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Producer Adoption of Genetically Modified Corn and Its Impact on Average U.S. Corn Yields

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PRODUCER ADOPTION OF GENETICALLY MODIFIED CORN AND ITS IMPACT ON AVERAGE U.S. CORN YIELDS

by

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U.S. average corn yields have been on a steady rise since the early 1900's. This rise has been attributed to many factors including improved breeding practices, machinery, nutrient management, more efficient tillage, and many other factors. Among some of the more recent advancements that may be attributed to increasing yields is the introduction of genetically modified corn varieties. The goal of this research is to determine whether or not the adoption of these genetically modified corn varieties has had a significant effect on average U.S. corn yields. Other similar studies have been done in this area (Xu, Hennessy, & Moschini, 2010) (Zulauf & Hertzog, 2011), but this research is unique in that it examines these factors on a much broader national level and analyzes all categories of biotech corn varieties as a whole, as well as individually. This study uses the Ordinary Least Squares (OLS) method to analyze five models, one lumping them all together in one Total Biotech variable, three evaluating each individual type of biotech variety in separate models, and the fifth model evaluating all three biotech variety types individually in the same model. Both t and F tests were utilized to test our hypotheses and determine the statistical significance of the explanatory variables in question. The analysis found that only one of the four tested explanatory variables (Insect Resistant) was statistically significant in explaining the variation in U.S. corn yields. In light of the results, a lot can still be said for the benefits of genetically modified corn. It helps reduce cost of chemical, fuel, equipment wear, and can improve grain quality, among many other benefits.

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CHAPTER 1

INTRODUCTION

Over the past 50 years, U.S. corn yields have been on a steady rise. This rise can be attributed to many factors, including better land management practices such as crop rotation and tillage practices, improved breeding practices, more efficient equipment such as precision planting equipment and combines capable of mitigating higher levels of harvest loss, and better nutrient management plans and fertilizer application equipment. Another factor that may be attributed to this steady rise in average corn yields is the introduction of genetically modified corn traits.

The first genetically modified corn trait, *Bacillus thuringiensis,* or Bt, was approved by the Environmental Protection Agency for use in corn in 1995 (USDA Agricultural Research Service, 2016). *Bacillus thuringiensis* is a bacterium found in soil throughout the world that naturally produces crystal-like proteins that selectively kill a few specific species of insects. This bacterium was introduced into the corn plant to control for the European Corn Borer and Corn Rootworm, both of which have devastating effects on corn yields (Hellmich & Hellmich, 2012). Over the last two decades many advancements have been made in the field of biotechnology. Genetic modification has expanded to most of the largely cultivated crops that we grow today. These include common row crops like corn, soybeans, wheat, rice, cotton, and other crops like potato, papaya, and sugar beets (Fernandez-Cornejo, Wechsler, Livingston, & Mitchell, 2014).

From 1995 and on, an increasing number of traits have been introduced into commercially available seed corn products. The functions of these traits range from herbicide and insecticide tolerance to drought tolerance. All of these traits were introduced into the plant to counteract some sour of biotic stress such as weeds, pathogens, and insect pests, or abiotic stress such as temperature, precipitation, compaction, and many others.

The first introduction of biotech corn consisted of low numbers of single trait varieties such as insect resistant, herbicide tolerant, and drought tolerant varieties. The numbers of each of these types of varieties continued to grow until stacked varieties, containing multiple resistant genes, were more widely introduced in the mid to late 2000's. Since then, stacked trait varieties have become the predominant choice of producers, with 80% of corn acres in 2018 planted with stacked trait varieties. Overall, the popularity of GM corn has significantly grown since their introduction with 92% of U.S. corn acreage being planted with GM corn in 2018 (USDA ERS, 2019).

While these traits can be greatly beneficial to producers and consumers alike, GM crops were not widely grown for a number of years after their introduction. It wasn't until the early 2000's, nearly ten years after their introduction, that GM crops began to be widely planted and accepted across the United States. This is most likely due to resistance to change, skepticism of these new products' effectiveness, trade approvals, and other political and public perception issues.

The goal of this research is to determine whether or not the introduction and adoption of genetically modified corn traits has had a statistically significant effect on average U.S. corn yields. Since the year 2000, the United States has seen a very significant increase in the percentage of acres planted in biotech traited corn varieties. The objective of this study is to determine the degree of significance that this increase in planted biotech acres has had in explaining the constant increase in the U.S. corn yield trend. Another goal of this research is to explore and show whether or not the introduction and adoption of biotech corn has had a statistically significant impact on the absolute percent variation of yield from the U.S. corn yield trend. This research is important because it can be used to justify producers' adoption of traited corn varieties, help analyze producers' returns on investments, and further explain the increasing trend in U.S. average corn yields.

Similar research has been done in this area examining the effects of drought tolerant traits on corn yields in the western corn belt where rain can be scarce (McFadden, Smith, & Wallander, 2018), examining consumer purchasing behavior and preferences (Yoo, 2012), and directly comparing genetically modified versus non-genetically modified corn yields to determine whether or not the biotech traits had an effect (Taheripour, Mahaffey, & Tyner, 2015). This research is different because it is examining whether or not the percentage of acres planted with biotech corn has had a statistically significant effect on the U.S. average corn yield overall. This research will also explore whether or not the introduction of biotech corn in the U.S. has decreased the absolute percent variation from trend from the period before it was introduced.

CHAPTER 2

REVIEW OF LITERATURE

United States average corn yields have been increasing, relatively steadily, since approximately the year 1940. This is due, in large part, to the introduction of modern breeding techniques, improved equipment, and improved cropping systems. More recently, researchers have speculated whether or not biotech seed traits have attributed to this rise in yield as well. Many studies, similar to this one, have been conducted in the past two decades to determine if this continuous upward trend in average yields can be partially attributed to the introduction of these biotech seed traits.

One such study was conducted at the University of Illinois in 2011. In this study Zulauf and Hertzog (2011) compare the U.S. average yield trends from 1940 to 1945, a period before biotech seeds were introduced, to the period from 1996 to 2011, the period after they were introduced. The authors chose the year 1940 because it is around the time when US average crop yields began to increase, partially due to traditional breeding methods as stated earlier. Yields per harvested acre were obtained for corn, all cotton, soybeans, and 11 crops for which adoption of biotechnology varieties is limited or non-existent. The study found that 7 of the 14 crops analyzed in this study had estimated yield trends that were higher during 1996-2011 than 1940-1995. The 7 crops are corn, cotton, soybeans, barley, peanuts, rice, and sugar beets. For each of the 7 crops, the yield trend for 1996-2011 exceeds the high end of the 95% confidence range for the 1940- 1995 yield trend. This finding suggests that, for these 7 crops, the 1996-2011 yield trend exceeds the 1940-1995 yield trend with 95% statistical confidence.

These findings are important because it shows that the yield trend increased for all 3 widely adopted biotech crops and increased for less than half of the crops (4 of 11) for which biotech varieties are not as widely used. This finding does not prove that biotechnology is the reason for the higher yield trend for corn, cotton, and soybeans. It only shows that the evidence on linear yield trends is not inconsistent with this kind of conclusion. It is possible that with more years of data to observe, a better conclusion can be made with more confidence (Zulauf, 2011). This research is very similar to that conducted by Zulauf and Hertzog in 2011; however, their research examines yields from two sets of time series data, and only accounts for five years in each period. The two examined time periods are significantly different in terms of technology and farming practices. This research examines yields from 1970 to 2018 compared to biotech corn acres from 1996-2018, a much larger sample size, which may make the results more accurate. Furthermore, the continuous time series analysis more accurately represents the changes throughout the time period.

Research by the USDA has been done to breakdown the yield trend effects between the different types of biotech genes in corn, cotton, and soybeans. In this article, the authors Fernandez-Cornejo (2014) examine the adoption trends of herbicide tolerant (HT), Bacillus thuringiensis (Bt), and stacked trait row crop seed and the reasons for these trends. The first genetically engineered (GE) crops became commercially available in 1996. Over about a 15-year period, 1996 to 2013 (when this article was released), the adoption of GE seed by U.S. producers has been on a steady rise.

It was found that U.S. producers tend to adopt HT seed more than seed with insect resistance (Bt) because weed pressure is a very pervasive problem compared to insect pressure. HT adoption was more rapid in soybeans with producers planting 93% of their acres in HT soybeans in 2013. HT cotton was planted on 82% of acreage and HT corn accounted for 85% on U.S. corn acreage in 2013 as well. These percentages are compared to Bt cotton acreage of 75%

Bt seeds have been adopted at a lower rate because of the tendency for insect infestations to be more localized compared to weed pressure.

Not surprisingly, adoption of stacked seed varieties has increased much more quickly than single resistance seed (HT only or Bt only). Use of stacked corn grew from 1% of planted acres in 2000 to 71% in 2013. This is due to the 37-bushel average increase from conventional corn to stacked gene corn as examined by a 2010 ARMS study (Fernandez-Cornejo, Wechsler, Livingston, & Mitchell, 2014). A factor deterring producers from adopting these GE seeds is the cost. The cost of GE soybeans and corn seed grew by 50% (adjusted for inflation) from 2001 to 2010. The increase in price can be attributed to improvement in seed genetics (germplasm). It costs biotech companies quite a bit of money, time, and resources to develop these traits and bring them to market. This cost is reflected in the price of a bag of seed.

Though some researchers found a significant yield increase from conventional to GE seed, some researchers found no significant difference. Despite this, GE seed continues to be adopted. The reason for this is the other added benefits that GE seeds bring besides yield increase. One of the larger benefits include the improved flexibility and simplicity of weed control for GE crops. This allows producers to spend more time pursuing other off-farm income opportunities or to simply enjoy more leisure time. Economic Research Service research shows that HT adoption is directly associated with off-farm household income for U.S. soybean farmers (Fernandez-Cornejo, Wechsler, Livingston, & Mitchell, 2014).

Studies based on field trials and on-farm surveys have examined the extent of the effect of GE crop adoption has on pesticide use, and most results show that there has been a significant reduction in pesticide use overall. A 2010 National Research Council study showed similar evidence that GE crops lead to reduced pesticide use and/or the use of pesticides with lower toxicity compared to pesticides used on conventional crops (Fernandez-Cornejo, Wechsler, Livingston, & Mitchell, 2014). Generally, Bt gene adoption can be associated with decreased levels of insecticide use. Insecticide use trends suggest that insect infestation levels on corn and cotton farms were lower in 2010 than in earlier years and are consistent with the fact that European corn borer populations have steadily declined over the last decade. In addition, several researchers have shown that areawide suppression of certain insects such as the European corn borer and the pink bollworm are associated with Bt corn and Bt cotton use, respectively. This suggests that Bt seeds have benefited not only producers who have adopted them but producers who have not adopted the GE varieties as well.

It seems that the adoption of GE crops is on a steady rise and shows no sign of slowing down. New HT and insect resistance traits may give producers more pest management options and help to slow the increasing amount of pesticide resistance in some pest populations, especially weeds like waterhemp and Palmer amaranth. Approval of new traits that increase yields or reduce yield losses could result in the continued and increased adoption of these traits by U.S. producers. As more "second generation" traits, or traits that alter the quality of the end product become approved. Producers should and will be more cautious when considering their adoption. Producers will no doubt benefit from these traits but need to wait for assurance of consumer acceptance of these traits. In short, the future of GE seed use depends on the ability of farmers to adopt best management practices, the ability of biotech companies to develop new GE varieties, and consumer acceptance of products from GE sources (Fernandez-Cornejo et al., 2014).

McFadden, Smith, and Wallander (2018) examine the recent adoption of drought tolerant (DT) corn hybrids in the U.S. The authors recognized that U.S. producers have historically had very few options for reducing risk from increasing drought frequency and intensity. However, one increasingly available option is the adoption of DT corn varieties. Just over 22% of U.S. corn acres were planted to DT corn varieties in 2016 (McFadden, Smith, & Wallander, 2018). This was very rapid adoption considering DT trait varieties were commercialized during the 2011-2012 season. They determine how drought risk and recent drought exposure has led to the widespread adoption of these traits. The analysis of the data is motivated by a framework dependent on each state that accounts farmers' beliefs about future drought and based on passed drought risk and exposure.

McFadden, Smith, and Wallander's analysis of the data shows that exposure to drought in 2013 and 2014 led to an increase in adoption of DT varieties in 2016. Many of these 2016 DT corn acres consisted of dry regions in the Western Corn Belt, especially Kansas and Nebraska, though they were also planted across and beyond the traditional Corn Belt. It was also found that the adoption of these varieties was stronger in areas with higher drought severity in 2013 and 2014. Recent evidence suggests that the 2012 drought did not significantly affect agricultural advisors' climate change beliefs or adaptation attitudes. However, advisers indicated greater concern about risks from pests and drought arising from 2012 yield damages.

One issue with their analysis is that they were not able to calculate an average short-run effect of drought exposure on DT corn adoption. Since adoption data were only available for 2016, they could not completely isolate short-run drought effects from circumstances surrounding the 2012 or adjacent- year droughts. This is of less concern if shocks similar in magnitude, timing, and duration to the 2012 drought are not exceptionally rare events, which they deemed unlikely under climate change (McFadden, Smith, & Wallander, 2018)

CHAPTER 3

DATA

The goal of this data analysis as to determine whether or not the adoption of biotech seed traits has had a significant impact on the upward trend in average U.S. corn yields. In other words, percent biotech acres planted, and June, July, and August average temperatures were tested against average yearly U.S. corn yields to determine whether or not biotech corn acres were statistically significant in explaining the average yield's deviation from trend. In this case we are trying to see if the adoption of biotech traits has contributed to the upward trend in yields, or positive deviation from trend.

The research procedures for this yield deviation analysis required data to be collected on U.S. average corn yield from 1970 to 2018, which was given in bushels per acre. This data set reflects the average U.S. corn yield trend from 1970 to 2018. It also required data for the average temperature and precipitation in the months of June, July, and August from 1970 to 2018. The data for temperature was measured in degrees Fahrenheit and precipitation in inches. These data sets needed to be compared against the data for percentage of acres planted in biotech corn from 2000 to 2018. The temperature and precipitation data are required to test if the percentage of biotech acres planted is statistically significant in explaining the corn yield deviation from trend, all else equal. The 2000 to 2018-time horizon represents the most complete data collection on percent biotech corn acreage (biotech crops were not introduced until 1996).

The U.S. average corn yield and June, July, and August yearly average precipitation data was collected from the USDA National Agricultural Statistics Service (NASS) website. There, yield and weather data, and many other types of data, is readily available to the public. The yearly U.S. percent of biotech corn planted data was collected from the USDA Economic

Research Service (ERS) website. The ERS collected the data to analyze the amount of biotech corn, cotton, and soybeans that had been planted in the U.S. from 2000 to 2019. The data for 2019 was left out because the 2019 data for the other data sets had not been recorded at the time of this analysis.

CHAPTER 4

METHODS

The regression method used in this data analysis was the ordinary least squares (OLS) multiple linear regression model. The goal of multiple linear regression is to model the linear relationship between the independent, or explanatory variables and the dependent, or response variable. Essentially, a multiple regression model is the same as an ordinary least-squares regression model, but it involves more than one explanatory variable. The OLS estimator will be utilized to determine coefficients for the explanatory variables. The OLS method is used for estimating unknown parameters in linear regression models. The objective of the OLS estimator is to minimize the error sums of squares.

A number of assumptions are needed to effectively use the OLS estimator. The first assumption is the model is linear in parameters. This means that the dependent variable is a linear function of independent variables and the error term. Secondly, the number of observations must be larger than the number of parameters in the model. The third assumption is the sample of observations must be random as to not have any biases in the data. Assumption four is conditional mean should be zero, meaning there must be no relationship between the X's and the error term. Next is the fifth assumption of homoscedasticity meaning all of the error terms in the regression have the same variance. Assumption six is no auto correlation between the error terms and the seventh and final assumption is no multicollinearity. Multicollinearity is correlation among explanatory variables. Given these assumptions, the model for this research is expressed as:

(1) $Yield = \alpha + \beta_1\,(yield\ trend) + \beta_2(June\ temp.) + \beta_3(June\ precip.) + \beta_4(July\ temp.) + \beta_5(July\ precip.) + \beta_6(August\ temp.) + \beta_7(August\ precip.) + \beta_8(All\ Biotech) + \mathcal{E}_i$

In equation 1, U.S. corn yield is set as a function of its eight independent variables. The expected signs for the coefficients for June precipitation, July precipitation, August precipitation, June temperature, and trend are all positive. Intuitively we would expect for every 1 inch of precipitation in June, July, and August, respectively, the yield would increase by some amount. This can be assumed because we know that these are vital months where precipitation is needed to assist in plant and kernel development. We can also expect that for every 1-degree Fahrenheit increase in June temperature, there will be some amount of increase in yield. Conversely, we can expect the sign of the coefficients for July and August temperatures to be negative. We know that this is because excess heat in these months can be damaging to plant growth and kernel development.

The coefficient for trend, we can strongly expect to be positive, because we know from the data that average yields have in fact increased over the last fifty years. Finally, the coefficient for the variable of interest in this study, All Biotech, we expect to be positive. However, we do not know to what degree that will be and whether or not it will be significantly significant.

In running this regression model, we will use many approaches to interpret the effect of each independent variable on the dependent variable of corn yield in the United States. We will interpret the estimates to determine the effect of each variable on yield. Next, we will conduct a t-test and then use the T-statistic to determine significance or insignificance of each variable. Following that, R-squared can be used to determine how much of the variation in corn yields is explained by all of the variables as a whole. An F-test will also be utilized to explain variation in corn yield as explained by the eight explanatory variables. Hypothesis tests for this study can be expressed as:

Null Hypothesis	Alternative Hypothesis
H_o: $\beta_{Trend} = 0$	H_a: $\beta_{Trend} \neq 0$
H_o: $\beta_{AllAcresBiotech} = 0$	H_a: $\beta_{PercentAcresBiotech} \neq 0$
H_o: $\beta_{JunePrecipitation} = 0$	H_a: $\beta_{JunePrecipitaiton} \neq 0$
H_o: $\beta_{JulyPrecipitation} = 0$	H_a: $\beta_{JulyPrecipitation} \neq 0$
H_o: $\beta_{AugustPrecipitation} = 0$	H_a: $\beta_{AugustPrecipitation} \neq 0$
H_o: $\beta_{JuneTemperature} = 0$	H_a: $\beta_{JuneTemperature} \neq 0$
H_o: $\beta_{JulyTemperature} = 0$	H_a: $\beta_{JulyTemperature} \neq 0$
H_o: $\beta_{AugustTemperature} = 0$	H_a: $\beta_{AugustTemperature} \neq 0$

Additional regression models will be used in this research to compare further subsets of biotechnology acreage data with yields to determine whether a specific type trait has contributed to the increase in corn yields. These biotech subset groups include herbicide tolerant, insect resistant, and stacked trait varieties. The models for these regressions will be expressed in the following figures:

(2) $Yield = \alpha + \beta_1\,(trend) + \beta_2(June\ temp.) + \beta_3(June\ precip.) + \beta_4(July\ temp.) + \beta_5(July\ precip.) + \beta_6(August\ temp.) + \beta_7(August\ precip.) + \beta_8(Herbicide\ Tolerance) + \mathcal{E}_i$

(3) $Yield = \alpha + \beta_1\,(yield\ trend) + \beta_2(June\ temp.) + \beta_3(June\ precip.) + \beta_4(July\ temp.) + \beta_5(July\ precip.) + \beta_6(August\ temp.) + \beta_7(August\ precip.) + \beta_8(Insect\ Resistance) + \mathcal{E}_i$

(4) $Yield = \alpha + \beta_1\,(yield\ trend) + \beta_2(June\ temp.) + \beta_3(June\ precip.) +$

$\beta_4(July\ temp.) + \beta_5(July\ precip.) + \beta_6(August\ temp.) + \beta_7(August\ precip.) +$

$\beta_8(Stacked) + \varepsilon_i$

Each of the previously stated regression models are identical to the original model with each new explanatory variable substituted for the original variable (percent biotech). We decided to run a fifth regression model to test each individual biotech category in the same regression. The model for this regression is expressed in the figure below:

(5) $Yield = \alpha + \beta_1\,(yield\ trend) + \beta_2(June\ temp.) + \beta_3(June\ precip.) +$

$\beta_4(July\ temp.) + \beta_5(July\ precip.) + \beta_6(August\ temp.) + \beta_7(August\ precip.) +$

$\beta_8(Herbicide\ Tolerance) + \beta_9(Insect\ Resistance) + \ \beta_{10}(Stacked) + \ \varepsilon_i$

All the statistical analysis testing for the new models will be identical to the original model. F-test, t-test, and adjusted R squared will all be examined to determine each variable’s statistical significance in explaining U.S. corn yields.

CHAPTER 5

RESULTS

The regression results for all models are shown in tables 2 and 3 of the appendix. The coefficients are interpreted relative to the average U.S. corn yield in bushels per acre for each year. First and foremost, the estimates are interpreted using the estimated coefficient from table 3 in the appendix. The coefficients for model 1 are defined as follows: β_{Trend}= each additional year, yield increases by 1.665 bushels per acre; $\beta_{\text{AllBiotech}}$= for every 1% increase in total percentage of acres planted with biotech corn, yield increases by 0.091 bushels per acre; $\beta_{\text{JunePrecipitation}}$= for every 1 inch increase in June precipitation, yield increases by 0.216 bushels per acre; $\beta_{\text{JulyPrecipitation}}$= for every 1 inch increase in July precipitation, yield increases by 1.946 bushels per acre; $\beta_{\text{AugustPrecipitation}}$= for every 1 inch increase in August precipitation, yield increases by 1.598 bushels per acre; $\beta_{\text{JuneTemperature}}$= for every 1 ºF increase in average June temperature, yield increases by 0.283 bushels per acre; $\beta_{\text{JulyTemperature}}$= for every 1 ºF increase in average July temperature, yield decreases by 2.352 bushels per acre; $\beta_{\text{AugustTemperature}}$= for every 1 ºF increase in average August temperature, yield decreases by 1.612 bushels per acre.

For the next three models, the important coefficients to note are for the insect resistant, herbicide tolerant, and stacked gene explanatory variables. These coefficients are defined from table 3 as follows: model 2; $\beta_{\text{InsectResistant}}$ = for every 1% increase in acres planted with insect resistant corn, yield increases by 0.254 bushels per acre. Model 3; $\beta_{\text{HerbicideTolerant}}$ = for every 1% increase in acres planted with herbicide tolerant corn, yield increases by 0.241 bushels per acre. Model 4; β_{Stacked} = for every 1% increase in acres planted with stacked gene corn varieties, yield increases by 0.03 bushels per acre. The coefficients for model 5 are represented in table 3 as follows: $\beta_{\text{HerbicideTolerant}}$ = for every 1% increase in acres planted with herbicide tolerant corn, yield decreases by 0.665 bushels per acre; $\beta_{\text{InsectResistant}}$ = for every 1% increase in acres planted with insect resistant corn, yield increases by 0.858 bushels per acre; β_{Stacked} = for every 1% increase in acres planted with stacked gene corn, yield increases by 0.259 bushels per acre.

The next step is to define the significance or insignificance of each variable using a t-test. With degrees of freedom being 48 and level of significance being .05 for all four models, the t critical value was established at -2.0106 and 2.0106. With those values in mind, every t statistic in the regression results that falls between the critical values, we fail to reject. Likewise, every t statistic falling outside -2.0106 and 2.0106, we reject. The respective t-values for each variable can be found in Table 3 of the appendix. For three of the variables in Model 1, we are able to reject the null hypothesis. These variables are July temperature, August temperature, and trend. These variables are the ones showing a significant effect on yearly average corn yields. July temperature and August temperature both show a negative significant effect while yield trend shows a positive significant effect. These effects can be shown in Figures 1, 4, and 5 of the appendix. For Model 5, there was one variable the was statistically significant. This variable was Insect Resistance, which has a positive significant effect on corn yields. It is also worth noting that Stacked Gene was marginally significant with a t-statistic of 2.0003975. As for the rest of the variables in each model, we failed to reject the null hypothesis. This means that the t statistic for each variable fell between the critical -2.0106 and 2.0106.

The next method of analysis that is crucial to interpreting this research is the R-squared interpretation. As a general rule of thumb, we will examine the adjusted R^2 because it accounts for the number of predictors in the model, thus making the analysis slightly more accurate. The adjusted R^2 for Model 1 shown in table 2 is expressed as 0.919. This means that 91.9% of variation in corn yields can be explained by the independent variables in Model 1, which includes the total percentage of acres planted with all biotech varieties of corn. The adjusted R^2 for Model 2 is expressed as 0.921. This means that 92.1% of variation in corn yields can be explained by insect resistant varieties and the other independent variables in the model. For Model 3, the adjusted R^2 is expressed as 0.918, or 91.8% of variation in corn yields can be explained by herbicide tolerant varieties and the other independent variables in the model. The adjusted R^2 for Model 4 is expressed as 0.917, or 91.7% of variation in corn yields can be explained by stacked gene varieties and the rest of the independent variables in the model. Finally, the adjusted R^2 for Model 5 is expressed as 0.924, or 92.4% of variation in corn yields can be explained by the independent variables in this model.

In addition to examining the R^2, an F-test was conducted for all models to test the R-squared. This is used to determine if R^2 is equal to zero. With degrees of freedom being identified as (8,40), level of significance set at .05, a critical value of 2.18, and F being calculated as 69.4985, the null hypothesis of $R^2 = 0$ is rejected for Model 1. This agrees with the R-squared test that 91.9% of variation in U.S. corn yield can be explained by the variables examined in this study. The other three models produced the same result.

CHAPTER 6

DISCUSSION

This study presents an analysis of factors affecting average U.S. corn yields over the last 48 years, and more specifically, the last 22 years since biotechnology was introduced. This 48-year data set was chosen due to the availability of data. It was also chosen because of the significant sample size to give the analysis a more accurate result. The data set includes yield, temperature, and precipitation data from 1970 to 2018 including the dependent variable, average corn yield, along with seven independent variables.

The second data set includes the percentage of acres planted with each type of biotech corn from 1996-2018. The main objective of this analysis was to determine if the adoption of these biotech varieties has contributed to the increasing trend in U.S. corn yields. The data was analyzed using a multiple linear regression, which recognized three of the explanatory variables as statistically significant in explaining yield. These variables were July temperature, August temperature, and Trend.

None of the biotech variables that we were testing in models one through four were statistically significant in explaining average corn yields; however, their coefficients had the correct signs that we had predicted. This tells us that these variables may have a slightly positive effect on average corn yields, but they are not significant enough that we can say for sure.

The only variables with statistical significance were July and August Temperatures and the yield trend. These data sets are visually represented in Figures 1, 4, and 5 of the appendix. You can see in Figures 4 and 5 that July and August temperatures have a nearly perfect inverse relationship with corn yields. When July and August temperatures are low, yield is high and when July and August temperatures are high, yield is low. These figures give a great visual representation of their relationship. For Model 5; however, one additional independent variable was found to be statistically significant. This variable was Insect Resistance. Stacked Gene varieties were also found to be marginally significant with a t-statistic of 2.0003975. While these variables in Model 5 proved to be more statistically significant than in their counterparts in three of the other models, their coefficients were not nearly as large. A one percent increase in acres planted with insect resistant corn only increases yield by 0.858 bushels per acre. Likewise, with Stacked Gene varieties, a one percent increase in acres planted with stacked gene corn only increases yield by 0.259 bushels per acre.

Model 5 seems to show the best results for our study of each biotech corn variety. Adding each individual biotech category into the same regression model may have provided a more accurate result. All three categories had larger coefficients and larger t-statistics than each of the individually tested variables in Models 2 through 4. One very interesting result of this model was that the sign of the coefficient for Herbicide Tolerant varieties was negative, suggesting that these varieties have a negative effect on corn yields. Model 5 also had the largest adjusted R^2 value at 0.924, which further solidifies this model as being the most accurate of each model that was tested.

While insect resistant varieties were the only statistically significant variety in explaining yield variation, there are many advantages to planting all types of biotech corn varieties. A lot can be said for genetically modified corn when it comes to other aspects of raising a healthy corn crop. After all, there must be some reason why producers continue to utilize traited corn in their fields, year in and year out. One of the greatest advantages of GM corn is the ability to utilize herbicides for weed control. This technology saves producers in time and labor expenses and reduces competition for water and nutrients between weeds and corn plants. The benefits of this technology may not increase yields, but they most likely result in a reduction in potential yield loss due to the decreased plant competition.

Another advantage of GM corn is the resistance to insects. Insects cause large amounts of yield loss and crop destruction every year. Insect resistant corn varieties can greatly reduce yield loss caused by insects like corn earworm, European corn borer, and other insects that are detrimental to corn plant health and yields. Insect resistant varieties also contribute to plant health and yield loss reduction by protecting against ear molds that enter the ear through sites of insect damage. This helps to improve yields and overall grain quality and greatly reduces exposure to mycotoxins for corn end users like swine producers. Insect resistant varieties also greatly reduce or completely eliminate the need for insecticides. This saves producers money in chemical, fuel, equipment wear, and time. All of which are very valuable things in row crop production.

Now that we know that not all biotech corn varieties have a statistically significant effect on average corn yields, we may have a clearer picture of what variables should be tested in similar future research to determine why U.S. corn yields continue to increase. Things like improved planting and harvesting equipment, better nutrient management and prescription tools, seed treatments, and many other practices and tools may be subject of interest in future research. This research can also be used to justify the adoption of GM corn in future GMO versus Non-GMO debates and conversations.

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APPENDIX

Table 1: Yield/Biotech/Weather Data for Corn in United States, 1970-2018

Year	Average corn yield (bu/ac)	Average June Temp. (°F)	Average July Temp. (°F)	Average August Temp. (°F)	Average June Precip. (in)	Average July Precip. (in)	Average August Precip. (in)	All Biotech Acreage (%)
1970	72.4	70.2	74.6	73.2	3.72	3.29	2.80	0
1971	88.1	73.7	71.3	71.2	3.83	3.90	2.09	0
1972	97.0	68.4	72.5	71.8	3.55	4.59	3.80	0
1973	91.3	71.3	74.2	73.9	3.85	4.31	2.51	0
1974	71.9	67.5	76.7	70.0	4.18	1.85	4.24	0
1975	86.4	69.9	74.5	73.8	4.99	2.38	4.40	0
1976	88.0	70.3	74.6	71.6	3.07	2.81	1.77	0
1977	90.8	70.5	76.5	70.3	3.29	3.52	5.90	0
1978	101.0	70.3	73.9	72.2	3.41	4.51	3.36	0
1979	109.5	69.4	72.9	71.2	3.68	4.71	4.93	0
1980	91.0	69.9	77.2	74.6	3.92	2.64	5.46	0
1981	108.9	71.1	74.2	71.0	4.65	4.88	4.69	0
1982	113.2	65.5	74.7	70.9	3.60	4.41	3.62	0
1983	81.1	69.4	77.4	77.6	4.48	2.39	2.41	0
1984	106.7	71.5	72.8	74.0	4.53	3.16	1.98	0
1985	118.0	67.4	73.5	69.6	3.32	3.19	4.28	0
1986	119.4	71.7	76.1	69.2	4.25	4.63	3.24	0
1987	119.8	72.7	76.1	71.7	3.18	4.28	4.80	0
1988	84.6	73.4	76.1	75.7	1.44	2.83	3.28	0
1989	116.3	68.5	75.0	71.7	3.84	3.64	3.58	0
1990	118.5	71.0	73.0	72.0	5.32	4.55	3.87	0
1991	108.6	73.2	74.7	73.0	3.16	2.88	2.88	0
1992	131.5	67.0	70.3	67.3	3.02	6.72	3.15	0
1993	100.7	67.9	73.7	72.7	6.39	6.87	4.91	0
1994	138.6	72.0	72.1	69.9	4.57	3.97	3.54	0
1995	113.5	70.3	74.8	76.6	3.43	3.34	3.68	0
1996	127.1	70.3	71.6	71.5	4.45	3.97	3.13	5
1997	126.7	70.1	73.9	70.2	4.03	3.19	3.69	10
1998	134.4	68.9	74.6	73.6	6.17	3.76	3.76	15
1999	133.8	69.8	77.0	71.4	4.76	3.75	2.96	20
2000	136.9	68.9	73.0	73.5	5.36	3.88	2.84	25
2001	138.2	69.2	75.3	73.7	3.74	3.57	3.23	26
2002	129.3	72.8	77.1	73.0	3.40	3.00	4.42	34
2003	142.2	67.5	74.2	74.6	4.22	4.08	2.40	40
2004	160.4	67.8	71.8	67.9	3.92	4.36	3.90	47
2005	148.0	72.7	75.4	73.2	4.02	3.33	3.69	52
2006	149.1	70.6	76.5	73.2	3.27	3.36	4.52	61

2007	150.7	71.0	73.7	75.1	3.41	3.01	6.06	73
2008	153.9	70.4	73.9	71.0	5.88	4.36	2.30	80
2009	164.7	69.6	69.7	69.9	4.64	3.83	4.37	85
2010	152.8	72.2	75.8	75.5	7.22	5.45	3.44	86
2011	147.2	70.8	78.5	73.5	4.59	3.70	3.00	88
2012	123.1	72.0	79.8	72.3	2.29	1.97	2.88	88
2013	158.1	70.0	73.1	72.3	4.89	2.88	2.27	90
2014	171.0	70.9	70.3	72.3	7.33	2.88	4.77	93
2015	168.4	70.4	73.3	70.8	6.38	4.76	3.66	92
2016	174.6	72.9	74.6	73.8	3.35	5.13	5.42	92
2017	176.6	71.3	75.1	69.4	3.54	3.98	3.86	92
2018	180.7	73.2	74.2	73.0	5.93	3.82	4.83	92

Table 2: Model Summary

Model Summary			
Model	R^2	Adjusted R^2	Standard Error of the Estimate
1	0.933	0.919	8.338
2	0.934	0.921	8.283
3	0.932	0.918	8.404
4	0.931	0.917	8.487
5	0.940	0.924	8.082

Table 3: Coefficients Summary

Coefficients Summary						
Model		**Estimated Coefficient**	**Coefficients Standard Error**	**t Stat**	**P-value**	**Hypothesis Test Outcomes**
1	Intercept	338.012152	69.9370091	4.83309419	0.00002012	
	June Precipitation	0.21608968	1.20506096	0.17931847	0.85859291	Fail
	July Precipitation	1.94570527	1.37753337	1.412456	0.16554925	Fail
	August Precipitation	1.59770778	1.19470787	1.33732087	0.18867324	Fail
	June Temperature	0.28251518	0.71247902	0.39652421	0.69382593	Fail
	July Temperature	-2.352446	0.68904003	-3.414092	0.00147887	Reject
	August Temperature	-1.6116868	0.66485385	-2.4241219	0.01995866	Reject
	Trend	1.66580031	0.18368063	9.06900379	0.00000000	Reject
	Total Biotech	0.09091291	0.07189003	1.26461088	0.00002012	Fail
2	**Insect Resistant**	0.25399171	0.17325472	1.46600169	0.15046554	Fail
3	**Herbicide Tolerant**	0.24081549	0.24810544	0.97061752	0.33757169	Fail
4	**Stacked**	0.03002277	0.0768332	0.39075256	0.69805363	Fail
5	**Insect Resistant**	0.85841442	0.37664073	2.27913324	0.02836362	Reject
	Herbicide Tolerant	-0.6654387	0.46196584	-1.4404501	0.15792919	Fail
	Stacked	0.25926459	0.12960653	2.00039752	0.05264033	Fail

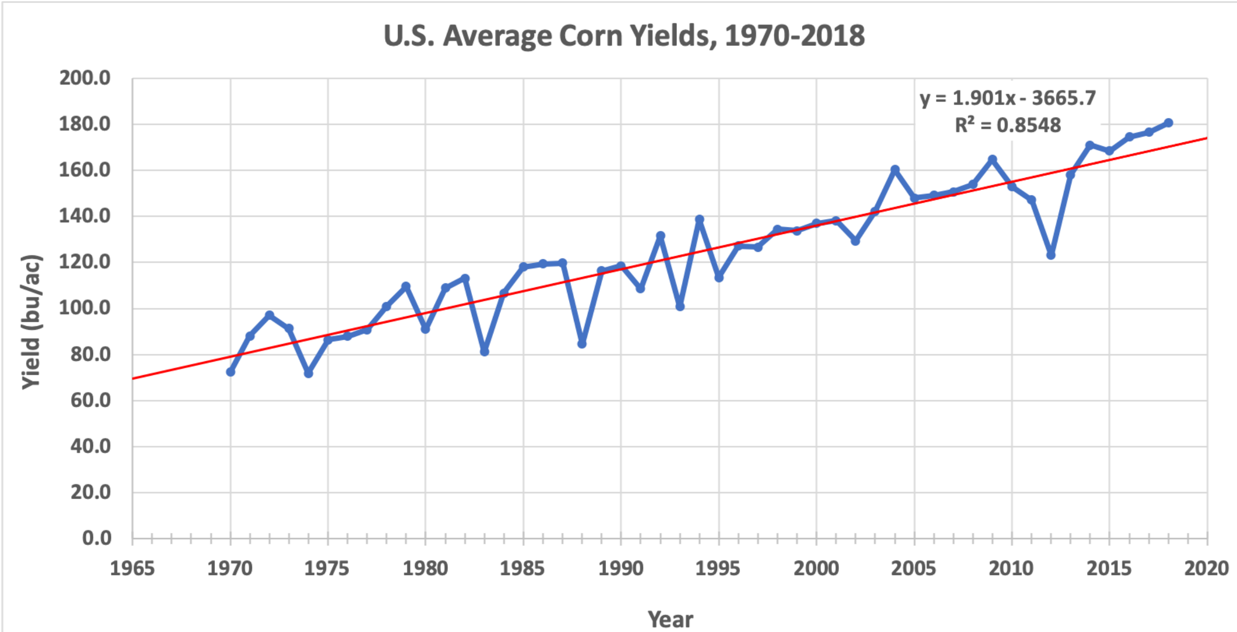

Figure 1: U.S. Average Corn Yields, 1970-2018

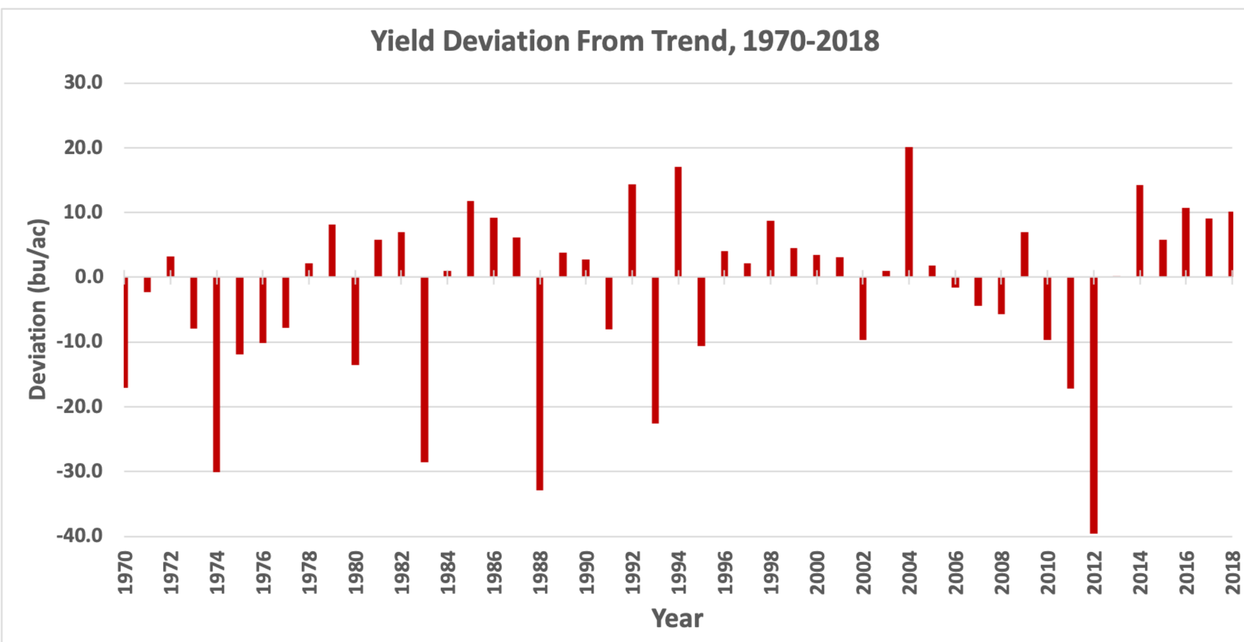

Figure 2: Yield Deviation from Trend, 1970-2018

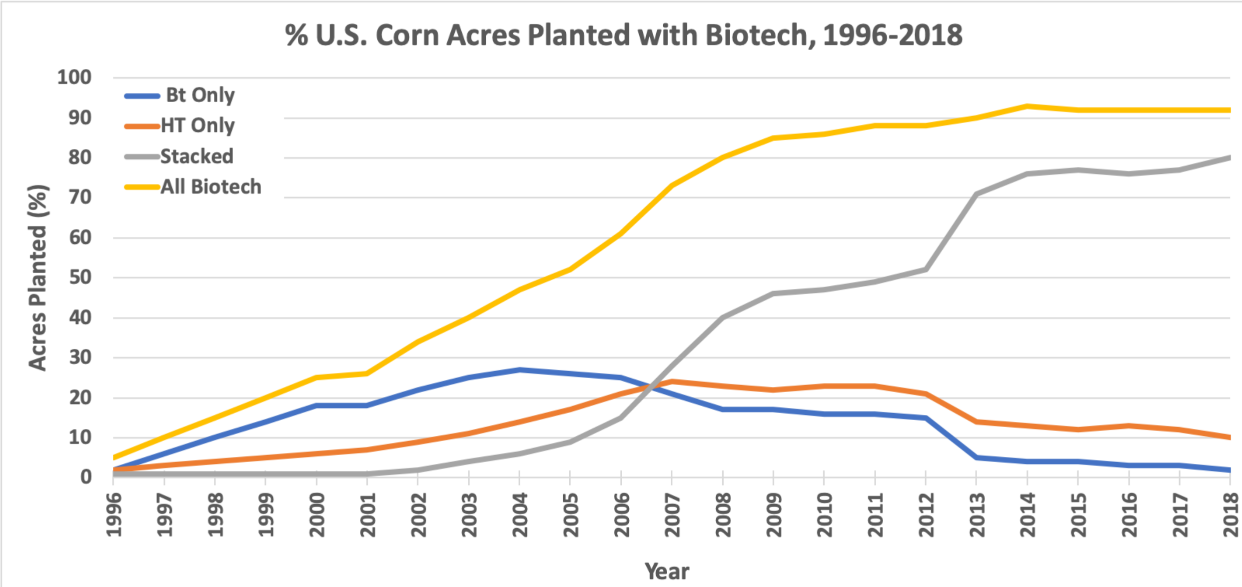

Figure 3: % U.S. Corn Acres Planted with Biotech, 1996-2018

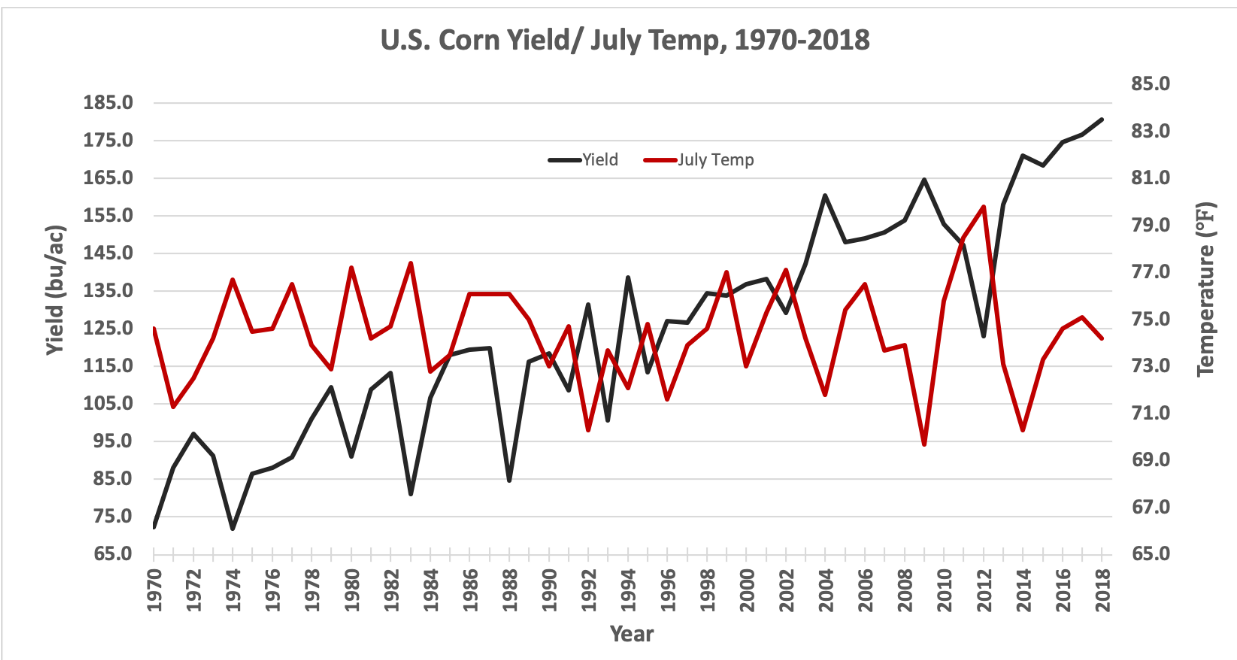

Figure 4: U.S. Corn Yield/ July Temp, 1970-2018

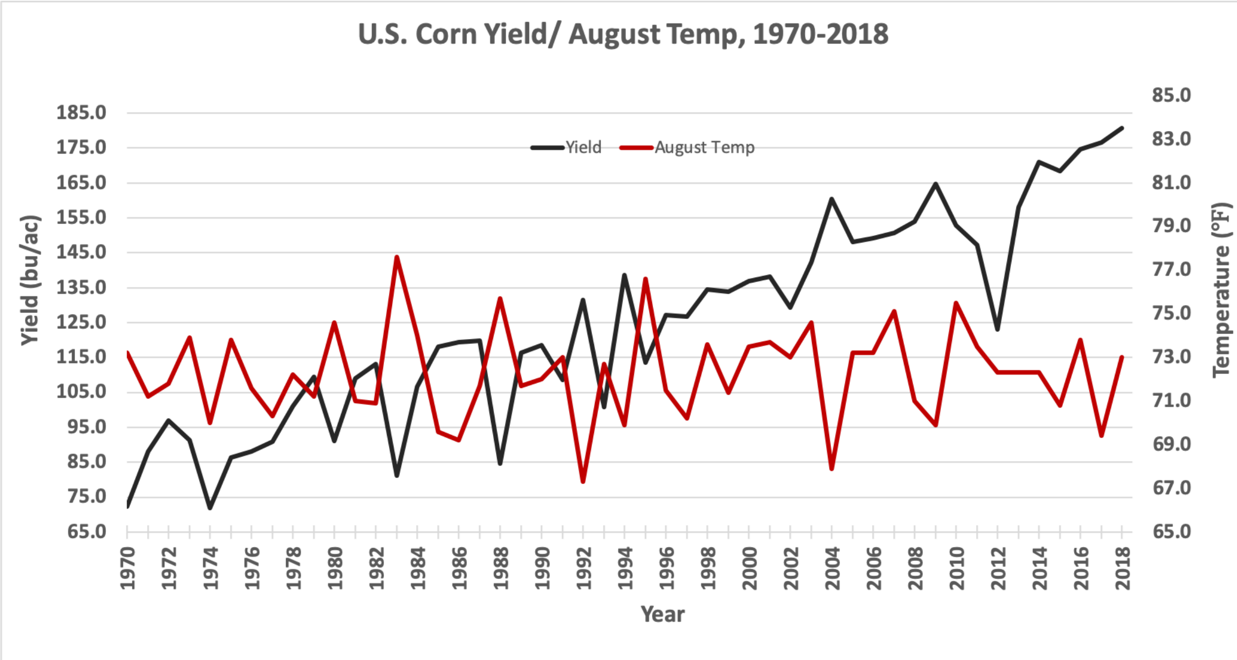

Figure 5: U.S. Corn Yield/ August Temp, 1970-2018

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