Analyzing the Effects of Weather and Biotechnology Adoption on Corn Yields and Crop Insurance Performance in the U.S. Corn Belt

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Abstract

Favorable weather and the adoption of Genetically Modified (GM) corn hybrids are often argued to be factors that explain recent corn yield increases and risk reduction in the U.S. Corn Belt. The focus of this analysis is to determine whether favorable weather is the main factor explaining increased and more stable yields or if biotechnology adoption is the more relevant driving force. The hypothesis that recent biotechnology advances have increased yields and reduced risks by making corn more resistant to pests, pesticides, and/or drought is tested. Fixed effects models of yields and crop insurance losses as functions of weather variables and genetically modified corn adoption rates are estimated taking into account the non-linear agronomic response of crop yields to weather. Preliminary results show that genetically modified corn adoption rates, especially insect-resistant corn adoption, have had a significant and positive effect on average corn yields in the U.S. Corn Belt over the last years. Furthermore, genetically modified corn adoption has not only increased corn's tolerance to extreme heat but has also improved corn's tolerance to excessive and insufficient rainfall.

1 Introduction

The U.S. Corn Belt has experienced good crop insurance results over the past twelve years, presenting low loss cost ratios and annual loss ratios less than one since 1995. Loss cost ratios, given by the ratio of actual indemnities to liabilities, are usually referred to as empirical premium rates. They are a measure of risks or the actual loss over a specific liability amount. Lower and less variable loss cost ratios reflect lower levels of yield or price risk, according to the insurance plan[1]. This relatively good crop insurance experience has caused several points of controversy in the agricultural sector. Some policy analysts argue that due to their relatively good experience, farmers in the region are subsidizing insurance in other regions experiencing higher loss ratios, and that Corn Belt farmers are paying more than they should for insurance (Babcock 2008). On the other hand, policy makers have considered budgetary cuts to the federal crop insurance program fund due to high levels of returns experienced by the industry in recent years. In response to this, the crop insurance industry argues that profitability is necessary to maintain high level services to farmers and build reserves for possible future widespread losses (Vergara, Zuba, Doggett, and Seaquist 2008). Regardless of these encountered views, the relatively good crop insurance experience in the Corn Belt is beneficial for most players, and the factors that drive it should be identified if benefits are to be expanded to other areas of the country. Favorable weather conditions for corn production and biotechnology-driven improvements in seed genetics have been argued to be the major factors explaining recent good crop

[1]Loss ratios, measured as the ratio of actual indemnities to premiums, are not only a measure of risk, but also reflect the accuracy with which crop insurance premiums are estimated.

insurance results.

Corn yields in the U.S. Corn Belt have increased by 40% over the last 30 years, rising from an average yield of 119 bu/acre in 1981 to 167 bu/acre in 2008 (See Figure 1). Tannura, Irwin, and Good (2008) argue that relatively benign weather for corn development since the mid-1990s, should not be discounted as the explanation for relatively high corn yields in the region (Tannura, Irwin, and Good 2008). Furthermore, Babcock (2008) and Yu and Babcock (2009) add that, besides the favorable weather conditions, characterized by above average rainfall and below average temperature during July and August, rapid advances in technology have reduced production risks, increased yields and contributed to the relatively good crop insurance experience in the area. Loss cost ratios and loss ratios for the U.S. Corn Belt in the 1981-2008 period are depicted in Figure 1. Between 1981 and 1994, loss cost ratios show great volatility, varying from 2% to 20%. Relatively bad loss experience due to adverse weather events is reflected in the graph, especially in 1988 due to summer-long drought in the Midwest, and in 1993 due to floods in the Corn Belt States. Loss cost ratios and their volatility consistently decreased over the 1995-2008 period, fluctuating in the 1%-8% range.

The time pattern of loss ratios (indemnities/premiums) is similar to that of loss cost ratios. Loss ratios oscillated between 0 and 5 from 1981 to 1994, but they substantially decreased to the 0-1 range after 1995. Analysts argue that the improvement of crop insurance loss results have been due to favorable weather conditions in the Corn Belt, and the fact that no catastrophic events, like droughts or floods have affected the area since 1993. However, besides good weather, reduced yield risk and improved loss history after 1995 coincides with the introduction of Genetically Modified (GM) corn seeds in the Corn Belt.

Genetically modified (GM) corn seeds with herbicide-tolerant and/or insect-resistant traits have been adopted by American producers since 1996. Adoption rates of GM corn seeds increased from 8% in 1997 to 85% in 2008 in the Corn Belt region at the expense of conventional corn seeds, whose share decreased from 92% to 15% over the same period. Genetically modified corn adoption rates follow the typical logistic s-shaped pattern laid out by Griliches (1957), where the percentage rate of new adoption decreases with time (See last plot in Figure 2). Taking into account EPA's mandated refuge of around 20%, the U.S. Corn Belt GM corn adoption rate approached its ceiling of approximately 80% in 2008. Five trait types of genetically modified corn are currently available in the market: herbicide-tolerant, European Corn Borer resistant (Cb), rootworm resistant (Rw), double insect resistant (to Cb and Rw), and triple stacks, which are tolerant to herbicide, corn borer and rootworm. The effects of GM corn adoption rates on corn yields and yield risk measures have not been analyzed. These effects are especially important in the current, highly dynamic genetically engineered seed market. While triple stack corn was the most innovative biotechnology product available in the market in 2008 (with a Corn Belt adoption rate of 50% in 2008), a new biotech corn seed product, $Genuity^{TM} SmartStax^{TM}$ (hereinafter SmartStax), was launched in the market in 2010. This product features eight genetic traits stacked to provide higher yields, better insect protection, better grain quality, and broader herbicide tolerance than competitive products (Mittendorf, Caron, Paul, Sullivan, Turner, and Zhao 2009). Importantly, EPA regulations allowed the reduction of the typical structured farm refuge from 20% to 5% for SmartStax in the Corn

Belt region, which means that these GM hybrids will have the potential to reach a 95% adoption rate in the region. SmartStax launch is considered to represent the largest introduction of a corn biotech seed product in the history of agriculture (Dow-Chemical 2009).

Despite the rapid adoption rate of GM corn seeds in the Corn Belt and the rapid progress of GM technology advancement, opposing positions on the effects of GM adoption on corn yields are still encountered. On one hand, GM advocates and policy makers argue that average corn yields have increased and stabilized due to the adoption of improved genetics and biotechnology traits (Babcock 2008, Mittendorf, Caron, Paul, Sullivan, Turner, and Zhao 2009). On the other hand, environmental groups, such as the Union of Concerned Scientists, have argued that GM corn seeds have done little to increase overall crop yields (Gurian-Sherman 2009). They argue that corn yields have only increased marginally as a result of GM adoption, and that other non-genetic engineering approaches such as improved conventional plant breeding techniques have contributed the most to corn yield increases.

The Biotech Endorsement (BE) pilot program provides discounted crop insurance premiums to farmers planting certain GM corn seeds in the Corn Belt. An average of 13% premium discount for the pilot program's book of business is estimated by RMA on the grounds that these GM hybrids have lower yield risks. However, empirical effects of the adoption of genetically modified hybrids on crop insurance loss performance has not been analyzed within an econometric framework. Given the presumption that biotechnology traits mitigate crop production risks not only from insect infestation, but also from extreme weather, this paper studies the relative effects of weather and biotechnology adoption on crop yields and crop insurance results.

The objective of this paper is to analyze the effects of weather and GM adoption on corn yields and crop insurance program performance in the U.S. Corn Belt. The pertinent question for this paper is whether biotechnology adoption rates have contributed to the recent good crop insurance experience in the Corn Belt. The study focuses on finding out whether favorable weather is the main factor for increased yields or if biotechnology adoption is the driving force, by making crops more resistant to pests, pesticides and/or drought, increasing yields and reducing risks. The hypothesis that the adoption of genetically modified corn has changed corn's response to weather factors, such as high extreme temperatures; insufficient or excessive rainfall is analyzed. The analysis uses newly available data on disaggregated GM corn adoption rates and weather variables to answer these questions.

Agronomists postulate that yield growth is linear in temperature within a certain range, between specific lower and upper temperature thresholds and that there is a plateau at the upper threshold beyond which higher temperatures become harmful in another negative linear fashion (Ritchie and Smith 1991). The concepts of Growing Degree Days (GDD) and Harmful Degree Days (HDD) capture this non-linear response of crop yields to temperature. GDD is the cumulative sum of degree days or heat units that are beneficial for crop yields, which for corn ranges between a lower threshold of $8°C$ and an upper threshold of $29°C$ Ritchie and Smith 1991,Schlenker and Roberts 2009). HDD is the cumulative sum of degree days or heat units that are harmful for crop growth, higher than

$30°C$ for corn. Fixed effects models of corn yields and corn crop insurance loss measures are estimated as a function of GDD, HDD, precipitation, and genetically modified corn adoption rates. GDD, HDD and precipitation are the weather variables used (as opposed to monthly weather or weather indices used in previous literature) because they are the weather variables producing the best out-of-sample yield predictions (Schlenker and Roberts 2009). Results show that genetically modified corn adoption rates, especially insect-resistant corn adoption, have had a significant and positive effect on the percentage change in corn yields in the U.S. Corn Belt over the last 13 years. Interaction effects between temperature measures and biotechnology in both yields and insurance loss models support a decrease in yield losses triggered by high extreme temperatures as a result of the adoption of insect-resistant corn.

2 Literature Review

2.1 Yield Models

The issue of how weather and technology affects crop yields has been widely studied. A recent article by Tannura, Irwin, and Good (2008) finds strong evidence that weather variables and a linear time trend to represent technology explained all but a small portion of the variation in corn and soybean yields in the U.S. Corn Belt. Tannura, Irwin, and Good (2008) estimated a modified Thomson model, which included monthly precipitation and temperature variables from May through August (entered with both linear and quadratic terms) a pre-season precipitation variable, and a time trend. High R^2 and F tests led them to conclude that the regression models jointly explained a significant proportion of the variation in yields. Tannura, Irwin, and Good (2008) also analyzes the technology acceleration hypothesis that improved technology has caused corn yields to increase at an increasing rate in recent years. They fail to identify a significant break in corn yields in the mid-1990s in the Corn Belt region. The authors state that relatively benign weather for the development of corn since the mid 1990s should not be disregarded as the driving factor for seemingly high yields in the region.

Despite the fact that a time term in the production function has been extensively used to represent technological change, its validity to account for all non-weather factors affecting yields has been widely criticized. It is argued that the development and application of technology does not necessarily occur in a smooth and continuously increasing pattern over time. Shaw and Durost (1965) hypothesize that the pattern of yield increases is one of plateaus, with technological improvements making the movement from one plateau to another. More recently, Zilberman (2009) argues that technology changes are discrete breakthroughs followed by adjustment. Hallauer (2004) illustrates that discrete technology changes have caused jumps in corn yields trends in several periods of time. Double cross hybrid caused the first corn yield jump in the 1930's, followed by single cross hybrids in the 1960's, and genetically modified seeds in the mid-1990's (Hallauer 2004). Shaw and Durost (1965) estimate corn yields in the Corn Belt for the 1929-1962 period. Their yield equation includes a weather index, the adoption rate of hybrid seed used to represent technology, the percentage of fertilizer used on corn, and plant density. They find that technological improvement, represented by hybrid seeds adoption rates, was the major factor contributing to the increase in corn yields during the period. Weather variation also had a significant effect on yields.

The non-linear effect of weather variables on crop yields, especially of temperature has also been widely documented. For instance, Schlenker and Roberts (2006) analyze the relationship between weather and yields taking into account the agronomic evidence that describes plant growth as a highly non-linear function of heat. They use the time distributions of temperatures over a given county, precipitation, a time trend to account for technological change and county fixed effects. They find a significant non-linear relationship between temperature and corn yields, which indicates that yields are increasing in temperature for moderate temperatures, but become quickly harmful once temperatures exceed $86°F$ $(30°C)$. They also find support for the inverted u-shaped relationship between precipitation and corn yields.

Recent studies have analyzed the effects of climate change on agriculture. Many of these papers use measures of GDD and HDD to estimate the non-linear relationship between heat and plant growth postulated in agronomic literature. For instance, Schlenker and Roberts (2009) link farmland values to climatic, soil and socioeconomic variables for non-irrigated U.S. counties using a hedonic model. Their climatic variables are derived from the Parameter-Elevation Regressions on Independent Slopes (PRISM) climate grid, which provides estimates of monthly precipitation and temperature on a 2.5 by 2.5 miles scale for the entire U.S. The authors use Growing Degree Days (GDD) and Harmful Degree Days (HDD) in their equations, which they derive from monthly temperature averages, using the Thoms (1996) formula, which assumes daily temperatures are normally distributed. Deschenes and Greenstone (2007) measures the economic impact of climate change on U.S. agricultural land by estimating the effect of random year-to-year variation in temperature and precipitation on agricultural yields and profits. They model county level agricultural profits per acre of farmland and crop yields as a function of soil characteristics, weather and socioeconomic variables. They use daily level weather station temperature data collected from National Climatic Data Center (NCDC) to calculate growing season degree days. This paper follows the Deschenes and Greenstone (2007) approach to compute GDD and HDD measures.

Gurian-Sherman (2009) examine findings of multiple studies which evaluate the yield effect of genetically engineered seeds in the U.S. They find that herbicide-tolerant crops have not increased operational yields compared to other methods relying on other herbicides. Bt corn was found to provide a 7%-12% range of advantage in corn yield when compared to other conventional practices, including insecticide use, when pest infestations are high. However, Bt corn was found to provide little or no yield advantage when pest infestations are moderate to lower, even when compared with conventional corn not treated with pesticides. Their overall result is that genetically modified crops have done little to affect overall corn yields. They argue that the recent increase in corn yields is attributable to non-genetic engineering approaches, such as improved conventional breeding methods, more extensive crop rotations, and improvements in irrigation, fertilization and fertilizer use.

Yu and Babcock (2009) analyze whether corn and soybean yields have become more drought tolerant in the Corn Belt. They build a drought index to test this hypothesis and find that drought triggered corn yield losses have decreased in absolute and percentage terms since 1980 in the Corn Belt. The authors argue that these gains in drought tolerance are presumably due to genetic improvements in corn. Schlenker and Roberts (2010) examine the evolution of weather effects on corn yields in Indiana, paying particular attention to how these effects have changed over time with the adoption of new crop varieties and farming techniques from 1900 to 2005. The authors estimate time varying cubic spline functions of the natural log of corn yields as a function of GDD, HDD, precipitation, time and interaction effects between time and weather variables. It is important to note that while Yu and Babcock (2009) use a composite drought index of hot weather and insufficient rainfall to test changes in drought tolerance, Schlenker and Roberts (2010) point out that corn yields' responses to precipitation and high extreme temperatures have changed differently over time as a result of technology adoption. While detrimental effects of not only too little, but of too much rainfall seem to have consistently diminished over time, the evolution of corn yields' heat-tolerance has been highly non-linear, growing with the adoption of single-cross hybrids in the 1940's, peaking in 1960 and then declining sharply as single-cross hybrids were adopted. Furthermore, Schlenker and Roberts (2010) argue that while single-cross corn hybrids increased average corn yields, these corn hybrids showed reduced heat tolerance. While these last two papers have tested how the response of corn yields has changed over time, none of them has taken explicit measures of genetically modified corn seeds adoption into account. Whether genetically modified crops have improved agricultural productivity is a question of increased interest and controversy. An important question remains whether genetically modified corn adoption has not only increased average corn yields, but also changed its response to precipitation and heat.

2.2 Crop Insurance Policy

In 2008, the Corn Belt states of Iowa, Indiana, Illinois, Missouri and Ohio accounted for 50% of the total corn (for grain) produced in the U.S. Of the 37 million acres planted to corn in the Corn Belt, about 30 million (80%) were enrolled in the federal crop insurance program in 2008. This translated into a total liability of around $US 19 billion or 21% of total liabilities covered by the program for all states and crops in 2008. Any econometric study analyzing the federal crop insurance program should take into account important policy changes that have affected and shaped the program over time. Smith and Goodwin (2009) point out that most policy changes made to the federal crop insurance program were implemented from 1980 to 2008. The scope of the federal crop insurance program has been expanded in three different ways: subsidized coverage has been expanded to a wider range of crops and livestock; new insurance products have been developed; and premium subsidies have steadily risen (Smith and Goodwin 2009).

The most important policy changes impacting U.S. crop insurance programs have been implemented through the 1980 Federal Crop Insurance Act (FCIA), the 1994 Crop Insurance Reform Act (CIRA), the 2000 Agricultural Risk Protection Act (ARPA) and the farm bills. For instance, the 1980 FCIA introduced premium subsidies of 30%; expanded the number of crops covered by subsidized insurance;

and expanded the scope of the program to a national level. In addition, the 1980 FCIA allowed the introduction of the Group Risk Plan (GRP) in 1993. The 1994 CIRA introduced catastrophic insurance coverage, mandated the development of revenue insurance products and the expansion of the program to cover even more crops. As a result, Revenue Assurance (RA) and Crop Revenue Coverage (CRC) were made available to farmers between 1995 and 1998. The acreage and liability share of revenue insurance products (RI) increased from 0% in 1996 to 82% and 87% in 2008, respectively in the Corn Belt region. On the other hand, GRP's acreage and liability share increased from 0% in 1994 to 4% and 5% in 2008 respectively. This reflects that farmers have preferred revenue insurance over both APH and GRP insurance over time. The 1994 Act also tightened indemnity procedures, so the ratio of indemnity to premiums declined.

The 2000 ARPA further expanded premium subsidies to 60% of the actuarially fair premium rate and mandated the development of whole farm revenue insurance. As a result of numerous policy changes, participation rates (the percentage of insured acreage of total planted acreage) increased from 12.4% in 1980 to 30% in 1990. Participation rates further increased to 60% in 2000 as a result of the introduction of new insurance products, such as revenue insurance. In response to the ARPA premium subsidy increase to 60%, participation rates continued increasing until reaching 77% in 2007 and 85% in 2008 (Smith and Goodwin 2009). While subsidies as a percentage of premium averaged 4% in 1981, they represented 54% of premium in 2008.

Another relevant policy change for this analysis is the introduction of premium discounts to farmers planting Monsanto's triple stack corn, and other Pioneer and

Syngenta hybrids in irrigated and non-irrigated land in selected states [2]. The Biotech Endorsement pilot program (BE) provides a premium discount of 20% to producers purchasing Actual Production History insurance plan (APH) under 70-75% coverage. The percentage premium rate discount will be smaller for producers buying revenue insurance products since yield risk is only a part of the risk covered by these policies. According to the RMA, the overall premium discount for the total pilot book of business is 13% of the premium. However, in spite of the fact that the endorsement of the BE was based on the seed industry demonstration that its triple stacks provide lower yields risks than their conventional corn hybrids counterparts, the systematic effect of these corn traits on yield levels, yield risks and crop insurance loss history has not been assessed. The introduction and expansion of genetically modified crops has dramatically changed the American agricultural sector, having impacts not only on productivity, but also on risk management programs such as crop insurance. On the other hand, crop insurance policies, which have shaped the program over time, have had also important effects on the agricultural sectors, and more specifically on crop insurance results. This analysis will try to understand what are the factors explaining crop insurance program results over the last few years. An attempt is made to not only to account for weather and GM adoption, but also to take crop insurance policy changes into account.

[2]States eligible to the biotech premium discount include Colorado, Iowa, Illinois, Indiana, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota and Wisconsin

3 Data

County level corn yield data for the 1981-2008 period were obtained from the NASS website. Crop insurance results were obtained from the RMA book of business and include two measures of crop insurance performance, namely, loss cost ratios and loss ratios. Loss cost ratios (indemnity/liability) are a measure of risks and translate to the expected loss over a specific liability amount. Historical loss cost ratios are commonly used to set empirical premium rates. Loss ratios (indemnities/premium) are a measure of the accuracy of premium rates. An actuarially fair premium rate is set at the level at which loss ratio equals one, or total premium equals expected indemnity.[3] County level weather variables, such as GDD and HDD are calculated with daily precipitation, minimum and maximum temperatures weather station data downloaded from the National Climatic Data Center (NCDC). Several measures had to be taken to select counties with good weather data. For instance, only stations having 28 years of observations (1981-2008) were included, and station that had more than 20% of their annual daily precipitation data missing were excluded. All counties which did not have relatively complete weather data were excluded from the analysis. The result was a panel composed of 199 counties and 28 years of data, totaling 5,572 observations. Finally, genetically modified corn seed adoption rates data were provided by Monsanto.

Table 1 contains summary statistics of county level corn yields, weather variables and biotechnology adoption rates for Corn Belt states of Iowa, Illinois, Missouri, Indiana, and Ohio. Abbreviated names for estimation variables are also

[3]The 2008 Farm Bill reduced the crop insurance loss ratio target from 1.075 to 1.00

presented. Corn yields averaged 125 bu/acre in the region, with a minimum of 19 bu/acre and a max of 206 bu/acre. The loss cost ratio mean is 6%, with a 0% minimum, and a maximum of 93%. Loss ratios averaged 0.99 but reached a maximum of 23.62. The total GM corn adoption rate averaged 16% in the estimation period, with a minimum of 0% but reaching a maximum of 93%. Insect-resistant traits' adoption rates dominated herbicide-tolerant traits, with a 13% average adoption rate and a maximum of 78%. Of all GM corn, the triple stacks group of corn seeds reached the highest adoption rate at the end of the period, presenting a maximum of 57% share of total acreage in the U.S. Corn Belt in 2008.

Table 2 contains a list of the seed hybrids included in each of the trait groups. The groups were delineated based on the number of insect resistant traits since they are the ones that affect yields and yield risks. Seed group A contains all conventional seeds, that is, with no herbicide or insect resistant traits. Group B includes seeds that have herbicide-tolerant traits only. Herbicide-tolerant corn seeds have been genetically engineered to be tolerant to common herbicides, such as glyphosphate, or Roundup, so that the corn plants don't get killed or affected when the herbicide is applied. Group C includes seeds with a single insect resistant trait, Bt, which have been genetically modified to control European Corn Borer insect species (Cb-resistant or Bt corn). Group D includes corn seeds with a single insect resistant trait to control corn rootworm (RW). Group E includes corn seeds with two insect resistant traits, which can be resistant to both European Corn Borer (Cb) and Rootworm (Rw). Group F includes corn seeds with three traits, which include traits to tolerate herbicides and resist corn root worm and corn borer. Figure 2 depicts the rates of adoption for the six corn seed groups. The graph shows how the acreage share of the conventional corn seed group has sharply decreased over the period, from 92% in 1997 to only 15% in 2008. On the other hand, adoption rates of seed group C (Cb-resistant trait adoption rate or CBAR) showed an increasing tendency up to 2006, when seed group F adoption rate (triple-stack adoption rate TSAR) takes off from 5% to 50% in 2008. Combining all genetically modified corn traits, total GM adoption rates (GMAR) reached 85% in 2008 in the Corn Belt region.

4 Econometric Models

Fixed effects models of log-yields, loss cost ratio, and loss ratio are estimated as a function of weather variables and genetically modified corn adoption rates. Total growing season precipitation with a quadratic specification is used to capture the inverted U-shape relationship between precipitation and yields observed in previous literature. The agronomic concepts of Growing Degree Days (GDD) and Harmful Degree Days (HDD) are included in the model to account for non-linear effects of temperatures on yields. According to the plant physiology literature, plant development is a linear positive function of temperature within a range of temperature between minimum and maximum thresholds (Ritchie and Smith, 1991). The minimum temperature below which the plant development rate equals zero is termed the base temperature T_b. The high temperature above which the linear relationship no longer holds is termed peak temperature, T_p. For temperatures above T_p, plant development rates fall rapidly in another linear negative relationship (Ritchie and Smith, 1991). Schlenker and Roberts (2009) showed that the three weather variables that produce the best corn yields out-of-sample predictions are precipitation, growing degree days and harmful degree days. Thus, the log linear model specification of corn yields as a function of weather and biotechnology variables is as follows (Model LY I):

$$\begin{aligned} Log(y_{it}) &= \alpha_i + \beta_{pspcp}PSPCP + \beta_{pcp}PCP_{it} + \beta_{pcp2}PCP_{it}^2 + \beta_{GDD}GDD_{it} \\ &+\beta_{HDD}HDD_{it} + \beta_{GMAR}GMAR_{it} + \beta_{HDGM}HDGM_{it} + \beta_{PCPGM}PCPGM_{it} + \beta_t T + e_{it} \end{aligned} \tag{1}$$

where $Log(y_{it})$ is the log of corn yields, y, in county i and year t, α_i are estimated county fixed effects, PSPCP is pre-season precipitation and PCP and PCP^2 are growing season precipitation and precipitation squared. GDD is calculated as the sum of the difference between daily average temperature and the base temperature, $GDD = \sum_k^g T_a - T_b$, where g is the number of days over the growing season. Harmful Degree Days (HDD) is calculated as the sum of the daily difference between maximum daily temperature and a harmful temperature threshold (T_h), or $HDD = \sum_k^g T_m - T_h$. It is customary to use average daily temperature for the construction of HDD, but maximum daily temperature might reflect extreme temperatures more accurately than average daily temperature, and reveal a higher effect. Ritchie and Smith (1991) document a base temperature of $8°C$, a peak temperature of $32°C$, and a harmful temperature threshold of $34°C$. More recently, Schlenker and Roberts (2009) finds that corn yields rise with temperatures up to $29°C$ and decreases with temperatures greater or equal to $30°C$. Although it is possible that Genetically Modified corn adoption has changed these thresholds, this study uses Ritchie and Smith (1991) and Schlenker and Roberts (2009)'s results that corn yield growth increases gradually with temperatures between $8°C$ and $29°C$, and then decreases sharply with temperatures greater or equal to $30°C$. The temperature thresholds used to calculate GDD and HDD are $T_b = 8°C$, $T_p = 29°C$, and $T_h = 30°C$. Growing Degree Day for a given day is calculated such that GDD equals:

$$\begin{bmatrix} 0 & if & T_a < T_b \\ T_a - T_b & if & T_a > T_b \\ 21°C & if & T_a > T_b \end{bmatrix} \tag{2}$$

Harmful Degree Days for a given day are calculated such that HDD equals:

$$\begin{bmatrix} 0 & if & T_m < T_h \\ T_m - T_h & if & T_m > T_h \end{bmatrix} \tag{3}$$

(4)

GMAR stands for genetically modified corn adoption rates and it is the sum of all genetically modified corn group's adoption rates, $GMAR = HRAR + CBAR + RWAR + DOAR + TRAR$, where HRAR, CBAR, RWAR, DOAR and TRAR are herbicide-tolerant, corn-borer-resistant, rootworm-resistant, double-insect-resistant (Cb and Rw) and triple stacks corn adoption rate, respectively. HDGM is an interaction term between HDD and GMAR and PCPGM is an interaction term between precipitation and GMAR. The growing season is assumed to span from May through August. Different measures of GMAR were used according to the degree of GM corn aggregation. For instance, Model LY II is specified as follows:

$$
\begin{aligned}
&Log(y_{it}) = \alpha_i + \beta_{ps_pcp} PSPCP + \beta_{pcp} PCP_{it} + \beta_{pcp2} PCP_{it}^2 \\
&+\beta_{GDD} GDD_{it} + \beta_{HDD} HDD_{it} + \beta_{IRAR} IRAR_{it} + \beta_{HRAR} HRAR_{it} \\
&+\beta_{HDIR} HDIR_{it} + \beta_{PCPIR} PCPIR_{it} + \beta_t T + e_{it}
\end{aligned}
\tag{5}
$$

where IRAR is insect-resistant corn adoption rate, $IRAR = CBAR + RWAR + DOAR + TRAR$, HRAR is herbicide-tolerant corn adoption rate, and HDIR and PCIR are interaction terms between IRAR and HDD and PCP, respectively.

Including the adoption rates of the 5 groups of genetically modified corn brings about estimates' instability problems related to multicollinearity since these five groups compete for acreage between each other and thus their acreage shares (adoption rates) are highly negatively correlated. For instance, Figure 2 shows that the adoption rate of Cb-resistant corn started decreasing in 2005, when double-stack corn adoption rates sharply increased to reach a peak in 2006, and let triple-stack corn adoption rates take off to reach an adoption rate of 50% in 2008 in the Corn Belt. Thus, newer, better genetically modified corn varieties have been rapidly adopted and replaced old ones.

While a time trend can account for other important factors changing over time, it can also confound the effect of genetically modified adoption on yields and insurance losses. Thus, all models are estimated with and without time trend to compare estimated effects. Models estimated for loss cost ratio (LCR) and loss ratio (LR) follow the same procedure explained above for log yields but with a linear specification. Hausman specification test for Random Effects (RE) reject RE in favor of fixed effects for all models. Thus, fixed effects models are estimated for all yield and insurance models. All models are estimated with an Arellano (1987) version of White's (1980) heteroscedasticity-corrected-covariance-matrix, which is suitable for panel model estimation and is robust to the presence of heteroscedasticity and correlation in the error term.

5 Results

5.1 Corn Yield Models

Table 3 presents results for log-linear yield models with different biotechnology adoption rates specifications. Models LY I- LY II include a time trend, while models LY III-IV do not. Results for all models support the inverted-U shaped relationship between precipitation and corn yields. Results for all log-yield models report an optimal growing season precipitation of 16 inches, which is roughly total mean precipitation for the estimation sample. Growing season precipitation lower or higher than this level seems to decrease corn yield's percentage change. Pre-season precipitation seems to have a negative effect on yields' percentage change. This is robust to different specification of these variables and to all log-yield models.

Estimated coefficients for GDD are positive and statistically significant at the 5% significance level for all models. This is consistent with the agronomic evidence that temperatures between 8° C and 29° C affect corn yields positively and linearly.

Estimated coefficients for HDD have the expected negative sign and are significant at the 5% level. This supports previous findings that temperatures higher than 30° C are harmful for corn yield growth.

First order estimated coefficients for GM adoption rate (GMAR) and insect-resistant corn adoption rate (IRAR) are positive and significant in log yield models with time trend. When a time trend is included, first order coefficients for GMAR indicates that one percentage point increase in genetically modified corn seed adoption rates increases corn yields by 12%. This is primarily driven by insect-resistant adoption rate, which estimated coefficient is also 12%. Evaluated at mean yield and HDD, GMAR and IRAR have increased average yields by 25 bu/acre. When a time trend is removed, estimated coefficients for genetically modified adoption rates are even higher. Results imply that a 1% increase in GMAR has increased corn yields by 36% in the Corn Belt, while a percentage increase in IRAR increases corn yields by 44%. This translates to an average increase of 57 bu/acre per percentage point increase in GMAR and 70 bu/acre per percentage point increase in IRAR.

Figure 3 plots logged corn yields as a function of precipitation while keeping all other variables at their median level. The first row of plots uses model estimates with time trend and the second row models without time trend. The plots show that for all groups of genetically modified corn adoption rates depicted, the first order effects on corn yields percentage change dominate interaction effects. For high levels of GMAR and IRAR, corn yields percentage change is higher for all levels of precipitation, but the slope does not seem to significantly differ across GM adoption levels. Thus, any level of genetically modified corn yield percentage change requires less growing season rainfall than the equivalent yield percentage change for non-GM corn. In its most basic definition, drought is defined on the basis of the degree of dryness or insufficient rainfall in comparison with some normal rainfall amount. Taking sample mean growing season precipitation as "normal" (16 inches), the graphs in Figure 3 show that corn yields' percentage change is higher when genetically modified corn adoption is higher not only for negative deviations of "normal rainfall," but also for positive deviations, or excessive rainfall. Based on the preferred models with time trend, it can be concluded that the adoption of genetically modified corn (GMAR), especially insect-resistant corn (IRAR), has increased corn-yields's tolerance not only to insufficient rainfall (negative deviations from normal or drought), but also to excessive rainfall or positive deviations from normal rainfall.

The interaction terms between harmful degree days (HDD) and total GMAR and IRAR are positive and statistically significant for models LY I and II. This indicates that biotechnology adoption has reduced the harmful effect of high temperatures on corn yields. The effect of harmful degree days on yield percentage change as by Model I is:

$$\frac{\partial(log(y))}{\partial(HDD)} = -0.0024 + 0.0008GMAR$$

When GM adoption rate quals zero, the effect of HDD on corn yields percentage change is -0.0024. However, as GM adoption rates increase, the harmful effect of HDD is reduced by up to 0.0008 in percentage terms when GMAR equals 1. The estimated coefficient for the interaction term between the insect-resistant corn adoption rate and HDD is also positive and significant, being 0.0009. When the time trend is removed from the models, HDD interaction terms increase to 0.0010 and 0.0013 for GMAR and IRAR respectively (Models LY III and IV). Figure 4 shows these interaction effects. The first row plots interaction effects from models including a time trend and the lower panel plots interaction effects from models without a time trend. It is evident that the interaction effects of GM corn adoption rates with HDD are larger when no time trend is included in the model. In both cases, corn yields percentage change seem to be higher with high levels of GM corn adoption than with lower GM corn adoption rates for all levels of HDD. The plots show a clear yield advantage of insect-resistant corn. This result might be due to the strong correlation between high temperatures and insect infestations. It has been documented that insects emerge and develop in response to heat, and that insect development is slower under cool temperatures and faster under warm temperatures (University 1999). Thus, even though none of the genetic traits commercially available has been targeted to improve corn's ability to withstand drought or high temperatures, insect resistant corn is showing evidence of reduced vulnerability to high temperatures through its resistance to insects infestations. Furthermore, Schlenker and Roberts (2009) observes that the largest heat shocks in history (HDD positive deviations from its mean) occurred in major drought years of 1934, 1936, 1983, and 1988. Thus, improved heat tolerance of GM corn translates to drought-tolerance improvements. This result is also consistent with past findings documented in Gurian-Sherman (2009), showing evidence that rw-resistant corn provides substantial gains in yields in sites experiencing weather stress. A study by Toffelson and Oleson 2005 found that rw-resistant corn yield advantage in sites experiencing serious drought was at least 69% in 2005.

Interaction terms between precipitation and GM adoption rates were included to test whether the adoption of GM corn has changed yield's response to precipitation. Estimated coefficients were not significant for interaction terms between precipitation and total GM (GMAR) or insect-resistant (IRAR) corn adoption rates (Models LY I-IV). Figure 3 show that first order effects of genetically modified corn adoption rates dominates slope effects with respect to precipitation, and thus, logged corn yields seem to be higher under high levels of GM corn adoption than for the case of no adoption for all levels of growing season precipitation.

Time trend coefficients are always positive and significant but of much smaller magnitude than GM adoption rates estimated coefficients. These coefficients indicate that corn yields have increased from 0.88% to 0.91% yearly as a result of non-genetic factors changing over time. The Hausman test for random effects results are reported in the table. Random effects models are rejected in favor of fixed effects models for all log-yield model specifications. F test of genetically modified adoption rates coefficients were performed to jointly test weather these coefficients are equal to zero. This hypothesis is rejected for all log-yield models.

In summary, the effect of GM corn adoption rates on corn yields % change is measured taking into account the agronomic non-linear relationship between weather variables and crop yield development. Results support the hypothesis that GM corn adoption rates, specially the adoption of insect-resistant corn has had a positive and significant effect on corn yields' percentage change. The hypothesis that this hybrids' adoption rate has increased corn tolerance to high extreme temperatures over the growing season is strongly supported. The hypothesis that GM adoption rates have increased corn's tolerance to drought is also strongly supported. First order effect of genetically modified corn variables suggest that GM adoption has increased corn yields percentage change for all levels of precipitation. Thus, genetically modified corn adoption has not only significantly increased corn yield's tolerance to insufficient rainfall (drought), but also to excessive rainfall.

5.2 Insurance Loss Models

Table 4 present results for loss cost ratio (LCR) and loss ratio (LR) models with and without time trend. The U-shaped relationship between precipitation and corn yield losses as given by LCR is supported for all LCR models, whereby the linear precipitation term is always negative and significant and the quadratic precipitation effect is always positive and significant. Estimated coefficients for GDD are always negative and significant, whereas HDD estimated coefficients are always positive and significant, giving evidence that higher GDD increases yields and reduces crop insurance losses, and higher HDD decreases corn yields and increases insurance losses. Estimated coefficients imply that an additional GDD unit over the growing season decreases loss cost ratio by 0.0001 and an additional unit of HDD increases loss cost ratio by 0.0010. Based on the total 2008 Corn Belt corn liability of US$ 19 billions, these numbers imply that an additional unit of GDD decreases total corn indemnities by US$ 1.9 million in the U.S. Corn Belt, and an additional unit of HDD over the growing season increases total indemnities by US$ 19 million. Thus, detrimental effect of high extreme temperatures seem to be 10 times the beneficial effects brought about by good weather.

When a time trend is included, the first order genetically modified (GMAR), insect-resistant (IRAR) and herbicide-tolerant (HRAR) corn adoption rates estimated coefficients are not statistically significant in loss cost ratio models (LCR I-II). Given that higher order interaction coefficients are estimated, all this means is that the effect of genetically modified corn adoption rates on the loss cost ratio is not significantly different from zero when HDD equal zero. On the other hand, the interaction effects between total genetically modified and insect-resistant corn adoption rates and HDD are negative and statistically significant in all LCR models, with and without time trend. This indicates that when HDD is nonzero, the adoption of genetically modified corn, especially insect resistant corn, decreases yield losses triggered by high extreme temperatures as given by HDD. Plots of loss cost ratios for low and high levels of GMAR and IRAR against different levels of HDD[4] are shown in the upper panel of Figure 5. The plots show that for low levels of HDD, loss cost ratios for low and high genetically modified corn adoption rates are similar. However, as HDD increases, loss cost ratios for high levels of genetically modified corn adoption rates are lower with respect to those corresponding to low levels of GM corn adoption.

Loss ratio (LR) models support the same response to precipitation, GDD and HDD as LCR models. An additional unit of GDD decreases the loss ratio by 0.0011, while an additional unit of HDD increases loss ratios by 0.0188. Of all first order GM adoption rate coefficients estimated, only the ones corresponding to GMAR and IRAR with no time trend are statistically different from zero. First order estimated coefficients for genetically modified corn adoption rates are not statistically significant for the preferred models with time trend. On the other

[4]The range for HDD is its mean minus (plus) one standard deviation. Likewise, Low(high) levels of GMAR and IRAR are defined as their mean less(plus) one standard deviation

hand, interaction effects between HDD and GMAR, IRAR, and HRAR are all negative and statistically significant for both, models with and without time trend. The lower panel of Figure 5 illustrates plots of loss ratios for high and low GM corn adoption rate levels. Loss ratios for high levels of GM adoption rates are lower than those for lower levels of GM adoption, and the higher the HDD, the bigger the loss reducing effect of GM corn due to extreme high temperatures.

Interaction terms between precipitation and GMAR and IRAR are positive and significant in Models LR I,II with time trend. Loss ratios as a function of precipitation while holding all other variables at their median levels are depicted in Figure 6 for zero and maximum adoption rates of GM corn (GMAR) and insect-resistant corn (IRAR). For growing season precipitation levels lower than 30 inches, loss ratios for maximum GMAR adoption are lower than those corresponding to no GMAR adoption. However for precipitation levels higher than 30 inches, loss ratios are higher for maximum GMAR adoption than those for no GMAR. These results seem to indicate that adoption of genetically modified corn has decreased yield losses stemming from rainfall shortfalls (rainfall lower than normal) and small positive deviations of growing season precipitation up to 30 inches[5]. Interaction effects of GM adoption, HDD and precipitation estimated without the time trend present coefficients of similar magnitude and significance than those reported for models with time trend.

In summary, LCR and LR model results provide strong evidence that the adoption of genetically modified corn has reduced crop insurance losses in the Corn Belt triggered by extreme high temperatures. These results migt be explained by

[5]Normal growing season precipitation equals around 16 inches in our estimation sample

the higher resistance of the new hybrids to insect infestations and by the fact that insect pests are positively correlated to high temperatures. A conclusive result is that crop insurance losses triggered by high maximum temperatures have decreased. Less conclusive is the effect of GM corn adoption on yield losses triggered by rainfall shortfalls. Interaction effect indicate that loss ratios seem to be lower under higher levels of GM corn adoption up to 30 inches of growing season rainfall, but higher for cumulative precipitation beyond this point. Loss ratio models indicate that the adoption of GM corn has decreased corn loss ratios for negative and small positive deviations from normal rainfall, but increased yield losses for sufficiently high positive deviations of normal rainfall.

5.2.1 Insurance Policy Implications

Insurance losses have also been affected by several crop insurance policy changes over time. For instance, participation rates in the Corn Belt increased from 30% in 1990 to 85% in 2008 mainly driven by increasing government subsidies. Higher crop insurance participation driven by higher premium subsidies might be a factor contributing to reduced crop insurance loss performance in recent years in the Corn Belt. At lower level of premium subsidies the pool of farmers insured has been observed to be adversely selected. That is, at lower levels of premium subsidies, higher risk farmers are more likely to enroll in the crop insurance program because their expected returns from the program are higher. On the other hand, as premium subsidies increase, the crop insurance program becomes more attractive and affordable for lower risk farmers. Thus, the pool of insured farmers in 2008, with average premium subsidies of 54%, can be expected to be less risky than the insured pool in 1981, when subsidies represented only 4% of premiums. Furthermore, revenue insurance acreage share increased from 0% in 1996 to 82% in 2008. Unlike APH, revenue insurance covers not only yield shortfalls risks, but also price risks, thus it is likely that insurance loss performance varies by insurance plan. It has been observed that catastrophic weather events, such as droughts and floods were more frequent over the 1980s than in subsequent periods. Crop insurance loss history for the estimation period depicted in Figure 1 reflects an apparent break point in the mid 1990s. Chow tests were performed to test the hypothesis of a break point in yields and insurance loss response to weather in the mid 1990s. The hypothesis of no structural break in 1996 is not rejected for all models.

Crop insurance losses in the 1980's were exclusively APH insurance plan losses since that was the only existent crop insurance plan back then, whereas losses in 2008 were primarily driven by revenue insurance programs. To take into account possible different responses of insurance losses according to the plan, independent loss insurance models are estimated according to the insurance plan group for the period 1996 to 2008. This period is characterized by having higher premium subsidies and higher revenue insurance liability than previous periods. Possible differences in response to weather variables with respect to the general model are analyzed. Tables 5 and 6 contain insurance losses models for two insurance plan groups, individual history multiple peril crop insurance (APH) and revenue insurance (RI) with different GM adoption rates specifications. GRP models are not included since the plan has zero liabilities in many counties and time periods, creating a high number of missing values.

Results in Tables 5, and 6 show the same U-shaped relationship between total precipitation and insurance losses for both APH and RI group loss models. Results presented in Table 5 indicate that the GDD effect is positive but of very small magnitude for the APH and RI LCR models. This effect is not significantly different from zero for most models. This is a different effect than that observed for aggregated loss for the entire estimation period (1981-2008), where GDD has always statistically significant and negative effects on insurance loss measures. On the other hand, the effect of HDD on loss insurance plan groups is positive and statistically significant for all models ranging from 0.0006 to 0.0008 for loss cost ratio models and from -0.0088 to -0.0089 for loss ratios. These estimated effects are slightly lower than those estimated for HDD in aggregated loss models. This reduced negative response of loss measures to harmful degree days for the 1996-2008 period compared to that estimated for the entire period (1981-2008) might reflect higher tolerance of genetically modified corn to HDD since genetically modified hybrids were not available before 1996. Estimated coefficients for GMAR are negative and significant for all loss models but APH LR with time trend and APH LCR and APH LR with no time trend. GMAR estimated coefficients are higher (in absolute value) for revenue insurance loss models than for APH loss cost ratio and loss ratio models with and without time trend. These effects were also higher in absolute value than those estimated for the entire estimation period for aggregated loss models. Overall, results suggest that revenue insurance loss measures have been reduced more significantly by the adoption of genetically modified corn than those corresponding to APH. This is also a result of the fact that revenue insurance liability share has taken over APH share to reach 87% in

2008, while the APH liability share consistently fell to roughly 13% in 2008. Hence, since revenue insurance accounts for a higher share of losses, revenue insurance losses can also be expected to be more sensitive to yield risk factors.

The interaction effects between GMAR and HDD are negative and statistically significant for all insurance group loss models. This provides support to the hypothesis that the adoption of genetically modified corn has decreased yield losses triggered by excessively high temperatures. The interaction effect between precipitation and GMAR is positive and significant only for RI-LCR (with time trend), APH-LR and RI-LCR (with no time trend). Thus, results strongly support the hypothesis that revenue insurance loss cost ratio response to precipitation has changed due to the adoption genetically modified corn.

GDD and HDD effects reported in Table 6 are similar in nature and magnitude to those reported in Table 4. Estimated coefficients for insect-resistant corn adoption rates are negative and significant for revenue insurance loss models, but not for APH models (Table 6). In most instances, these first order insect-resistant adoption rate coefficients are higher in absolute value than the one for total genetically-modified corn adoption rates reported in Table 4. On the other hand, of all estimated coefficients for herbicide-tolerant corn adoption rates, only the one estimated for RI LR with time trend was negative and statistically significant. These results seem to support the hypothesis that it is insect-resistant traits, not herbicide-tolerant traits the ones increasing yields and reducing yield risks. Moreover, interaction effects between HDD and IRAR are negative and significant for all but the RI-LCR model (with no time trend). Further, these estimated coefficients are higher in absolute value to those estimated for GMAR.

These results provide further evidence that insect-resistant corn is more tolerant to high extreme temperature than other corn hybrids that do not contain the insect-resistant genes. Estimated coefficients for the interaction between precipitation and IRAR are positive and significant for 5 of the 8 models. These estimated coefficients are very similar in magnitude to the ones reported for the general model and depicted in the second graph of Figure 6.

In summary, a significant first order loss reducing effect of insect-resistant corn adoption is supported for most insurance plans and model specifications. This first order reducing effects of insect-resistant corn provides evidence of lower corn yield losses for all levels of precipitation. Though, interaccion effects with respect to precipitation do not provide robust support to the hypothesis of changed response of insurance losses to precipitatio as a result of the adoption of genetically modified corn. On the other hand, the risk reducing effect of GM corn adoption to high extreme temperatures is strongly supported for all insurance plans and most model specifications.

6 Concluding Remarks

The effects of genetically modified corn adoption on yields and crop insurance loss performance are analyzed taking the non-linear effects of weather on crop yields into account. Genetically modified corn adoption, especially the adoption of insect-resistant corn, have had a positive and significant effect on the percentage change of corn yields in the U.S. Corn Belt. The general model with time trend provides evidence that the adoption of genetically modified corn, especially insect-resistant corn has increased corn yields by 12%. Evaluated at the corn yield sample mean, this translates to an overall increase of 25 bushels per acre. This effect is even higher when a time trend is excluded from the model, which may be explained by the fact that the time trend captures the non-genetic improvements in germplasm and plant breeding contribution to yield increases. Excluding the time trend leads the GM corn adoption to capture not only genetic but also non-genetic yield enhancing factors. Genetically modified corn, especially insect-resistant corn, is found to provide higher yields than conventional corn not only for normal growing season rainfall, both also for both cases of rainfall stress- insufficient rainfall or drought and excessive rainfall (positive deviations from normal). In other words, insect-traited corn hybrids are less susceptible to precipitation stress than non-traited corn hybrids.

An important and robust result for both log-yields and insurance loss models is the risk reducing effect of genetically modified corn to yield losses triggered by high temperatures. This result might be explained by the widespread fact that insect infestations are highly correlated with temperature, and that insect development is lower under cool temperatures and higher under warm temperatures. Since genetically modified insect-resistant corn is intrinsically resistant to major insect pests, even unobservable, minor risks of insect infestations are totally eliminated by these genetic traits.

Overall, the effect of genetically modified corn adoption on corn yield response to precipitation is dominated by first order or intercept effects, meaning genetically modified corn yields are higher not only for normal growing season precipitation, but also for negative and positive deviations from it. On the other hand, genetically modified corn adoption effect on yield response to heat is dominated by interaction or slopes effects, meaning that the negative response of corn yields to heat decreases as heat and genetically modified adoption increases. This improvement in corn yield heat tolerance is robust to insurance loss models estimated by group of insurance plan, and models estimated with alternative specifications of corn genetic traits adoption. Thus, results provide evidence that the adoption of genetically modified corn has contributed to recent improvements in crop insurance performance in the Corn Belt by increasing yields and reducing yield risks to losses triggered by high temperatures and precipitation stress.

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Table 1: Summary Statistics

Variable	Abbreviation	No. of Obs.	Mean	Std. Dev.	Min	Max
Yield	**Yield**	5628	125.71	30.28	19.10	206.00
Loss Cost Ratio	**LCR**	5628	0.06	0.11	0.00	0.93
Loss Ratio	**LR**	5628	0.99	1.94	0.00	23.62
Farmer Loss Ratio	**FLR**	5628	1.57	2.83	0.00	50.27
Pre-Season Precipitation	**PSPCP**	5628	21.29	6.37	0.10	56.00
Total Precipitation	**PCP**	5628	16.99	5.31	2.11	42.78
Total Precipitation Squared	**PCP 2**	5628	317.04	204.34	4.45	1830.13
Growing Degree Days	**GDD**	5628	1612.08	198.19	197.00	2223.22
Harmful Degree Days	**HDD**	5628	92.20	71.71	0.00	458.33
Total GM Corn Adoption Rate	**GMAR**	5628	16%	24%	0%	93%
Insect-resistant Corn Adoption Rate	**IRAR**	5628	13%	20%	0%	78%
Herbicide-tolerant Corn Adoption Rate	**HRAR**	5628	3%	5%	0%	16%
Conventional Corn Adoption Rate	**CCAR**	5628	27%	35%	0%	95%
Cb-Resistant Corn Adoption Rate	**CBAR**	5628	10%	14%	0%	48%
Rw-Resistant Corn Adoption Rate	**RWAR**	5628	0%	1%	0%	8%
Double-insect-resistant Corn adoption rate	**DOAR**	5628	0%	1%	0%	4%
Triple Stacks Adoption Rate	**TSAR**	5628	3%	10%	0%	57%

Table 2: Corn Seed Groups by Number of Insect Resistant Traits

Seed Type	Seed Group	Seed Type	Seed Group
Conventional	A	YGRW-RR2	D
YGCB	C	Herculex	C
IMI	B	YGPlus-RR2	F
LL	B	Agrisure GT	B
RR	B	Herculex I-LL-IMI	C
IMI-LL	B	YGCB-LL	C
YGCB-RR	C	Agrisure CB-LL-GT	C
YGCB-IMI	C	HX RW- LL	D
YGCB-IMI-LL	C	HX XTRA-LL	F
Herculex I-LL	C	HX RW-LL-RR2	D
YGRW	D	HX XTRA-LL-RR2	F
YGRW-RR	D	YGCB-GT	C
Agrisure CB-RW-LL	F	YGPlus-IMI	F
Agrisure RW	D	Agrisure 3000GT	F
Agrisure RW-GT	E	YGCB	C
YGRW-IMI	D	Agrisure CB-LL	C
YGPlus	E	YGCB-IMI	C
RR2	B	YGVT3	F
YGCB-RR2	C	YGVT RW-RR2	E
Agrisure CB-IMI-LL	C		

Table 3: Corn Yield Log-Linear Models Parameter Estimates

	...With Time Trend...		...With No Time Trend...	
Models	**LY I**	**LY II**	**LY IV**	**LY V**
Intercept	4.4717 *	4.4717*	4.5850*	4.5921*
Pre-season Precipitation	-0.0050*	-0.0049*	-0.0060*	-0.0059*
Total Precipitation	0.0360*	0.0360*	0.0360*	0.0362*
Total Precipitation Squared	-0.0011*	-0.0011*	-0.0011*	-0.0011*
Growing Degree Days (GDD)	0.0001*	0.0001*	0.0002*	0.0002*
Harmful Degree Days (HDD)	-0.0024*	-0.0024*	-0.0026*	-0.0026*
GMAR	0.1282*		0.3639*	
IRAR		0.1203*		0.4445*
HDD x GMAR	0.0008*		0.0010*	
HDD x IRAR		0.0009*		0.0013*
PCP x GMAR	0.0012		-0.0010	
PCP x IRGM		0.0011		-0.0018
Time	0.0088*	0.0091*		
R Squared	69%	70%	67%	66%
Hausman Test for RE	18.26	44.06	33.69	41.76
F Test of GM's $\beta' s$	178.42	169.09	1942.8	1892.7

* indicates significance at the 5% level

Table 4: Crop Insurance Loss Cost Ratio and Loss Ratio Models Parameter Estimates

	With Time Trend		**With No Time Trend**		**With Time Trend**		**With No Time Trend**	
Models	**LCR I**	**LCR II**	**LCR III**	**LCR IV**	**LR I**	**LR II**	**LR III**	**LR IV**
Intercept	0.1428*	0.1416*	0.1556*	0.1532*	4.0066*	3.9912*	3.9170*	3.8981*
Pre-season Prec.	0.0018*	0.0018*	0.0017*	0.0017*	0.0142*	0.0140*	0.0150*	0.0148*
Total Prec.	-0.0137*	-0.0137*	-0.0136*	-0.0137*	0.3587*	-0.3583*	-0.3589*	-0.3586*
Total Prec. 2	0.0004*	0.0004*	0.0004*	0.0004*	0.0104*	0.0104*	0.0104*	0.0104*
GDD	-0.0001*	-0.0001*	-0.0001*	-0.0001*	-0.0011*	-0.0011*	-0.0011*	-0.0011*
HDD	0.0010*	0.0010*	0.0010*	0.0010*	0.0188*	0.0187*	0.0189*	0.0189*
GMAR	-0.0014		0.0294		-0.4572		-0.6717*	
IRAR		-0.0081		0.0103		-0.5587		-0.7933*
HRAR		0.0302		0.1026*		0.1231		
HDD x GMAR	-0.0006*		-0.0006*		-0.0124*		-0.0126*	
HDD x IRAR		-0.0008*		-0.0007*		-0.0150*		-0.0153*
HDD x HRAR								-0.0143
PCP x GMAR	0.0000		-0.0002		0.0465*		0.0482*	
PCP x IRAR		0.0001		-0.0001		0.0551*		0.0573*
Time	0.0010*	0.0010*			-0.0073	-0.0075		
R Squared	38%	38%	39%	39%	38%	38%	38%	38%
Hausman Test for RE	24.42	36.44	41.43	38.42	135.38	150	135.69	126.7
F Test of GM's $\beta's$	89.32	91.72	132.41	216.83	126.19	127	104	107

* indicates significance at the 5% level Null Hypothesis for F Test: $\beta_{gms} = 0$

Table 5: Loss Models by Insurance Group-Total Genetically Modified Corn Adoption Rates

	..........**With Time Trend**..........				..........**With No Time Trend**..........			
Models	**APH-LCR**	**APH-LR**	**RI-LCR**	**RI-LR**	**APH-LCR**	**APH-LR**	**RI-LCR**	**RI-LR**
Intercept	-0.0209	-0.2553	-0.0269	0.2489	0.0242	0.6437*	0.0504	0.7905*
PSPCP	0.0017*	0.0281*	0.0032*	0.0322*	0.0016	0.0259*	0.0030*	0.0310*
PCP	-0.0046*	-0.1071*	-0.0067*	-0.1251*	-0.0044	-0.1043*	-0.0064*	-0.1234*
PCP 2	0.0001*	0.0028*	0.0002*	0.0031*	0.0001	0.0028*	0.0002*	0.0031*
GDD	0.0000*	-0.0001	0.0000	0.0000	0.0000	-0.0002	0.0000*	0.0000
HDD	0.0006*	0.0088*	0.0008*	0.0088*	0.0006*	0.0089*	0.0008*	0.0089*
GMAR	-0.0520*	-1.1581	-0.1133*	-1.2496*	-0.0210	-0.5404	-0.0604*	-0.8795*
HDD x GMAR	-0.0006*	-0.0099*	-0.0006*	-0.0081*	-0.0006	-0.0095*	-0.0006*	-0.0079*
PCP x GMAR	0.0016	0.0413	0.0025*	0.0357	0.0015	0.0393*	0.0024	0.0345*
Time	0.0021*	0.0413*	0.0036*	0.0253*				
R Squared	30%	25 %	32%	29 %	29%	24%	32%	29%
F Test	92.29	75.67	121.41	110.56	119.09	135.49	106.19	206

* indicates significance at the 5% level

Table 6: Loss Models by Insurance Group-Insect/Herbice resistant corn Adoption Rates

	..........With Time Trend..........				..........With No Time Trend..........			
Models	**APH LCR**	**APH LR**	**RI LCR**	**RI LR**	**APH LCR**	**APH LR**	**RI LCR**	**RI LR**
Intercept	-0.0185	-0.2596	-0.0286	0.2047	0.0186	0.5677	0.0461	0.7862*
Pre-season Precipitation	0.0017*	0.0278*	0.0032*	0.0315*	0.0017*	0.0264*	0.0030*	0.0305*
Total Precipitation	-0.0047*	-0.1075*	-0.0067*	-0.1243*	-0.0046*	-0.1064*	-0.0066*	-0.1234*
Total Precipitation Squared	0.0001*	0.0028*	0.0002*	0.0031*	0.0001*	0.0028*	0.0002*	0.0031*
Growing Degree Days (GDD)	0.0000*	-0.0001	0.0000	0.0001	0.0000*	-0.0002	0.0000*	0.0000
Harmful Degree Days (HDD)	0.0006*	0.0089*	0.0008*	0.0089*	0.0006*	0.0091*	0.0009*	0.0090*
HRAR	0.0124	-0.5596	-0.1043	-1.7465*	0.0761	0.8613	0.0211	-0.7693
IRAR	-0.0615*	-1.2248*	-0.1128*	-1.1571*	-0.0445	-0.8440*	-0.0781*	-0.8870*
HDD x IRAR	-0.0008*	-0.0125*	-0.0008*	-0.0102*	-0.0007*	-0.0121*	-0.0007	-0.0099*
PCP x IRAR	0.0020	0.0493*	0.0030*	0.0431*	0.0019	0.0478*	0.0029	0.0421*
Time	0.0018*	0.0405*	0.0036*	0.0284*				
R Squared	30%	25%	33%	25%	30%	24%	32%	30%
F Test of GM's $\beta's$	99.73	131.50	80.08	117.95	131.50	148	111.50	212.67

* indicates significance at the 5% level

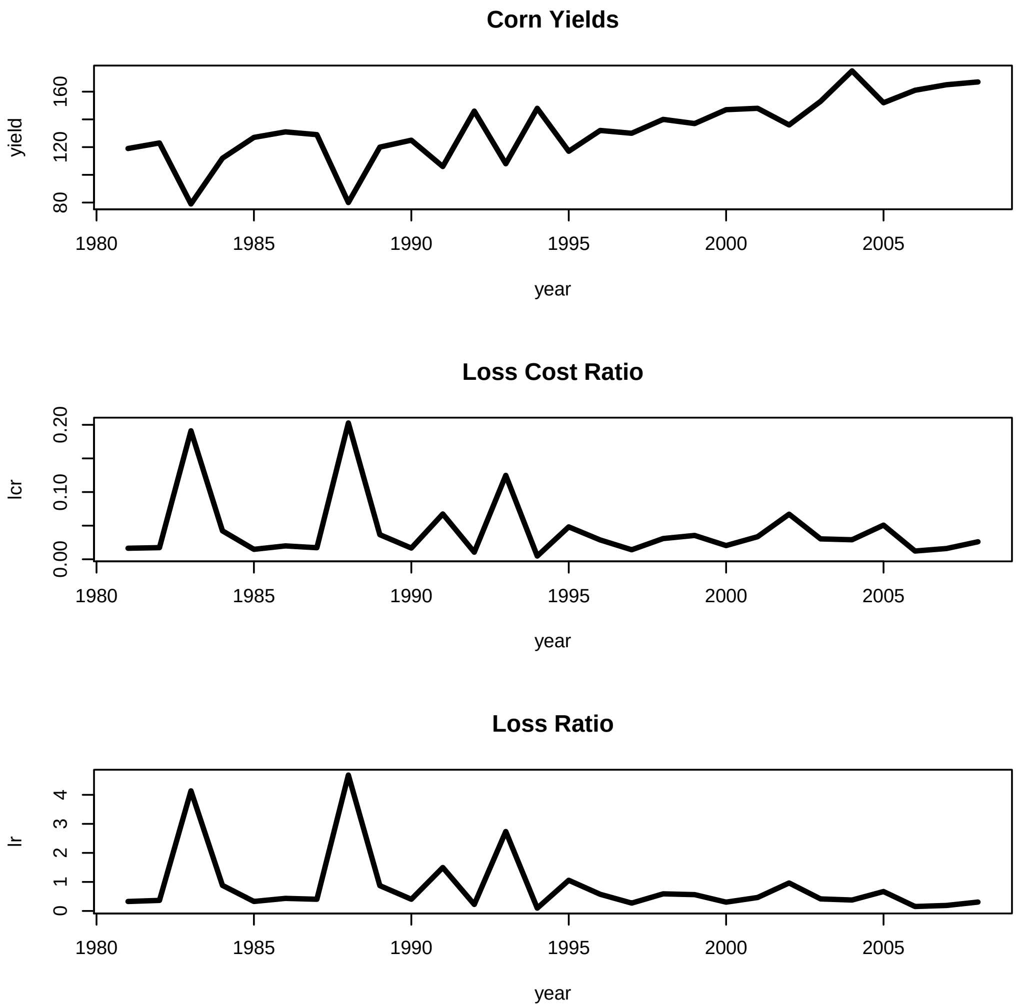

Figure 1: Corn Belt Corn Yields and Crop Insurance Loss History, 1981-2008

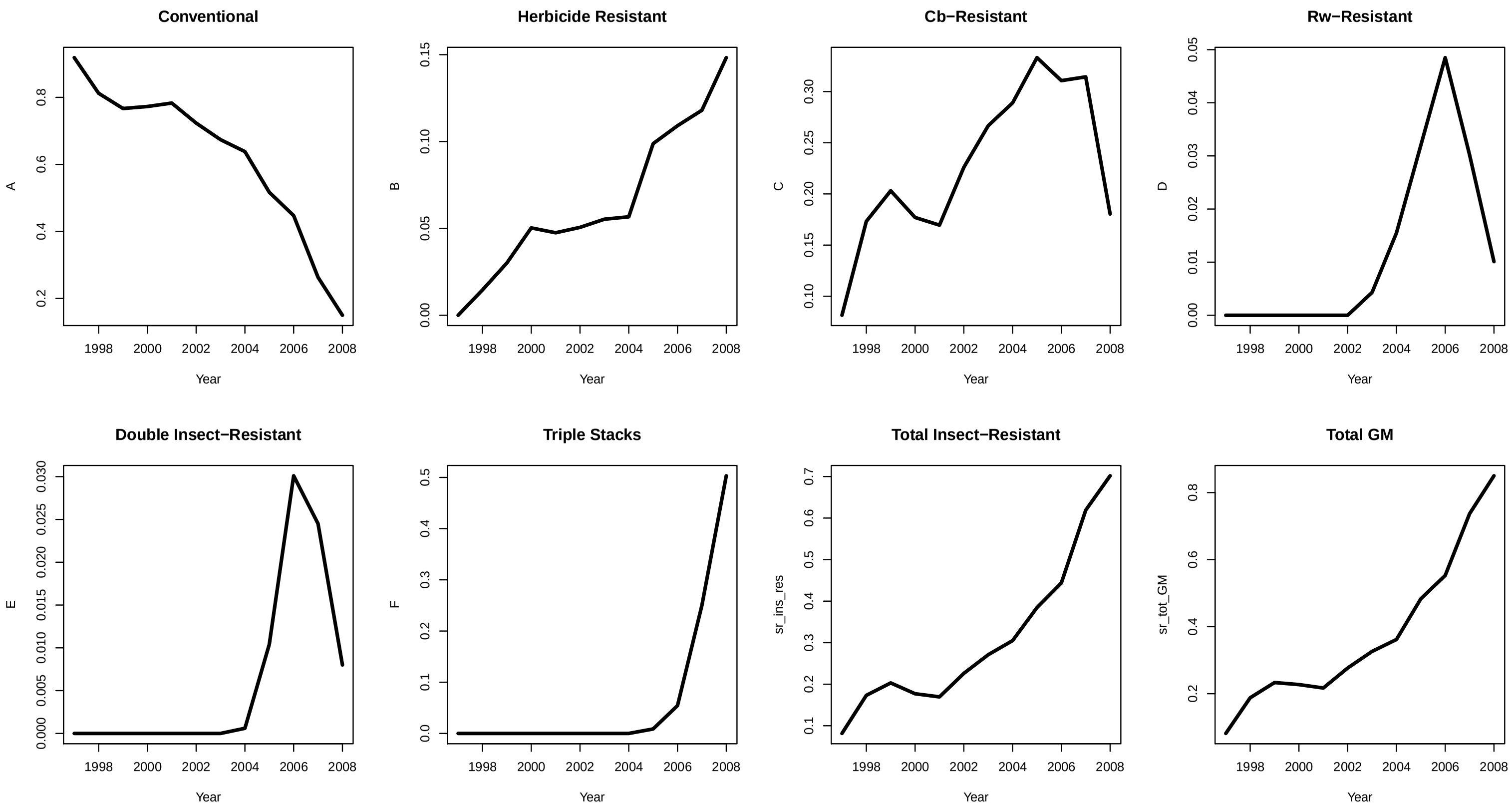

Figure 2: Genetically Modified vs. Conventional Corn Acreage Shares in the Corn Belt, 1981-2008

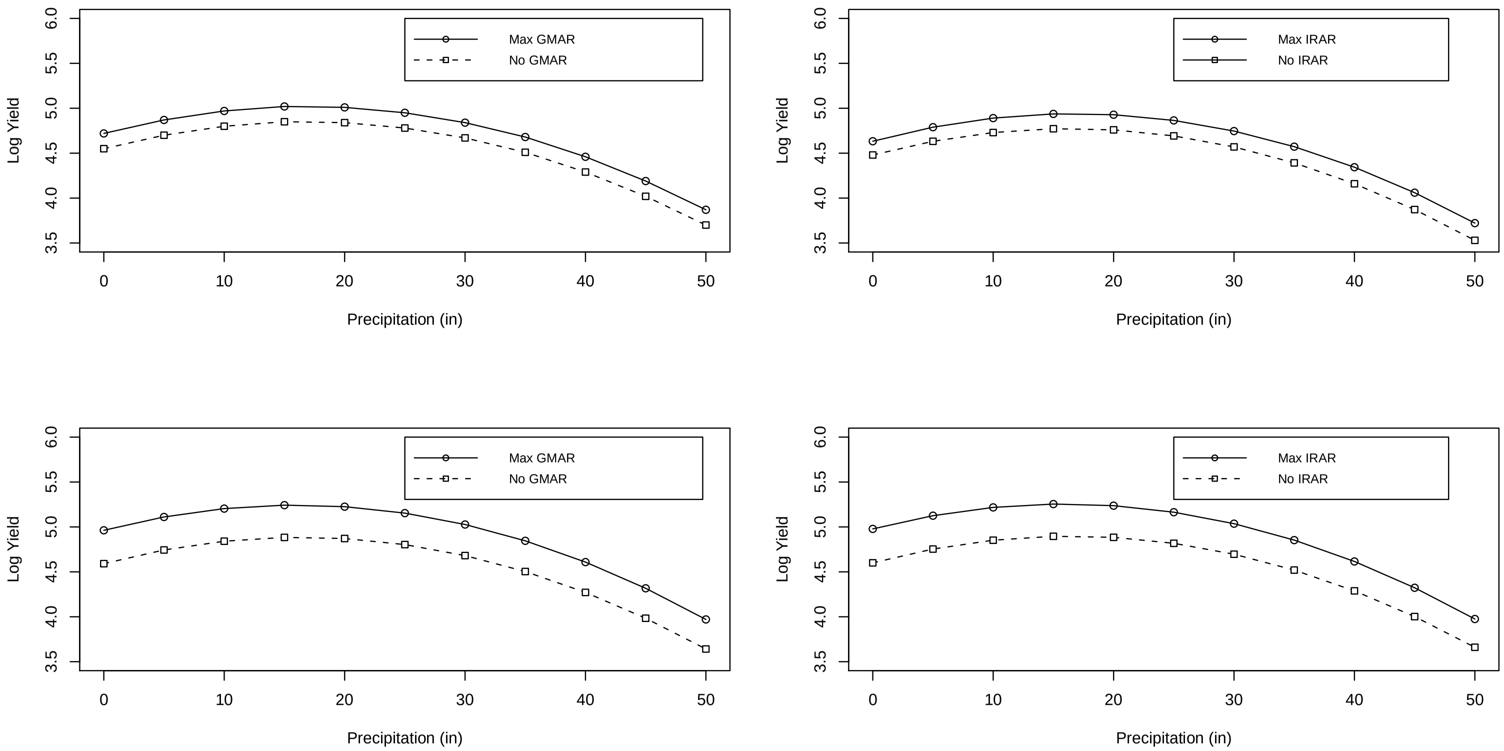

Figure 3: Log Yields vs. Precipitation under Different Adoption Rates of Genetically Modified corn

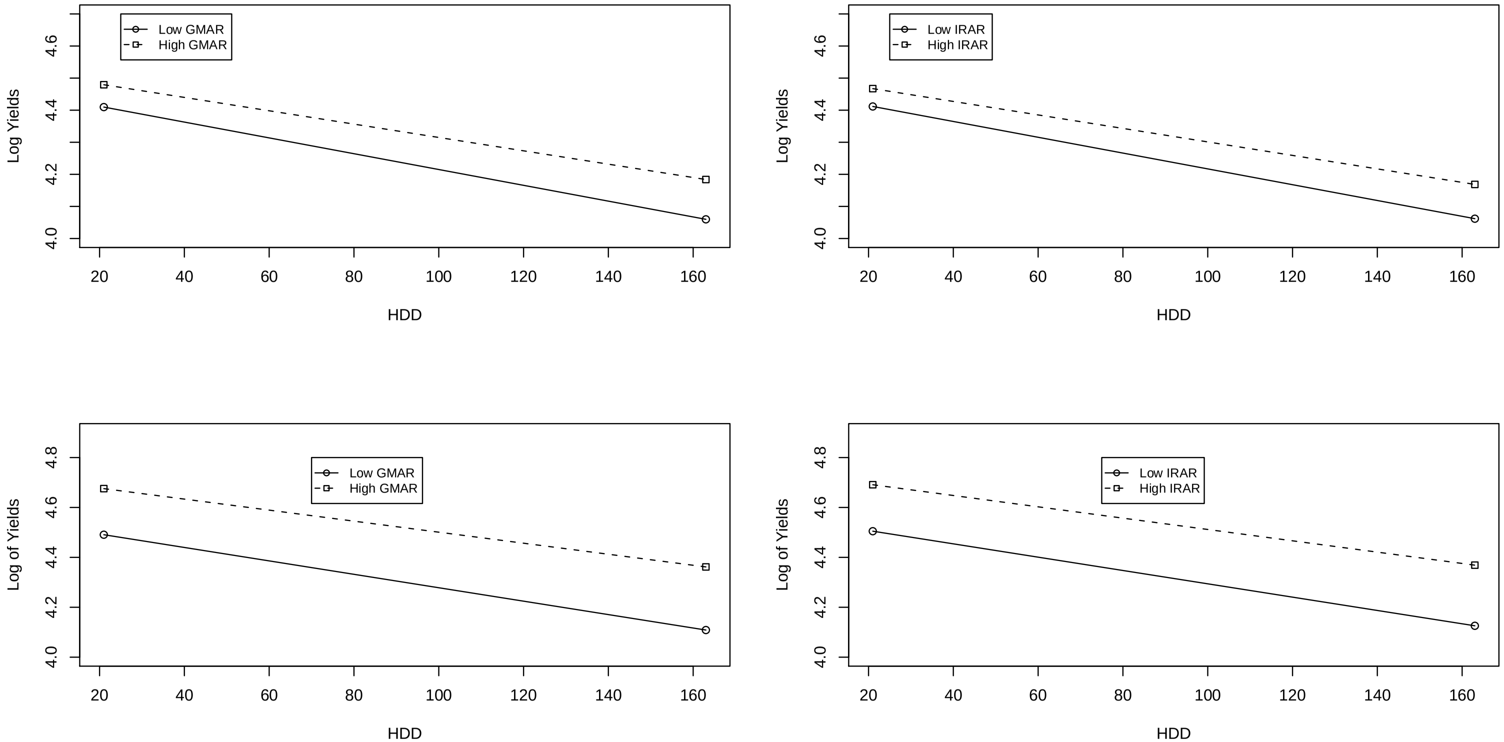

Figure 4: Log Yields Interaction Effects between HDD and Genetically Modified corn Adoption Rates

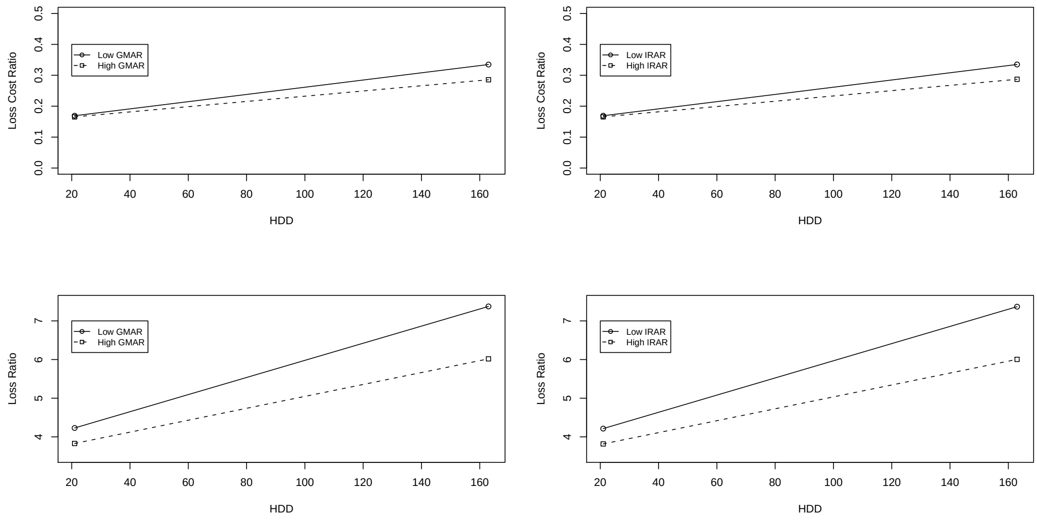

Figure 5: Loss Cost Ratio and Loss Ratio Interaction Effects between HDD and Genetically Modified Corn Adoption Rates

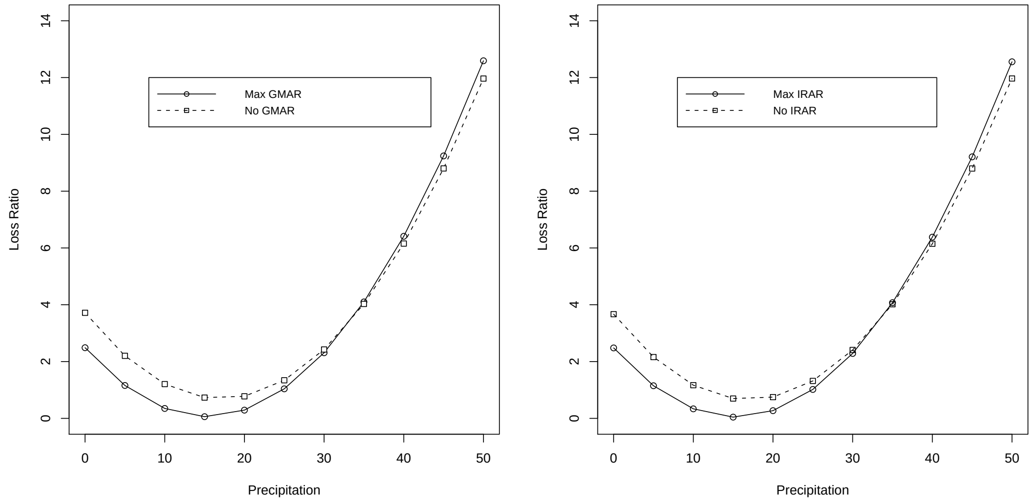

Figure 6: Loss Ratio Interaction Effects between Precipitation and Genetically Modified Corn Adoption Rates