***	0.0105	0.000359**	0.0442***
	(0.00103)	(0.0163)	(0.000156)	(0.00641)	(0.000140)	(0.00912)
Constant	14807.2***	423556.2***	2516.1***	42461.7	1450.1**	178987.7***
	(4163.6)	(66110.2)	(632.8)	(26024.2)	(567.2)	(37055.0)
Observations	2787	713	3045	5388	14785	5177
No. of counties	300	232	1400	1118	1199	1076
R-squared (overall)	0.0793	0.1332	0.0611	0.0759	0.0570	0.0534
Adj. R-squared	0.11507	0.24357	0.0928616	0.3528020	0.085408	0.2836600
F-Statistics	10.02	16.12	59.93	171.82	58.90	125.26
Prob > F	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: Numbers in parenthesis are the standard errors; significance levels are 1% (***), 5% (**), 10% (*). The table displays the comparison between the third fixed effect model and the fourth model with the logit transformation.

The first variable “High price” maintains the same coefficient signs and significance, as in the third fixed effect model without the logit transformation. Therefore, the results show that in the case of cotton, each 1% increase in the adjusted expected harvest price, would reduce the odds of prevent planting acres by 7.3%. However, according to the model, in the case of corn and soybeans, each 1% increase in the adjusted expected harvest price, would increase the odds of prevent planting acres by 2.6% and 1.4%, respectively.

The second modified variable “Continuous Low Price” remains statistically insignificant for cotton, becomes statistically insignificant for corn and remains significant for soybean. Also, all crops maintain the same coefficient signs. Furthermore, the results show that in the case of soybeans each 1% increase in the adjusted expected harvest price below the equilibrium price, would increase the odds of prevent planting by 0.4%.

The third variable “Projected Price Ratio” maintains the same layout as before in the third fixed effect model, where the projected price for cotton is positive and the only significant variable. In the case of cotton, the results show that each 1% increase in the projected price ratio, would increase the odds of prevent planting by 4.1%.

The fourth variable “Cost Index”, becomes statistically significant for cotton and corn at the 10% and 1% level of significance. Additionally, the coefficient for soybeans improves its significance from 5% level to 1%. All three crops maintain the same coefficient sign, which is positive for cotton and soybeans, and negative for corn.

The results show that in the case of cotton, the increase of $1/acre of input cost, would increase the odds of prevent planting by 0.04%. Similarity, in the case of soybean, the increase of $1/acre of input cost, would increase the odds of prevent planting by 0.04%. Conversely, in the case of corn, the increase of $1/acre of input cost, would reduce the odds of prevent planting by

0.02%.

Likewise, the fifth variable “Days Suitable for Farming Operations” keeps the same negative coefficient signs and significance, for corn and soybeans. However, cotton becomes statistically insignificant. The results show that in the case of corn, the increase of 1 day suitable for farming operations, would reduce the odds of prevent planting by 0.0856% acres. Alternatively, in the case of soybean, the increase of 1 day suitable for farming operations, would reduce the odds of prevent planting by 0.07%.

The sixth variable “Pre-season Precipitation” also maintains the same layout as the third fixed effect model. Meaning the three coefficients are positive and significant. The results show that in the case of cotton, the increase of 1 millimeter of rain, would increase the odds of prevent planting by 0.003 %. Similarly, in the case of corn, the increase of 1 millimeter of rain, would increase the odds of prevent planting by 0.004%. Likewise, in the case of soybeans, the increase of 1 millimeter of rain, would increase the odds of prevent planting by 0.002%.

The seventh variable “Excess Moisture” becomes insignificant for cotton and corn. Additionally, the level of significance for soybeans get reduced from 1% to 5% level. The results in the case of soybeans show that the increase of 1 millimeter of rain above the monthly average, would increase the odds of prevent planting by 0.000454.

Furthermore, the eight variable “Year”, the ninth variable “Year Squared” and the tenth variable “Constant” remains the same for cotton. On the other hand, corn losses all the statistical significance and soybeans improves its statistical significance from a 5% to 10%.

For the data used in this study the logit fixed effect model performs better, given that the dependent variable is a proportion. Further research may investigate the goodness of fit of the logit fixed effects model in this type of data.

Chapter 4. Summary and Conclusions

This research examines the presence of ex-post moral hazard in the prevent planting provision from the crop insurance program in cotton, corn and soybeans for the Plains and Southeast Regions of the U.S. Furthermore, three fixed effect and one logit fixed effect model, were developed. The first model was based on previous research from Wu, Goodwin, and Coble (2019), and Kim and Kim (2018). Moreover, the second and third model integrates the break-even point variable, that helps to highlight the change in behavior under or above that line. Finally, the fourth model introduces the logit transformation, in order to correct for irrational predictions as specified in the Stata Journal (Baum, 2008). From the start of the research, it was always expected that weather variables would have a strong effect in the amount of PP claims or in this case the proportion of prevent planting acres, which was the dependent variable used for the first 3 models. Since the PP provision is defined as "failure to plant an insured crop by the final planting date, or within any applicable late planting (LP) period," because of severe weather events, like drought or excess moisture (2013 Crop insurance handbook, USDA-RMA, 2013). It is expected that if there is no presence of moral hazard, most if not all of the explanatory power from the model would fall upon weather variables, however, this was not the case. After analyzing the results, it was found that other non-weather-related variables have a great effect in the proportion of prevent planting, as well as the odds of prevent plant for two out of the three crops used in the analysis.

In fact, it was found that the proportion of prevent planting acres and the odds of prevent plant, were endogenous to changes in the input price, expected harvest price and break-even point, in the case of cotton and soybeans. Therefore, confirming the presence of ex-post moral hazard in these two crops in the Plains and Southeast Regions. Other studies like Wu, Goodwin, and Coble (2019), have found similar results with strong evidence suggesting that cotton is indeed affected by moral hazard.

In contrast, this was not the case for corn which was mostly affected by the weather variables and which results were inconclusive with the expected theory. Therefore, there is no conclusive evidence that suggest corn is being affected by moral hazard in the Plains and Southeast region of the U.S. On the other hand, our results seem to contradict or may not be consistent with the ones from Wu, Goodwin, and Coble (2019) which found moral hazard for corn and soybeans in the Prairie Pothole Region.

Furthermore, this could actually be a good indicator that the proper corrections to the program are being made in the case of corn. Since the main objective of the insurance program is to help farmers without discouraging them to abandon production.

4.1. Recommendations

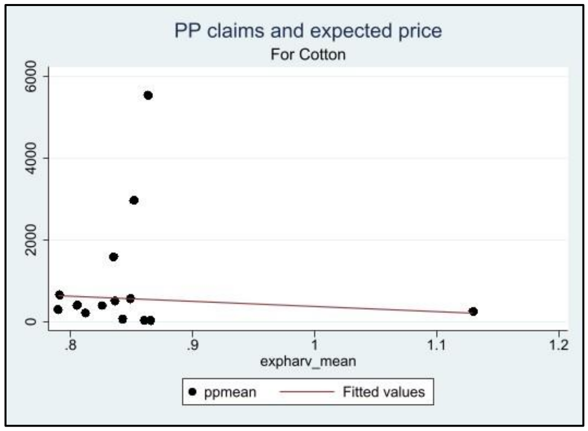
Based on the results, it is recommended for further research to analyze the quantity of acres of corn has shifted to cotton or soybean production. One of the theories that could explain the inconsistency with the results for corn, is that when input cost are higher farmers might change their production toward other crops. In effect, transferring the moral hazard effect from this crop to another.

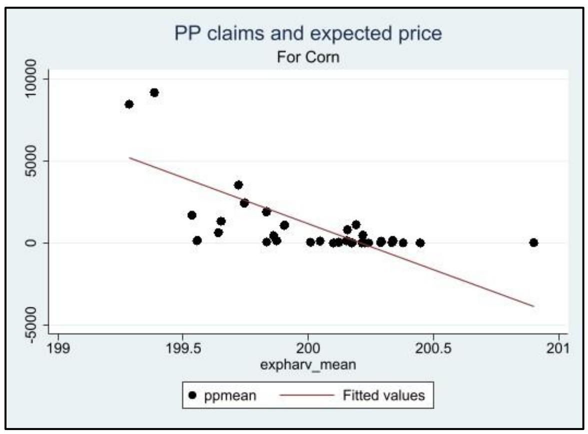
Additionally, it is necessary to clarify, that even though natural causes could be involved in the increase in PP claims, weather changes should be assess further, to adjust the PP provisions to account for those changes.

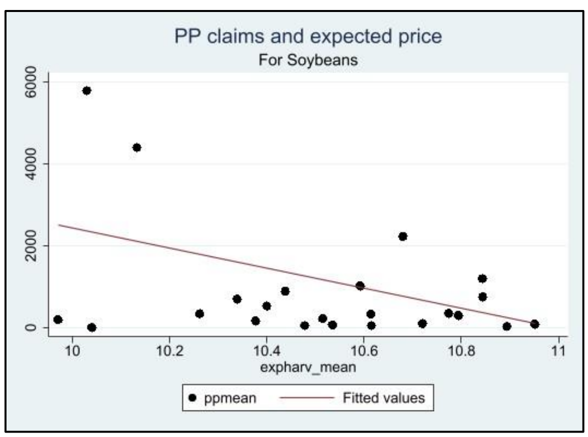
In addition, the logit fixed effects model seems to perform better, given the dependent variable is a proportion. However, further research recommended in order to identify the best model to approach this type of study and data.

It is beyond the scope of the study to propose a policy change to reduce ex-post moral hazard. However, it is recommended more research regarding the incentive's farmer could receive if they do not go through with PP. According to the Office of the Inspector General (OIG) report in 2013 the RMA needs to be more cost effective, encouraging farmers to plant a second crop when is possible by making the eligibility criteria clearer. Perhaps, one way to do so, could be by adapting the indemnity payments, increasing the benefits for the late planting (LP) and review each claim more carefully.

Appendix. Correlation between PP claims and expected price







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Vita

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