THE IMPACT OF BT CROPS ON AFLATOXIN REDUCTION

By

Jina Yu

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food and Resource Economics — Doctor of Philosophy

2019

ABSTRACT

THE IMPACT OF BT CROPS ON AFLATOXIN REDUCTION

By

Jina Yu

Bt seed is a genetically modified organism including proteins toxic to common crop insect pests. It has reduced insecticide usage, saved cost for controlling insects, and increased yield. Multiple experimental studies found that the level of aflatoxin, a fungal toxin that commonly contaminates food crops such as corn and peanuts, can be mitigated by reducing the presence of insects because fungi colonize corn through kernel wounds from insect feeding. However, the relationship between Bt corn and aflatoxin has yet to be examined in field settings, wherein many environmental factors are at play.

In the first essay, I developed a regression model that estimates causal relationships between aflatoxin-related insurance claims and Bt corn adoption rates, drought index, and climatic variables. From 2001-2016, a significant inverse correlation existed between Bt corn planting and aflatoxin-related insurance claims in the United States when controlling for temperature, drought, state, and year. Estimated benefits of Bt corn's aflatoxin reduction were about \$120 million to \$229 million per year in over 16 states on average. These results suggest that Bt corn is an important strategy with corresponding economic benefits for reducing aflatoxin risk in the United States.

Climate change—typically increased temperature—may expand prevalence zones for aflatoxin because warm temperatures and dry conditions are associated with aflatoxin accumulation. The second essay's objectives were to predict both areas with high aflatoxin risks in 2031-2040 based on 16 climate models, as well as the extent of aflatoxin-related economic loss

due climate change. To do so, growing season impacts on aflatoxin risk were modeled by allowing for the adjustment of planting season under different climate scenarios. It was found that more than 89% of corn planting areas are likely to experience increased aflatoxin risks in 2031-2040 when compared to aflatoxin risks from 2007-2016 in the United States. Ignoring health-related costs, aflatoxin-related economic loss was expected to amount to $36 million - $70 million per year.

In the third essay, I examined an additional potential benefit of Bt crops (corn and cotton): a decrease in the incidence of aflatoxin in peanuts (non-Bt crops). the effect of Bt crops should not be limited to the adopted crops, because insects controlled by Bt have a relationship with other crops and insects in the broader ecosystem.–The results indicate that a county with a higher Bt crops adoption rate was less likely to have aflatoxin-related insurance claims in peanuts. This means that, by reducing the incidence of aflatoxin, Bt crops adoption in the United States has saved losses of $0.45 million per year.

Overall, my dissertation study increases current understandings of the unintended effects of Bt in protecting crops from aflatoxin damage in the broader ecosystem. It aims to shed light on the benefits of Bt crops in countries that suffer from aflatoxin-related damage and transgenic seed traits that are not planted. Additionally, this study contributes to improved knowledge about climate conditions that affect either aflatoxin levels or host plants (corn and peanut). As climate change is expected to increase temperature and dryness, it is likely to increase the risk of aflatoxin in the US. Bt crops and new biotechnology are thus expected to play an important role in protecting crops from aflatoxin damage.

ACKNOWLEDGEMENTS

Throughout my PhD program, I have received enormous support and assistance. I would first like to thank my advisor, Dr. Felicia Wu. Her patient guidance and encouragement were invaluable in writing this dissertation. I would also like to express my appreciation to Dr. David A. Hennessy for his constructive comments and assistance. I will always be in his debt for his patience and time. I am also deeply grateful to Dr. Jeffery M. Wooldridge for his professional suggestions and guidance in regard to econometrics. In addition, I warmly thank Dr. Roy Black for his detailed comments and valuable advice.

I also wish to thank my family and friends. Without their emotional support, this dissertation would not have been possible. Most of all, I thank my dear husband, Chankyung Pak for providing emotional and academic support throughout the duration of my PhD program. Everything I have achieved was only possible because of his devotion and love.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

KEY TO ABBREVIATIONS

2SLS	Two Stage Least Squares
AGDD	Accumulated Growing Degree Days
APE	Average Partial Effect
APH	Actual Production History
AWC	Available Water Capacity
Bt	Bacillus thuringiensis
CF	Control function approach
CMIP5	Coupled Model Intercomparison Project Phase 5
CO2	Carbon Dioxide
CRC	Crop Revenue Coverage
CRE	Correlated Random Effect
FDA	The US Food and Drug Administration
GCM	General Circulation Model
GDD	Growing Degree Days
IRM	Insect Resistance Management
NASA	The National Aeronautics and Space Administration
NASS	USDA National Agricultural Statistics Service
NEX-GDD	NASA Earth Exchange Global Daily Downscaled Projections
NOAA	National Oceanic and Atmospheric Administration
RA	Revenue Assurance
RCPs	Representative Concentration Pathways
RMA	Risk Management Agency

RP	Revenue Protection
RPHPE	Revenue Protection with Harvest Price Exclusion
USDA	United States Department of Agriculture
YP	Yield Protection

CHAPTER 1

Introduction

Aflatoxin is a toxic chemical produced by the fungi *Aspergillus flavus* and *A. parasiticus*, which commonly infect corn, peanuts, and tree nuts. Aflatoxin, among all known chemicals including alcohol, is the most potent naturally occurring human liver carcinogen. It also causes immune system suppression, growth impairment in children, and acute toxicity. According to the World Health Organization, it is estimated that 25% or more of the world's food crops are destroyed annually due to aflatoxin contamination (World Health Organization 2018). There are, however, several ways to mitigate aflatoxin contamination, such as breeding resistance in crops to the field conditions that favor fungal infection and biocontrol. Bt corn, a transgenic, or genetically modified, corn that includes proteins toxic to common corn insect pests, can also be used as a tool to mitigate the risk of aflatoxin contamination by reducing kernel wounds from insect feeding.

First commercialized in the United States in 1996, Bt corn has become one of the most commonly grown transgenic crops worldwide. It has been widely planted as it improves yields and reduces insecticide usage in the United States (Wu 2004). However, the effect of Bt corn on insect pests should not be limited to corn production, because insects controlled by Bt have a relationship with other crops, insects, and fungal infections in the broader ecosystem. Multiple experimental studies have found that the level of aflatoxin, a fungal toxin, can be mitigated by reducing the presence of insects, because fungi colonize corn through kernel wounds from insect feeding. However, the relationship between Bt corn and aflatoxin has not yet been examined in field settings, where many environmental factors are at play. Revealing the mechanism whereby Bt corn reduces aflatoxin mediated by temperature and drought can better inform farmers' decision making regarding crop choice. A study design for the field setting calls for consideration of the particular ways environmental factors affect aflatoxin risk and how those factors relate to human decisions. For example, experimental evidence shows that hot summers and drought stress increase aflatoxin levels in corn, which are in turn partially determined by farmers' decisions regarding crop choice and aflatoxin mitigation tool. Therefore, understanding the effect of a risk prevention method, such as Bt corn, necessitates careful research design and methodological innovations that take into account the complexity these multiple factors generate.

To explore the unknown relationship between aflatoxin and environmental factors, I devised the following research questions: (a) Does the Bt gene protect corn from aflatoxin contamination given climate conditions in US?; (b) How does climate change affect the risk of aflatoxin?; (c) In reducing aflatoxin risk, do Bt crops have unintended benefits on other crops in geographically neighboring?; and

My first essay focuses on the relationship between Bt corn and the incidence of aflatoxin. With the assistance of my committee in this work, I hypothesized that Bt corn has a causal relationship with aflatoxin incidence, based on interactions between corn growing stages and environmental factors— temperature and drought, in particular. Through my research, I discovered that counties in the US South with a higher Bt corn adoption rate had lower aflatoxin-related insurance from 2001-2016. The estimated economic benefit of Bt corn was around $229 million per year on average. Moreover, maximum temperature 30-40°C and drought conditions in June and July along with Bt corn planting were significant determinants of aflatoxin. To control and find meaningful effects of temperature on aflatoxin, which fluctuates highly in the field, I tested the effects of multiple maximum temperature ranges on the incidence of aflatoxin. Since other unobserved environmental factors not controlled by Bt corn—such as soil conditions and insects—can also affect aflatoxin incidence and their effect can bias the estimated impact of Bt corn, I adopted econometric tools, such as the correlated random effect model and the control function approach, to control for such unobservables. The adoption of aflatoxin-related insurance claims as data to measure county level aflatoxin occurrence is another contribution of this study. To my knowledge, this is the first data set that allows for testing the effect of Bt corn on aflatoxin across the nation.

The second essay is concerned with increased aflatoxin risks from global warming and the role of Bt corn in the future. Typically predicted outcomes of climate change such as warm temperatures and dry conditions are known to increase aflatoxin. Thus, I predicted aflatoxin risks in 2031-2040 based on sixteen climate change models projected by ten institutes from nine counties. From this analysis, more than 87 % of counties were expected to have a higher risk of aflatoxin as measured by aflatoxin-related insurance claims from 2001-2016. While aflatoxin risks are currently concentrated in the South, the prediction shows that Kansas and other parts of the corn belt area are expected to experience the highest increase in aflatoxin risk. This means loss from aflatoxin accelerated by climate change is likely to substantially affect the US corn market in the near future. To predict aflatoxin risk, I predicted the calendar time of the corn growing season. Corn growing seasons in the future may be earlier than they are presently due to global warming, and the effect of climate on aflatoxin depends largely on corn growing stages. To predict corn planting seasons in the future, I used hundreds of climate variables that are measured in specific periods and interacted with each other and introduce the elastic net and cross-validation techniques, which are commonly used for discrete prediction and variable selection problems.

The third essay focused on the spillover or “halo” effect, an unintended beneficial effect of Bt corn and cotton on aflatoxin in peanuts. This potential positive externality of Bt crops raises an interesting question about the relevance of co-decision on crop choices between neighboring farms.

I hypothesized that aflatoxin-related insurance claims in peanuts are negatively correlated with Bt corn and cotton adoption rates in a given county. Corn earworm and fall armyworm, both of which are controlled by Bt corn, are hosted not only by corn but also by peanuts. Given that Bt peanuts are not commercialized and that sales of aflatoxin contaminated peanuts are also under regulation, the negative relationship between Bt crops and aflatoxin in peanuts means that Bt corn and cotton can also provide a meaningful unintended benefit to peanut farmers by reducing aflatoxin. To examine if Bt crops are associated with lower aflatoxin rates, I tested to see if a county has less insurance claims caused by aflatoxin in peanut farms when more Bt crops are planted in the county. For more accurate estimations of Bt effects on aflatoxin in peanut, I included climate conditions that affect the growth of peanut and aflatoxigenic mold. The results suggest that there was a spillover effect of Bt on aflatoxin in peanuts. In other words, Bt crops can benefit non-adopters by reducing aflatoxin-related damage, thereby providing safe food—aflatoxin free peanuts—in the market. The estimated economic benefits of Bt crops via the reduction of aflatoxin-related damage in peanuts were US $ 0.23 million - US $0.45 million per year. This is the first study that examines the effects of Bt crops in regards to reducing aflatoxin in non-Bt crops.

Overall, my dissertation study increases current understandings of the unintended effects of Bt in protecting crops from aflatoxin damage in the broader ecosystem. It aims to shed light on the benefits of Bt crops in countries that suffer from aflatoxin-related damage and transgenic seed traits that are not planted. Additionally, this study contributes to improved knowledge about climate conditions that affect either aflatoxin levels or host plant (corn and peanut). As climate change is expected to increase temperature and dryness, it is likely to increase the risk of aflatoxin in the US. Bt crops and new biotechnology are thus expected to play an important role in protecting crops from aflatoxin damage.

REFERENCES

REFERENCES

World Health Organization. 2018. Aflatoxins. REF. No.: WHO/NMM/FOS/RMA/18.1 available at https://www.who.int/foodsafety/FSDigest_Aflatoxins_EN.pdf

Wu F. 2004. Explaining public resistance to genetically modified corn: An analysis of the distribution of benefits and risks. Risk Analysis: An International Journal 24:715-726.

CHAPTER 2

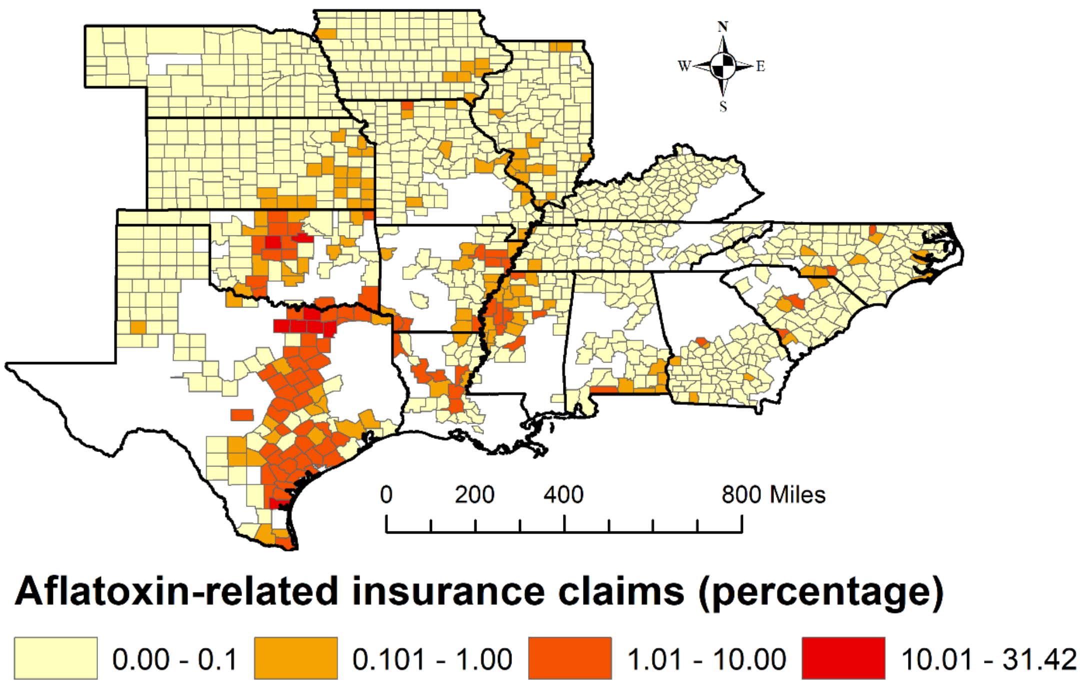
The Impact of Bt Corn on Aflatoxin-Related Insurance Claims in the United States

2.1 Introduction

Bt corn is one of the most commonly planted transgenic crops worldwide. First commercialized in the United States in 1996, Bt corn contains transgenes from the soil bacterium *Bacillus thuringiensis*, which enable it to produce proteins toxic to certain insect pests. Aside from improving corn growers' yields (Wu 2006; Xu et al. 2013; Fernandez-Cornejo et al. 2014), it has also resulted in 11% less insecticide use for Bt adopters compared to non-adopters from 1998 to 2011 (Perry et al. 2016). Bt corn adoption among US corn growers rose from 19% in 2001 to 82% in 2018, including stacked events, which contain genes to combat multiple insect pests and confer herbicide tolerance (Halpin 2005). Bt corn planting has caused area-wide suppression of the European corn borer, resulting in improved yields for both adopters and non-adopters, even for vegetable growers (Dively et al. 2018; Hutchison et al. 2010). This study advances the literature by examining another potential benefit of Bt corn adoption: reduced aflatoxin contamination, which leads to fewer aflatoxin-related crop insurance claims in the US.

Aflatoxin is a group of mycotoxins produced by the fungi *Aspergillus flavus and A. parasiticus* that commonly infect food crops such as corn, peanuts, pistachios, and almonds. Aflatoxin causes liver cancer, immune system dysfunction, and growth impairment in humans and animals (Wu et al. 2014). The International Agency for Research on Cancer has classified "naturally occurring mixes of aflatoxins" as a Group 1 carcinogen (WHO 1993). Thus, over 100 nations worldwide have set regulatory standards for maximum tolerable levels of aflatoxin in food (Wu and Guclu 2012). Even so, Liu and Wu estimated that between 25,000 and 155,000 aflatoxin-related liver cancer cases occur worldwide every year (Liu and Wu 2010). Very few, if any, of these aflatoxin-related cancer cases occur in the US. Among other reasons for this, the US Food and Drug Administration (FDA) has set action levels for allowable aflatoxin in human food and animal feed: 20 micrograms per kilogram of aflatoxin in human food (20 parts per billion, or ppb), and varying standards for livestock and poultry. Although this ensures a safer food supply in the US, corn growers experience economic loss through rejected or discounted lots for excessively high aflatoxin levels.

Figure 2.1 Number of aflatoxin-related insurance claims by county in 16 selected corn-planting states: 2001-2016



White portions in the sixteen states area were excluded from analysis, because data on corn plantings were missing over some or all of the study period.

Figure 2.1 shows the time average of aflatoxin-related insurance claims on corn in 16 corn-planting states for 2001-2016: Alabama, Arkansas, Georgia, Illinois, Iowa, Kansas, Kentucky, Louisiana, Missouri, Mississippi, North Carolina, Nebraska, Oklahoma, South Carolina, Tennessee, and Texas. These states were chosen based on completeness of data concerning Bt corn planting, aflatoxin-related insurance claims, and other factors necessary to conduct the analyses.

The percentages in Figure 2.1 represent the proportion of insured corn-planting acres in each county, averaged over 16 years, for which aflatoxin-related insurance claims were filed.

A secondary benefit to Bt corn planting, less well-known than insect control (its intended purpose), could be more important from a public health perspective. In the late 1990s, it was first discovered that Bt corn had lower levels of the fungal disease Fusarium ear rot than non-Bt isolines, because it controls the insect pest European corn borer (*Ostrinia nubilalis*), which in turn reduces fungal infection by *Fusarium verticillioides* (Munkvold et al. 1999). Hence, fumonisin – a mycotoxin produced by *F. verticillioides* that is associated with neural tube defects and growth impairment – is significantly lower in Bt corn than in non-Bt isolines (Bowers et al. 2014; De La Campa et al. 2005; Hammond et al. 2004; Munkvold et al. 1999).

These results for fumonisin might suggest that any effort to reduce kernel wounds can help to reduce fungal infection and aflatoxin problems in corn. However, the relationship between Bt corn planting and aflatoxin levels has been less clear. In field trials, Bt corn has not consistently shown lower aflatoxin levels than non-Bt isolines (Abbas et al. 2008; Bowen et al. 2014; Buntin et al. 2001; Masoero et al. 1999; Wiatrak et al. 2005; Williams et al. 2010). One practical limitation of these past studies is that they were conducted in artificial field conditions: in many cases, the corn was inoculated with either insects conducive to *Aspergillus* infection (corn earworm, *Helicoverpa zea*; or fall armyworm, *Spodoptera frugiperda*) or the fungus itself. What remains unknown is whether commercial Bt corn planting on US farms results in lower aflatoxin levels.

Current challenges to examining Bt's effects on aflatoxin include evolution of insect resistance to Bt, and new events of Bt containing Viptera. Insect resistance against certain Bt toxins has been reported worldwide (Dively et al. 2016; Gassmann 2012; Huang et al. 2014). Higher Bt adoption rates can reduce aflatoxin accumulation, but insect resistance to Bt toxins could reduce this beneficial effect. On the other hand, adoption of Viptera traits, to which no insect resistance has yet been reported, can reduce aflatoxin concentrations more efficiently. Viptera events specifically control the pests corn earworm and fall armyworm, which have been associated with aflatoxin in corn.

Previous studies have shown that drought stress makes corn more susceptible to fungal infection (Chen et al. 2004; Jones et al. 1981; Payne et al. 1986). Temperature is also critical for both maize growth and aflatoxin levels. Maize yields increase with temperatures between 12-25°C, but decrease with temperatures above 30°C (Schlenker and Roberts 2006). Warm temperature is also associated with high aflatoxin (Payne et al. 1988; Widstrom et al. 1990). In experiments, temperatures between 28-30°C increase *A. flavus* growth, while temperatures above 37°C decrease aflatoxin production (O'Brian et al. 2007; Smith et al. 2008). Although climatic conditions affect aflatoxin accumulation, previous studies about Bt and aflatoxin did not examine these; they were constant in field studies measuring aflatoxin differences in Bt vs. non-Bt isolines. To determine if Bt corn has an impact on aflatoxin in commercial corn fields, climatic conditions need to be controlled across the multiple corn planting regions in the US.

This study sought to fill that knowledge gap by determining if Bt corn planting results in fewer aflatoxin-related crop insurance claims by corn growers. Hence, my analysis reflects what is actually happening in US commercial cornfields regarding the relationship between Bt corn planting and aflatoxin levels: a critical question, as this corn is sold in the marketplace for human food and animal feed, with implications for health (as well as non-food uses). I developed a set of models that estimates causal relationship between the risk of aflatoxin-related insurance claims and Bt corn adoption rate, drought index, and climate variables. I also estimate benefits of Bt corn by reducing aflatoxin-related loss.

2.2 Data and Methods

2.2.1 Materials

Aflatoxin-related insurance claims data were collected from the USDA Risk Management Agency (RMA) (https://www.rma.usda.gov/data/sob.html, accessed 12-11-18). According to the RMA, over 85% of US corn area are insured through contracts underwritten by the RMA. Although these data do not include uninsured areas, and low levels of aflatoxin are not indemnified, it is the only data source that includes nationwide incidence of mycotoxin concentrations in corn at economically problematic levels. I measure aflatoxin incidence as the percentage of all insured corn area in a county where indemnified losses are ascribed to mycotoxins in the RMA database.

Because aflatoxin is the only mycotoxin regulated by FDA action levels, I assumed that for the specific states chosen, mycotoxin-related indemnities (labeled "Mycotoxins [Aflatoxin]") were for aflatoxin problems. The insurance claims data were collected over the main part of the corn growing season when aflatoxin problems would emerge in the field (June to October), to rule out the possibility that claims are made for corn in storage. I narrowed my focus to 16 states where aflatoxin was the predominant mycotoxin causing economic damage within the data window, 2001-2016. These states are Alabama, Arkansas, Georgia, Iowa, Illinois, Kansas, Kentucky, Louisiana, Missouri, Mississippi, North Carolina, Nebraska, Oklahoma, South Carolina, Tennessee, and Texas. Among all year-county pairs in sixteen states, I only used observations with a record of insured corn planting, which amounted to 14,429 observations. I excluded 19 county-year interactions out of 14,429 that did not have *any* insured corn area from 2001-2016: Prairie Co., AR, in 2005; Pendleton Co., KY in 2002; Franklin Co., KY in 2004 and 2005; Clinton Co., KY in 2003; Granville Co., NC, in 2001; Custer Co., OK, in 2003 and 2006; Comanche Co., OK in 2007; Ellis Co., OK in 2001-2004; Cotton Co., OK in 2003; Fentress Co., TN in 2002; Crosby Co., TX in 2001 and 2002; Potter Co., TX in 2012; Grainger Co., TX in 2015. Thus, I had 14,410 observations after excluding these cases.

Bt corn adoption rates (including stacked Bt hybrids: containing multiple bioengineered traits) are my explanatory variable of primary interest. I obtained data on Bt corn planting rates at the crop reporting district level in these 16 states from Kynetec Ltd., a survey and market analysis firm that specializes in agricultural markets. Each state contains four to sixteen districts, and each district includes about nine counties.

I also included daily maximum temperatures from June to July as an explanatory variable, to determine which temperatures were most conducive to aflatoxin accumulation. The temperature variables are calculated as a proportion of the number of days with favorable / unfavorable temperatures for aflatoxin accumulation. I tested multiple models with different temperature ranges to find favorable and unfavorable temperature levels in a field. Specifically, I created six pairs of potentially favorable and unfavorable daily (including nighttime) maximum temperature ranges: 26^{o}C-36^{o}C vs. 38^{o}C and above, 26^{o}C-36^{o}C vs. 40^{o}C and above, 26^{o}C-36^{o}C vs. 42^{o}C and above, 28^{o}C-38^{o}C vs. 40^{o}C and above, 28^{o}C-38^{o}C vs. 42^{o}C and above, and 30^{o}C-40^{o}C vs. 42^{o}C and above. I used the mean of temperatures observed from multiple weather stations within a county as a county level temperature. There are, on average, five weather stations within a county. Daily maximum temperatures were obtained from the US National Oceanic and Atmospheric Administration (NOAA) (Menne et al. 2012).

I also included Palmer Z drought indices for several months as explanatory variables. The Palmer Z drought indices for each of the months of June through September were included as potential predictors of aflatoxin incidence (Palmer 1965; Karl 1986). Drought can affect aflatoxin accumulation on corn in several ways, including increasing plant stress that may make it more vulnerable to fungal infection and create an environment in which insect pests are more likely to damage corn. Palmer Z indices measure soil moisture availability over a month, rather than recent precipitation. Thus, it is a measure of the stock of water available for plant growth. It is available at the climate district level, accounting for water retention capacity of typical soils in the district. Each climate district includes several counties. NOAA provides the climate district level Palmer Z index as a monthly drought index (https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv, accessed 12-11-18). Index values of 3.5 or higher indicate that the area is extremely wet for the area, while values of -2.75 or lower indicate that the area is extremely dry for the area. Summary statistics and data sources are in Table 2.A.2.

Among the 14,410 available observations, temperature and Bt adoption data are missing for some. These cases were excluded for analysis: 377 observations (168 counties) with incomplete Bt adoption data, and 1,906 observations (330 counties) with incomplete temperature data. As a result, 12,127 observations remained. I assumed that whether temperature or Bt adoption was observed is not systematically correlated with aflatoxin incidence. This assumption is supported by the market context. Aflatoxin control is not a major motivation for adopting Bt traits in corn. Major motives include removing the need for insecticide materials and spraying costs as well as yield damage avoidance. The assumption allows for an estimation without explicitly modeling incidence of missing data. To check if incidence of missing data is correlated with aflatoxin occurrence, I included a dummy variable that has value zero if a county has all sixteen year of data (no missing data) and value one otherwise. The statistically insignificant coefficient for the 'missing' dummy indicates that the 'missing data' event is uncorrelated with aflatoxin-related insurance claims.

2.2.2 Methods

To assess the impact of Bt corn and climatic factors on aflatoxin problems in US corn, I developed an econometric model with the following reduced form:

$$\begin{aligned} y_{i,t}^{*} &= \hat{y}_{i,t}^{*} + c_i + u_{i,t}; \\ \hat{y}_{i,t}^{*} &\equiv \beta_B B_{i,t} + \sum\nolimits_{m\in\{6,7,8,9\}} \beta_Z^m Z_{i,t}^m + \sum\nolimits_{m\in\{6,7\}} (\beta_F^m F_{i,t}^m + \beta_U^m U_{i,t}^m) + \beta_M M_i + \beta_T T + \beta_S S; \end{aligned} \tag{1}$$

where $y_{i,t}^{*}$ is the aflatoxin occurrence rate in county *i* in year *t*; $B_{i,t} \in [0,100]$ is the year *t* adoption rate for Bt and stacked genes for the county's crop reporting district; $Z_{i,t}^m$ is the month *m* Palmer Z index for the climate zone in which the county is located (where 6=June, 7= July, 8=August, 9=September), $F_{i,t}^m$ is favorable temperature (for aflatoxin production) in the relevant county, month and year; $U_{i,t}^m$ is unfavorable temperature in the relevant county, month and year; M_i is a 'missing data' dummy; *T* is a vector of year dummy variables; *S* is a vector of state dummy variables; c_i is a county-specific unobserved factor; and $u_{i,t}$ is a normally distributed error term. I refer to the set of 12,127 observations as H .

For many US counties in many years, no aflatoxin-related crop insurance claims were made. Thus, I used a type I Tobit model instead of the standard linear model. A type I Tobit model takes account of the zero bound, i.e., the "latent" variable $y_{i,t}^{*}$ is not always observed. Type I Tobit models assume that $y_{i,t}^{*}$ satisfies classical linear model assumptions (Wooldridge 2010), but $y_{i,t}$ (aflatoxin insurance claims) never falls below zero (as it could in a standard linear model). Specification of the Tobit model is as follows:

$$y_{i,t} = \max(0, y_{i,t}^{*}); \tag{2}$$

where $y_{i,t}^{*}$ is as given in (1).

Geography-specific and time-invariant unobserved factors such as topography and soil characteristics can affect aflatoxin risk. Since they were not observed, I allowed county-specific unobserved factors, c_i, to be correlated with explanatory variables. Such a model is often called the Correlated Random Effects (CRE) model, in which I assume that the mean values of explanatory variables explain possible correlations (Chamberlain 1980; Mundlak 1978):

$$c_i = \psi + \bar{\boldsymbol{x}}_i \boldsymbol{\xi} + e_i; \tag{3}$$

$$v_{i,t} \mid \boldsymbol{x}_{i,t} \sim \text{Normal}(0, \sigma_v^2); \tag{4}$$

where ψ is a constant, $\bar{x}_i$ is the vector of mean values for the explanatory variable vector $\boldsymbol{x}_{i,t}$ across time, e_i is an error term, and $v_{i,t} = e_i + u_{i,t}$ is composite error. The coefficient vector $\boldsymbol{\xi}$ measures the effect of time-averaged $\boldsymbol{x}_{i,t}$ on the unobserved county-specific feature c_i.

To estimate the CRE Tobit model, pooled maximum likelihood estimation (MLE) allowing serial correlation was used. With indicator function given by $1(\cdot)$, having the value one when a given condition is satisfied and the value zero otherwise, the density of $y_{i,t}$ given $\boldsymbol{x}_{i,t}$ is

$$\begin{aligned} & f(y_{i,t} \mid \boldsymbol{x}_{i,t}) = \{1 - \Phi(J_{i,t} / \sigma_v)\}^{1(y_{i,t}=0)} \{\sigma_v^{-1} \phi[(y_{i,t} - J_{i,t}) / \sigma_v]\}^{1(y_{i,t}>0)}; \\ & J_{i,t} \equiv \boldsymbol{x}_{i,t}\boldsymbol{\beta} + \psi + \bar{\boldsymbol{x}}_i \xi; \end{aligned} \tag{5}$$

where $\phi(\cdot)$ is the standard normal probability density function and $\Phi(\cdot)$ is the standard normal cumulative density function. Then the log likelihood for Correlated Random Effects Tobit is

$$\mathcal{L}(\cdot) = \sum\nolimits_{(i,t)\in H} \log f(y_{i,t} \mid \boldsymbol{x}_{i,t}, \bar{\boldsymbol{x}}_i; \boldsymbol{\beta}, \sigma_v^2); \tag{6}$$

where H is the set of observations, and $\boldsymbol{\beta} = \{\beta_B, \beta_Z^6, \beta_Z^7, \beta_Z^8, \beta_Z^9, \beta_F^6, \beta_F^7, \beta_U^6, \beta_U^7, \beta_M, \beta_T, \beta_s\}$. The maximum likelihood estimators are given by the K dimensional parameter set $\Upsilon = \boldsymbol{\beta} \bigcup \{\psi, \xi, \sigma_{\boldsymbol{v}}^2\}$. The maximum likelihood estimators are the parameter values that solve $\max_{\Upsilon \in \mathbb{R}^K} \mathcal{L}(\cdot)$ where I follow the notation and explanation from Wooldridge (2010).

If the "true" error term is correlated with Bt adoption, then some of the error term is subsumed as part of the estimated Bt adoption effect: often referred to as an "endogeneity problem." For example, variations in soil conditions and populations of certain insects might be correlated with both Bt seed choice and aflatoxin incidence. In this case, the estimated effect of Bt adoption on aflatoxin already includes the effect from soil conditions. The instrumental variable (IV) method is a reliable method to correct for this form of bias (Wooldridge 2010). An IV is a variable that is correlated with Bt adoption conditional on the other covariates, but is uncorrelated with the error term in the aflatoxin equation given that equation's covariates. I used two IVs: expected yield and seed cost per expected yield. Farmers make Bt corn adoption decisions to maximize profits. Demand for Bt corn should increase as expected yield increases to the extent that the Bt trait is a value protecting input. Corn seed markets are imperfectly competitive, with two major providers over the period. They are also geographically separated because seed genetics must suit the local climate and soils. Seed providers should be able to charge more where demand is higher. My second instrument is seed cost per expected bushel yield. Expected yield is measured out of sample, namely by crop district mean yield over 1991-2000 as reported by the USDA's National Agricultural Statistics Service. Seed cost data are obtained from Kynetec Ltd.

Two common estimators using an IV are the two stage least squares (2SLS) method and the control function (CF) method (Guo and Small 2016). Since the 2SLS method for nonlinear models does not result in consistent estimations (Wooldridge 2015), I used the control function

(CF) approach. Intuitively, the CF approach estimates the causal relationship by detaching the part that might cause endogeneity problems, such as unobserved populations of certain insects and soil quality, from the error term. See Wooldridge for details on the CF (Wooldridge 2010; Wooldridge 2015). Table 2.A.3 indicates first stage regression results.

Since asymptotic variances for two-step estimators are difficult to derive, I used the bootstrap standard method with 1,000 replications (Efron 1979; Wooldridge 2010). The fact that I collected data from only counties with insurance uptake may cause selection bias; uninsured areas are not considered. However, I believe that this bias is negligible, as only 19 observations were excluded due to the absence of crop insurance for corn over 16 years. Year dummy variables are included to account for differences in the natural and economic environments, including commodity price levels and pertinent farm bill legislation. State dummy variables are included to control for state dependent features such as topography, proximity to the ocean and associated weather effects, and fungal populations in the soil. To ensure the robustness of the results, I use other econometric models: specifically probit and fractional probit models. For the fractional probit model, the dependent variables are normalized to range over the [0, 1] interval. For the probit model, a discrete variable with value one if aflatoxin related-insurance claims are reported and value zero otherwise is used as the dependent variable. I apply the control function approach with two IVs and correlated random effects to both probit and fractional probit models. For technical specifics on the method see Wooldridge (2010).

To examine the potential effect of Viptera events (better control of corn earworm, an insect associated with aflatoxin risk), I used the same model with the main model. The differences are 1) the time window becomes 2011-2016; 2) the seed cost per expected yield and expected yield are used as IVs for Viptera, and the yield effect is used as an IV for non-Viptera Bt. Viptera is more likely to have an endogeneity problem than non-Viptera Bt because a farmer is likely to adopt the Viptera trait when aflatoxin damage is more likely. However the coefficient on the first stage residual from Viptera adoption was not statistically significant. Therefore any endogeneity in the Viptera adoption choice seems unlikely. The results and F-statistics of IVs are reported in Table 2.A.4.

2.2.3 Method for Estimating Benefit of Bt Adoption due to Aflatoxin Reduction

I defined the benefit of Bt adoption as the difference between loss due to aflatoxin and hypothetical loss when the Bt adoption rate was zero. The estimated loss due to the aflatoxin is calculated by multiplying the aflatoxin-related indemnities by a markup factor. A markup adjustment is necessary to account for the fact that indemnities only cover losses beyond a large deductible. In the Supplementary Materials, I infer that a markup in the range of 1.43 to 2.74 is appropriate when transforming indemnities payouts to losses.

The benefit of Bt corn planting is estimated as the markup times the difference between predicted indemnities from the fitted model using historic data and hypothetical indemnities without Bt adoption. Specifically, the benefit of Bt adoption can be written as follows:

$$\text{markup} * \sum_{(i,t)\in H} \left(\hat{L}_{i,t} \,|_{B_{i,t}=0, x_{i,t}} - \hat{L}_{i,t} \,|_{B_{i,t}, x_{i,t}} \right); \tag{7}$$

where $\hat{L}_{i,t} \,|_{B_{i,t}, x_{i,t}}$ is the conditional expectation of aflatoxin related indemnities in county *i* in year *t*, $\boldsymbol{x}_{i,t}$ represents the set of explanatory variables other than Bt adoption, and $B_{i,t}$ is the Bt adoption rate. The hypothetical indemnity payment in a county, $\hat{L}_{i,t} \,|_{B_{i,t}=0, x_{i,t}}$, is defined as $E[\hat{L}_{i,t} \,|\, B_{i,t} = 0, \boldsymbol{x}_{i,t}]$.

I obtained coefficients by regressing indemnities on Bt adoption, the Palmer Z drought index, temperatures, year effect, state effect, insured area, and insurance coverage with a Tobit specification. Since indemnities depend on disease occurrence, insured area and insurance coverage, the insured area and the insurance coverage variables were included in the regression with the same explanatory variables as in the main model. The reduced form is as follows:

$$
\begin{aligned}
L_{i,t}^{*} &\equiv \beta_B B_{i,t} + \sum\nolimits_{m\in\{6,7,8,9\}} \beta_Z^m Z_{i,t}^m + \sum\nolimits_{m\in\{6,7\}} (\beta_F^m F_{i,t}^m + \beta_U^m U_{i,t}^m) \\
&\quad + \beta_M M_i + \beta_T T + \beta_S S + \beta_A A_{i,t} + \beta_I I_{i,t} + c_i + e_{i,t}; \\
L_{i,t} &= \max[0, L_{i,t}^{*}];
\end{aligned}
\tag{8}
$$

where $L_{i,t}$ represents indemnities, $A_{i,t}$ is insured area in county *i* in year *t*, and $I_{i,t}$ is average insurance coverage in county *i* in year *t*. The insured area and the insurance coverage data are from USDA RMA. As with the main model, I controlled for county-specific and time-invariant unobserved factors, c_i, using the CRE model. The endogeneity problem was also addressed for these models using the control function approach with the expected yield and seed cost per expected yield as instruments. The bootstrap standard errors with 1,000 replications are reported in model 2 of Table 2.1.

The dollar value of indemnities, $\hat{L}_{i,t} \,|_{B_{i,t}=0, x_{i,t}}$, is estimated as

$$
E[L_{i,t} \mid B_{i,t} = 0, \boldsymbol{x}_{i,t}] = E[\max[L_{i,t}^{*}, 0] \mid B_{i,t} = 0, \boldsymbol{x}_{i,t}] = \Phi(\boldsymbol{x}\hat{\boldsymbol{\beta}} / \sigma)\boldsymbol{x}\hat{\boldsymbol{\beta}} + \sigma\phi(\boldsymbol{x}\hat{\boldsymbol{\beta}} / \sigma); \tag{9}
$$

where $\boldsymbol{x}\hat{\boldsymbol{\beta}}$ denotes

$$
\begin{aligned}
&\hat{\beta}_B \underset{=0}{B_{i,t}} + \sum\nolimits_{m\in\{6,7,8,9\}} \hat{\beta}_Z^m Z_{i,t}^m + \sum\nolimits_{m\in\{6,7\}} (\hat{\beta}_F^m F_{i,t}^m + \hat{\beta}_U^m U_{i,t}^m) + \hat{\beta}_M M_i + \hat{\beta}_T T + \hat{\beta}_s S \\
&\quad + \hat{\beta}_A A_{i,t} + \hat{\beta}_I I_{i,t} + \hat{\beta}_c \tilde{c}_i;
\end{aligned}
\tag{10}
$$

and $\tilde{c}_i = \psi + \bar{\boldsymbol{x}}_i \boldsymbol{\xi}$.

Note that where y^* is normally distributed then $y = \max[0, y^*]$ is truncated normal;

$$
\begin{aligned}
\mathrm{E}(y \mid \boldsymbol{x}) &= \Pr(y=0 \mid \boldsymbol{x}) \times 0 + \Pr(y>0 \mid \boldsymbol{x}) E(y \mid \boldsymbol{x}, y>0) \\
&= \Pr(u > -\boldsymbol{x\beta} \mid \boldsymbol{x}) \mathrm{E}(y \mid \boldsymbol{x}, y>0) = [1-\Phi(-\boldsymbol{x\beta}/\sigma)] \mathrm{E}(y \mid \boldsymbol{x}, y>0) \\
&= \Phi(\boldsymbol{x\beta}/\sigma) \mathrm{E}(y \mid \boldsymbol{x}, y>0) = \Phi(\boldsymbol{x\beta}/\sigma)\{\boldsymbol{x\beta} + \sigma\phi(\boldsymbol{x\beta}/\sigma)/\Phi(\boldsymbol{x\beta}/\sigma)\} \\
&= \Phi(\boldsymbol{x\beta}/\sigma)\boldsymbol{x\beta} + \sigma\phi(\boldsymbol{x\beta}/\sigma).
\end{aligned}
\tag{11}
$$

The estimated benefits of Bt are reported in Table 2.2.

2.3 Results

To account for the fact that many corn-planting counties in the US do not have any aflatoxin-related insurance claims in certain years, I have applied Tobit analysis. My interest is in the marginal effects: the amount by which the expected value of a dependent variable (aflatoxin-related insurance claims) changes when a particular covariate increases by one unit (Bt corn planting) while other covariates are held fixed. Table 2.1 provides marginal effects for three models. Model 1 shows the estimated marginal effect of Bt corn and climate variables on aflatoxin insurance claims. Model 2 shows the estimated Viptera and non-Viptera Bt effects. Model 3 indicates the estimated economic effects of each variable on aflatoxin insurance claim indemnity payouts. Details on calculation of marginal effects are provided in the Supplementary Materials.

Table 2.1 Estimated marginal impacts of Bt corn, humidity/drought, and temperature on aflatoxin-related insurance claims and indemnities

Variables	Aflatoxin-related insurance claims (percentage) (1)	Aflatoxin-related insurance claims (percentage) (2)	$1,000 indemnities (3)
Bt/stacked corn adoption rate (%)	-0.016***	-	-14.10***
	(0.003)	-	(3.041)
Viptera corn adoption rate (%)	-	0.252	-
	-	(0.163)	-
Non-Viptera Bt corn adoption rate (%)	-	-0.292**	-
	-	(0.139)	-
Palmer Z index (index range -6.44 ~ 11.58)			
Palmer Z in June	-0.044***	-0.129	-41.42***
	(0.012)	(0.200)	(14.53)
Palmer Z in July	-0.041***	-0.997***	-44.32***
	(0.011)	(0.292)	(11.24)
Palmer Z in August	0.006	-0.229	6.525
	(0.008)	(0.211)	(7.479)
Palmer Z in September	0.020***	0.046	16.84**
	(0.008)	(0.194)	(6.710)
Temperature in June (proportion of the temperature range, 0-1 value)			
Range 30-40°C	0.908***	5.761**	893.1***
	(0.194)	(2.658)	(215.2)
Above 42°C	-3.188	25.032	-3,576
	(2.727)	(25.471)	(2,302)
Temperature in July (proportion of the temperature range, 0-1 value)			
Range 30-40°C	0.325**	10.206***	289.9**
	(0.140)	(3.395)	(137.5)
Above 42°C	-0.675	2.466	-602.9
	(1.210)	(21.173)	(1,081)
Insurance			
Insurance coverage (ratio with range 0 and 1)	-	-	2,047**
	-	-	(797.1)
Insured area (hectare)	-	-	0.031***
	-	-	(0.010)
State Effects Controlled	Yes	Yes	Yes
Year Effects Controlled	Yes	Yes	Yes
Observations	12,127	4,198	12,127

Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Results for alternative temperature combinations as well as details on year and state effects are provided in Table 2.A.5. The *marginal effect* for Bt corn adoption rate, -0.016, indicates that an increase of one percentage point in Bt adoption in a county reduces aflatoxin-related insurance claims by about 0.016% in that county on average (model 1 in Table 2.1) .[1] This indicates that aflatoxin levels high enough to induce crop insurance claims are significantly lower in counties with high Bt corn adoption rates. Table 2.A.6 provides the results of the same analyses using other econometric models: probit and fractional probit models. The results support an inverse association between Bt corn planting and aflatoxin risk. The marginal effects for the Palmer Z index, are significant and negative in both June and July (lower, negative values for the Palmer Z index correspond to drought conditions). This indicates that drought during these corn-growing months leads to greater aflatoxin risk. The positive sign in September indicates that wetter post-silking conditions increase aflatoxin problems.

The marginal effect for the June and July temperature range of 30-40°C are significant and positive: consistent with previous experimental results (OBrian et al. 2007; Smith et al. 2008), these warm temperatures are positively correlated with higher aflatoxin incidence. On the other hand, temperatures above 42°C in June and July are not statistically significant, suggesting that unfavorably high temperature ranges may not exists in field settings.

In Model 2, I included Viptera adoption rates and non-Viptera Bt adoption rates to examine the potential effect of Viptera traits introduced in 2011. The Viptera effect was not statistically significant, while non-Viptera Bt corn planting reduced aflatoxin-related insurance claims by 0.292%. However, it is difficult to interpret this result as implying that any Viptera effect was not significant, because Viptera adoption rates have been low, particularly in the early years of adoption. These rates are reported in Table 2.A.7.

For the sixteen states assessed in this study, the indemnities per year due to aflatoxin was

[1] Bt corn adoption rate is summation of Viptera corn adoption rate and Non-Viptera Bt corn adoption rate.

US $10.6 million in 2001-2016 on average (Table 2.A.8 reports aflatoxin-related insurance claims and indemnities by states). The average payout per indemnified area was $415 per hectare. Given the assumption that non-insured areas have the same loss probability as insured areas, then aflatoxin causes losses ranging from $17.5 million to $33.6 million per year on average.

I also estimated hypothetical indemnities when Bt adoption rates were zero across the United States. Model 3 in Table 2.1 shows the estimated impacts of Bt corn adoption, drought, temperatures, insured area, and insurance coverage on the cost of aflatoxin-related indemnities.[2] Here, insurance coverage provides the fraction of historical average yield below which yield shortfalls are recompensed. The estimated economic benefit of Bt corn planting due to reduced aflatoxin is estimated at $120 million to $229 million per year for the selected 16 states. This estimated loss averted by Bt corn adoption is solely through reducing aflatoxin-related insurance claims, and does not take into account any economic effects of Bt traits on yield improvement or pesticide reduction. According to the USDA, the value of corn production over the selected sixteen states in 2001-2016 was $27.4 billion per year on average. Table 2.2 reports value of corn production and also estimated benefit of Bt adoption. Thus, the estimated benefit corresponds to 0.4-0.8% of the total value of corn production in the 16 states.

[2] The marginal effect of Bt/stacked corn adoption, -14.1, in the model (3) means that an increase of one percentage point in Bt adoption rate in a county is associated with lowering aflatoxin-related insurance indemnities by $14,100 in that county, on average.

Table 2.2 Value of corn production and Tobit model estimates of Bt adoption benefits in sixteen states

Year	Value of corn production [a]	Loss due to aflatoxin [b]	Benefit of Bt adoption using aflatoxin indemnities	
	Million $	Million $	Million $	Estimated benefit of Bt over Value of Corn production (%)
2001	11,600	0.8 - 1.5	0.6 - 1.2	0.01 - 0.01
2002	13,020	15.6 - 29.9	23.9 - 45.9	0.18 - 0.35
2003	14,993	8 - 15.4	8 - 15.3	0.05 - 0.1
2004	15,256	0.1 - 0.2	4.5 - 8.6	0.03 - 0.06
2005	13,402	35.5 - 68	89.6 - 171.7	0.67 - 1.28
2006	19,560	10.4 - 19.8	64.6 - 123.9	0.33 - 0.63
2007	34,665	5.5 - 10.5	77 - 147.6	0.22 - 0.43
2008	30,318	31.3 - 59.9	140.1 - 268.4	0.46 - 0.89
2009	28,689	29.7 - 56.8	140.2 - 268.7	0.49 - 0.94
2010	38,707	49.1 - 94	236.2 - 452.6	0.61 - 1.17
2011	46,412	31.2 - 59.9	264.9 - 507.5	0.57 - 1.09
2012	41,762	54.4 - 104.2	457.3 - 876.3	1.1 - 2.1
2013	36,515	7.1 - 13.6	167.2 - 320.4	0.46 - 0.88
2014	32,236	0.8 - 1.5	81.1 - 155.3	0.25 - 0.48
2015	29,952	0.1 - 0.3	72.8 - 139.5	0.24 - 0.47
2016	31,540	0.7 - 1.3	83.3 - 159.5	0.26 - 0.51
Average per year	27,414	17.5 - 33.6	119.5 - 228.9	0.44 - 0.83

[a] Value of corn production data over the sixteen states per year come from the USDA National Agricultural Statistics Service (NASS) (https://quickstats.nass.usda.gov/)
[b] Loss due to aflatoxin is calculated as the product of aflatoxin-related indemnities per hectare, planted corn area, and markup. Markup adjusts actual indemnity claims to estimate the underlying loss given that crop insurance contracts stipulate deductibles of about 30% of expected yield. I use the markup range 1.43 to 2.74.

2.4 Discussion

These results suggest that Bt corn planting reduces aflatoxin in US corn to an extent that causes a significant economic benefit to corn growers. By using aflatoxin-related crop insurance claims from US corn growers, my analysis attempted to remove the impact of artificial field conditions in past studies (e.g., inoculation of corn plants with insects or fungi) to determine whether Bt corn has significantly lower aflatoxin levels than non-Bt isolines. If similar agronomic principles hold true in other world regions, then Bt corn planting may also reduce aflatoxin-related health risks in humans and animals. In the United States, these health effects are mitigated by enforcement of FDA action levels for allowable aflatoxin in human food and animal feed.

This study also examined the impact of climatic conditions on aflatoxin risk in US corn, independent of the effect of Bt corn planting. As previous studies had shown, warmer temperatures during the corn growing season increase aflatoxin risk. Additionally, drought conditions in June and July, but wet conditions in September, are associated with higher aflatoxin levels. On balance, climate projections suggest that more corn across the United States and worldwide will be vulnerable to aflatoxin in coming decades (Battilani et al. 2016; Wu and Mitchell 2016). In this light, Bt corn can be viewed as a means of potentially mitigating increased aflatoxin risk due to climate change.

However, Bt corn is by no means the only possible route through which aflatoxin can be mitigated. Other interventions to reduce aflatoxin risk can be applied at the preharvest level: good agricultural practices, breeding resistance to field conditions that increase risk of *Aspergillus* infection, or biocontrol. Postharvest interventions to reduce aflatoxin include good storage practices and appropriate drying (Wu 2014). More research is warranted on whether Bt corn planting is associated with lower aflatoxin levels elsewhere worldwide, and on alternative control methods appropriate for high-risk areas for aflatoxin contamination of corn.

APPENDIX

APPENDIX

Crop insurance in the United States.

Crop insurance in the United States is a public-private partnership, whereby government actuaries set rates and insure much of the crop-related risk to farmers, while private firms market and retain some of the contracts. Public involvement commenced during the 1930s, and public support has expanded over the years. It is now the centerpiece of public support for incomes in crop agriculture. Details on the program's history can be found in Glauber (2013).[3]. Public subsidies come in various forms, including rate-setting services, compensation for administration costs, and subsidized premiums. Since the late 1990s, the most widely used contracts for the main crops have been revenue insurance and yield insurance, whereby loss beyond a fraction of projected average revenue or yield is indemnified. Coverage levels offered range from 50% to 90% of projected revenue, depending on insurance contract chosen and location. The entity within the US Department of Agriculture that administers the program is called the Risk Management Agency, or RMA.

A critical feature of the process is loss assessment, for which procedures are described in a frequently updated Loss Adjustment Manual Standards Handbook: https://www.rma.usda.gov/handbooks/25000/2018/18_25010-2h.pdf. For most contracts, when a farmer makes a claim of a nature that requires a visit, an employee or contracting agent from the crop insurance marketing company that originated the contract visits the insured land tract to assess losses. The adjustor provides a report that includes, among other data, the primary cause of loss.

[3] Glauber JW (2013) The growth of the federal crop insurance program, 1990–2011. American Journal of Agricultural Economics 95(2):482-488.

Several months after the end of the crop growing season, reported data are aggregated to county level of analysis and summary reports are placed in the public domain, see https://www.rma.usda.gov/data/cause.html. Cause of loss data are available since 1948, but loss area and month of loss have only been available since 2001. Reported causes of crop loss include - among others - drought, excess moisture/precipitation/rain, freeze, heat, decline in price, plant disease, insects, wildlife, wind, and mycotoxins (aflatoxin).

Finding a favorable / unfavorable temperature range

I started by testing a variety of temperature ranges as favorable and unfavorable temperatures for aflatoxin accumulation, respectively. Table 2.A.5 shows the estimated coefficients for six pairs of potentially favorable and unfavorable temperature ranges. I excluded, among different bands of the favorable temperature ranges, those that did not show positive correlations with aflatoxin-related insurance claims. Since the temperature range 30-40°C has a positive coefficient and the range was only paired with ≥ 42°C, the range 30-40°C and ≥ 42°C (model 6) were chosen as favorable and unfavorable temperature ranges for aflatoxin accumulation, respectively.

Inferring total loss

I estimated the economic loss due to aflatoxin, as well as the economic benefit of Bt corn specifically through reducing aflatoxin. The economic loss from aflatoxin is calculated based on the amount of indemnity payout attributed to aflatoxin. Since indemnity payout is lower than total loss, I calculate mark up to transform indemnities payouts to losses. Suppose that the average corn crop insurance coverage level over the period is 70%, with a corn price of $3 per bushel. Average yield is assumed to be 400 bushels per hectare. In addition, I assume a uniformly distributed loss (uniform is used as a probability distribution function). Then revenue protected is $1,200 per hectare. Seventy percent coverage, which was typical for corn in most southern states during 2001-2016, would provide $840 total coverage per hectare. If revenue *L* is less than $840, then the indemnity is $840-*L*. Therefore, the indemnity is the maximum of 0 and 840-*L*. Upon integrating over the relevant domain, I obtain $\int_0^{840}[(840-L)/1,200]dL=\$294$, which is somewhat lower than $415, the average indemnity per aflatoxin occurred area for 2001-2016 (Table 2.A.8). An integration over the entire domain yields $\int_0^{1200}[(1200-L)/1200]dL=\$600$, suggesting a markup of $600/294\approx 2$ when transforming indemnity payouts to losses. Alternatively, if it is assumed that losses are total, as in issuing a total destruction order, then the indemnity paid would be $840 per hectare, loss would be $1,200 per hectare, and the markup would be 1.43. A third plausible possibility is that all indemnity payments amount to $415 per hectare. If I solve $415=0.7(1,200)-x$, then the certain market revenue, conditional on the aflatoxin loss event occurring, that gives a $415 indemnity, is $x=\$425$ and total loss per event is $1,200-$425=$775 so that the markup is $775/415\approx 1.8$.

The last potential mark-up ranges were calculated based on actual data. Farmers who purchased Crop Revenue Coverage (CRC) insurance, were indemnified when revenue guarantee was higher than final revenue. Revenue guarantee per acre was the approved yield (Average Production History [APH]) multiplied by coverage rate, multiplied by corn price. Among projected corn price and harvest corn price, the higher rate was selected. Final revenue per acre was calculated by multiplying yield by discounted price. Discount rates varied in aflatoxin contamination level. Then indemnity per acre can thus be written as follows:

$$Indemnity\ per\ acre\ (CRC)=\max[Revenue\ guarantee\ per\ acre-Final\ revenue\ per\ acre\ ,0]$$

$$Revenue\ guarantee\ per\ acre = APH\ \ yield * Coverage * max(Projected\ \ price,\ \ Harvest\ \ price)$$

$$Final\ revenue\ per\ acre = yield * (1 - discount\ \ rate) * Harvest\ \ price$$

Actual loss can be defined by:

$$Loss\ \ per\ \ acre = \max[APH\ \ yield * Harvest\ \ price - Final\ revenue\ per\ acre\ \ , 0]$$

Many factors affect the determination process of indemnity, such as the insurance products and coverage chosen by each farmer. Due to the limit of availability of farm level data, I estimated indemnity and loss by aggregated level: county level. Loss was estimated using county level indemnities and acres that were claimed for aflatoxin and the indemnity decision process. Specifically, 10 years average historic yield (county level) was used for APH yield. For example, yields between 1996 and 2005 were averaged and the average yields were used for APH yields in 2006. County level coverage rate data were from U.S. Department of Agriculture, Risk Management Agency (USDA RMA). RMA provides county level coverage that varies in insurance products and year. The projected price was the December CME group futures contract price during February and the harvest price was the December CME group futures contract price during October. However, the price of US Corn Futures in February and the price of US Corn Futures in October were used, respectively, due to the limited availability of CME group futures data. US Corn Futures Historical Data were obtained from *Investing.com*, a global financial portal providing stock market quotes and financial news.

Although specific discounts factors are unknown, loss was calculable by

$$Loss\ \ per\ acre = \max[APH\ \ yield * Harvest\ \ price - (Indemnity\ \ per\ acre - Revenue\ guarantee\ per\ \ acre), 0]$$

Indemnity per acres data and yield data were taken from the USDA RMA and USDA National Agricultural Statistics Service (NASS), respectively.

Along with CRC, Actual Production History (APH), Revenue Assurance (RA), Revenue Protection (RP), Revenue Protection with Harvest Price Exclusion (RPHPE), and Yield Protection (YP) insurance products were purchased by corn farmers historically. Below are the specific rules of indemnification depending on insurance products.

$$\begin{aligned} Indemnity\ \ per\,acres\ \ (YP) = \max[&APH\ \ yield * Coverage * Projected\ \ price \\ &- yield * (1 - discount\ \ rate) * Projected\ \ price\ \ , 0] \end{aligned}$$

$$\begin{aligned} Indemnity\ \ per\,acres\ \ (RP) = \max[&APH\ \ yield * Coverage * \max(Projected\ \ price,\ \ Harvest\ \ price) \\ &- yield * (1 - discount\ \ rate) * Harvest\ \ price\ \ , 0] \end{aligned}$$

$$\begin{aligned} Indemnity\ \ per\,acres\ \ (RPHPE) = \max[&APH\ \ yield * Coverage * Projected\ \ price \\ &- yield * (1 - discount\ \ rate) * Harvest\ \ price\ \ , 0] \end{aligned}$$

$$\begin{aligned} Indemnity\ \ per\,acres\ \ (RA\ without\ \ harvest\ \ option) = \max[&APH\ \ yield * Coverage * Harvest\ \ price \\ &- yield * (1 - discount\ \ rate) * Harvest\ \ price\ \ , 0] \end{aligned}$$

$$\begin{aligned} Indemnity\ \ per\,acres\ \ (APH) = \max[&APH\ \ yield * Coverage * Elected\ \ price \\ &- yield * (1 - discount\ \ rate) * Elected\ \ price\ \ , 0] \end{aligned}$$

$$\begin{aligned} Indemnity\ \ per\,acres\ \ (RPHPE\ \ with\ \ harvest\ \ option) = \max[&APH\ \ yield * Coverage * Harvest\ \ price \\ &- yield * (1 - discount\ \ rate) * Harvest\ \ price\ \ , 0] \end{aligned}$$

where elected price is RMA price established before sales closing.

Loss per acre was calculated using insurance-specific rules for indemnification. Specific indemnity and loss by insurance product are described in Table 2.A.1. 10 years (2007-2016) of aflatoxin-related insurance claims data for 15 states were used: Alabama, Arkansas, Illinois, Iowa, Kansas, Kentucky, Louisiana, Mississippi, Missouri, Nebraska, North Carolina, Oklahoma, Tennessee, Texas, and Virginia. Overall, I infer that a markup in the range of 1.43 to 2.74 is appropriate.

Table 2.A.1 Indemnity, loss and mark up by insurance product

Insurance	Reported Acres per county	Indemnity per acre per county ($)	Loss per acre per county ($)	Mark-up
Yield Protection (YP)	147.2	173.8	465.9	2.68
Revenue Protection (RP)	546.9	292.3	523.9	1.79
Revenue Protection with Harvest Price Exclusion (RPHPE)	123.7	282.1	647.2	2.29
Revenue Assurance (RA)	791.1	215.8	371.5	1.72
Crop Revenue Coverage (CRC)	1408.8	196.9	359.8	1.83
Actual Production History (APH)	550.3	117.1	320.4	2.74
Average	1009.2	241.6	578.7	2.40

Indemnity amounts for RA, CRC were smaller than indemnity for RP and RPHPE. Also, indemnity for APH was smaller than indemnity for YP. The reason is that corn price between 2011-2013 was higher than other years. Insurance product RA, CRC, APH have been sold until 2010 while YP, RP, and RPHPE have been being sold after 2011. Therefore, increased revenue after 2010 caused higher indemnities. YP and APH protect yield rather than revenue. These yield protection products caused less indemnity amount compared to revenue protection productions. Calculated mark-up range was 1.72-2.74. Overall, I infer that a markup in the range of 1.43 to 2.74 is appropriate.

Calculation of marginal effect

The estimated marginal effect of Bt corn on aflatoxin is provided to capture the response of aflatoxin-related insurance claims upon a one percentage point increase in Bt adoption. The estimated marginal effect varies across the population because other model variables differ across the population. In order to capture a representative marginal effect I used the unconditional mean, i.e., the average marginal effect is calculated by $[N^{-1}\sum_{i=1}^{N}\Phi(\boldsymbol{x}_t\hat{\boldsymbol{\beta}}+\hat{\psi}+\overline{\boldsymbol{x}}_i\hat{\boldsymbol{\xi}}/\hat{\sigma}_v^2)]\hat{\boldsymbol{\beta}}_j$. This summary statistic is commonly called the Average Partial Effect (APE). When the model is non-linear, as with my model, then the APE is a more accurate estimation of the marginal effect.

Table 2.A.2 Summary statistics and data sources

Variables	Definition	Mean	St. Dev.	Data source	Availability	Unit
Aflatoxin occurrence rate	Aflatoxin claimed area over insured area*100	0.26[a]	2.51	USDA RMA	2001-2016	County
Bt adoption	Bt/Stacked gene adoption rate	52.5	30.7	GfK	2001-2016	Crop-District
seed cost per expected yield	Ratio of average seed cost per unit to average yield between 1991-2000 ($ per bushels)	0.59	0.28	GfK & NASS	2001-2016	Crop-District
Expected yield	Average yield in each crop district in 1991-2000 (bu/hectare)	280	62.1	NASS	1991-2000	
Palmer Z INDX (JUN)	Palmer Z index in June	0.20	2.28	NOAA	1895-2016	Climate District
Palmer Z INDX (JUL)	Palmer Z index in July	0.17	2.28	NOAA	1895-2016	Climate District
Palmer Z INDX (AUG)	Palmer Z index in August	0.30	2.19	NOAA	1895-2016	Climate District
Palmer Z INDX (SEP)	Palmer Z index in September	0.11	2.13	NOAA	1895-2016	Climate District
Favorable temperature (JUNE)	Ratio of the number of days with maximum temperatures between 30-40°C to the number of measured days	0.55	0.26	NOAA	1763-2016	Weather station
Unfavorable temperature (JUNE)	Ratio of the number of days with maximum temperatures above 42°C to the number of measured days	0.00	0.01	NOAA	1763-2016	Weather station
Favorable temperature (JULY)	Ratio of the number of days with maximum temperatures between 30-40°C to the number of measured days	0.70	0.25	NOAA	1763-2016	Weather station
Unfavorable temperature (JULY)	Ratio of the number of days with maximum temperatures above 42°C to the number of measured days	0.00	0.01	NOAA	1763-2016	Weather station
Aflatoxin related indemnities	Indemnity amount caused by aflatoxin ($1000)	10.7	130	USDA RMA	2001-2016	County
Insurance coverage	Weighted average of insurance coverage	0.68	0.07	USDA RMA	1980-2016	County

[a] This is the simple mean of aflatoxin occurrence rate. The weighted average is 0.13 (%) for 12,127 observations

Table 2.A.3 First stage of main regression (coefficient)

	Bt adoption rate					
	Coefficient and standard errors					
Variables	model (1)	model (2)	model (3)	model (4)	model (5)	model (6)
IV1: Seed cost per expected yield	80.758***	80.816***	80.962***	79.503***	79.965***	79.529***
	(4.043)	(4.094)	(4.061)	(3.876)	(3.877)	(3.826)
IV2: Expected yield	0.260***	0.260***	0.264***	0.255***	0.257***	0.252***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Palmer Z index						
Palmer Z in June	0.045	0.054	0.069	0.023	0.054	0.090
	(0.070)	(0.069)	(0.069)	(0.074)	(0.074)	(0.083)
Palmer Z in July	-0.133	-0.146*	-0.160*	-0.203**	-0.203**	-0.360***
	(0.086)	(0.086)	(0.086)	(0.085)	(0.085)	(0.089)
Palmer Z in August	-0.053	-0.055	-0.051	-0.075	-0.067	-0.075
	(0.072)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)
Palmer Z in September	0.512***	0.511***	0.504***	0.508***	0.497***	0.496***
	(0.070)	(0.070)	(0.069)	(0.069)	(0.069)	(0.069)
Temperature in June						
Range 26-36°C	-1.023	-0.327	0.267			
	(1.432)	(1.278)	(1.263)			
Range 28-38°C				-0.958	-0.279	
				(1.452)	(1.430)	
Range 30-40°C						1.506
						(1.411)
Above 38°C	-11.909**					
	(5.102)					
Above 40°C		-22.868***		-27.473***		
		(7.252)		(7.102)		
Above 42°C			-6.497		-13.441	-13.911*
			(8.770)		(8.474)	(8.395)

Table 2.A.3 (cont'd)

	Bt adoption rate					
	Coefficient and standard errors					
Variables	model (1)	model (2)	model (3)	model (4)	model (5)	model (6)
Temperature in July						
Range 26-36°C	-0.634	-1.573	-2.113*			
	(1.452)	(1.254)	(1.170)			
Range 28-38°C				-5.458***	-5.227***	
				(1.157)	(1.058)	
Range 30-40°C						-8.045***
						(1.199)
Above 38°C	4.601*					
	(2.645)					
Above 40°C		5.606		-0.508		
		(3.938)		(4.083)		
Above 42°C			-21.143		-31.147**	-38.232***
			(12.985)		(13.503)	(13.629)
State dummies						
AL	-9.623***	-10.406***	-9.999***	-6.643***	-6.655***	-5.751**
	(2.530)	(2.578)	(2.545)	(2.386)	(2.387)	(2.377)
AR	4.426**	3.535	3.222	7.004***	6.917***	7.355***
	(2.179)	(2.180)	(2.167)	(2.153)	(2.110)	(2.120)
GA	-21.745***	-22.429***	-22.245***	-19.760***	-19.790***	-18.809***
	(2.155)	(2.179)	(2.169)	(2.139)	(2.134)	(2.144)
IA	13.226***	11.720***	11.493***	12.488***	12.568***	10.892***
	(1.546)	(1.400)	(1.373)	(1.648)	(1.611)	(1.815)
IL	6.593***	5.217***	5.140***	7.478***	7.519***	6.515***
	(1.434)	(1.329)	(1.312)	(1.478)	(1.444)	(1.695)
KS	13.419***	11.911***	12.233***	12.485***	12.746***	11.820***
	(1.262)	(1.003)	(0.932)	(1.258)	(1.130)	(1.438)
KY	-0.900	-2.104	-2.063	1.709	1.656	1.476
	(1.428)	(1.391)	(1.356)	(1.362)	(1.322)	(1.555)
LA	-3.704***	-4.259***	-4.447***	-1.270	-1.294	-0.371
	(1.411)	(1.446)	(1.416)	(1.350)	(1.304)	(1.321)
MO	14.146***	12.991***	13.032***	15.048***	15.184***	14.998***
	(1.316)	(1.197)	(1.163)	(1.428)	(1.383)	(1.632)
MS	-12.922***	-13.617***	-13.604***	-10.470***	-10.475***	-9.677***
	(1.712)	(1.731)	(1.720)	(1.638)	(1.619)	(1.611)
NC	10.962***	9.883***	10.052***	13.782***	13.718***	13.978***
	(1.937)	(1.968)	(1.920)	(1.760)	(1.735)	(1.793)

Table 2.A.3 (cont'd)

	Bt adoption rate					
	Coefficient and standard errors					
Variables	model (1)	model (2)	model (3)	model (4)	model (5)	model (6)
NE	12.060***	10.769***	10.527***	10.458***	10.464***	10.345***
	(1.528)	(1.400)	(1.346)	(1.689)	(1.618)	(1.770)
OK	9.097***	8.023***	8.102***	8.732***	8.664***	8.094***
	(2.932)	(2.847)	(2.815)	(2.811)	(2.750)	(2.697)
SC	-4.767**	-5.532***	-5.231***	-2.850	-2.907	-2.086
	(1.903)	(1.962)	(1.926)	(1.794)	(1.785)	(1.805)
TN	10.525***	9.476***	9.750***	13.553***	13.559***	14.000***
	(1.300)	(1.294)	(1.254)	(1.117)	(1.093)	(1.240)
TX (omitted)	-	-	-	-	-	-
Year Dummies	-	-	-	-	-	-
	-	-	-	-	-	-
Year 2001	25.153***	24.999***	24.718***	25.911***	25.496***	25.506***
	(2.585)	(2.577)	(2.552)	(2.466)	(2.456)	(2.428)
	-	-	-	-	-	-
Year 2002	18.539***	18.477***	18.337***	19.091***	18.779***	18.735***
	(2.451)	(2.464)	(2.450)	(2.368)	(2.371)	(2.356)
	-	-	-	-	-	-
Year 2003	19.339***	19.131***	18.813***	20.147***	19.623***	19.507***
	(2.517)	(2.496)	(2.472)	(2.411)	(2.400)	(2.366)
	-	-	-	-	-	-
Year 2004	14.908***	14.832***	14.687***	16.394***	15.962***	16.520***
	(2.383)	(2.384)	(2.363)	(2.308)	(2.299)	(2.254)
Year 2005	-6.845***	-6.738***	-6.599***	-7.510***	-7.207***	-7.233***
	(2.287)	(2.293)	(2.282)	(2.205)	(2.206)	(2.185)
Year 2006	-7.230***	-7.214***	-6.995***	-7.924***	-7.509***	-7.582***
	(2.142)	(2.156)	(2.143)	(2.080)	(2.080)	(2.069)
Year 2007	2.266	2.368	2.490	1.500	1.787	1.099
	(2.007)	(2.011)	(1.998)	(1.929)	(1.927)	(1.886)
Year 2008	-0.455	-0.403	-0.359	-0.918	-0.748	-0.942
	(1.586)	(1.592)	(1.584)	(1.551)	(1.551)	(1.540)
Year 2009	-3.476***	-3.471***	-3.391***	-4.859***	-4.649***	-5.691***
	(1.158)	(1.155)	(1.142)	(1.130)	(1.117)	(1.087)
Year 2010	-5.234***	-5.220***	-5.167***	-5.318***	-5.269***	-5.414***
	(1.070)	(1.067)	(1.064)	(1.048)	(1.049)	(1.045)
Year 2011	-0.196	-0.101	-0.003	-0.060	-0.010	0.593
	(1.038)	(1.021)	(1.019)	(1.014)	(1.007)	(0.998)
Year 2012	-8.507***	-8.271***	-8.576***	-8.174***	-8.599***	-7.730***
	(0.889)	(0.895)	(0.902)	(0.908)	(0.899)	(0.911)

Table 2.A.3 (cont'd)

	Bt adoption rate					
	Coefficient and standard errors					
Variables	model (1)	model (2)	model (3)	model (4)	model (5)	model (6)
Year 2013	-5.196***	-5.109***	-5.156***	-5.765***	-5.788***	-6.245***
	(0.760)	(0.759)	(0.760)	(0.789)	(0.786)	(0.789)
Year 2014	-5.283***	-5.310***	-5.366***	-6.421***	-6.348***	-7.133***
	(0.747)	(0.738)	(0.733)	(0.798)	(0.780)	(0.794)
Year 2015	-3.928***	-3.881***	-3.854***	-4.205***	-4.142***	-4.114***
	(0.763)	(0.763)	(0.764)	(0.774)	(0.774)	(0.752)
Year 2016 (omitted)	-	-	-	-	-	-
Missing data dummy	-0.438	-0.592	-0.510	-0.613	-0.603	-0.563
	(0.487)	(0.487)	(0.485)	(0.516)	(0.511)	(0.523)
Observations	12,127	12,127	12,127	12,127	12,127	12,127

Standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$
A value for partial F-statistics of IV1=IV2=0 is 416.86.

Table 2.A.4 Estimated marginal impact of Viptera and non-Viptera Bt corn on insurance claims

	Viptera adoption rate (First stage)	Non-Viptera Bt adoption rate (First stage)	Aflatoxin–related insurance claims (Second stage)
Variables	coefficients model (1)	coefficients model (2)	Marginal effect and bootstrapped standard errors model (3)
IV1: Seed cost per expected yield	-22.647***		
	(3.683)		
IV2: Expected yield	-0.067***	0.058***	
	(0.011)	(0.007)	
Viptera corn adoption rate			0.252
			(0.163)
Non-Viptera Bt corn adoption rate			-0.292**
			(0.139)
Palmer Z index			
Palmer Z in June	-0.189*	0.583***	-0.129
	(0.108)	(0.137)	(0.200)
Palmer Z in July	0.950***	-0.610***	-0.997***
	(0.121)	(0.177)	(0.292)
Palmer Z in August	-0.126	-0.387***	-0.229
	(0.109)	(0.139)	(0.211)
Palmer Z in September	-0.287**	0.058	0.046
	(0.132)	(0.151)	(0.194)
Temperature in June			
Range 30-40°C	3.967**	1.976	5.761**
	(1.992)	(2.256)	(2.658)
Above 42°C	-23.963*	68.346***	25.032
	(13.438)	(13.830)	(25.471)
Temperature in July			
Range 30-40°C	1.545	9.670***	10.206***
	(1.675)	(2.137)	(3.395)
Above 42°C	-54.719***	80.263***	2.466
	(18.057)	(20.422)	(21.173)
State dummies			
AL	-22.375***	4.490	0.140
	(2.078)	(3.168)	(13.782)
AR	-12.026***	2.276	3.308
	(1.858)	(2.389)	(2.413)
GA	-15.439***	-18.293***	-6.961
	(1.619)	(3.263)	(12.957)

Table 2.A.4 (cont'd)

Variables	Viptera adoption rate (First stage) coefficients model (1)	Non-Viptera Bt adoption rate (First stage) coefficients model (2)	Aflatoxin–related insurance claims (Second stage) Marginal effect and bootstrapped standard errors model (3)
State dummies			
IA	-0.528	-4.446*	-0.088
	(1.783)	(2.325)	(2.247)
IL	1.222	-4.304*	3.973*
	(1.755)	(2.284)	(2.140)
KS	4.910***	-7.404***	0.518
	(1.360)	(1.601)	(2.122)
KY	-5.664***	-6.791***	-3.773
	(1.840)	(2.197)	(13.564)
LA	-17.960***	13.803***	10.490*
	(1.555)	(2.014)	(5.466)
MO	4.043***	-2.855*	-1.190
	(1.459)	(1.705)	(2.033)
MS	-12.255***	-3.637	6.330**
	(2.367)	(2.438)	(2.524)
NC	-16.171***	11.382***	5.549
	(1.648)	(2.509)	(3.946)
NE	1.947	-7.835***	-4.408**
	(1.597)	(2.179)	(2.185)
OK	-5.066	7.947***	10.651***
	(3.354)	(2.943)	(3.102)
SC	-12.185***	8.496***	-1.978
	(1.533)	(2.657)	(13.620)
TN	-2.798*	3.314*	-2.320
	(1.544)	(1.860)	(14.024)
TX (omitted)	-	-	-
Year Dummies			
Year 2011	-31.237***	8.484***	14.620***
	(1.139)	(1.136)	(4.994)
Year 2012	-25.718***	4.528***	15.143***
	(1.050)	(1.188)	(4.486)
Year 2013	-11.749***	4.783***	10.044***
	(0.972)	(1.218)	(2.876)
Year 2014	-5.176***	4.616***	5.153*
	(0.992)	(1.248)	(2.993)

Table 2.A.4 (cont'd)

	Viptera adoption rate (First stage)	Non-Viptera Bt adoption rate (First stage)	Aflatoxin–related insurance claims (Second stage)
	coefficients	coefficients	Marginal effect and bootstrapped standard errors
Variables	model (1)	model (2)	model (3)
Year Dummies			
Year 2015	-3.226***	-0.418	1.334
	(0.901)	(1.050)	(3.198)
Year 2016 (omitted)	-	-	-
First stage residual from model (1)			-0.190
			(0.156)
First stage residual from model (2)			0.345**
			(0.141)
Missing data dummy	0.030	-0.229	-0.183
	(0.490)	(0.713)	(0.552)
Observations	4,198	4,198	4,198

Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
A value for partial F-statistics of IV1=IV2=0 is 19.83 (model1)
A value for partial F-statistics of IV2=0 is 69.77 (model2)

Table 2.A.5 Estimated marginal impact of Bt corn, humidity, and temperature on aflatoxin–related insurance claims using Tobit model

	Aflatoxin–related insurance claims					
	Marginal effect and bootstrapped standard errors					
Variables	model (1)	model (2)	model (3)	model (4)	model (5)	model (6)
Bt/stacked corn adoption rate (%)	-0.015***	-0.015***	-0.016***	-0.013***	-0.015***	-0.016***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.003)
Palmer Z index (index range-6.44 ~ 11.58)						
Palmer Z in June	-0.073***	-0.073***	-0.072***	-0.065***	-0.061***	-0.044***
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.012)
Palmer Z in July	-0.046***	-0.046***	-0.050***	-0.046***	-0.053***	-0.041***
	(0.010)	(0.010)	(0.011)	(0.010)	(0.011)	(0.011)
Palmer Z in August	0.003	0.003	0.002	0.004	0.003	0.006
	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.008)
Palmer Z in September	0.021***	0.020***	0.021***	0.017**	0.018**	0.020***
	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
Temperature in June (proportion of the temperature range, 0-1 value)						
Range 26-36°C	-0.357***	-0.205*	-0.151			
	(0.118)	(0.105)	(0.105)			
Range 28-38°C				0.724***	0.880***	
				(0.194)	(0.201)	
Range 30-40°C						0.908***
						(0.194)
Above 38°C	-1.639***					
	(0.434)					
Above 40°C		-2.546***		-1.683**		
		(0.816)		(0.803)		
Above 42°C			-4.129		-3.522	-3.188
			(2.717)		(2.680)	(2.727)

Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.A.5 (cont'd)

	Aflatoxin–related insurance claims					
	Marginal effect and bootstrapped standard errors					
Variables	model (1)	model (2)	model (3)	model (4)	model (5)	model (6)
Temperature in July (proportion of the temperature range, 0-1 value)						
Range 26-36°C	0.186	-0.019	-0.077			
	(0.136)	(0.106)	(0.105)			
Range 28-38°C				0.086	-0.061	
				(0.143)	(0.121)	
Range 30-40°C						0.325**
						(0.140)
Above 38°C	0.746***					
	(0.210)					
Above 40°C		0.615*		0.765**		
		(0.317)		(0.360)		
Above 42°C			-2.119*		-1.618	-0.675
			(1.166)		(1.131)	(1.210)
State dummies						
AL	-0.924***	-0.920***	-0.910***	-0.870***	-0.825***	-0.745***
	(0.197)	(0.197)	(0.203)	(0.186)	(0.191)	(0.189)
AR	-0.486***	-0.487***	-0.393***	-0.379***	-0.230**	-0.072
	(0.131)	(0.128)	(0.129)	(0.117)	(0.114)	(0.118)
GA	-1.446**	-1.411**	-1.451**	-1.441**	-1.458**	-1.436**
	(0.640)	(0.630)	(0.644)	(0.627)	(0.638)	(0.639)
IA	-0.329**	-0.263**	-0.108	0.165	0.352***	0.361***
	(0.134)	(0.118)	(0.117)	(0.118)	(0.121)	(0.135)
IL	-0.490***	-0.426***	-0.329***	-0.052	0.087	0.163
	(0.122)	(0.106)	(0.105)	(0.098)	(0.100)	(0.118)
KS	-0.614***	-0.580***	-0.471***	-0.302***	-0.198**	-0.021
	(0.114)	(0.096)	(0.086)	(0.096)	(0.084)	(0.110)
KY	-1.632	-1.576	-1.566	-1.194	-1.138	-0.995
	(1.227)	(1.197)	(1.229)	(1.199)	(1.243)	(1.245)
LA	-0.408**	-0.423**	-0.361*	-0.478***	-0.373**	-0.304
	(0.194)	(0.190)	(0.196)	(0.182)	(0.187)	(0.186)
MO	-0.662***	-0.629***	-0.521***	-0.254**	-0.113	0.049
	(0.128)	(0.115)	(0.110)	(0.110)	(0.105)	(0.127)
MS	-0.605***	-0.589***	-0.567***	-0.517***	-0.455***	-0.382***
	(0.141)	(0.138)	(0.144)	(0.126)	(0.130)	(0.132)

Table 2.A.5 (cont'd)

	Aflatoxin–related insurance claims					
	Marginal effect and bootstrapped standard errors					
Variables	model (1)	model (2)	model (3)	model (4)	model (5)	model (6)
State dummies						
NC	-0.977***	-0.968***	-0.897***	-0.830***	-0.709***	-0.501***
	(0.174)	(0.167)	(0.169)	(0.161)	(0.158)	(0.160)
NE	-0.778***	-0.750***	-0.608***	-0.387***	-0.255*	-0.182
	(0.160)	(0.141)	(0.137)	(0.144)	(0.137)	(0.156)
OK	-0.376***	-0.453***	-0.357***	-0.266**	-0.168	-0.021
	(0.137)	(0.129)	(0.119)	(0.129)	(0.121)	(0.137)
SC	-1.219***	-1.212***	-1.218***	-1.147***	-1.129***	-1.013***
	(0.219)	(0.217)	(0.224)	(0.206)	(0.211)	(0.212)
TN	-1.100**	-1.072**	-1.028*	-0.883	-0.786	-0.599
	(0.545)	(0.544)	(0.546)	(0.545)	(0.546)	(0.553)
TX (omitted)	-	-	-	-	-	-
Year Dummies						
Year 2001	-1.246***	-1.175***	-1.273***	-1.002***	-1.129***	-1.220***
	(0.258)	(0.254)	(0.263)	(0.270)	(0.283)	(0.295)
Year 2002	-0.622***	-0.544***	-0.642***	-0.403**	-0.523***	-0.597***
	(0.189)	(0.182)	(0.190)	(0.190)	(0.198)	(0.202)
Year 2003	-0.780***	-0.682***	-0.769***	-0.458**	-0.558***	-0.595***
	(0.198)	(0.190)	(0.199)	(0.204)	(0.211)	(0.213)
Year 2004	-0.874***	-0.794***	-0.884***	-0.604**	-0.711***	-0.777***
	(0.259)	(0.252)	(0.262)	(0.269)	(0.275)	(0.284)
Year 2005	-0.115	-0.051	-0.129	0.061	-0.032	-0.072
	(0.163)	(0.160)	(0.162)	(0.167)	(0.170)	(0.168)
Year 2006	-0.451***	-0.393**	-0.449***	-0.276*	-0.347**	-0.336**
	(0.166)	(0.160)	(0.163)	(0.166)	(0.170)	(0.169)
Year 2007	-0.263*	-0.197	-0.247	-0.078	-0.140	-0.156
	(0.156)	(0.151)	(0.155)	(0.157)	(0.161)	(0.160)
Year 2008	0.222	0.265*	0.218	0.341**	0.279*	0.269*
	(0.145)	(0.141)	(0.143)	(0.146)	(0.148)	(0.144)
Year 2009	0.223	0.258*	0.217	0.431***	0.375**	0.366**
	(0.151)	(0.147)	(0.149)	(0.158)	(0.158)	(0.154)
Year 2010	0.399***	0.439***	0.407***	0.467***	0.425***	0.379***
	(0.149)	(0.146)	(0.148)	(0.147)	(0.149)	(0.144)
Year 2011	0.253*	0.302**	0.289**	0.410***	0.398***	0.368**
	(0.149)	(0.145)	(0.146)	(0.150)	(0.152)	(0.146)

Table 2.A.5 (cont'd)

	Aflatoxin–related insurance claims					
	Marginal effect and bootstrapped standard errors					
Variables	model (1)	model (2)	model (3)	model (4)	model (5)	model (6)
Year Dummies						
Year 2012	0.509***	0.554***	0.512***	0.656***	0.640***	0.627***
	(0.145)	(0.141)	(0.142)	(0.151)	(0.154)	(0.151)
Year 2013	0.275*	0.310**	0.275*	0.425***	0.397**	0.441***
	(0.155)	(0.151)	(0.152)	(0.160)	(0.161)	(0.157)
Year 2014	0.081	0.091	0.089	0.114	0.108	0.203
	(0.173)	(0.168)	(0.170)	(0.173)	(0.173)	(0.173)
Year 2015	0.062	0.090	0.082	0.134	0.138	0.160
	(0.253)	(0.249)	(0.253)	(0.254)	(0.258)	(0.255)
Year 2016 (omitted)	-	-	-	-	-	-
First stage residual	0.017***	0.016***	0.018***	0.015***	0.017***	0.018***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Missing data dummy	-0.071*	-0.062	-0.063	-0.065	-0.072	-0.074
	(0.042)	(0.043)	(0.043)	(0.045)	(0.046)	(0.048)
Observations	12,127	12,127	12,127	12,127	12,127	12,127

Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.A.6 Estimated marginal impact of Bt corn, humidity, and temperature on aflatoxin–related insurance claims using Probit and Fractional Probit model

	Aflatoxin–related insurance claims	
	Marginal effect and bootstrapped standard errors	
Variables	Probit	Fractional Probit*
	(1)	(2)
Bt/stacked corn adoption rate	-0.002***	-0.014***
	(0.000)	(0.003)
Palmer Z index		
Palmer Z in June	-0.006***	-0.074***
	(0.002)	(0.019)
Palmer Z in July	-0.005***	-0.028*
	(0.001)	(0.016)
Palmer Z in August	-0.001	0.022
	(0.001)	(0.014)
Palmer Z in September	0.002***	0.013
	(0.001)	(0.009)
Temperature in June		
Range 30-40°C	0.111***	0.843***
	(0.020)	(0.260)
Above 42°C	-0.531	-1.335
	(0.396)	(3.509)
Temperature in July		
Range 30-40°C	0.050***	-0.074
	(0.018)	(0.235)
Above 42°C	-0.024	-1.856
	(0.169)	(1.959)
State dummies		
AL	-0.093***	-0.724***
	(0.018)	(0.206)
AR	-0.012	-0.062
	(0.015)	(0.131)
GA	-0.178***	-1.542***
	(0.031)	(0.458)
IA	0.048**	-0.085
	(0.019)	(0.207)
IL	0.025	-0.222
	(0.017)	(0.177)
KS	0.013	-0.375**
	(0.014)	(0.161)
KY	-0.089***	-1.402***
	(0.025)	(0.485)
LA	-0.051**	-0.164
	(0.022)	(0.164)

Table 2.A.6 (cont'd)

	Aflatoxin–related insurance claims	
	Marginal effect and bootstrapped standard errors	
Variables	Probit	Fractional Probit*
	(1)	(2)
State dummies		
MO	0.009	-0.236
	(0.017)	(0.182)
MS	-0.047***	-0.303**
	(0.018)	(0.136)
NC	-0.070***	-0.735***
	(0.019)	(0.237)
NE	-0.024	-1.007***
	(0.019)	(0.267)
OK	0.026	-0.137
	(0.020)	(0.187)
SC	-0.129***	-0.906***
	(0.018)	(0.246)
TN	-0.072***	-0.658*
	(0.023)	(0.397)
TX	-	-
(omitted)		
Year Dummies		
Year 2001	-0.091**	-1.417***
	(0.037)	(0.419)
Year 2002	-0.037	-0.636**
	(0.029)	(0.310)
Year 2003	-0.039	-0.577*
	(0.031)	(0.314)
Year 2004	-0.042	-0.736**
	(0.033)	(0.352)
Year 2005	0.019	-0.320
	(0.024)	(0.273)
Year 2006	-0.019	-0.447
	(0.023)	(0.287)
Year 2007	0.008	-0.515*
	(0.022)	(0.298)
Year 2008	0.057***	-0.064
	(0.018)	(0.258)
Year 2009	0.067***	0.031
	(0.019)	(0.265)
Year 2010	0.067***	0.070
	(0.018)	(0.264)

Table 2.A.6 (cont'd)

	Aflatoxin–related insurance claims	
	Marginal effect and bootstrapped standard errors	
Variables	Probit	Fractional Probit*
	(1)	(2)
Year Dummies		
Year 2011	0.062***	0.035
	(0.017)	(0.280)
Year 2012	0.107***	0.057
	(0.017)	(0.274)
Year 2013	0.071***	-0.043
	(0.019)	(0.297)
Year 2014	0.036*	-0.183
	(0.020)	(0.318)
Year 2015	0.030	-0.395
	(0.020)	(0.342)
Year 2016 (omitted)	-	-
First stage residual	0.002***	0.015***
	(0.000)	(0.004)
Missing data dummy	-0.010*	-0.007
	(0.006)	(0.068)
Observations	12,127	12,127

Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.A.7 Viptera adoption rates (%) by states over two-year intervals, 2011-2016 [a]

	2011-2012	2013-2014	2015-2016
AL	0.5	5.4	10.3
AR	1.3	11.9	9.1
GA	0.0	12.0	10.2
IL	1.4	21.3	19.9
IA	1.4	16.1	21.9
KS	4.3	21.3	36.4
KY	1.9	24.9	30.1
LA	0.4	4.8	2.3
MS	1.8	4.6	17.1
MO	2.5	24.8	43.6
NE	2.8	21.9	31.9
NC	1.1	6.1	11.9
OK	0.0	19.1	30.5
SC	4.3	4.4	10.8
TN	3.6	18.1	25.4
TX	6.4	11.9	26.9
Sixteen States Total	2.2	18.8	25.8

[a] Two years average value is calculated by mean value of each year's adoption rate

Table 2.A.8 Summary of aflatoxin related insurance claims (indemnities and percentage), time averages 2001-2016 [a]

	(A) Aflatoxin related indemnities per year (1,000 $)	(B) Indemnities per insured area (US $/hectare)	(C) Indemnity per area reporting aflatoxin as primary cause of loss (US 1,000$/hectare)	(D) Aflatoxin related claims (%) [b]
AL	11.4	0.16	285	0.06
AR	1,040	7.04	733	0.96
GA	15.5	0.15	588	0.03
IL	756	0.20	676	0.03
IA	638	0.13	449	0.03
KS	391	0.28	575	0.05
KY	14.4	0.04	854	0.00
LA	289	1.47	365	0.40
MS	2,490	10.51	894	1.18
MO	355	0.33	658	0.05
NE	32.7	0.01	681	0.00
NC	104	0.37	511	0.07
OK	255	2.70	443	0.61
SC	17.6	0.17	148	0.12
TN	49.0	0.23	696	0.03
TX	4,150	5.46	264	2.07
Sixteen States Total	10,613	0.63	415	0.15

[a] Data for this table covers all counties in the set, including those not included in the regression due to unobserved covariates.

[b] Aflatoxin-related claims are defined by 100 times the gross area lost due to aflatoxin divide by insured area.

REFERENCES

REFERENCES

Abbas HK, Accinelli C, Zablotowicz RM, Abel CA, Bruns HA, Dong Y, et al. 2008. Dynamics of mycotoxin and aspergillus flavus levels in aging bt and non-bt corn residues under mississippi no-till conditions. Journal of Agricultural and Food Chemistry 56:7578-7585, PMID: 18642924, https://doi.org/10.1021/jf801771a.

Agricultural Marketing Service (AMS), Federal Docket 2018-09389, https://www.regulations.gov/document?D=AMS_FRDOC_0001-1709.

Battilani P, Toscano P, Van der Fels-Klerx H, Moretti A, Leggieri MC, Brera C, et al. 2016. Aflatoxin b 1 contamination in maize in Europe increases due to climate change. Scientific Reports 6:srep24328 PMID: 27066906, https://doi.org/10.1038/srep24328.

Bowen K, Flanders K, Hagan A, Ortiz B. 2014. Insect damage, aflatoxin content, and yield of bt corn in alabama. Journal of Economic Entomology 107:1818-1827, PMID: 26309272, https://doi.org/10.1603/EC13442.

Bowers E, Hellmich R, Munkvold G. 2014. Comparison of fumonisin contamination using hplc and elisa methods in bt and near-isogenic maize hybrids infested with european corn borer or western bean cutworm. Journal of Agricultural and Food chemistry 62:6463-6472, PMID: 24964132, https://doi.org/10.1021/jf5011897.

Buntin GD, Lee RD, Wilson DM, McPherson RM. 2001. Evaluation of yieldgard transgenic resistance for control of fall armyworm and corn earworm (lepidoptera: Noctuidae) on corn. Florida Entomologist:37-42, https://doi.org/10.2307/3496660.

Chamberlain G. 1980. Analysis of covariance with qualitative data. The Review of Economic Studies 47:225-238, https://doi.org/10.2307/2297110.

Chen Z-Y, Brown RL, Cleveland TE. 2004. Evidence for an association in corn between stress tolerance and resistance to aspergillus flavus infection and aflatoxin contamination. African Journal of Biotechnology 3:693-699.

De La Campa R, Hooker DC, Miller JD, Schaafsma AW, Hammond BG. 2005. Modeling effects of environment, insect damage, and bt genotypes on fumonisin accumulation in maize in argentina and the Philippines. Mycopathologia 159:539-552, PMID: 15983741, https://doi.org/10.1007/s11046-005-2150-3.

Dively GP, Venugopal PD, Finkenbinder C. 2016. Field-evolved resistance in corn earworm to cry proteins expressed by transgenic sweet corn. PloS One 11:e0169115, PMID: 28036388, https://doi.org/10.1371/journal.pone.0169115.

Dively GP, Venugopal PD, Bean D, Whalen J, Holmstrom K, Kuhar TP, et al. 2018. Regional pest suppression associated with widespread bt maize adoption benefits vegetable growers.

Proceedings of the National Academy of Sciences 115:3320-3325, PMID: 29531049, https://doi.org/10.1073/pnas.1720692115.

Efron B. 1979. Bootstrap methods: Another look at the jackknife. The Annals of Statistics:1-26, https://doi.org/10.1214/aos/1176344552.

Fernandez-Cornejo J, Wechsler S, Livingston M, Mitchell L. 2014. Genetically engineered crops in the United States, Economic Research Report 164263, United States Department of Agriculture, Economic Research Service, http://dx.doi.org/10.2139/ssrn.2503388.

Gassmann AJ. 2012. Field-evolved resistance to bt maize by western corn rootworm: Predictions from the laboratory and effects in the field. Journal of Invertebrate Pathology 110:287-293, PMID: 22537837, https://doi.org/10.1016/j.jip.2012.04.006.

Guo Z, Small DS. 2016. Control function instrumental variable estimation of nonlinear causal effect models. The Journal of Machine Learning Research 17:3448-3482.

Hammond BG, Campbell KW, Pilcher CD, Degooyer TA, Robinson AE, McMillen BL, et al. 2004. Lower fumonisin mycotoxin levels in the grain of bt corn grown in the united states in 2000− 2002. Journal of Agricultural and Food Chemistry 52:1390-1397, PMID: 14995151, https://doi.org/10.1021/jf030441c.

Halpin C. 2005. Gene stacking in transgenic plants–the challenge for 21st century plant biotechnology. Plant Biotechnology Journal 3:141-155, PMID: 17173615, https://doi.org/10.1111/j.1467-7652.2004.00113.x.

Huang F, Qureshi JA, Meagher Jr RL, Reisig DD, Head GP, Andow DA, et al. 2014. Cry1f resistance in fall armyworm *spodoptera frugiperda*: Single gene versus pyramided bt maize. PLoS One 9:e112958, PMID: 25401494 https://doi.org/10.1371/journal.pone.0112958.

Hutchison W, Burkness E, Mitchell P, Moon R, Leslie T, Fleischer SJ, et al. 2010. Areawide suppression of european corn borer with bt maize reaps savings to non-bt maize growers. Science 330:222-225, PMID: 20929774, https://doi.org/10.1126/science.1190242.

Jones R, Duncan H, Hamilton P. 1981. Planting date, harvest date, and irrigation effects on infection and aflatoxin production by aspergillus flavus in field corn. Phytopathology 71, 810–816, https://doi.org/10.1094/Phyto-71-810.

Karl TR. 1986. The sensitivity of the palmer drought severity index and palmer's z-index to their calibration coefficients including potential evapotranspiration. Journal of Climate and Applied Meteorology 25:77-86, http://dx.doi.org/10.1175/1520-0450(1986)025<0077:TSOTPD>2.0.CO;2.

Liu Y, Wu F. 2010. Global burden of aflatoxin-induced hepatocellular carcinoma: A risk assessment. Environmental Health Perspectives 118:818, PMID: 20172840, https://doi.org/10.1289/ehp.0901388.

Masoero F, Moschini M, Rossi F, Prandini A, Pietri A. 1999. Nutritive value, mycotoxin contamination and in vitro rumen fermentation of normal and genetically modified corn (Cry1Ab) grown in Northern Italy. Maydica 44, 205-209.

Menne MJ, Durre I, Vose RS, Gleason BE, Houston TG. 2012. An overview of the global historical climatology network-daily database. Journal of Atmospheric and Oceanic Technology 29:897-910, https://doi.org/10.1175/JTECH-D-11-00103.1.

Mundlak Y. 1978. On the pooling of time series and cross section data. Econometrica: Journal of the Econometric Society:69-85 , https://doi.org/10.2307/1913646.

Munkvold GP, Hellmich RL, Rice LG. 1999. Comparison of fumonisin concentrations in kernels of transgenic bt maize hybrids and nontransgenic hybrids. Plant Disease 83:130-138, https://doi.org/10.1094/PDIS.1999.83.2.130.

O'Brian G, Georgianna D, Wilkinson J, Yu J, Abbas H, Bhatnagar D, et al. 2007. The effect of elevated temperature on gene transcription and aflatoxin biosynthesis. Mycologia 99:232-239, PMID: 17682776, https://doi.org/10.3852/mycologia.99.2.232.

Palmer WC. 1965. Meteorological drought, US Department of Commerce, Weather Bureau Washington, DC, Vol. 30, (1965).

Payne G, Cassel D, Adkins C. 1986. Reduction of aflatoxin contamination in corn by irrigation and tillage. Phytopathology 76:679-684, https://doi.org/DOI:10.1094/Phyto-76-679.

Payne G, Thompson D, Lillehoj E, Zuber M, Adkins C. 1988. Effect of temperature on the preharvest infection of maize kernels by aspergillus flavus. Phytopathology.

Perry ED, Ciliberto F, Hennessy DA, Moschini G. 2016. Genetically engineered crops and pesticide use in us maize and soybeans. Science Advances 2:e1600850, , https://doi.org/10.1126/sciadv.1600850.

Schlenker W, Roberts MJ. 2006. Nonlinear effects of weather on corn yields. Applied Economic Perspectives and Policy 28:391-398, https://doi.org/10.1111/j.1467-9353.2006.00304.x.

Smith CA, Robertson D, Yates B, Nielsen DM, Brown D, Dean RA, et al. 2008. The effect of temperature on natural antisense transcript (nat) expression in aspergillus flavus. Current Genetics 54:241-269, PMID: 18813928, https://doi.org/10.1007/s00294-008-0215-9.

World Health Organization. 1993. Some naturally occurring substances: Food items and constituents, heterocyclic aromatic amines and mycotoxins. IARC Monographs on the Evaluation of the Carcinogenic Risk of Chemicals to Humans 56.

Wiatrak P, Wright D, Marois J, Wilson D. 2005. Influence of planting date on aflatoxin accumulation in bt, non-bt, and tropical non-bt hybrids. Agronomy Journal 97:440-445, http://dx.doi.org/10.2134/agronj2005.0440.

Widstrom N, McMillian W, Beaver R, Wilson D. 1990. Weather-associated changes in aflatoxin contamination of preharvest maize. Journal of Production Agriculture 3:196-199, https://doi.org/10.2134/jpa1990.0196.

Williams WP, Windham GL, Krakowsky MD, Scully BT, Ni X. 2010. Aflatoxin accumulation in bt and non-bt maize testcrosses. Journal of Crop Improvement 24:392-399, https://doi.org/10.1080/15427528.2010.505111.

Wooldridge JM. 2010. Econometric analysis of cross section and panel data. Second edition. ed. Cambridge, MA:MIT Press.

Wooldridge JM. 2015. Control function methods in applied econometrics. Journal of Human Resources 50:420-445, https://doi.org/10.3368/jhr.50.2.420.

Wu F. 2006. Mycotoxin reduction in bt corn: Potential economic, health, and regulatory impacts. Transgenic Research 15:277-289, PMID: 16779644, https://doi.org/10.1007/s11248-005-5237-1.

Wu F, Guclu H. 2012. Aflatoxin regulations in a network of global maize trade. PloS One 7:e45151, PMID: 23049773, https://doi.org/10.1371/journal.pone.0045151.

Wu F. 2014. Global impacts of aflatoxin in maize: Trade and human health. World Mycotoxin Journal 8:137-142, PMID: 16779644, https://doi.org/10.1007/s11248-005-5237-1.

Wu F, Groopman JD, Pestka JJ. 2014. Public health impacts of foodborne mycotoxins. Annual Review of Food Science and Technology 5:351-372, PMID: 24422587, https://doi.org/10.1146/annurev-food-030713-092431.

Wu F, Mitchell N. 2016. How climate change and regulations can affect the economics of mycotoxins. World Mycotoxin Journal 9:653-663, https://doi.org/10.3920/WMJ2015.2015.

Xu Z, Hennessy DA, Sardana K, Moschini G. 2013. The realized yield effect of genetically engineered crops: Us maize and soybean. Crop Science 53:735-745, https://doi.org/10.2135/cropsci2012.06.0399.

CHAPTER 3

The Impact of Climate Change on Aflatoxin Contamination in U.S. Corn

3.1 Introduction

Aflatoxin is a fungal toxin that has caused between 25,000 and 155,000 cases of liver cancer worldwide (Liu and Wu 2010). Chronic aflatoxin exposure causes childhood stunting (Mitchell et al. 2017) and malnutrition (McMillan et al. 2018) in humans. *Aspergillus flavus* and *A. parasiticus* on food crops, such as corn, peanuts, and almonds produce aflatoxin under warm temperatures and dry environmental conditions (Cotty and Jaime-Garcia 2007). Consequently, global warming is likely to increase the risk of aflatoxins and threaten food safety.

It is challenging to predict the impact of climate change on aflatoxin risk, because there are a variety of ways in which temperature and drought can affect corn growth. For instance, warmer weather prevents corn from being susceptible to fungal infection by reducing low temperature stress, but warm conditions are also associated with high aflatoxin production (Wu et al. 2011). Overall drought conditions, which are also associated with high aflatoxin via increased water stress, are also difficult to predict (Burke et al. 2015).

Multiple review papers have suggested that increased temperatures and water stress raise aflatoxin accumulation (Magan et al. 2011; Medina et al. 2014; Wu and Mitchell 2016; Gilbert et al. 2016; Assunção et al. 2018). However, less research has focused on empirically studying the relationship between aflatoxin in corn and future climate change. Bailliani et al. (2012) predicted that the risk of *A. flavus* contaminations is likely to increase in corn when daily temperature increases by either 2°C or 5 °C in the southern European countries. They also forecast that predicted that Greece, southern Italy, Bulgaria, and Albania are likely to have high aflatoxin risks due to expected increases in daily temperatures by 2°C (Battilani et al. 2016). Salvacion et al.

(2015) assessed that the risk of aflatoxin contamination is expected to decrease due to increased rainfall in the Philippines.

This study predicted aflatoxin risk in the United States under sixteen climate change models. Considering that the United States is the world's largest corn-producing country, predicting aflatoxin risk in corn in the United States is a meaningful step toward gauging worldwide aflatoxin risk to the global corn crop. A common assumption made in studies on climate change is that a crop's future growing season will be unaffected by climate change (Kucharik and Serbin 2008; Rosenzweig et al. 2002; Schlenker and Roberts 2009). However, it is more reasonable to expect that farmers will adjust planting season to adapt to global warming, which will consequently change the crop's growing season (Kawasaki 2018).

To more critically examine this assumption, I predicted the calendar time of corn growing season and used climate variables over the growing season to improve predictions of future aflatoxin risks. Warmer temperature is likely to change not only planting date but also reduce the number of days from planting to harvest (Kawasaki 2018). In that case, the meaning of monthly temperature such as June in the future can be different to historic one. Especially, the use of a drought variable in the main growing season is important because droughts' effects on aflatoxin varies across corn growing stage. Chapter two presents the drought effect varies across corn growing stage using monthly drought variables.

Using two adaptations implemented by farmers, I examine how global warming will impact aflatoxin risk in corn in the United States from 2031to 2040. These adaptations involved changing planting periods and adopting a new technology for aflatoxin control. In this study, I estimated the historical relationship between climate variables and aflatoxin between 2007 and 2016, and thereby predicted aflatoxin risk from 2031 to 2040. These estimations were made under the assumption that other conditions—except climate conditions—would remain the same. Median temperature and precipitation from 16 climate models were used as the baseline.

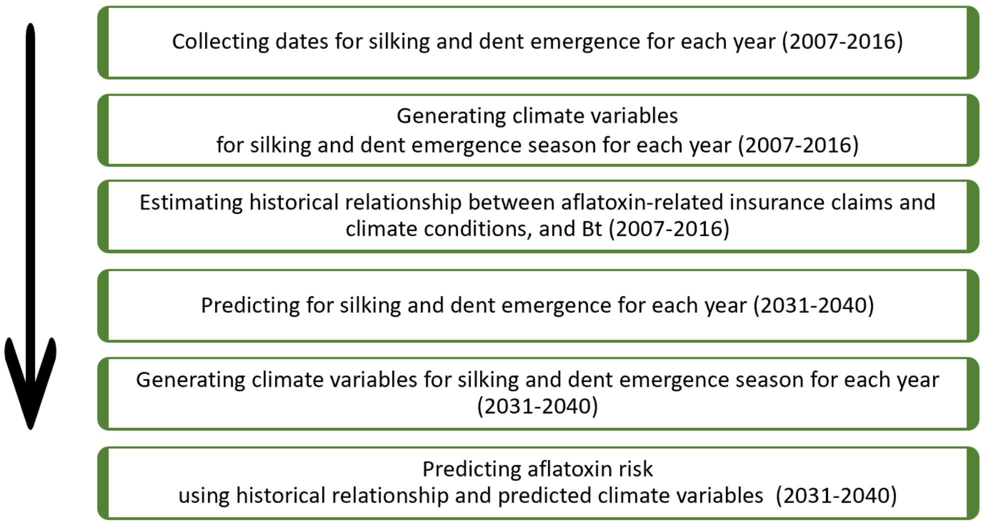
3.2 Biologically Motivated Climate Risk Prediction Framework

To estimate the effect of temperature and precipitation on aflatoxin risk, I used historical data. The main model in this chapter is thus similar to that in chapter two, but the corn growing season's climate variables were used instead of monthly climate variables. For a given year the corn growing season at a given locations varies according to the locations' Springtime climate and also with that year's weather realization. For example, the corn-silking stage in Texas typically begins in June, while in Iowa began in July in 2013. Additionally, in 2014, the corn-silking stage in Texas shifted to May based on changes in the aforementioned factors (Table 3.A.1).

As the second chapter of this dissertation indicated, the effects of temperature and drought on aflatoxin risk vary in the key stage of corn growth. Drought weakens corn, making it susceptible to fungal infection. Because fungus most commonly infects corn right after the silking stage (hereafter referred to as AS season), drought increases aflatoxin accumulation at this stage. To see whether drought effect changes after AS, I also included drought variables after the season, which is assumed to occur right after dent emergence (hereafter referred to as AD season).

Given this, analysis in the current chapter is designed to estimate differing climate effects on aflatoxin between the AS and AD seasons. In particular, the analysis was carried out in the following order (Figure 3.1). First, to generate climate variables for AS and AD seasons, I matched extant climate information with crop progress data from the United States Department of Agriculture (USDA). The USDA provides weekly state level crop progress information, including planting, silking and dent emergence season. Second, to obtain information on how climate affects aflatoxin, I regressed the AS and AD climate variables on aflatoxin incidence. These estimated parameters were then used as the temperature and drought effect in the prediction procedure. Lastly, I estimated future aflatoxin risks using the predicted climate variables. By matching predicted calendar times of AS and AD seasons in 2031-2040, as well as using predicted climate data from sixteen climate models, I generated temperature and precipitation variables for predicting future aflatoxin risk.

Figure 3. 1 Analysis steps



3.3 Historical Data

3.3.1 Aflatoxin-Related Insurance Claims

I operationalized aflatoxin risk as a percentage of aflatoxin-related insurance claims in a given county. Specifically, I obtained data on acres with crop insurance claims regarding aflatoxin and divided them by insured acres. The United States Department of Agriculture Risk Management Agency (USDA RMA) provides data about insured and indemnified acres that includes the amount of indemnity for each crop and the county, as well as cause of loss. To my knowledge, these data are the only sources that provide a proxy for the nation-wide level of aflatoxin incidence. They do, however, have two notable limitations. One is that the only claims recorded are on insured land units. Yet, because crop insurance covered 86% of corn planting areas from 2007 to 2016 for fifteen states, this will not have a significant impact on the study results; as only two cases (counties and year) were excluded from the regression due to a lack of insurance data. The other limitation is that insurance contracts carry deductibles, which generally account for between 15% and 50% of expected crop value. The average size of the deductible taken varies by crop and by location, but has generally declined over the past quarter century. Consequently, minor incidences of aflatoxin-related loss that do not trigger an insured loss will not be recorded, while the incidence of losses that are not reported varies somewhat across states and over time.

To examine the impact of temperature and drought in the corn growing stage, I collected insurance claims data for only the main corn growing seasons of June through September.

3.3.2 Climate Variables

To estimate the effect of drought on aflatoxin-related insurance claims, I used precipitation and maximum temperature on days without rain as explanatory variables instead of the Palmer Z Index that I used in the second chapter. The Palmer Z Index measures the departure of moisture conditions from normal in a given region (Quiring and Papakryiakou 2003). Because normal status is likely to shift due to climate change, I used precipitation directly instead of drought indices. Drought generally depends on the amount of moisture absorbed into the soil, on soil retention properties , and on temperature (Dai et al. 2004; Jacobi et al. 2013). Thus, to complement precipitation that only measures moisture content, I used maximum temperature on days without rain, which affects the rate of evapotranspiration.

In order to measure temperature's effect, I included the proportions of days that had a maximum temperature of 36-40°C and days that had a maximum temperature of above 42°C in AS. For AD season, I included days that had a maximum temperature 28-34°Cand days that had a maximum temperature of above 36°C. According to O'Brian et al. (2007) and Smith et al. (2008), aflatoxin production by *Aspergillus flavus* is maximized in temperatures of 28-30°C and decreases as temperatures reaches 37°C. Because temperatures fluctuate in field settings, I tested the following sets of temperature variables to find a favorable temperature range to increase the incidence of aflatoxin: [32-38°C (AS) and 28-34°C (AD)], [32-38°C (AS) and 30-36°C (AD)], [36-40°C (AS) and 28-34°C (AD)], [36-40°C (AS) and 30-36°C (AD)]. Temperatures above 42°C in AS and Temperatures above 36°C and above 38°C in AD seasons were used as unfavorable temperature ranges. Among these test sets, [36-40°C and 42°C+ (AS) and 28-34°C and 36°C+ (AD)] showed the most appropriate temperature ranges as favorable temperature ranges for aflatoxin. Table 3.A.2 reports these results.

It was necessary to distinguish the temperature/precipitation in AS season from the temperature/precipitation in AD season because the effect of temperature/precipitation can differ across crop growing stages. For instance, as corn kernels are infected early after silking, weather variables just after silking primarily affect whether fungal infection occur in this season. Furthermore, weather variables just after denting primarily affect the extent of any aflatoxin problem. To create the AS and AD seasons' temperature/precipitation variables, I obtained crop growing stage period data from the USDA National Agricultural Statistics Service (NASS). These data provide the percentage of acres that have reached the growth stage in a given week and state. The weather station's daily maximum temperature and precipitation data were drawn from the National Oceanic and Atmospheric Administration (NOAA) (Menne et al. 2012). I used the average temperature and precipitation at the weather station as a county-level temperature-precipitation variable. On average, there are 4.83 weather stations within a county.

3.3.3 Irrigation

I used county level irrigation as an explanatory variable. Drought's effect on aflatoxin can be mitigated by irrigation. Jones et al. (1981) suggested that infection and aflatoxin concentration by *Aspergillus flavus* are released under irrigation by comparing irrigated and non-irrgated plots in North Carolina. Payne et al. (1986) also concluded that irrigation has reduced aflatoxin contamination.

I used county level proportion of land that is irrigated, i.e., the share of toal acres in a county that are irrigated. County level irrigation data were obtained from United States Geological Survey (USGS). Total irrigated acres were only available in 2005, 2010, and 2015. Since analysis with only these three years have few observations, I generated three types of irrigated acres variables. First, I assumed that irrigated acres does not change during five years (irrigation_5year). For example, irrigated acres in 2004, 2005, 2006, 2007 and 2008 are the same as irrigated acres in 2005. Similarly, irrigated acres in 2009-2012 are the same as irrigated acres in 2010. Second, I assumed that irrigated acres increase continuously. Irrigated acres in 2008 is calculated by irrigated acres in 2005 + 3/5*(irrigated acres in 2010-irrigated acres in 2005). Lastly, I assumed that irrigation level in 2007 - 2016 are the average value of irrigated acres in 2005, 2010, and 2015. I used the third variable as a main irrigation variable because it minimizes the number of data points that are missing. In other words, a county has an irrigation variable if at least one year of irrigation data exist when we use the last assumption. County size (total acres) data were from U.S. Census Bureau.

For future irrigation level in 2031-2040, I assume that irrigation level in 2031-2040 are the same as those in 2015. It is difficult to expect that irrigation level decrease in the future because reversal of the irrigation requires high cost. Predicting irrigation level is also difficult because the demand depends on climate condition, cost of irrigation, and land use decision.

3.3.4 Bt Corn Adoption Rate

To measure farmers' adaptation behaviors, Bt corn adoption was included in this study. Bt corn is a genetically engineered corn seed that reduces damage by insects. As chapter two highlights, Bt corn adoption has been shown to reduce aflatoxin-related insurance claims. The reason for this is that the reduction of insect damage by Bt corn can decrease fungal infections in damaged corn. Therefore, Bt corn adoption has been an important factor in explaining aflatoxin-related insurance claims, historically. However, recent studies identifying resistance against Bt have raised concerns about the future viability of this control strategy (Bernardi et al. 2015; Dively et al. 2016; Gassmann 2012; Huang et al. 2014; Yang et al. 2018). If resistance is not effectively controlled, Bt corn may not be an efficient control method for aflatoxin in the future. In the prediction model of this study, I assumed that there is a hypothetical new biotechnology in the future, and it has an aflatoxin-preventing effect equivalent to that of Bt technology, and that the adoption rate is the same as that of Bt. These assumptions mean new technology adoption will continuously increase and reach the maximum allowance. Recently, Bt adoption rate have almost reached maximum allowance under the Insect Resistance Management (IRM) which allows Bt corn adoption rate up to 80% in the corn belt area for resistance control. As an example of a hypothetical technology, a biological control may be an efficient method for reducing aflatoxin in the future (Abbas et al. 2017; Yin et al. 2008). In particular, I included the Bt corn adoption rate as an index of new technology adoption that reduces aflatoxin accumulation. Historical data on Bt corn adoption rates were drawn from GfK Kynetec, a survey company specializing in agriculture. The survey provides crop district-level of Bt adoption rates from 2000 to 2016. Each state consists of nine crop districts on average. I collected data for the following 15 states that had aflatoxin-related insurance claims as well as silking and dent emergence season records: Alabama, Arkansas, Illinois, Iowa, Kansas, Kentucky, Louisiana, Mississippi, Missouri, Nebraska, North Carolina, Oklahoma, Tennessee, Texas, and Virginia. Georgia and South Carolina are not included in the analysis due to the lack of crop progress data. I used the previous ten years of data that ranged from 2007 to 2016.

Arkansas, Louisiana, and Virginia, however, only showed crop progress data for 2014-2016. To supplement the limited nature of the data for these states, I imputed information from 2010-2013 for these states by assuming that the silking and dent emergence periods were the same as five years average periods in 2014, which were obtained from USDA. These states have reported aflatoxin-related insurance claims historically, but claims from 2014-2016 are missing. Because using only data from 2014-2016 for these three states can be potentially misunderstood (some might assume these three states have never had aflatoxin-related claims), I imputed information from 2010 to 2013. Yet, I did not impute the data for Alabama, Mississippi, and Oklahoma that also have crop progress only for 2014-2016 because aflatoxin-related insurance claims were reported in these years.

3.4 Methods

3.4.1 The Historical Relationship between Climate Conditions and Aflatoxin Risk

Temperatures, precipitation, maximum temperature on days without rain, irrigation and the Bt corn adoption rate are included as covariates to estimate the historical relationship between climate conditions and the incidence of aflatoxin. The reduced form is as follows:

$$y^*_{c,s,t} \equiv \beta_0 + \sum_{p=AS,AD} (\beta_F^p F^p_{c,s,t} + \beta_U^p U^p_{c,s,t} + \beta_Z^p Z^p_{c,s,t} + \beta_W^p W^p_{c,s,t}) + \beta_R R_{c,s,t} + \beta_B B_{c,s,t} + \beta_T T + \beta_s S + a_{c,s} + u_{c,s,t};$$

(1)

where $y^*_{c,s,t}$ is the aflatoxin risk measured by aflatoxin-related insurance claims in county *c*, state *s* and year *t*; $F^p_{c,s,t}$ is the proportion of days with a maximum temperature of 36-40°C / 28-34°C in county *c*, state *s*, and year *t* during the period *p* (superscript), where *p* is either the AS season or the AD season; $U^p_{c,s,t}$ is the proportion of days with a maximum temperature above 42°C / above 36°C during the AS season / the AD season; $Z^p_{c,s,t}$ is precipitation in the AS season or the AD season; $W^p_{c,s,t}$ is the maximum temperature on days without rain; $R_{c,s,t}$ is proportion of irrigated area within a county; $B_{c,s,t}$ is the Bt corn adoption rate in the crop district where the county is located and year (ranges are 0 to 1); $a_{c,s}$ is the county-specific unobserved factor; and $u_{c,s,t}$ is a normally distributed error term. The calendar time of the AD and AS seasons, described by superscript *p*, varies for each state and year.

I estimated the above model using type I Tobit specifications to explain the fact that 94% of aflatoxin-related insurance claims in my data were zeroes, meaning that in most counties in most years, aflatoxin-related insurance claims were not made by corn growers. This model allows for the probability that aflatoxin-related insurance claims are zero to be positive, $\Pr(y^*_{c,s,t} = 0) > 0$. To allow for county-specific, unobserved factors that affect aflatoxin-related claims, I assumed unobserved factors to be a function of the time averaged value of covariates using the Correlated Random Effect (CRE) model with the Chamberlain-Mundlak approach (Chamberlain 1980; Mundlak 1978). Specific assumptions are as follows:

$$y_{c,s,t} = \max(0, \mathbf{x}_{c,s,t}\boldsymbol{\beta} + a_{c,s} + u_{c,s,t}); \quad (2)$$

$$a_{c,s} = \psi + \bar{\mathbf{x}}_{c,s}\boldsymbol{\xi} + e_{c,s}; \ (3)$$

$$v_{c,s,t} \mid \mathbf{x}_{c,s,t} \sim Normal(0, \sigma^2_v)\ (4)$$

The max(.,.) statement in equation (2) seeks to account for the fact that aflatoxin-related insurance claims were observed only when the fitted model value ($y^*_{c,s,t}$) exceeded zero. Equation (3) indicates an assumption that unobserved county-specific heterogeneity was a linear function of time average of covariates. Equation (4) imposes the normality assumption on composite error $v_{c,s,t} = e_{c,s} + u_{c,s,t}$.

It is important to note that there is an endogeneity issue with Bt adoption. This is because a farmer may adopt Bt corn to reduce aflatoxin, although this is not the main reason most farmers do – rather it is for pest control more generally. However, I did not control for this issue because correlation rather than a causal relationship is more important for predicting aflatoxin risk. If the increased aflatoxin risk due to global warming raises the Bt corn adoption rate, I sought to estimate the adjusted aflatoxin risk from increased Bt corn adoption, because adoption of Bt corn is a natural human adaptation. Predicting the aflatoxin risk based on the causal effect of Bt—rather than the correlation—the estimated risk will be biased because it does not account for farmer seed choice adjustments in the prevention of increased aflatoxin risk.

3.4.2 The Historical Relationship between Climate Conditions and Aflatoxin-related Indemnity

To predict future economic loss, I predicted the potential indemnity claimed for aflatoxin damage. Indemnity is part of the economic loss, and varies across insurance coverage and insurance products, such as those that guarantee yield and revenue. Indemnity data from USDA RMA are the only data available on economic loss from aflatoxin. In addition, the data include information about aflatoxin incidence as well as the severity of aflatoxin, because indemnity varies according to the level of aflatoxin accumulation. I thus estimated the impact of climate conditions on aflatoxin-related indemnity and predicted future indemnity assuming other conditions—except climate—to be the same. Using a mark-up range (from chapter one) that converts indemnity to economic loss, I assumed economic loss to be 1.43 – 2.74 times the indemnity. I estimated the economic loss in each county, invariant to the insurance coverage, by assuming that all corn planting areas had the same probability of aflatoxin incidence conditional on other environmental conditions.

Similar to aflatoxin-related insurance claims, I followed the methods from chapter one to estimate the future economic loss from the aflatoxin accumulation

$$\begin{aligned} E^{*}_{c,s,t} \equiv \beta_0 + \sum_{p=AS,AD} (\beta^{p}_{F} F^{p}_{c,s,t} + \beta^{p}_{Z} Z^{p}_{c,s,t} + \beta^{p}_{W} W^{p}_{c,s,t} + \beta_R R_{c,s,t}) + \beta_B B_{c,s,t} \\ + \beta_I I_{c,s,t} + \beta_T T + \beta_s S + a_{c,s} + u_{c,s,t}; \end{aligned} \tag{5}$$

where $E^{*}_{c,s,t}$ is the aflatoxin-related indemnity per insured acres in county *c*, state *s* and year *t*; and $I_{c,s,t}$ is the average insurance coverage. This equation was estimated by a Tobit model, and the unobserved factor $a_{c,s}$ was estimated by a Correlated Random Effect model. The results are reported in Table 3.A.3.

3.4.3 Predicting Temperature and Precipitation data

To predict aflatoxin risk in the period between 2031and 2040, I used a daily maximum temperature, a minimum temperature, and precipitation data from 16 climate change models. The projected climate data were drawn from different assumptions about the carbon cycle, the ocean model, and economic growth. However, there is insufficient evidence that a certain model is more reliable than others (Burke et al. 2015). Thus, I used the median temperature and precipitation values of the 16 climate models (called a median-climate model) as baseline model.

I calculated temperature and precipitation values for each climate model by adding the average, daily, climate difference to the historical, daily, climate value. The average, daily, climate differences were calculated by finding the difference between the daily temperature and precipitation from 2007 to 2016 for each climate change model, as well as the daily values from 2031 to 2040 for the model. Predicted, daily temperature can therefore be represented by $T^{S}_{c,y,m,d} = T^{H}_{c,y-24,m,d} + \Delta T^{S}_{c,y,y-24,m,d}$

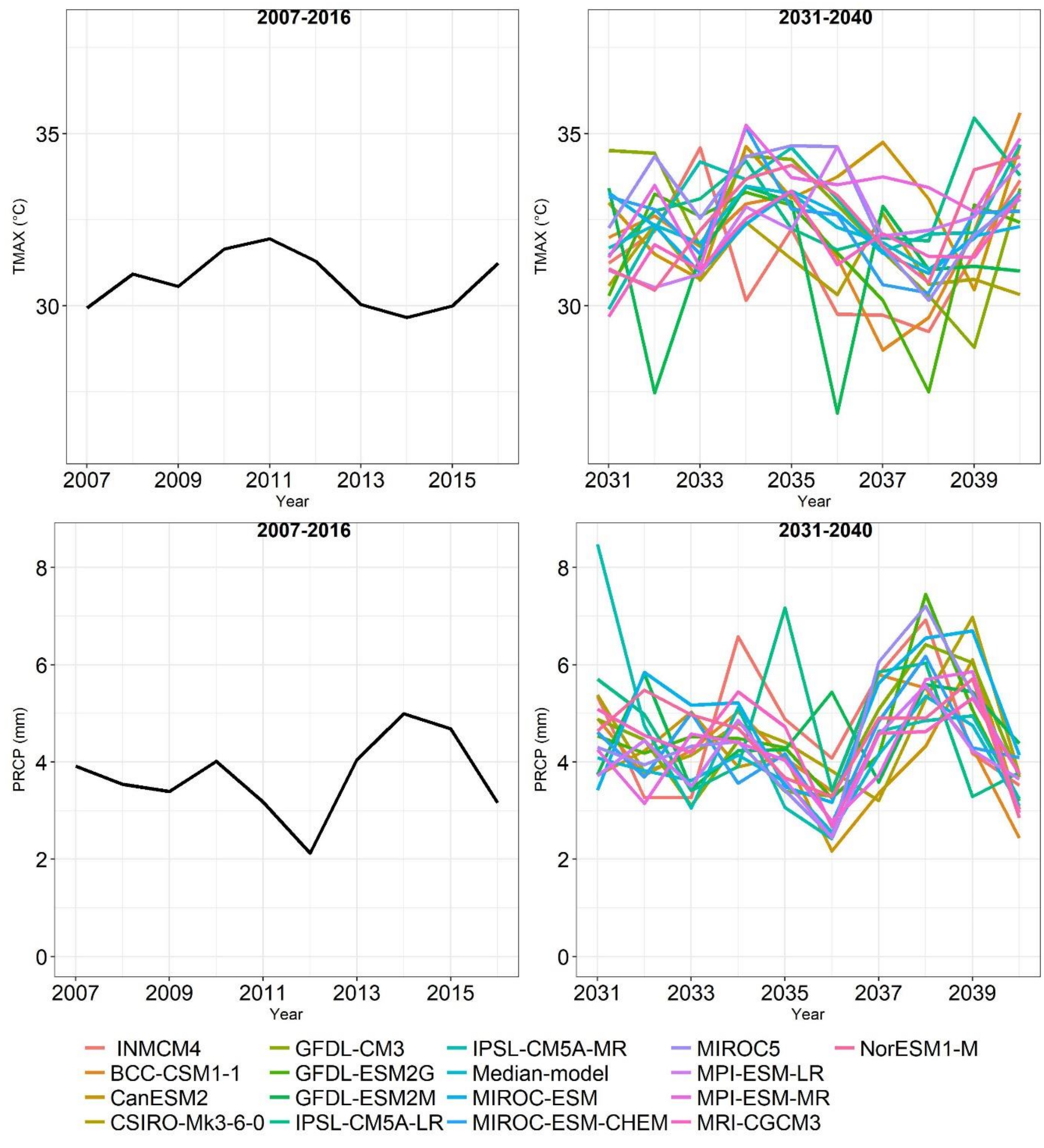
$$\Delta T^{S}_{c,y,y-24,m,d} = \frac{\sum_{i=-15}^{15} T^{S}_{c,y,m,d+i} - T^{S}_{c,y-24,m,d+i}}{31}$$

where $T^{S}_{c,y,m,d}$ is the temperature in county *c*, year $y \in \{2031,\ 2032,\ \ldots\ 2040\}$, month *m*, and day *d* for climate model *S*; $T^{H}_{c,y-24,m,d}$ is the historical temperature in county *c*, year *y-24*, $y \in \{2031,\ 2032,\ \ldots\ 2040\}$, month *m*, and day *d*; $\Delta T^{S}_{c,y-24,m,d}$ is the difference between the temperature in year *y* and year *y-24* for climate model *S*. The difference was averaged by 31 days moving average (Arora et al. working paper). Predicted daily precipitation is represented by adding predicted deviations in the climate forecaset data sets to the historical precipitation data that we used, i.e., $P^{S}_{c,y,m,d} = \max(0, P^{H}_{c,y-24,m,d} + \Delta P^{S}_{c,y,y-24,m,d})$ where $\Delta P^{S}_{c,y,y-24,m,d} = \frac{\sum_{i=-15}^{15} P^{S}_{c,y,m,d+i} - P^{S}_{c,y-24,m,d+i}}{31}$. A maximum function was added to prevent the predicted precipitation from having a negative value.

This particular method was chosen instead of using the projected values of each climate model (which were originally included in each climate model) because each model differs in both previous weather values and projected weather (Burke et al. 2015). Thus, the difference between the two is what each model actually predicted. From here on, I use the term “predicted climate value” for the calculated value to distinguish the originally projected climate value from the climate model.

The projected daily maximum and minimum temperatures and the precipitation data were drawn from the National Aeronautics and Space Administration (NASA). NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDD) provides 21 downscaled climate models and two greenhouse gas emission scenarios. These 21 models are derived from the General Circulation Model (GCM) under the Coupled Model Intercomparison Project Phase 5 (CMIP5). GCM is a climate model for forecasting weather using a mathematical representation of the Earth's atmosphere or ocean. The two greenhouse gas emission scenarios are Representative Concentration Pathways 4.5 and 8.5 (RCPs 4.5 and RCPs 8.5). Each scenario assumes that the carbon dioxide (CO2) concentration in the year 2100 is 538 ppm (RCPs 4.5) (Clarke et al. 2007; Smith and Wigley 2006; Wise et al. 2009) and 936 ppm (RCPs 8.5) (NASA ; Riahi et al. 2007), respectively. Because the projected climate data were drawn from different assumptions about the carbon cycle, the ocean model, and economic growth, there is not enough evidence that a certain model is more reliable than other models (Burke et al. 2015); thus, I did not use a single model. I instead used 16 models with RCPs 8.5 scenario; CSIRO-Mk3-6-0 (Jeffrey et al. 2013), CanESM2 (Chylek et al. 2011), GFDL-CM3 (Griffies et al. 2011), GFDL-ESM2G (Dunne et al. 2013), GFDL-ESM2M (Dunne et al. 2013), IPSL-CM5A-LR (Dufresne et al. 2013), IPSL-CM5A-MR (Dufresne et al. 2013), MIROC-ESM-CHEM (Watanabe et al. 2011), MIROC-ESM (Watanabe et al. 2011), MIROC5 (Watanabe et al. 2010), MPI-ESM-LR (Giorgetta et al. 2013), MPI-ESM-MR (Giorgetta et al. 2013), MRI-CGCM3 (Yukimoto et al. 2012), NorESM1-M (Bentsen et al. 2013), BCC-CSM1-1 (Xiao-Ge et al. 2013), and INMCM4 (Volodin et al. 2010). I used the median value of temperature and precipitation from the 16 climate models (hereafter referred to as median-climate model) as the baseline. Figure 3.2 compares the predicted temperature in June and precipitation in the years 2031 to 2040 using the 16 climate models.[4] Figures 3.A.1 and 3.A.2 indicate each model's maximum temperature and precipitation by month in a key growing season.

Figure 3. 2 Maximum temperature (TMA) and precipitation (PRCP) for 15 states in June in 2031-2040 by climate models



[4] Climate variables are estimated by adding to historical climate records the difference between the numbers for 2031 to 2040 and 2007 to 2016 for each model. Details of the calculation is described in the methods section.

3.4.4 Predicting the Corn-Planting Season

I predicted future planting, AS and AD dates, then used the climate variables in the given period to predict aflatoxin risk because climate effect on aflatoxin varies in corn progress. To predict aflatoxin incidence, it is necessary to predict weather variables and the calendar time of crop stages because farmers adjust their decisions in accordance with changing climate conditions. As the silking and dent emergence stages follow the planting season, I predicted the latter first.

In order to predict planting season, I followed Sacks et al.'s (2010) rule of thumb for predicting corn planting season. They asserted that the corn planting season typically occurs when daily average temperatures reach 12-17°C in the United States (Sacks et al. 2010). Yet, even though my prediction was based on this rule of thumb, my method differed in that I used hundreds of climate variables that are measured in specific periods and interacted with each other and a technically rigorous method—variable shrinkage methods and cross validation—that is commonly used for discrete prediction and variable selection problems (Baumann 2003).

As an econometric prediction model, I used a logit model to predict whether or not a week is likely to be chosen for planting using historical planting records and climate data. A dummy variable was generated as the model's dependent variable where the value was 1 if a given week was in planting season and 0, otherwise. This variable was generated based on data from 2001 to 2016 for state-weekly level, historic corn planting periods. The data, provided by USDA NASS, include the percentage of a given planting process completed on a given Monday. The functional form can be written as follows:

$$p_{s,w,t} \equiv p^{*}_{s,w,t} - \eta_{s,w,t};$$

$$
\begin{aligned}
p^{*}_{s,w,t} \equiv k &+ \sum_{a\in\{min,mean,max\}}\{\sum_{n\in\{1,2,3,4\}} \beta^{a,w-n}_{TMIN} TMIN^{a,w-n}_{s,w,t} + \beta^{a,w-n}_{TMAX} TMAX^{a,w-n}_{s,w,t} + \beta^{a,w-n}_{TAVG} TAVG^{a,w-n}_{s,w,t} \\
&+ \beta^{a,w-n}_{PRCP} PRCP^{a,w-n}_{s,w,t} + \beta^{a,w-n}_{D12} D12^{a,w-n}_{s,w,t} + \beta^{a,w-n}_{D17} D17^{a,w-n}_{s,w,t} + \beta^{a,w-n}_{D1217} D1217^{a,w-n}_{s,w,t} \\
&+ \beta^{a}_{GDDf} GDDf^{a}_{s,w,t} + \beta^{a,2}_{GDDf} (GDDf^{2})^{a}_{s,w,t} + \beta^{a}_{A} A^{a}_{s}\} \\
&+ \sum_{i\neq j} \sum_{j=1}^{31} \beta^{j,i}_{V} V^{j}_{s,w,t} V^{i}_{s,w,t} + \beta_{w} W_{w,t} + \beta_{M} M_{t} + \beta_{T} T_{t} + \beta_{S} S \ ;
\end{aligned}
$$

$$
\begin{aligned}
V^{j}_{s,w,t} \in \{&TMIN^{mean,w-n}_{s,w,t},\ TMAX^{mean,w-n}_{s,w,t},\ TAVG^{mean,w-n}_{s,w,t},\ PRCP^{mean,w-n}_{s,w,t},\ D12^{mean,w-n}_{s,w,t},\ D17^{mean,w-n}_{s,w,t}, \\
&D1217^{mean,w-n}_{s,w,t},\ GDDf^{mean}_{s,w,t},\ (GDDf^{2})^{mean}_{s,w,t},\ A^{mean}_{s}\}
\end{aligned}
$$

where $p_{s,w,t}$ is the dummy variable and the value is 1 if a given week *w* is in planting season in state *s* and year *t*, and is 0, otherwise. $\eta_{s,w,t}$ are independent and identically distributed Type I extreme value;

$$
p_{s,w,t} = \begin{cases} 1 & if \quad p^{*}_{s,w,t} > 0 \\ 0 & if \quad p^{*}_{s,w,t} \leq 0 \end{cases}
$$

k is intercept, *TMIN* is county level-daily minimum temperature, averaged in state *s* by *minimum, maximum, and mean* (superscript *a*) and week *w-n* in year *t.* Superscript *w-n* means *n* weeks lagged variable where $n \in \{1,2,3,4\}$; *TMAX* is county-level, daily, maximum temperature; *TAVG* is daily, average temperature averaged in week *w*; *PRCP* is daily precipitation; *D12* is the proportion of days that had an average, daily temperature above 12°C; *D17* is the proportion of days that had an average, daily temperature above 17°C; *D1217* is the proportion of days that had an average, daily temperature between 12-17°C; $GDDf^{a}_{s,w,t}$ is the accumulated growing degree days from the first day of the year instead of the planting date in state *s*, in week *w* and year *t.* The *GDDf* is used for measuring moderate temperatures rather than measuring corn maturity. It is calculated by $[\min(TMAX, 86°F) + \max(TMIN, 50°F)]/2 - 50°F$; $(GDDf^{2})^{a}_{s,w,t}$ is square term of $GDDf^{a}_{s,w,t}$; A^{a}_{s} is available water capacity (AWC) averaged in state *s* by *minimum, maximum, and* *mean*; $V^j_{s,w,t}V^i_{s,w,t}$ is interaction term between $V^j_{s,w,t}$ and $V^i_{s,w,t}$ where

$$V^j_{s,w,t} \in \{TMIN^{mean,w-n}_{s,w,t},\ TMAX^{mean,w-n}_{s,w,t},\ TAVG^{mean,w-n}_{s,w,t},\ PRCP^{mean,w-n}_{s,w,t},\ D12^{mean,w-n}_{s,w,t},\ D17^{mean,w-n}_{s,w,t},\ D1217^{mean,w-n}_{s,w,t},\ GDDf^{mean}_{s,w,t},\ (GDDf^2)^{mean}_{s,w,t},\ A_s^{mean}\}$$

$j \in \{1, 2, ...31\}$ and $i \neq j$; W is week; M is month; T is year; and S is a vector of state dummy variables.

To have a high performing predictive model, I used K-fold cross validation (Tsamardinos et al. 2018). The K-fold cross validation method randomly partitions the available data into K subsets and uses K-1 subsets (training set) as data to estimate a set of models (Bishop 2007). The remaining one subset of data (test set) is used to measure the model's prediction power, i.e., how accurately the estimation based on the training set is in predicting the test set. By repeating this process K times (there will be K possible ways to choose one remaining subset), I calculate the average error across the different test sets, which is used for the model's performance. I then chose the best performance model based on average error. This method is different from more traditional methods that measure a model's performance— such as R^2—in that K-fold cross-validation maximizes the predictive power for out-of-sample data rather than explanatory power within-sample data, as in R^2. The predicted starting dates of planting are described in Figure 3.3.

3.4.5 Predicting the Corn Silking and Dent Emergence Seasons

Periods of AS and AD were predicted by adding the accumulated growing degree days (GDD) from the predicted planting week. The GDD is a heat index that represents the accumulated amount of heat available for crop growth in a given planting season. GDD for corn is calculated by $GDD \equiv [(TA + TI)/2] - 50°F$ where $TA = \min(\textit{Maximum daily temperature}, 86°F)$ and $TI = \max(\textit{Minimum daily temperature}, 50°F)$ (Nafziger 2009). According to Neild and Newman (1987), the commercial corn hybrid in the central Corn Belt typically requires 1,264 -1,430 accumulated GDD (AGDD) after planting to reach silking. Since required AGDD for maturity varies by location, I calculated each state's average AGDD from the middle of planting periods to reach silking and dent emergence season (Table 3.1). The actual silking season takes only several days, but a state takes several weeks to complete the season. Therefore, the length of the growing season varies in accordance with the size and location of the state. To consider this characteristic, I calculated AGDD from the middle of the planting date instead of the starting date. The calculated AGDD is close to what the literature suggested.

Table 3.1 Average accumulated Growing degree days by state

State	Silking	Dent Emergence	Number of years of data used for calculation
Alabama	229 - 1252	727 - 1781	2
Arkansas	296 - 1095	869 - 1733	3
Illinois	492 - 1152	988 - 1670	16
Iowa	542 - 1065	952 - 1509	16
Kansas	494 - 1254	1079 - 1781	16
Kentucky	529 - 1264	1036 - 1790	16
Louisiana	255 - 976	836 - 1627	3
Mississippi	343 - 1364	942 - 1951	3
Missouri	522 - 1261	1062 - 1785	16
Nebraska	478 - 1074	927 - 1531	16
North Carolina	528 - 1217	1059 - 1819	16
Oklahoma	425 - 1478	1211 - 1995	3
Tennessee	562 - 1224	1115 - 1766	16
Texas	608 - 1565	1202 - 2201	16
Virginia	425 - 1281	809 - 1836	3

3.5 Results

3.5.1 Historic Relationship

The estimated associations between aflatoxin-related insurance claims, climate variables, and Bt corn adoption rates are reported in Table 3.2. Temperatures between 36 and 40°C in AS and 28 and 34°C in AD were positively associated with aflatoxin-related insurance claims. One additional day with a maximum temperature of 36 to 40°C in AS and 28 to 34°C in AD increased the likelihood of insurance claims by 1% and 1.2%, respectively.[5] The marginal effect of temperature above 42°C in AS was -0.449 and marginal effect of temperature above 36°C in AD was 0.425 respectively. The negative effect of high temperature indicates that corn is likely to be susceptible to fungal infection due to high temperature stress in AS.

The effect of precipitation was not statistically significant in both AS and AD seasons. However, the maximum temperature on days without rain was shown to increase the incidence of aflatoxin, meaning higher temperatures without rain are associated with higher aflatoxin risk.

Table 3.2 The marginal effect of climate variables on aflatoxin-related insurance claims

Variables	Aflatoxin-related insurance claims (%)
After silking (AS) season	
Proportion of days with maximum temperature 36-40°C	0.516***
	(0.168)
Proportion of days with maximum temperature above 42°C	-0.449
	(0.841)
Precipitation	-0.002
	(0.001)
Maximum temperature on days without rain	0.006***
	(0.002)
After dent emergence (AD) season	
Proportion of days with maximum temperature 28-34°C	0.578***
	(0.199)
Proportion of days with maximum temperature above 36°C	-0.425*
	(0.242)
Precipitation	0.002*
	(0.001)
Maximum temperature on days without rain	0.005***
	(0.002)
Bt corn adoption rate	-0.017
	(0.103)
Irrigation	-0.202
	(0.211)
Observations	6,980

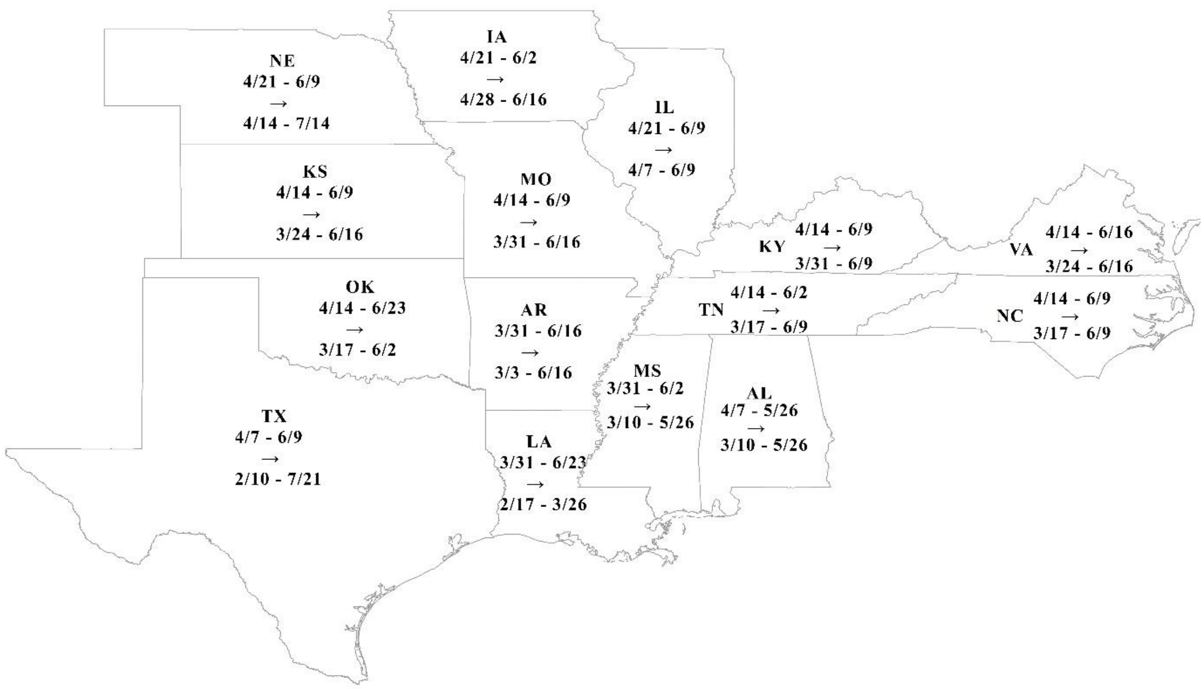
Year and state dummies were included in the regression. Details are reported in Table 3.A.2.
Bootstrapped standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1

[5] An increase of 1% in AS periods with maximum temperatures between 36 and 40°C was associated with a 0.516% increase in insurance claims. Because 2% of the period corresponds to one day, and I assume that it takes 50 days to have an AS season in a state, an increase of one day in the maximum temperature was associated with a 1% increase in the number of insurance claims.

3.5.2 Predicted Planting Season Between 2031 and 2040

Figure 3.3 compares average planting dates from 2007 to 2016 and predicted planting dates from 2031 to 2040. The predicted planting dates are expected to start earlier than the historical dates in all states except Iowa. The differences are relatively large in southern states, such as Oklahoma and Texas. The length of planting dates is expected to be longer than historical ones. This prediction was obtained based on a median-climate model.

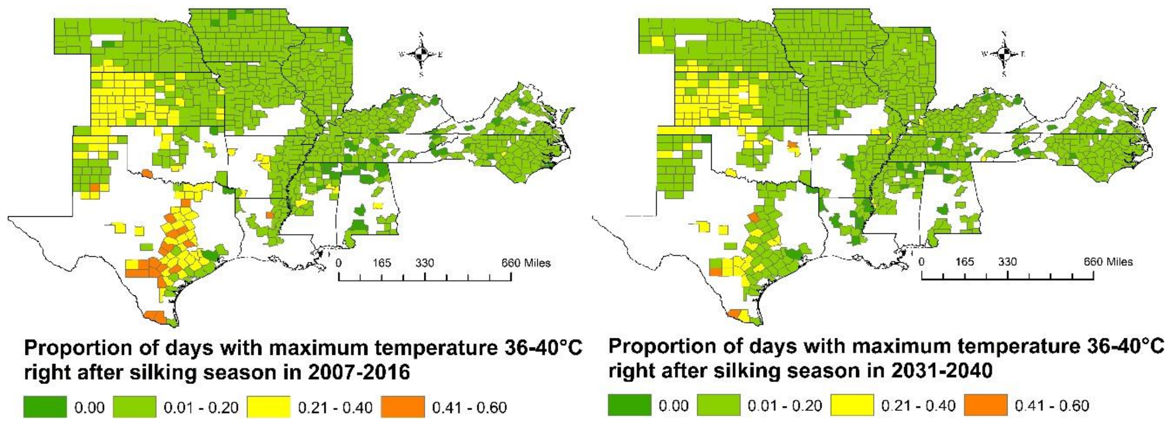
Figure 3.3 Historic planting date and estimated planting date by state



3.5.3 Predicted Climate Conditions Between 2031 and 2040

Figure 3.4 indicates the proportion of days with a maximum temperature between 36 and 40°C in the AS season, which represents favorable temperature ranges for the incidence of aflatoxin in 2007 to 2016 and 2031 to 2040. All states except Texas are likely to have the same number of days with this favorable temperature ranges, while Texas are expected to have had fewer days. In other words, Texas will have less aflatoxin risk by having less favorable temperature ranges in silking season.

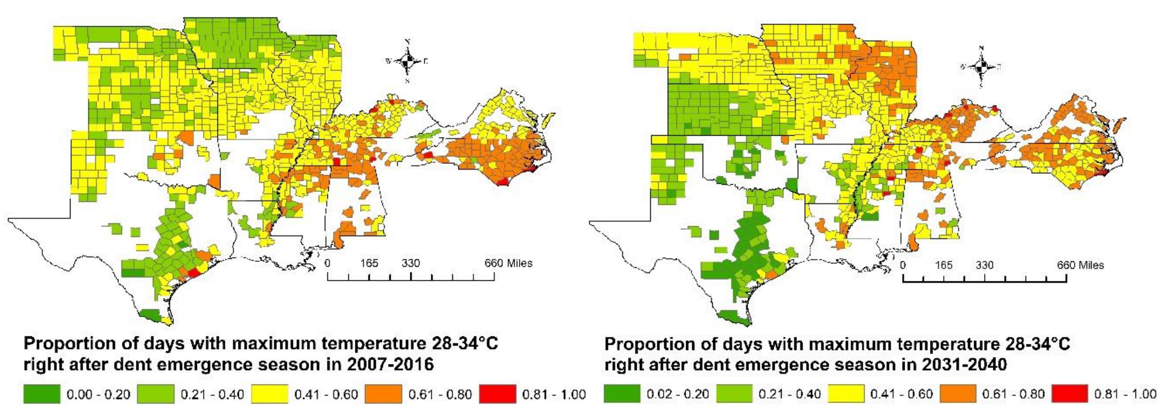
Figure 3.4 Proportion of days with maximum temperature 36-40°C in AS season per year



This figure was generated using the median-climate model. Empty spaces were excluded from the analysis due to lack of data, such as corn planting and temperature. Georgia and South Carolina are excluded in the analysis due to the lack of crop progress data.

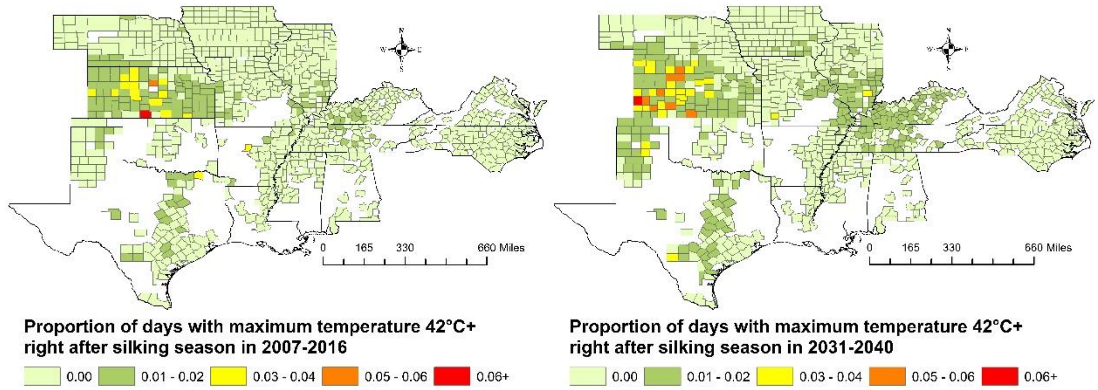
Figure 3.5 indicates the temperature range of 28-34°C in the AD season. Southern states such as Oklahoma, Texas, Missouri and North Carolina are likely to have fewer days with a temperature range of 28-34°C. On the other hand, northern states are expected to have more days with this temperature ranges. In particular, Illinois, Kentucky, and Virginia are expected to have more than 60% of their days (orange color) with maximum temperatures in that range. In other words, this temperature effect on the incidence of aflatoxin will differ across states.

Figure 3.5 Proportion of days with a maximum temperature of 28-34°C right after dent emergence per year



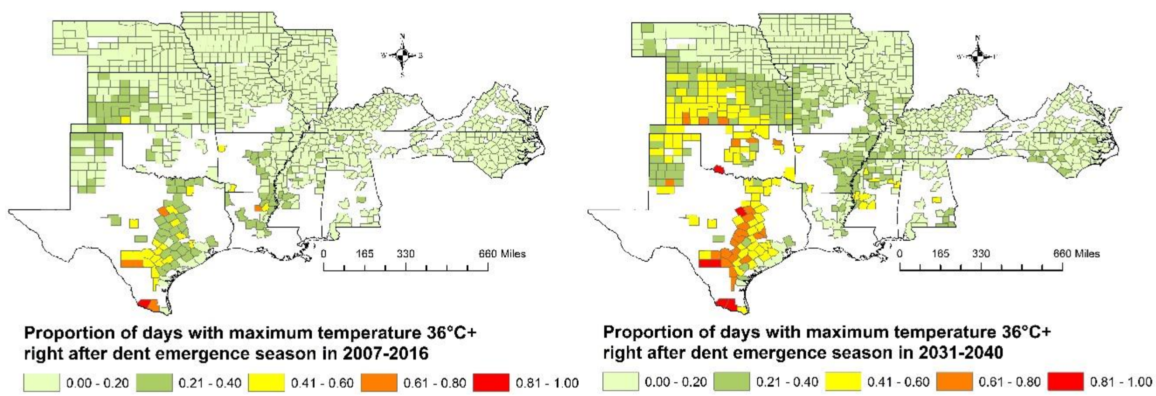
This figure was generated from the median-climate model. Empty spaces were excluded from the analysis due to lack of data, such as corn planting and temperature.

Figure 3.6 Proportion of days with a maximum temperature of 42°C+ right after silking per year



This figure was generated from the median-climate model. Empty spaces were excluded from the analysis due to lack of data, such as corn planting and temperature.

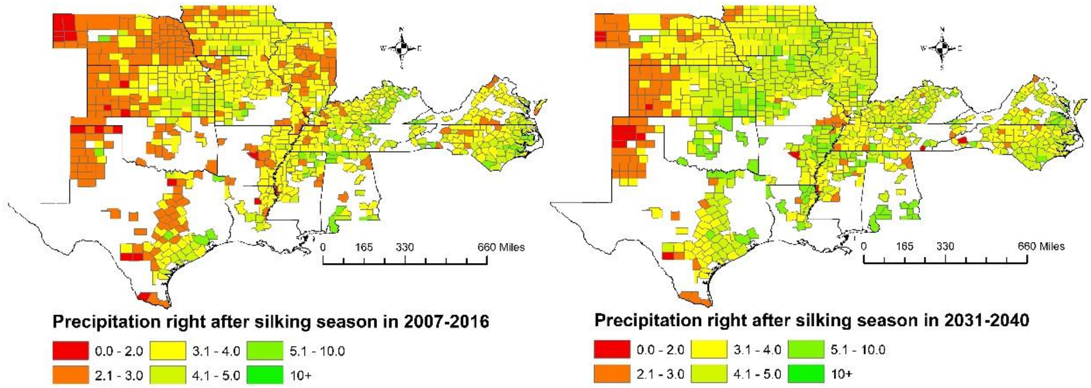
Figure 3.7 Proportion of days with a maximum temperature of 36°C+ right after dent emergence per year



This figure was generated from the median-climate model. Empty spaces were excluded from the analysis due to lack of data, such as corn planting and temperature.

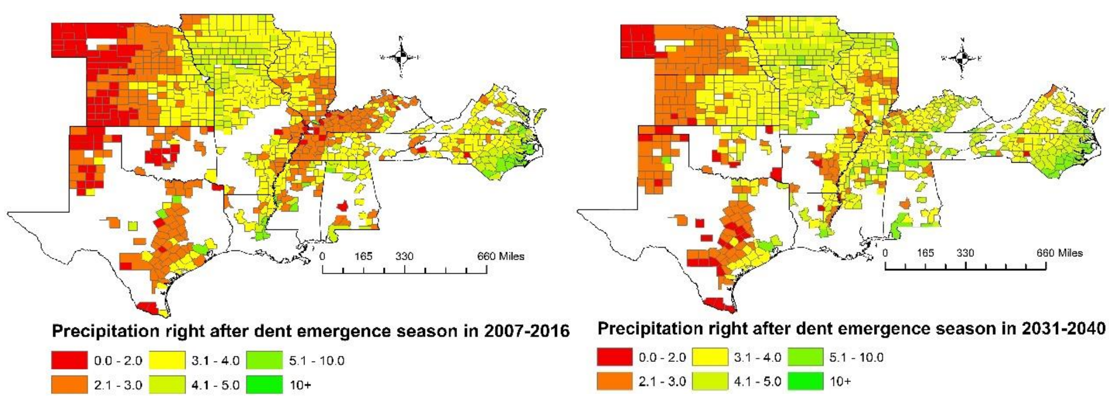
Figures 3.6 and 3.7 indicate temperature range of 42°C+ in the AS season and temperature range of 36°C+ in the AD season respectively. More counties are expected to have the temperature range of 42°C+ in the AS season due to climate change. For temperature range of 36°C+, counties in the southern state are highly likely to have the temperature ranges. Because a temperature of 36°C+ in the AD season is not favorable for aflatoxin contamination, the future temperature in this season is expected to decrease aflatoxin risk.

Figure 3.8 Average precipitation right after silking (mm)



This figure was generated from the median-climate model. Empty spaces were excluded from the analysis due to lack of data, such as corn planting and temperature.

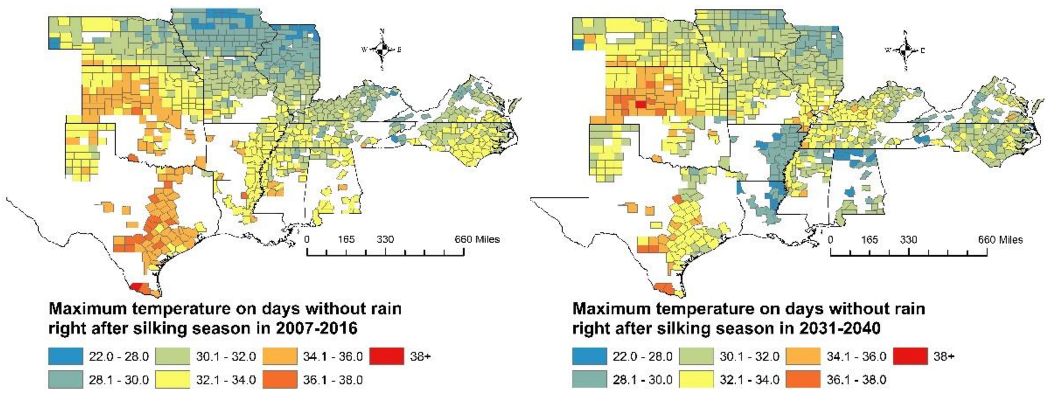
Figure 3.9 Average precipitation right after dent emergence (mm)



This figure was generated from the median-climate model. Empty spaces were excluded from the analysis due to lack of data, such as corn planting and temperature.

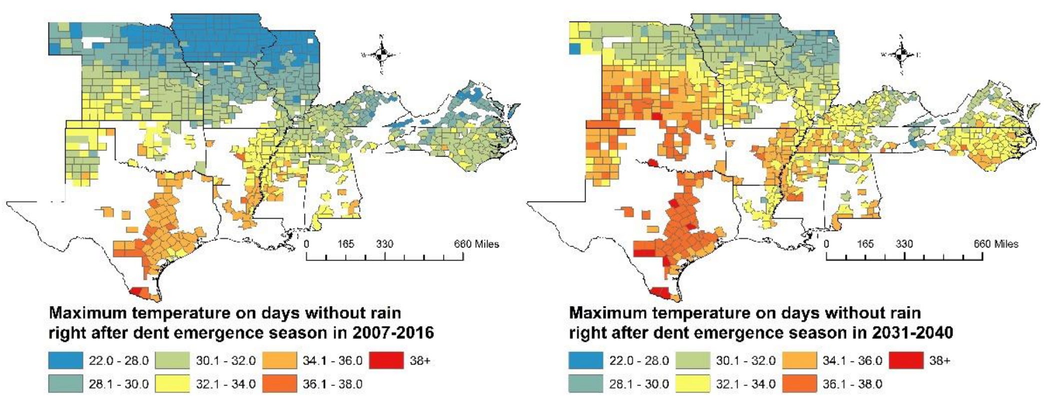
Figure 3.8 shows predicted precipitation in AS. All areas are expected to experience higher precipitation in 2031-2040 when compared to 2007-2016. Precipitation is also expected to increase in AD season (Figure 3.9). However, a few counties in Texas, and Arkansas are expected to have lower precipitation in the AD season.

Figure 3.10 Average maximum temperature on days without rain right after silking (°C)



This figure was generated from the median-climate model. Empty spaces were excluded from the analysis due to lack of data, such as corn planting and temperature.

Figure 3.11 Average maximum temperature on days without rain right after dent emergence (°C)



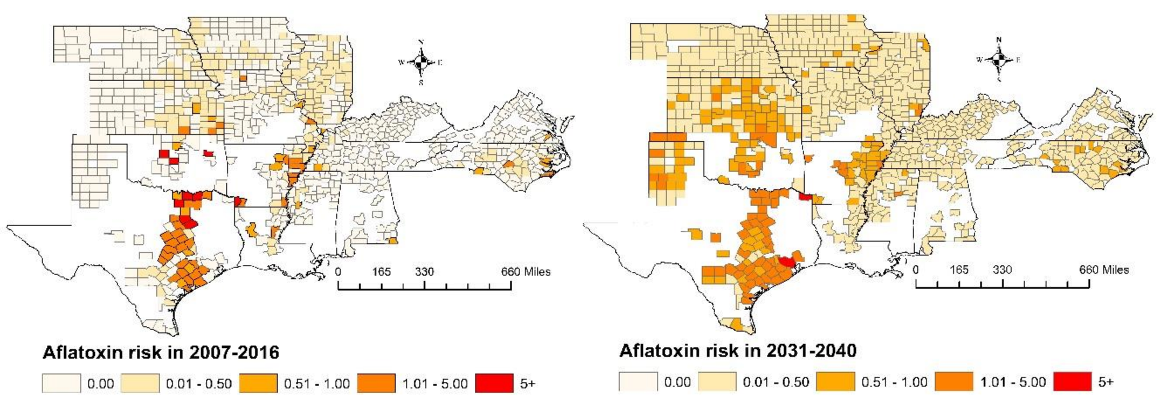
This figure was generated from the median-climate model. Empty spaces were excluded from the analysis due to lack of data, such as corn planting and temperature.

Figure 3.10 indicates maximum temperature on days without rain in AS, and specifically represents how the effects of temperature on aflatoxin vary in different locations. The maximum temperature on days without rain is likely to decrease in Texas, the state with that currently has the highest aflatoxin-related claims, under the median-climate model. On the other hand, many counties in the Corn Belt area, such as Kansas and Iowa, are expected to have higher temperatures in 2031-2040. Since this variable is associated with high aflatoxin, counties in the Corn Belt area are expected to have a higher risk of aflatoxin than in the past, but counties in Texas are expected to have lower risk of aflatoxin under the median climate models. Figure 3.11 represents maximum temperature on days without rain in AD. Unlike the AS season, almost all counties are expected to have higher temperatures on days without rain.

3.5.4 Predicted Aflatoxin Risk from 2031 to 2040

Figure 3.12 compares the estimated aflatoxin risk measured by aflatoxin-related insurance claims (%) from 2007 to 2016 and 2031 to 2040. Historically, aflatoxin-related claims were limited to a small number of counties in the southern states. However, aflatoxin risk is expected to expand toward the northern states between 2031 and 2040. Although Nebraska and Kentucky are currently relatively free from aflatoxin risk (ivory color), nearly all the counties in those states are expected to have aflatoxin accumulation in light of climate change (sepia color). In particular, half of counties in Kansas are likely to have higher than 0.5% of aflatoxin-related insurance claims. It means at least 0.5 % of corn planting area are expected to file an aflatoxin-related insurance claims in the counties. On the other hand, counties where aflatoxin is currently a significant issue— are projected to see lower aflatoxin risk under climate change, while overall risk in the states like Arkansas, Oklahoma, and Texas are expected to decrease. However, nearly all the counties are expected to be at risk. Again, this result was predicted based on the median-climate model.

Figure 3.12 Predicted aflatoxin risk measured by aflatoxin-related insurance claims per year (%)



This figure was generated from the median-climate model. Empty spaces were excluded from the analysis due to lack of data, such as corn planting and temperature.

Table 3.3 indicates how many areas are predicted to have increased aflatoxin risk as measured by aflatoxin-related insurance claims. More than 10% of the areas are predicted to have the same or lower risk than the current risk. However, 89.7% of the areas are likely to have increased risk. Specifically, 7.5% of the areas are expected to have increased risk by more than 1%. This 1% is not a low figure given that the average aflatoxin-related claim per year (%) in Texas, where aflatoxin-related insurance claims are the highest, is 1.34%.

Table 3.3 Change in aflatoxin risk measured by aflatoxin-related insurance claims

Change	Decrease	No change	Increase	
			Less than 1% point	1-10% point(s)
Percentage of observations	3.3%	7.0%	82.2%	7.5%

Table 3.4 shows how the average aflatoxin risk and indemnities are predicted to change by state. The risk of aflatoxin measured by insurance claims is highly likely to increase in the Corn Belt area. However, this risk is expected to decrease in southern states. The reasons for decreased risk in southern states is that these states are expected to have fewer days with favorable temperature ranges in AS and AD season and lower maximum temperature on days without rain in the AS season, which is also associated with high aflatoxin-related insurance claims. It is expected that at-risk areas are likely to move from southern areas, such as Oklahoma, Arkansas and Texas to more central areas, such as Illinois, Iowa, and Kansas.

In terms of economic loss, aflatoxin-related indemnities represent the possible monetary value of losses. Illinois, Iowa and Kansas are likely to experience high losses due to aflatoxin. Thus, overall indemnities per year are expected to triple from $7 million to $25 million. In multiplying the mark-up range, which converts indemnities to real losses and assumes that uninsured areas have the same possibility for incidence of aflatoxin within an insured area, it was found that possible losses are expected to amount to $36 million - $70 million per year.

Table 3.4 Aflatoxin-related insurance claims and estimated losses per year by state

States	Aflatoxin-related insurance claims (%)[a]		Aflatoxin-related indemnities ($1,000)	
	2007-2016	2031-2040	2007-2016	2031-2040
AL	0.03	0.09	2.7	5.1
AR	0.89	0.68	1,380.1	332.2
IL	0.05	0.31	1,014.9	6,661.9
IA	0.02	0.35	584.8	8,949.8
KS	0.10	0.48	560.5	3,389.0
KY	0.00	0.05	18.3	88.6
LA	0.18	0.17	101.2	48.5
MS	0.06	0.21	164.1	262.3
MO	0.07	0.23	446.2	1,341.6
NE	0.00	0.07	47.4	1,259.9
NC	0.07	0.34	158.2	220.1
OK	1.43	0.89	99.5	347.6
TN	0.02	0.10	37.5	69.4
TX	1.34	1.10	3,088.7	2,807.8
VA	0.01	0.02	0.5	5.2
Total	0.19	0.34	7,704.4	25,788.9

Indemnities vary not only due to the occurrence of aflatoxin but also due to corn prices, yields, and severity of aflatoxin contamination.
[a] This is the simple mean of each county's claims (%)

3.6 Discussion

This study provides a predictive economic model of aflatoxin risk in corn from climate change in the United States. By predicting the planting season in 15 states, this research contributes to efforts designed to increase the accuracy of predictions regarding the impacts of climate change. Moreover, this research seeks to capture humans might adapt to climate change. Severe aflatoxin contamination of corn remains a major concern for the future. The results of this study thus suggest that aflatoxin-related risk will increase due to climate change. Even though aflatoxin events are currently largely confined to southern states, prevalence will eventually shift to the Corn Belt. This shift may lead to disruptions in domestic and global corn markets. The expected economic impact of this increased risk will be great, because the risk of aflatoxin will greatly increase in the Corn Belt area. Therefore, there is an urgent need to plan for aflatoxin control strategies under future climate conditions to preserve a safe food supply in the United States and worldwide.

APPENDIX

APPENDIX

Figure 3.A.1 Predicted maximum temperature (TMAX) of 16 climate models and the median model by month

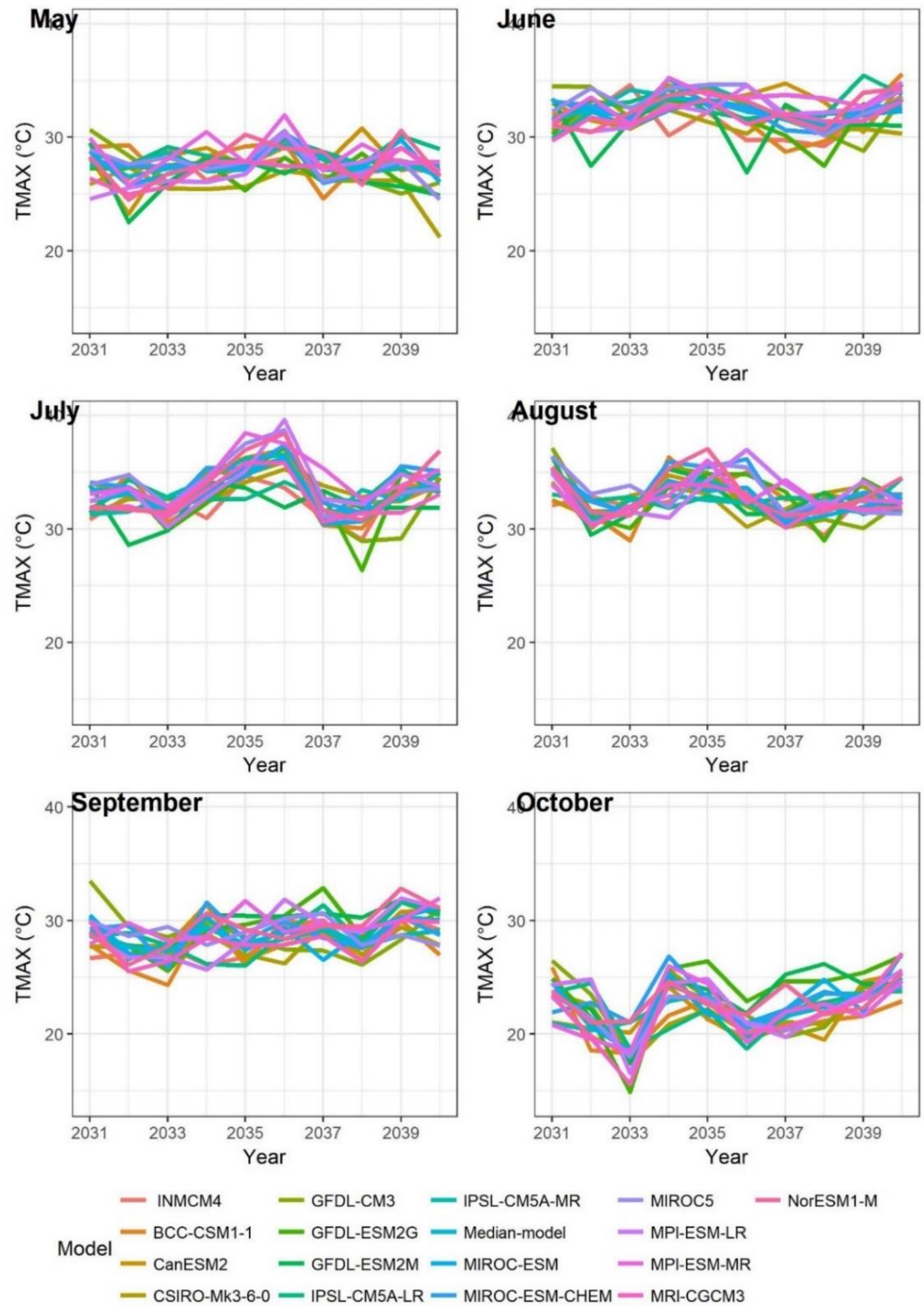


Figure 3.A.2 Predicted daily precipitation (PR) of 16 climate models and the median model by month

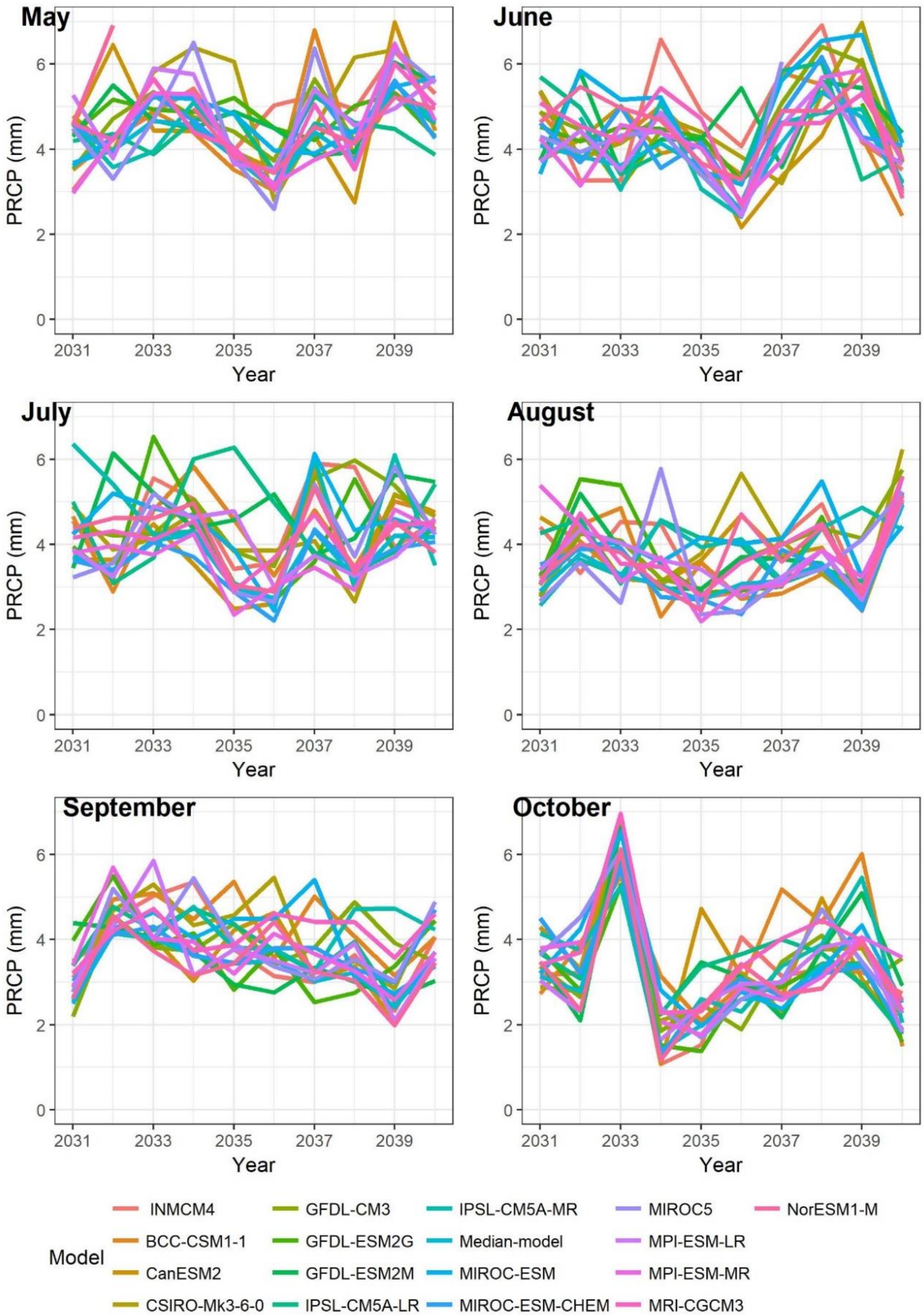


Table 3.A.1 Calendar time of silking season from 2007-2016

Year	Alabama	Arkansas	Illinois	Iowa
2007	-	-	Jun.23 - Aug.4	Jun.30 - Aug.4
2008	-	-	Jul.7 - Aug.18	Jul.14 - Aug.18
2009	-	-	Jun.30 - Aug.18	Jul.14 - Aug.18
2010	-	Jun.2 - Aug.4	Jun.30 - Aug.11	Jul.7 - Aug.11
2011	-	Jun.2 - Aug.4	Jul.7 - Aug.18	Jul.14 - Aug.18
2012	-	Jun.2 - Aug.4	Jun.23 - Aug.4	Jun.30 - Aug.11
2013	-	May 26 - Jul.28	Jun.30 - Aug.18	Jul.14 - Aug.18
2014	May 26 - Jul.21	Jun.9 - Jul.28	Jun.30 - Aug.11	Jul.7 - Aug.18
2015	May 26 - Aug.4	Jun.9 - Jul.21	Jun.30 - Aug.11	Jul.7 - Aug.11
2016	Jun.2 - Jul.14	May 26 - Jul.21	Jun.30 - Aug.11	Jul.7 - Aug.11
2031	Mar.31 - Jun.30	Apr.7 - Jun.16	Jun.9 - Jul.21	Jun.16 - Jul.21
2032	Apr.21 - Jul.7	Apr.28 - Jun.30	Jun.16 - Aug.4	Jul.7 - Aug.11
2033	Mar.24 - Jun.23	Apr.7 - Jun.23	Jun.9 - Jul.28	Jun.30 - Aug.11
2034	Apr.21 - Jul.7	Apr.28 - Jun.23	Jun.2 - Jul.14	Jun.16 - Jul.28
2035	Mar.24 - Jun.16	Apr.7 - Jun.16	Jun.9 - Jul.21	Jun.30 - Aug.4
2036	Mar.17 - Jun.16	Mar.31 - Jun.9	May 26 - Jul.14	Jun.16 - Jul.21
2037	Apr.21 - Jul.7	May 5 - Jun.30	Jun.16 - Aug.4	Jun.30 - Aug.11
2038	Apr.7 - Jun.30	Apr.28 - Jun.30	Jun.16 - Aug.4	Jun.30 - Aug.11
2039	Apr.14 - Jun.30	Apr.28 - Jun.30	Jun.2 - Jul.21	Jun.16 - Jul.28
2040	Apr.7 - Jun.30	Apr.14 - Jun.23	Jun.9 - Jul.21	Jun.23 - Jul.28
Year	Kansas	Kentucky	Louisiana	Mississippi
2007	Jun.23 - Aug.4	Jun.23 - Aug.4	-	-
2008	Jun.23 - Aug.18	Jun.30 - Aug.18	-	-
2009	Jun.30 - Aug.18	Jun.30 - Aug.18	-	-
2010	Jun.30 - Aug.11	Jun.30 - Aug.11	Jun.2 - Jul.7	-
2011	Jul.7 - Aug.18	Jul.7 - Aug.18	Jun.2 - Jul.7	-
2012	Jun.16 - Aug.11	Jun.16 - Aug.11	Jun.2 - Jul.7	-
2013	Jun.30 - Aug.18	Jun.30 - Aug.18	May 26 - Jun.30	-
2014	Jun.23 - Aug.11	Jun.30 - Aug.18	Jun.9 - Jun.30	Jun.2 - Aug.4
2015	Jun.23 - Aug.11	Jun.23 - Aug.11	May 26 - Jul.14	Jun.2 - Aug.4
2016	Jun.16 - Aug.11	Jun.23 - Aug.18	May 26 - Jul.14	Jun.2 - Jul.28
2031	May 26 - Jul.21	May 19 - Jul.14	Mar.24 - May 26	Apr.7 - Jun.30
2032	Jun.9 - Aug.4	Jun.16 - Aug.4	Mar.24 - May 26	Apr.21 - Jul.7
2033	Jun.2 - Jul.28	May 26 - Jul.21	Mar.17 - May 19	Apr.7 - Jun.23
2034	Jun.9 - Jul.28	Jun.2 - Jul.21	Apr.14 - Jun.9	Apr.28 - Jul.7
2035	May 26 - Jul.14	Jun.2 - Jul.21	Mar.17 - May 12	Apr.7 - Jun.23
2036	May 19 - Jul.14	May 19 - Jul.14	Mar.17 - May 12	Mar.31 - Jun.23
2037	Jun.9 - Aug.4	Jun.9 - Aug.4	Mar.24 - May 26	May 5 - Jul.14
2038	Jun.2 - Jul.28	Jun.2 - Jul.28	Mar.31 - Jun.2	Apr.28 - Jul.14
2039	May 26 - Jul.21	Jun.2 - Jul.28	Apr.7 - May 26	Apr.21 - Jul.7
2040	May 19 - Jul.14	May 26 - Jul.21	Mar.17 - May 19	Apr.28 - Jul.7

Table 3.A.1 (cont'd)

Year	Missouri	Nebraska	North Carolina	Oklahoma
2007	Jun.23 - Aug.4	Jun.30 - Aug.4	Jun.23 - Aug.4	-
2008	Jun.30 - Aug.18	Jul.7 - Aug.18	Jun.23 - Jul.28	-
2009	Jun.30 - Aug.18	Jul.7 - Aug.18	Jun.30 - Jul.28	-
2010	Jun.30 - Aug.11	Jul.7 - Aug.11	Jun.30 - Jul.14	-
2011	Jul.7 - Aug.18	Jul.14 - Aug.18	Jul.7 - Aug.18	-
2012	Jun.16 - Aug.11	Jun.30 - Aug.11	Jun.16 - Aug.11	-
2013	Jun.30 - Aug.18	Jul.7 - Aug.18	Jun.30 - Jul.28	-
2014	Jun.23 - Aug.4	Jun.30 - Aug.11	Jun.9 - Aug.11	Jun.23 - Aug.18
2015	Jun.30 - Aug.18	Jun.30 - Aug.11	Jun.16 - Aug.11	Jun.23 - Sep.1
2016	Jun.23 - Aug.4	Jun.30 - Aug.11	Jun.9 - Aug.18	Jun.16 - Aug.18
2031	May 26 - Jul.14	Jun.16 - Jul.28	May 19 - Jul.14	May 5 - Jul.14
2032	Jun.16 - Aug.4	Jun.23 - Aug.11	May 26 - Jul.14	May 19 - Jul.28
2033	Jun.2 - Jul.28	Jun.23 - Aug.4	May 19 - Jul.14	May 12 - Jul.21
2034	Jun.2 - Jul.21	Jun.23 - Aug.4	May 26 - Jul.7	May 12 - Jul.21
2035	Jun.2 - Jul.14	Jun.16 - Jul.28	May 12 - Jun.30	Apr.28 - Jul.7
2036	May 12 - Jul.7	May 26 - Jul.14	May 5 - Jun.30	Apr.28 - Jul.14
2037	Jun.16 - Aug.4	Jun.23 - Aug.4	Jun.2 - Jul.21	May 19 - Jul.28
2038	Jun.9 - Jul.28	Jun.16 - Aug.4	May 26 - Jul.14	May 12 - Jul.28
2039	Jun.2 - Jul.21	Jun.9 - Jul.21	May 26 - Jul.7	May 12 - Jul.21
2040	Jun.2 - Jul.21	Jun.16 - Jul.28	May 19 - Jul.7	Apr.28 - Jul.14
Year	**Tennessee**	**Texas**	**Virginia**	
2007	Jun.23 - Aug.4	Jun.23 - Aug.4	-	
2008	Jun.23 - Aug.11	Jun.23 - Aug.18	-	
2009	Jun.30 - Aug.11	Jun.30 - Aug.18	Jun.9 - Aug.11	
2010	Jun.30 - Aug.11	Jun.30 - Aug.11	Jun.16 - Aug.18	
2011	Jul.7 - Aug.11	Jul.7 - Aug.18	Jun.16 - Aug.18	
2012	Jun.16 - Aug.11	Jun.16 - Aug.11	Jun.16 - Aug.18	
2013	Jun.30 - Aug.11	Jun.30 - Aug.18	Jun.9 - Aug.11	
2014	Jun.23 - Aug.4	May 12 - Aug.11	Jun.16 - Aug.11	
2015	Jun.23 - Aug.11	May 12 - Aug.25	Jun.23 - Aug.18	
2016	Jun.30 - Aug.11	May 12 - Aug.11	Jun.30 - Aug.25	
2031	May 19 - Jul.7	May 5 - Jul.7	May 26 - Jul.28	
2032	Jun.9 - Jul.21	Apr.28 - Jun.30	Jun.2 - Aug.4	
2033	May 19 - Jul.7	Apr.21 - Jun.30	May 19 - Jul.28	
2034	May 26 - Jul.14	May 12 - Jul.14	May 26 - Jul.21	
2035	May 12 - Jun.30	Apr.14 - Jun.23	May 26 - Jul.21	
2036	May 12 - Jul.7	Apr.21 - Jun.30	May 12 - Jul.21	
2037	Jun.9 - Jul.21	Apr.28 - Jun.30	Jun.2 - Aug.4	
2038	Jun.2 - Jul.14	May 5 - Jul.7	Jun.2 - Jul.28	
2039	May 26 - Jul.14	May 12 - Jul.7	May 26 - Jul.21	
2040	May 26 - Jul.14	Apr.21 - Jun.30	May 19 - Jul.28	

Table 3.A.2 The marginal effect of temperature ranges on aflatoxin-related insurance claims from 2007-2016

	Aflatoxin-related insurance claims (%)					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
After Silking (AS) season						
Proportion of days with maximum temperature 32-38°C	0.119	0.342***	0.270**			
	(0.092)	(0.128)	(0.121)			
Proportion of days with maximum temperature 36-40°C				0.516***	0.419**	0.476***
				(0.168)	(0.165)	(0.162)
Proportion of days with maximum temperature above 42°C	-0.822	-0.519	-0.636	-0.449	-0.861	-0.676
	(0.806)	(0.836)	(0.851)	(0.841)	(0.851)	(0.856)
Precipitation	-0.002*	-0.001	-0.001	-0.002	-0.002	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Maximum temperature on days with no rain	0.009***	0.008***	0.008***	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
After Dent emergence (AD) season						
Proportion of days with maximum temperature 28-34°C	0.636***	0.775***		0.578***	0.766***	
	(0.210)	(0.201)		(0.199)	(0.195)	
Proportion of days with maximum temperature 30-36°C			0.984***			1.037***
			(0.196)			(0.200)
Proportion of days with maximum temperature above 36°C	-0.105			-0.425*		
	(0.233)			(0.242)		
Proportion of days with maximum temperature above 36°C		0.684**	1.224***		0.127	0.776***
		(0.272)	(0.313)		(0.195)	(0.242)
Precipitation	0.002*	0.002*	0.003**	0.002*	0.002*	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)

Table 3.A.2 (cont'd)

	Aflatoxin-related insurance claims (%)					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
After Dent emergence (AD) season						
Maximum temperature on days with no rain	0.004**	0.002	-0.001	0.005***	0.003*	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Bt corn adoption rate	-0.008	-0.035	-0.059	-0.017	-0.029	-0.053
	(0.099)	(0.100)	(0.102)	(0.103)	(0.103)	(0.104)
Irrigation (time average)	-0.214	-0.168	-0.147	-0.202	-0.154	-0.142
	(0.212)	(0.208)	(0.209)	(0.211)	(0.210)	(0.210)
Year 2007 dummy	0.361***	0.361***	0.308**	0.359***	0.340***	0.297**
	(0.131)	(0.130)	(0.132)	(0.127)	(0.124)	(0.127)
Year 2008 dummy	0.804***	0.784***	0.834***	0.758***	0.745***	0.808***
	(0.155)	(0.151)	(0.157)	(0.148)	(0.144)	(0.152)
Year 2009 dummy	0.780***	0.789***	0.807***	0.702***	0.692***	0.730***
	(0.175)	(0.175)	(0.175)	(0.164)	(0.162)	(0.167)
Year 2010 dummy	0.572***	0.536***	0.520***	0.590***	0.560***	0.545***
	(0.128)	(0.123)	(0.125)	(0.127)	(0.122)	(0.124)
Year 2011 dummy	0.432***	0.374***	0.372***	0.420***	0.376***	0.382***
	(0.126)	(0.121)	(0.121)	(0.122)	(0.119)	(0.119)
Year 2012 dummy	0.558***	0.538***	0.523***	0.558***	0.538***	0.528***
	(0.128)	(0.125)	(0.125)	(0.125)	(0.122)	(0.123)
Year 2013 dummy	0.469***	0.491***	0.495***	0.417***	0.418***	0.432***
	(0.134)	(0.137)	(0.139)	(0.127)	(0.126)	(0.130)
Year 2014 dummy	0.219*	0.233*	0.252*	0.186	0.172	0.205
	(0.130)	(0.129)	(0.134)	(0.124)	(0.124)	(0.128)
Year 2015 dummy	0.057	0.060	0.064	0.062	0.048	0.059
	(0.172)	(0.171)	(0.172)	(0.169)	(0.168)	(0.169)
Year 2016 dummy	-	-	-	-	-	-
AL state dummy	0.525	0.581	0.427	0.553	0.604	0.492
	(1.263)	(1.263)	(1.264)	(1.249)	(1.252)	(1.256)
AR state dummy	0.780	0.795	0.716	0.793	0.827	0.754
	(0.855)	(0.852)	(0.852)	(0.846)	(0.849)	(0.854)
IA state dummy	0.615	0.627	0.590	0.635	0.635	0.604
	(0.837)	(0.835)	(0.833)	(0.828)	(0.830)	(0.831)
IL state dummy	0.590	0.610	0.598	0.610	0.622	0.616
	(0.837)	(0.835)	(0.834)	(0.828)	(0.831)	(0.834)
KS state dummy	0.657	0.681	0.644	0.655	0.672	0.641
	(0.842)	(0.839)	(0.838)	(0.831)	(0.834)	(0.836)
KY state dummy	0.024	0.035	0.029	0.043	0.040	0.041
	(0.958)	(0.955)	(0.960)	(0.949)	(0.952)	(0.958)
LA state dummy	0.423	0.506	0.417	0.447	0.538	0.473
	(0.873)	(0.872)	(0.869)	(0.863)	(0.869)	(0.870)

Table 3.A.2 (cont'd)

	Aflatoxin-related insurance claims (%)					
Variables	(1)	(2)	(3)	(4)	(5)	(6)
MO state dummy	0.453	0.479	0.453	0.466	0.475	0.456
	(0.837)	(0.835)	(0.834)	(0.828)	(0.831)	(0.834)
MS state dummy	0.795	0.830	0.718	0.798	0.858	0.768
	(0.998)	(1.000)	(0.993)	(0.984)	(0.990)	(0.989)
NC state dummy	0.242	0.228	0.206	0.259	0.262	0.243
	(0.840)	(0.837)	(0.837)	(0.831)	(0.833)	(0.837)
NE state dummy	0.475	0.502	0.478	0.477	0.481	0.464
	(0.840)	(0.838)	(0.837)	(0.830)	(0.833)	(0.835)
OK state dummy	1.301	1.325	1.288	1.306	1.361	1.323
	(0.914)	(0.910)	(0.910)	(0.902)	(0.902)	(0.907)
TN state dummy	0.169	0.163	0.158	0.187	0.181	0.170
	(0.955)	(0.952)	(0.950)	(0.941)	(0.943)	(0.944)
TX state dummy	0.798	0.808	0.716	0.826	0.866	0.786
	(0.858)	(0.854)	(0.853)	(0.848)	(0.851)	(0.855)
VA state dummy (omitted)	-	-	-	-	-	-
Observations	6,980	6,980	6,980	6,980	6,980	6,980

Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 3.A.3 The marginal effect of climate variables, Bt corn adoption rate, year, and state dummies on aflatoxin-related indemnity per acre in 2007-2016

Variables	Aflatoxin-related indemnity per acre ($)
After Silking (AS) season	
Proportion of days with maximum temperature 36-40°C	2.268***
	(0.718)
Proportion of days with maximum temperature above 42°C	-0.494
	(4.336)
Precipitation	-0.006
	(0.005)
Maximum temperature on days with no rain	0.028***
	(0.009)
After Dent emergence (AD) season	
Proportion of days with maximum temperature 28-34°C	2.591***
	(0.993)
Proportion of days with maximum temperature above 36°C	-1.670
	(1.185)
Precipitation	0.007
	(0.004)
Maximum temperature on days with no rain	0.021***
	(0.008)
Bt corn adoption rate	0.382
	(0.523)
Irrigation (time average)	0.683
	(0.864)
Insurance coverage	-2.144
	(3.112)
Year 2007 dummy	1.573***
	(0.566)
Year 2008 dummy	3.091***
	(0.641)
Year 2009 dummy	2.959***
	(0.741)
Year 2010 dummy	2.500***
	(0.533)
Year 2011 dummy	1.705***
	(0.529)
Year 2012 dummy	2.452***
	(0.545)
Year 2013 dummy	1.820***
	(0.555)
Year 2014 dummy	0.667
	(0.578)
Year 2015 dummy	0.013
	(0.886)

Table 3.A.3 (cont'd)

Variables	Aflatoxin-related indemnity per acre ($)
Year 2016 dummy	-
AL state dummy	2.744
	(5.664)
AR state dummy	4.783
	(3.838)
IA state dummy	2.305
	(3.706)
IL state dummy	1.985
	(3.716)
KS state dummy	2.702
	(3.733)
KY state dummy	-0.146
	(4.278)
LA state dummy	2.703
	(3.876)
MO state dummy	2.362
	(3.719)
MS state dummy	3.472
	(4.444)
NC state dummy	1.744
	(3.728)
NE state dummy	1.435
	(3.726)
OK state dummy	6.043
	(4.184)
TN state dummy	0.751
	(4.178)
TX state dummy	3.761
	(3.788)
VA state dummy (omitted)	-
Observations	6,980

Bootstrapped standard errors in parentheses, *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.A.4 The marginal effect of irrigation aflatoxin-related indemnity per acre in 2007-2016

Variables	Aflatoxin-related insurance claims (%) (1)	(2)	(3)
Irrigation_5year	-0.331	-	-
	(0.978)		
Irrigation_cont	-	1.249	-
		(1.919)	
Irrigation (time average)	-	-	-0.202
			(0.211)
After Silking (AS) season			
Proportion of days with maximum temperature 36-40°C	0.515***	0.515***	0.516***
	(0.169)	(0.173)	(0.168)
Proportion of days with maximum temperature above 42°C	-0.448	-0.377	-0.449
	(0.842)	(0.867)	(0.841)
Precipitation	-0.002	-0.002	-0.002
	(0.001)	(0.001)	(0.001)
Maximum temperature on days with no rain	0.006***	0.006***	0.006***
	(0.002)	(0.002)	(0.002)
After Dent emergence (AD) season			
Proportion of days with maximum temperature 28-34°C	0.577***	0.577***	0.578***
	(0.199)	(0.202)	(0.199)
Proportion of days with maximum temperature above 36°C	-0.427*	-0.424*	-0.425*
	(0.242)	(0.252)	(0.242)
Precipitation	0.002*	0.002*	0.002*
	(0.001)	(0.001)	(0.001)
Maximum temperature on days with no rain	0.005***	0.006***	0.005***
	(0.002)	(0.002)	(0.002)
Bt corn adoption rate	-0.018	-0.042	-0.017
	(0.103)	(0.113)	(0.103)
Year 2007 dummy	0.359***	0.249	0.359***
	(0.127)	(0.153)	(0.127)
Year 2008 dummy	0.758***	0.698***	0.758***
	(0.148)	(0.154)	(0.148)
Year 2009 dummy	0.703***	0.636***	0.702***
	(0.165)	(0.167)	(0.164)
Year 2010 dummy	0.591***	0.498***	0.590***
	(0.127)	(0.143)	(0.127)
Year 2011 dummy	0.421***	0.330**	0.420***
	(0.122)	(0.142)	(0.122)
Year 2012 dummy	0.559***	0.469***	0.558***
	(0.125)	(0.142)	(0.125)

Table 3.A.4 (cont'd)

Variables	Aflatoxin-related insurance claims (%) (1)	(2)	(3)
Year 2013 dummy	0.417***	0.328**	0.417***
	(0.127)	(0.146)	(0.127)
Year 2014 dummy	0.185	0.112	0.186
	(0.125)	(0.140)	(0.124)
Year 2015 dummy	0.061		0.062
	(0.169)		(0.169)
Year 2016 dummy (omitted)	-	-	-
AL state dummy	0.554	0.573	0.553
	(1.247)	(1.376)	(1.249)
AR state dummy	0.799	0.911	0.793
	(0.845)	(0.922)	(0.846)
IA state dummy	0.634	0.691	0.635
	(0.826)	(0.892)	(0.828)
IL state dummy	0.608	0.671	0.610
	(0.827)	(0.894)	(0.828)
KS state dummy	0.654	0.719	0.655
	(0.830)	(0.896)	(0.831)
KY state dummy	0.041	0.062	0.043
	(0.948)	(1.019)	(0.949)
LA state dummy	0.450	0.538	0.447
	(0.862)	(0.960)	(0.863)
MO state dummy	0.467	0.517	0.466
	(0.827)	(0.892)	(0.828)
MS state dummy	0.798	0.926	0.798
	(0.983)	(1.037)	(0.984)
NC state dummy	0.257	0.293	0.259
	(0.830)	(0.890)	(0.831)
NE state dummy	0.475	0.529	0.477
	(0.829)	(0.890)	(0.830)
OK state dummy	1.304	1.039	1.306
	(0.900)	(1.356)	(0.902)
TN state dummy	0.184	0.236	0.187
	(0.939)	(1.024)	(0.941)
TX state dummy	0.827	0.926	0.826
	(0.847)	(0.916)	(0.848)
VA state dummy (omitted)	-	-	-
Observations	6,980	6,262	6,980

Bootstrapped standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

REFERENCES

REFERENCES

Abbas HK, Accinelli C, Shier WT. 2017. Biological control of aflatoxin contamination in us crops and the use of bioplastic formulations of aspergillus flavus biocontrol strains to optimize application strategies. Journal of Agricultural and Food Chemistry 65:7081-7087.

Assunção R, Martins C, Viegas S, Viegas C, Jakobsen LS, Pires S, et al. 2018. Climate change and the health impact of aflatoxins exposure in portugal–an overview. Food Additives & Contaminants: Part A 35:1610-1621.

Battilani P, Rossi V, Giorni P, Pietri A, Gualla A, Van der Fels-Klerx H, et al. 2012. Modelling, predicting and mapping the emergence of aflatoxins in cereals in the eu due to climate change. EFSA Supporting Publications 9:223E

Battilani P, Toscano P, Van der Fels-Klerx H, Moretti A, Leggieri MC, Brera C, et al. 2016. Aflatoxin b 1 contamination in maize in europe increases due to climate change. Scientific Reports 6:srep24328.

Baumann K. 2003. Cross-validation as the objective function for variable-selection techniques. TrAC Trends in Analytical Chemistry 22:395-406.

Bentsen M, Bethke I, Debernard J, Iversen T, Kirkevåg A, Seland Ø, et al. 2013. The norwegian earth system model, noresm1-m—part 1: Description and basic evaluation of the physical climate. Geoscientific Model Development 6:687-720.

Bernardi D, Salmeron E, Horikoshi RJ, Bernardi O, Dourado PM, Carvalho RA, et al. 2015. Cross-resistance between cry1 proteins in fall armyworm (*spodoptera frugiperda*) may affect the durability of current pyramided bt maize hybrids in brazil. PLoS One 10:e0140130.

Bishop C. 2007. Pattern recognition and machine learning (information science and statistics), 1st edn. 2006. Corr. 2nd printing edn. Springer, New York.

Burke M, Dykema J, Lobell DB, Miguel E, Satyanath S. 2015. Incorporating climate uncertainty into estimates of climate change impacts. Review of Economics and Statistics 97:461-471.

Chamberlain G. 1980. Analysis of covariance with qualitative data. The Review of Economic Studies 47:225-238.

Chylek P, Li J, Dubey M, Wang M, Lesins G. 2011. Observed and model simulated 20th century arctic temperature variability: Canadian earth system model canesm2. Atmospheric Chemistry and Physics Discussions:22893-22907.

Clarke L, Edmonds J, Jacoby H, Pitcher H, Reilly J, Richels R. 2007. Sub-report 2.1 a of synthesis and assessment product 2.1. Climate Change Science Program and the Subcommittee on Global Change Research, Washington DC.

Cotty PJ, Jaime-Garcia R. 2007. Influences of climate on aflatoxin producing fungi and aflatoxin contamination. International Journal of Food Microbiology 119:109-115.

Dai A, Trenberth KE, Qian T. 2004. A global dataset of palmer drought severity index for 1870–2002: Relationship with soil moisture and effects of surface warming. Journal of Hydrometeorology 5:1117-1130.

Dively GP, Venugopal PD, Finkenbinder C. 2016. Field-evolved resistance in corn earworm to cry proteins expressed by transgenic sweet corn. PloS one 11:e0169115.

Dufresne J-L, Foujols M-A, Denvil S, Caubel A, Marti O, Aumont O, et al. 2013. Climate change projections using the ipsl-cm5 earth system model: From cmip3 to cmip5. Climate Dynamics 40:2123-2165.

Dunne JP, John JG, Shevliakova E, Stouffer RJ, Krasting JP, Malyshev SL, et al. 2013. Gfdl's esm2 global coupled climate–carbon earth system models. Part ii: Carbon system formulation and baseline simulation characteristics. Journal of Climate 26:2247-2267.

Gassmann AJ. 2012. Field-evolved resistance to bt maize by western corn rootworm: Predictions from the laboratory and effects in the field. Journal of Invertebrate Pathology 110:287-293.

Gilbert M, Mack B, Payne G, Bhatnagar D. 2016. Use of functional genomics to assess the climate change impact on aspergillus flavus and aflatoxin production. World Mycotoxin Journal 9:665-672.

Giorgetta MA, Roeckner E, Mauritsen T, Bader J, Crueger T, Esch M, et al. 2013. The atmospheric general circulation model echam6-model description.

Griffies SM, Winton M, Donner LJ, Horowitz LW, Downes SM, Farneti R, et al. 2011. The gfdl cm3 coupled climate model: Characteristics of the ocean and sea ice simulations. Journal of Climate 24:3520-3544.

Huang F, Qureshi JA, Meagher Jr RL, Reisig DD, Head GP, Andow DA, et al. 2014. Cry1f resistance in fall armyworm *spodoptera frugiperda*: Single gene versus pyramided bt maize. PLoS One 9:e112958.

Jacobi J, Perrone D, Duncan LL, Hornberger G. 2013. A tool for calculating the palmer drought indices. Water Resources Research 49:6086-6089.

Jeffrey S, Rotstayn L, Collier M, Dravitzki S, Hamalainen C, Moeseneder C, et al. 2013. Australia's cmip5 submission using the csiro mk3. 6 model. Aust Meteor Oceanogr J 63:1-13.

Jones R, Duncan H, Hamilton P. 1981. Planting date, harvest date, and irrigation effects on infection and aflatoxin production by aspergillus flavus in field corn. Phytopathology 71, 810–816, https://doi.org/10.1094/Phyto-71-810.

Kawasaki K. 2018. Two harvests are better than one: Double cropping as a strategy for climate change adaptation. American Journal of Agricultural Economics 101:172-192.

Kucharik CJ, Serbin SP. 2008. Impacts of recent climate change on wisconsin corn and soybean yield trends. Environmental Research Letters 3:034003.

Liu Y, Wu F. 2010. Global burden of aflatoxin-induced hepatocellular carcinoma: A risk assessment. Environmental Health Perspectives 118:818.

Magan N, Medina A, Aldred D. 2011. Possible climate-change effects on mycotoxin contamination of food crops pre-and postharvest. Plant Pathology 60:150-163.

McMillan A, Renaud JB, Burgess KM, Orimadegun AE, Akinyinka OO, Allen SJ, et al. 2018. Aflatoxin exposure in nigerian children with severe acute malnutrition. Food and Chemical Toxicology 111:356-362.

Medina A, Rodriguez A, Magan N. 2014. Effect of climate change on aspergillus flavus and aflatoxin b1 production. Frontiers in Microbiology 5:348.

Menne MJ, Durre I, Vose RS, Gleason BE, Houston TG. 2012. An overview of the global historical climatology network-daily database. Journal of Atmospheric and Oceanic Technology 29:897-910.

Mitchell NJ, Riley RT, Egner PA, Groopman JD, Wu F. 2017. Chronic aflatoxin exposure in children living in bhaktapur, nepal: Extension of the mal-ed study. Journal of Exposure Science and Environmental Epidemiology 27:106.

Mundlak Y. 1978. On the pooling of time series and cross section data. Econometrica: journal of the Econometric Society:69-85.

NASA CMIP5: 21st Century Tmepratature Scenarios(https://svs.gsfc.nasa.gov/vis/a000000/a004100/a004105).

Nafziger E. 2009. Illinois agronomy handbook. Urbana, IL: University of Illinois Extension:224.

Neild RE, Newman JE. 1987. Growing season characteristics and requirements in the corn belt:Cooperative Extension Service, Iowa State University.

OBrian G, Georgianna D, Wilkinson J, Yu J, Abbas H, Bhatnagar D, et al. 2007. The effect of elevated temperature on gene transcription and aflatoxin biosynthesis. Mycologia 99:232-239.

Payne, G., Cassel, D. & Adkins, C. Reduction of aflatoxin contamination in corn by irrigation and tillage. Phytopathology 76, 679-684 (1986).

Riahi K, Grübler A, Nakicenovic N. 2007. Scenarios of long-term socio-economic and environmental development under climate stabilization. Technological Forecasting and Social Change 74:887-935.

Rosenzweig C, Tubiello FN, Goldberg R, Mills E, Bloomfield J. 2002. Increased crop damage in the us from excess precipitation under climate change. Global Environmental Change 12:197-202.

Sacks WJ, Deryng D, Foley JA, Ramankutty N. 2010. Crop planting dates: An analysis of global patterns. Global Ecology and Biogeography 19:607-620.

Salvacion AR, Pangga IB, Cumagun CJR. 2015. Assessment of mycotoxin risk on corn in the philippines under current and future climate change conditions. Reviews on Environmental Health 30:135-142.

Schlenker W, Roberts MJ. 2009. Nonlinear temperature effects indicate severe damages to us crop yields under climate change. Proceedings of the National Academy of sciences 106:15594-15598.

Smith CA, Robertson D, Yates B, Nielsen DM, Brown D, Dean RA, et al. 2008. The effect of temperature on natural antisense transcript (nat) expression in aspergillus flavus. Current genetics 54:241-269.

Smith SJ, Wigley T. 2006. Multi-gas forcing stabilization with minicam. The Energy Journal:373-391.

Tsamardinos I, Greasidou E, Borboudakis G. 2018. Bootstrapping the out-of-sample predictions for efficient and accurate cross-validation. Machine learning 107:1895-1922.

Volodin E, Dianskii N, Gusev A. 2010. Simulating present-day climate with the inmcm4. 0 coupled model of the atmospheric and oceanic general circulations. Izvestiya, Atmospheric and Oceanic Physics 46:414-431.

Watanabe M, Suzuki T, O'ishi R, Komuro Y, Watanabe S, Emori S, et al. 2010. Improved climate simulation by miroc5: Mean states, variability, and climate sensitivity. Journal of Climate 23:6312-6335.

Watanabe S, Hajima T, Sudo K, Nagashima T, Takemura T, Okajima H, et al. 2011. Miroc-esm 2010: Model description and basic results of cmip5-20c3m experiments. Geoscientific Model Development 4:845.

Wise M, Calvin K, Thomson A, Clarke L, Bond-Lamberty B, Sands R, et al. 2009. Implications of limiting co2 concentrations for land use and energy. Science 324:1183-1186.

Wu F, Bhatnagar D, Bui-Klimke T, Carbone I, Hellmich R, Munkvold G, et al. 2011. Climate change impacts on mycotoxin risks in us maize. World Mycotoxin Journal 4:79-93.

Wu F, Mitchell N. 2016. How climate change and regulations can affect the economics of mycotoxins. World Mycotoxin Journal 9:653-663.

Xiao-Ge X, Tong-Wen W, Jiang-Long L, Zai-Zhi W, Wei-Ping L, Fang-Hua W. 2013. How well does bcc_csm1. 1 reproduce the 20th century climate change over china? Atmospheric and Oceanic Science Letters 6:21-26.

Yang F, Chen M, Gowda A, Kerns DL, Huang F. 2018. Possibly similar genetic basis of resistance to bacillus thuringiensis cry1ab protein in 3 resistant colonies of the sugarcane borer collected from louisiana, USA. Insect Science 25:241-250.

Yin Y-n, Yan L-y, Jiang J-h, Ma Z-h. 2008. Biological control of aflatoxin contamination of crops. Journal of Zhejiang University Science B 9:787-792.

Yukimoto S, Adachi Y, Hosaka M, Sakami T, Yoshimura H, Hirabara M, et al. 2012. A new global climate model of the meteorological research institute: Mri-cgcm3—model description and basic performance—. Journal of the Meteorological Society of Japan Ser II 90:23-64.

CHAPTER 4

Does Bt crops Reduce Aflatoxin in Peanuts?

4.1 Introduction

Bt crop is a transgenic crop that contains insecticidal toxins derived from the bacterium *Bacillus thuringiensis*. Multiple studies show that Bt planting has reduced insecticide use (Brookes and Barfoot 2013; Perry et al. 2016), increased yields (Kathage and Qaim 2012; Xu et al. 2013), and thereby increased farm incomes (Brookes and Barfoot 2013). These effects have led to a high level of Bt crops adoption. The Bt corn-planted area reached 82% of the total corn-planted area, and Bt cotton was planted in 85% of the total cotton-planted area in the United States in 2018.

However, the effect is not limited to Bt-planted areas. According to Hutchison et al. (2010), Bt corn benefited both Bt planted farms and non-Bt planted farms as a result of area-wide pest suppression. Dively et al. (2018) also show that lower crop damage and insecticide use by vegetable growers (non-Bt plants) were associated with pest suppression from Bt plant. This reduced crop damage and insecticide usage benefit farmers in non-Bt fields without any cost. It means a farmer's decision to adopt Bt crops may affect his neighbor's decision about insecticide usage. It also affects his/her neighbor's insect control management. This study hypothesized that the benefits can be extended to the aflatoxin- (a fungal toxin) related damage in non-Bt fields. If Bt crops reduce the incidence of aflatoxin in non-Bt fields, Bt crops induce food safety as well as economic benefits.

Aflatoxins are fungal metabolites produced by the fungi *Aspergillus flavus* and *A. parasiticus*. Aflatoxin is one of the strongest carcinogens found in nature (Wiatrak et al. 2005). Aflatoxin exposure is associated with 25,200-155,000 cases of liver cancer annually (Liu and Wu 2010). The consumption of aflatoxin-contaminated food also causes immune system suppression, stunted growth in children, and acute toxicity possibly leading to death (Wu and Khlangwiset 2010; Wu et al. 2011). Aflatoxin occurs primarily in corn and peanut under warm temperatures and dry conditions (Cotty and Jaime-Garcia 2007; Wu et al. 2011). Along with chapter two study, several studies demonstrate that Bt corn is associated with a low incidence of aflatoxin (Wiatrak et al. 2005). As fungi colonize crops through kernel wounds from insect feeding, Bt corn can help decrease the aflatoxin level by reducing insect damage (see chapter two).

The purpose of this study is to determine whether Bt crops are associated with the occurrence of aflatoxin in peanut. Peanut is a non-Bt crop and has aflatoxin problems during the preharvest season. Bt is commercialized in corn and cotton, but not in peanut. However, peanuts share insects with corn and cotton. *Helicoverpa zea* (corn earworm) and *Spodoptera frugiperda* (fall armyworm), which are targeted by Bt corn, are hosted not only by corn but also by peanuts. Pink bollworm is controlled by Bt cotton and is hosted by peanuts as well. If these insects females do not distinguish between Bt and non-Bt crops for oviposition, as *Ostrinia nubilais* females do (Hutchison et al. 2010), pest population suppression would benefit peanut farms. Low insect damage can be associated with low incidence of aflatoxin in peanuts.

To examine whether the Bt crops are associated with lower aflatoxin, I examined whether a county had fewer insurance claims caused by aflatoxin in peanut farms when more Bt crops had been planted in that county. For more accurate estimation of Bt plants effect, I included climate conditions that affect the growth of peanuts and aflatoxigenic mold. Finally, I estimated the secondary "halo" economic benefit of Bt crops by reducing aflatoxin-related indemnities in peanuts.

4.2 Empirical Framework with Ecological Understanding of Peanuts and Aflatoxigenic Molds

The empirical model was anchored in the aflatoxin prediction model from chapter two. I included environmental variables that affect aflatoxigenic molds and peanuts (host plants) growth, as well as Bt crops adoption rate. The environmental conditions that affect peanuts (the host plant) are dry and hot temperatures late in the season (Dorner 2008). When the pod temperature is close to 35°C (Sanders et al. 1984) and moisture in the pod is reduced, the pod is susceptible to fungal invasion (Diener and Davis 1977; Dorner 2008). To measure the temperature effect, I used monthly temperature variables. Because temperatures vary in days and because the temperature effect on the occurrence of aflatoxin depends on periods of exposure to high temperature, I generated monthly variables considering temperature and exposure days: the proportion of days (%) on which the maximum temperature reached a certain level (36-42°C).

Dryness can increase the incidence of aflatoxin by increasing fungal infection. I expected that effect of drought variable varies in peanut growth (before and after the digging phase), because the most vulnerable period for fungal infection is before digging (Dorner 2008). Drought stress before digging is known to increase susceptibility of invasion (Diener and Davis 1977; Pettit et al. 1971). Table 4.1 indicates the average date on which peanuts reached the digging phase over fifteen years and eight states; Alabama, Arkansas, Florida, Georgia, Mississippi, Oklahoma, South Carolina, and Virginia. Digging occurred between August and November, and the average date was October 6. Based on the average date of digging, September represents the before digging season, and October represents the after digging season. To measure the drought effect, which varies in the progress level of peanuts, I included a monthly drought index. I expected that drought in September is associated with high aflatoxin.

Bt crops can contribute to a decrease in the risk of aflatoxin, because insect damage is associated with the occurrence of aflatoxin by providing entry for fungus (Klich 2007). Several studies show that Bt corn is associated with the level of aflatoxin (Masoero et al. 1999; Wiatrak et al. 2005). Wiatrak et al. (2005) show that aflatoxin levels were low in Bt corn-planted areas, when they used one to five weeks before the harvest season's temperature and precipitation as covariates. The second chapter of this dissertation also shows that a higher, Bt corn-adoption rate is associated with lower, aflatoxin-related insurance claims in sixteen southern states in the United States when climate effects are controlled for, the June and July temperatures ranged between 30 and 40°C and above 42°C, and the monthly drought index from June to September. These studies present the Bt effect on aflatoxin in corn (a Bt planted crop). However, this is the first time that the Bt effect is examined for aflatoxin in peanuts (a non-Bt adopted crop). There is sufficient evidence for this reasonable doubt; Bt corn suppresses insects in both Bt and non-Bt fields (Dively et al. 2018; Hutchison et al. 2010). Peanut is a crop that has aflatoxin, and it is a host of some insects, such as the corn earworm and the fall armyworm, which target Bt crops (corn and cotton). If Bt corn and Bt cotton reduce those insect pests, then peanut plants will be less attacked by the pest and aflatoxin contamination may go down in peanuts. Therefore, I set the incidence of aflatoxin in peanuts as a function of the adoption rate of Bt corn and cotton, temperature, and drought.

Table 4.1 Average date of peanut progress

	Average Date	Ranges
Seedbed Prepared	May 9th	March 29th - June 22th
Planted	May 23th	April 10th - July 19th
Emerged	June 12th	April 23th - July 30th
Blooming	July 10th	May 31th - August 16th
Pegging	July 19th	June 8th - September 10th
Matured	September 27th	July 31th - November 29th
Dug	October 6th	August 7th - November 23th
Harvested	October 19th	August 21th - December 31th

4.3 Data

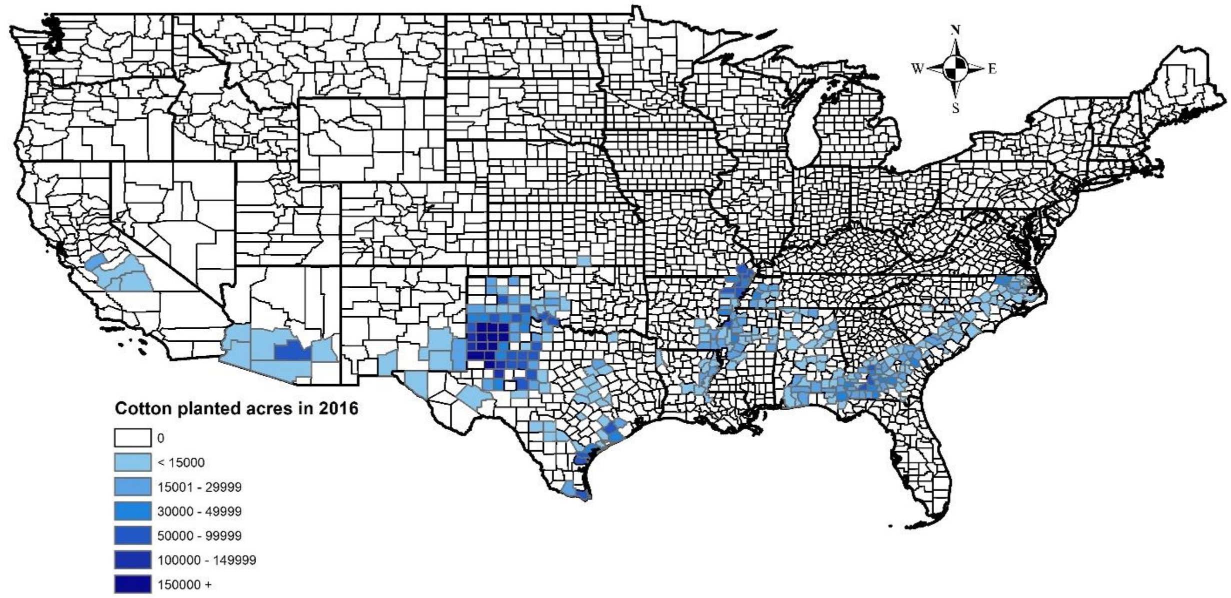
I used sixteen years of crop insurance data to measure aflatoxin incidence. The Risk Management Agency (RMA, an agency of the U.S. Department of Agriculture) has reported the county-level crop insurance purchases (unit of acres) and the indemnity by cause of loss (units of indemnity and acres). Aflatoxin incidence was measured by a proportion of the indemnified area caused by mycotoxin to all the insured peanut farm area (herein after % of aflatoxin-related insurance claims). Because aflatoxin is the only mycotoxin included in the U.S. Food and Drug Administration (FDA) regulations, I regarded claims caused by mycotoxin to be claims caused by aflatoxin. The FDA allows twenty micrograms per kilogram of aflatoxin in human food. Aflatoxin-contaminated peanuts cause economic losses, because they are discounted or rejected if the aflatoxin level exceeds the regulated level. The indemnities by cause of loss were collected for the main growing season from June to November.

Although uninsured farms were excluded from the estimation, the bias from the selection would be negligible. One reason is that a large proportion of the area was insured; 85% of U.S. peanut- growing areas were insured. Another reason is that aflatoxin is not a major damage that causes loss in peanut farms. In other words, farmers are likely to purchase insurance for non-aflatoxin- related damage. Therefore, an insured area does not have a higher possibility of having an aflatoxin problem than a non-insured area.

I generated the adoption rate of Bt crops by merging Bt corn and Bt cotton adoption data. Bt cotton was included along with Bt corn because Bt cotton can be associated with the incidence of aflatoxin in peanuts. If a target insect of Bt cotton such as *Helicoverpa Punctigera* that also attack peanuts were suppressed, peanut would have had less aflatoxin related damage due to the reduced insect damage. I obtained the Bt corn adoption data by crop-reporting district level from Kynetec, a private market survey company that specializes in agricultural markets. Bt cotton adoption rates data by state level were obtained from the USDA's National Agricultural Statistics Service (USDA NASS). I calculated the Bt crops adoption rate, which may affect non-Bt crops, as the ratio of Bt corn- and cotton-planted acres (numerator) to all field crops-planted acres (denominator) in a county. Field crops include barley, beans, canola, corn, cotton, flaxseed, lentils, mustard, oats, peanuts, peas, rice, rye, safflower, sorghum, soybeans, sugar beets, sunflowers, and wheat as USDA listed. The county- level, Bt corn/cotton-planted acres were calculated by multiplying the Bt corn/cotton adoption rates (defined by Bt corn/cotton-planted acres over corn/cotton-planted acres, and earned from Kynetec/USDA NASS) of the crop district/state where the county is located, to the corn/cotton- planted acres of the county. This approach is based on an assumption that the Bt corn/cotton adoption rate is uniformly distributed within each crop district level/state. One might be concerned about a bias from this assumption that the Bt cotton adoption level is uniformly distributed within an entire state. However, I believe that the bias is negligible, because only a small number of counties in the state have planted cotton, and the counties are close together. A county is likely to have a Bt cotton adoption rate that is similar to that of an adjacent county, because conditions such as soil and accessibility to a local seed store will be similar. Figure 4.1 indicates the cotton planted area in 2016. Cotton planted counties were concentrated except in Texas. Therefore, the state level of the Bt cotton adoption rate is expected to have little noise to explain county-level, aflatoxin-related insurance claims.

When Bt cotton adoption data were missing, it was regarded as zero to generate a Bt crops adoption rate. The purpose of this approach was to see the Bt corn effect even if Bt cotton data are not available. Bt cotton adoption rate data were only available in Alabama, Arkansas, Georgia, Mississippi, North Carolina, and Texas. Similarly, the Bt corn adoption rate was regarded as zero to generate a Bt crops (corn and cotton) adoption rate when Bt corn adoption data were missing. I also generated an alternative Bt crops adoption rate (Bt crops adoption rate_*alternative*). It has a missing value if either the Bt corn or Bt cotton adoption data are missing. The results are reported in column 3 in Table 4.5.

Figure 4.1 Cotton planted acres in 2016



The monthly (June to October) drought indices and temperature data were obtained from the National Oceanic and Atmospheric Administration (NOAA). The Z-index, a measure of the monthly wetness or dryness was used as a drought index (Guttman 1998). According to Karl 1986, the Z-index is desirable for measuring agricultural drought (Karl 1986). The Z-index has reported by climate district level. A climate district includes nine counties on average, and a state includes nine climate districts on average. NOAA also provides weather station-level, daily, maximum and minimum temperatures. I generated county-level monthly temperatures (percentage of days with a maximum temperature between 36 and 42°C) from the daily maximum temperature that is averaged by county. A county includes four weather stations on average.

All insured peanut-planted counties between 2001 and 2016 were included in the data set as long as data exist. The counties were located in twelve states: Alabama, Arkansas, Florida, Georgia, Louisiana, Mississippi, North Carolina, New Mexico, Oklahoma, South Carolina, Texas and Virginia. The time window was chosen because Bt crops adoption was speeded up after 2000, and indemnified acres data and Bt corn adoption rate data were available for the years between

2001 and 2016. Table 4.2 indicates summary statistics.

Table 4.2 Summary statistics

Variables	Obs	Mean	Std.Dev	Min	Max
Aflatoxin-related insurance claims (%)	3,435	0.03	0.41	0	14.85
Aflatoxin-related insurance claimed area (hectare)	3,435	0.97	15.72	0	571.52
Insured area (hectare)	3,435	2325.58	3111.04	1.62	33512.45
Bt crops adoption rate (0-1 value)	2,642	0.32	0.25	0	1
Bt corn adoption rate (0-1 value)	2,052	0.09	0.13	0	1
Bt cotton adoption rate (0-1 value)	1,861	0.36	0.23	0	0.96
Z-index in June	3,435	-0.48	2.01	-4.32	9.66
Z-index in July	3,435	0.13	2.37	-5.71	11.2
Z-index in August	3,435	-0.48	2.28	-5.23	11.13
Z-index in September	3,435	-0.03	2.27	-4.68	7.12
Z-index in October	3,435	-0.04	2.17	-3.63	10.72
Proportion of days with maximum temperature between 36 and 42°C in June (%)	3,087	0.13	0.18	0	1
Proportion of days with maximum temperature between 36 and 42°C in July (%)	3,073	0.18	0.23	0	1
Proportion of days with maximum temperature between 36 and 42°C in August (%)	3,072	0.17	0.22	0	1
Proportion of days with maximum temperature between 36 and 42°C in September (%)	3,071	0.03	0.08	0	0.87
Proportion of days with maximum temperature between 36 and 42°C in October (%)	3,057	0	0.01	0	0.26
Irrigation (Time average, 0-1 value)	3,343	0.06	0.08	0	0.58
Insurance claims for drought (%)	3,435	8.53	15.41	0.00	100.00
Insurance claims for extra moist (%)	3,435	5.66	13.06	0.00	100.00
Insurance claims for heat (%)	3,435	1.63	6.62	0.00	100.00
Insurance claims for wildlife (%)	3,435	0.62	4.76	0.00	100.00
Insurance claims for hot wind (%)	3,435	0.59	4.88	0.00	100.00
Insurance claims for plant disease (%)	3,435	0.39	1.80	0.00	40.00
Insurance claims for hurricane (%)	3,435	0.26	1.84	0.00	40.31
Insurance claims for wind (%)	3,435	0.21	2.07	0.00	69.11
Insurance claims for cold wet (%)	3,435	0.19	1.98	0.00	69.78
Insurance claims for freeze (%)	3,435	0.17	1.92	0.00	62.98
Insurance claims for hail (%)	3,435	0.11	2.00	0.00	100.00
Insurance claims for irrigation supply failure	3,435	0.07	1.10	0.00	49.68

4.4 Methods

I used the type I Tobit model to estimate parameters consistently by restricting the value range: 98% of data were piled up at zero value. I assumed that aflatoxin risk ($y_{i,t}^{*}$) is a function of the Bt crops adoption rate, temperature, drought indices, and irrigation level. Aflatoxin-related insurance claims ($y_{i,t}$) are observed only if the risk is greater than zero. In other words, aflatoxin-related insurance claims have only non-negative values. The reduced form is as follows;

$$\begin{aligned} y^*_{i,t} &\equiv \beta_B B_{i,t} + \sum\nolimits_{m\in\{6,7,8,9,10\}} (\beta^m_Z Z^m_{i,t} + \beta^m_F M^m_{i,t}) + \beta_R R_{c,s} + \beta_P P_i + \beta_L L_i + \beta_T T_t + c_i + u_{i,t}; \\ y_{i,t} &= \max(0, y^*_{i,t}); \end{aligned} \tag{1}$$

where $y^*_{i,t}$ is the aflatoxin-related insurance claims in peanuts (%) in county *i* in year *t*. $B_{i,t}$ is the Bt corn and cotton adoption rate (%) in county *i* and year *t*; $Z^m_{i,t}$ is the Z-index for the month *m* for the climate district in which the county is located, where month *m* is June, July, August, September and October, $M^m_{i,t}$ is the percentage of days with maximum temperature range between 36 and 42°C; $R_{c,s}$ is time average of proportion of irrigated area within a county. Year averaged county level proportion of land that is irrigated (obtained from USGS) were used because irrigation can mitigate drought effect; P_i is a dummy variable that represents Piedmont regions to consider potential topographical effects. It has the value one if the county is located in Alabama, Georgia, South Carolina, North Carolina, and Virginia, and zero otherwise; L_i is a dummy variable that represents missing data. This dummy variable tests if the occurrence of missing data is correlated with aflatoxin occurrence. It has the value zero if a county has all sixteen years of covariates and has one otherwise; $T_t^{'} = \{TMAX_t, TMIN_t, PRCP_t)$ is vector of yearly weather conditions. Variable T_t is included to capture unobserved year-specific characteristics. I assumed that year effect is a function of weather conditions; the main growing season's maximum temperature, minimum temperature, and precipitation level ($TMAX_t$, $TMIN_t$ *and* $PRCP_t$). Unlike the percentage of days with a maximum temperature range between 36 and 42°C ($M^m_{i,t}$), which captures the temperature range that affect aflatoxin occurrence, $TMAX_t$ measures the overall temperature difference between years. Whereas the Z-index ($Z_{i,t}^m$) measures moisture availability, $PRCP_t$ measures overall precipitation differences between years. The yearly maximum and minimum temperatures and precipitation levels were calculated as

$$TMAX_t = \frac{1}{N_t}\sum_{i=1}^{N_t} Maximum\ Temperature_{i,t};$$

$$TMIN_t = \frac{1}{N_t}\sum_{i=1}^{N_t} Minimum\ Temperature_{i,t}; \quad \text{and} \quad PRCP_t = \frac{1}{N_t}\sum_{i=1}^{N_t} PRCP_{i,t}$$ where $N_t = \{223,\ 214,\ 202,\ 209,\ 211,\ 205,\ 204,\ 212,\ 214,\ 215,\ 211,\ 228,\ 219,\ 220,\ 228,\ 220\}$ is the number of peanut insurance purchased counties in each year.

Unobserved county-specific characteristics, c_i, such as soil quality, can affect the aflatoxin incidence in peanuts. To consider the unobserved county-specific characteristics, I assumed that the characteristics are a function of time average values of covariates, $\bar{x}_i$ (Correlated Random Effect model). This can be written as $c_i = \alpha + \bar{x}_i\rho + e_i$; where α is constant, e_i is error term. The composite error $v_{i,t} = u_{i,t} + e_i$ is normally distributed.

To validate the correlation between aflatoxin-related insurance claims in peanuts and Bt corn and cotton adoption rate, the relationship between Bt crops adoption rate and insurance claims caused by non-aflatoxin related reasons were tested. The purpose of this analysis was to verify whether Bt crops are correlated with hypothetically non-related insurance claims in peanuts. Even though this analysis does not guarantee the causal relationship, false relationships can be evidence of robustness in Bt crop impact on aflatoxin-related insurance claims in peanuts.

The reasons for insurance claims that caused higher losses than aflatoxin caused were collected. These reasons included: drought, extra moist, heat, plant disease, hot wind, wildlife, wind, cold wet, freeze, hail, and irrigation supply failure. Using the same method described above, the marginal effect of Bt crops adoption on insurance claims caused by each damage was estimated. The estimated results are described in Table 4.4.

The benefit of Bt crops by reducing aflatoxin in peanuts was estimated by the same method as the one used in chapter two (the method to estimate Bt corn benefit by reducing aflatoxin in corn). The benefit of Bt crops was defined as the difference between loss caused by aflatoxin and hypothetical loss due to aflatoxin without Bt crops adoption. Because indemnity amounts are only a part of the actual loss, I used the markup (1.43-2.74) that was estimated in chapter two. The markup converts indemnity to loss. Even though it was calculated for corn, I believe the markup may be appropriately applied to peanuts because they are indemnified for the loss just as corn is indemnified. Details of the calculation of markup are in chapter two.

To calculate the hypothetical indemnity caused by aflatoxin without Bt crops adoption, I estimated the effect of Bt, climate conditions, insurance coverage, and insured areas on aflatoxin-related indemnity ($). The difference with the main model is that the dependent variable is indemnity amounts caused by aflatoxin, and two additional variables are included (insurance coverage and insured area), because indemnity amounts in a county depend on the area of insurance, the insurance coverage, and the incidence of aflatoxin. The correlated Random Effect Tobit model was used for estimation, and the result was reported in column 6 in Table 4.3. The estimated parameters were used to calculate the hypothetical indemnity due to aflatoxin without Bt crops adoption. By setting the Bt adoption rate as zero, I obtained hypothetical indemnity amounts.

4.5 Results

Table 4.3 indicates the marginal effects of Bt crops adoption rate, weather conditions, and year and location information about aflatoxin-related insurance claims (%). Column 1 (main model) is estimated by the Tobit model, column 2 is also estimated by the Tobit model, but for aflatoxin-related insurance-claimed areas (hectare) instead of insurance claims (%). Columns 3, 4 and 5 are are estimated by an alternative econometric model: a fractional probit, a probit model, and a poisson model respectively. For the fractional probit model, the dependent variable (% of aflatoxin-related insurance claims) was converted to having a range [0,1]. The dependent variable for the probit model was converted to a binary variable (one if there are aflatoxin-related insurance claims, and zero otherwise). Column 6 in Table 4.3 indicate the marginal effects of Bt crops adoption rate, weather conditions, irrigation level, insurance coverage, and areas that have peanut insurance on aflatoxin-related indemnity ($).

Table 4.3 Marginal effect of Bt crops on aflatoxin-related insurance claims in peanuts estimated by Tobit, Probit and Fractional probit models

Variables	(1) Tobit Aflatoxin-related insurance claims (%)	(2) Tobit Area-reported aflatoxin-related insurance claims (hectare)	(3) Fractional Probit Area-reported aflatoxin-related insurance claims (range 0-1)	(4) Probit Aflatoxin-related insurance claims (binary)	(5) Poisson Aflatoxin-related insurance claims (%)	(6) Tobit Aflatoxin-related indemnity ($1000)
Bt crops adoption rate (Bt corn and cotton planted area /field crops planted area)	-0.074**	-2.877**	-0.001***	-0.051***	-0.090***	-1,462**
	(0.035)	(1.286)	(0.000)	(0.020)	(0.031)	(699.0)
Z-index in June	0.003	0.168	-0.000	0.003	-0.001	97.18
	(0.002)	(0.116)	(0.000)	(0.002)	(0.004)	(64.06)
Z-index in July	-0.001	-0.053	-0.000**	-0.000	-0.013**	-37.06
	(0.003)	(0.136)	(0.000)	(0.002)	(0.006)	(72.94)
Z-index in August	-0.001	-0.049	-0.000**	-0.001	-0.005	-18.57
	(0.002)	(0.096)	(0.000)	(0.002)	(0.004)	(52.57)
Z-index in September	-0.005**	-0.230**	-0.000	-0.004**	-0.003	-115.8**
	(0.002)	(0.109)	(0.000)	(0.002)	(0.003)	(57.72)
Z-index in October	0.009***	0.425***	0.000***	0.006***	0.013***	253.1***
	(0.003)	(0.115)	(0.000)	(0.001)	(0.003)	(65.90)
Proportion of days with temperature range between 36 and 42°C in June (%)	-0.023	-0.684	-0.001	-0.007	-0.071	-475.4
	(0.035)	(1.507)	(0.000)	(0.026)	(0.052)	(859.7)
Proportion of days with temperature range between 36 and 42°C in July (%)	0.016	1.929	-0.000	0.022	-0.066	984.4
	(0.031)	(1.644)	(0.000)	(0.027)	(0.049)	(913.2)
Proportion of days with temperature range between 36 and 42°C in August (%)	-0.041	-1.741	-0.001***	-0.024	-0.079	-859.0
	(0.034)	(1.612)	(0.000)	(0.025)	(0.050)	(834.0)

Table 4.3 (cont'd)

Variables	(1) Tobit Aflatoxin-related insurance claims (%)	(2) Tobit Area-reported aflatoxin-related insurance claims (hectare)	(3) Fractional Probit Area-reported aflatoxin-related insurance claims (range 0-1)	(4) Probit Aflatoxin-related insurance claims (binary)	(5) Poisson Aflatoxin-related insurance claims (%)	(6) Tobit Aflatoxin-related indemnity ($1000)
Proportion of days with temperature range between 3 and 42°C in September (%)	0.161*	9.158**	0.002***	0.048	0.254***	5,090**
	(0.092)	(3.974)	(0.001)	(0.049)	(0.064)	(2,118)
Proportion of days with temperature range between 36 and 42°C in October (%)	0.957**	45.603***	0.004	1.058***	0.567	19,481**
	(0.432)	(15.719)	(0.003)	(0.373)	(0.491)	(7,563)
Yearly maximum temperature in June-October	0.042*	2.639***	0.000	0.036**	0.066***	726.1
	(0.024)	(0.819)	(0.000)	(0.016)	(0.020)	(570.6)
Yearly precipitation in June-October	-0.005	-0.036	0.000	-0.008	-0.001	-69.24
	(0.008)	(0.099)	(0.000)	(0.006)	(0.003)	(198.5)
Yearly minimum temperature in June-October	-0.130*	-0.507	-0.004***	-0.078*	-0.021	-5,617***
	(0.070)	(0.657)	(0.001)	(0.047)	(0.022)	(1,945)
Piedmont dummy which is 1 if state is AL, GA, SC, NC, VA	0.055***	1.717	0.001***	0.038***	0.029	1,547***
	(0.020)	(1.161)	(0.000)	(0.009)	(0.026)	(466.3)
Missing dummy	-0.000	-0.210	-0.000	-0.001	0.008	-7.793
	(0.002)	(0.351)	(0.000)	(0.002)	(0.009)	(54.36)
Irrigation (time average, range 0-1)	-0.014	-12.753***	-0.000	-0.006	-0.447***	-366.6
	(0.015)	(4.101)	(0.000)	(0.011)	(0.159)	(363.4)
Insured area		0.000**				0.168***
		(0.000)				(0.062)
Insurance coverage						-2,438
						(3,531)
Observations	2,248	2,248	2,248	2,248	2,248	2,248

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

I found a statistically significant negative relationship between Bt crops adoption rate and aflatoxin-related insurance claims in peanut fields (column 1 in Table 4.3). This can be interpreted that the one percentage increase in Bt crops adoption rate is associated with the 0.074% fewer insurance claims that were caused by aflatoxin in peanut fields. This result means that there is a spillover effect of Bt crops on aflatoxin in peanuts. In other words, the Bt crops, which are not intended to affect either non-Bt crops or aflatoxin, are associated with a low incidence of aflatoxin in peanuts (a non-Bt crop). Alternative econometric models also support the results: the negative relationship between the Bt crops adoption rate and aflatoxin-related insurance claims in peanuts (Columns 2, 3, 4, and 5 in Table 4.3).

The marginal effect of monthly Z-indices is only meaningful in September and October (column 1 in Table 4.3), but the directions are the opposite. The negative, marginal effect of the Z-index (a lower value means dryer conditions) means drought in September is associated with a high incidence of aflatoxin. This result is consistent with the expectation that drought before digging is correlated with high aflatoxin infestation. However, the drought effect in October is opposite of the effect in September. The positive effect of the Z-index in October means drought is correlated with fewer aflatoxin-related insurance claims. Because the average dug date was October 6, the result implies that drought before digging increased fungal invasion by increasing the water stress for peanuts. However, drying well after dug reduces aflatoxin production.

Temperature effects also indicate that September and October are the critical months for the incidence of aflatoxin in peanuts (column 1 in Table 4.3). High temperatures in September and October are associated with a high number of aflatoxin-related insurance claims. Even though the temperature range (36-42°C) is very high, more days with the temperature range are correlated with greater aflatoxin. Because the temperatures in the field vary by hour and day, meaningful temperature ranges in fields are much higher than the optimum temperature to produce aflatoxin in the experiment.

Table 4.4 indicates the marginal effect of Bt crops on insurance claims caused by non-aflatoxin related reasons such as drought, extra moist, heat, plant disease, hot wind, wildlife, wind, cold wet, freeze, hail, and irrigation supply failure. Bt crops adoption rate is correlated with insurance claims caused by drought (model 1), heat (model 3), plant disease (model 4) and hot wind (model 5). These damages are related to temperature and dryness/humidity and might affect aflatoxin occurrence. In other words, Bt crops adoption rate that affect aflatoxin-related insurance claims in peanuts can be correlated with drought, heat, plant disease, and hot wind due to the correlation between aflatoxin and these damages.

Bt crops adoption rate are not correlated with other damages, such as extra moist, wildlife, wind, cold wet, freeze, hail, and irrigation supply failure. These damages do not have reason to have a correlation with Bt corn and cotton adoption, which is confirmed by the analysis results. Such results mean that the impact of Bt crops adoption on insurance claims in peanuts occurred only where ecological paths exist.

Table 4.4 Falsification test results: marginal effect of Bt crops on insurance claims caused by the most common loss

Variables	(1) Tobit Insurance claims for Drought	(2) Tobit Insurance claims for Extra moist	(3) Tobit Insurance claims for Heat	(4) Tobit Insurance claims for Plant disease	(5) Tobit Insurance claims for Hot wind	(6) Tobit Insurance claims for Wildlife	(7) Tobit Insurance claims for Wind	(8) Tobit Insurance claims for Cold wet	(9) Tobit Insurance claims for Freeze	(10) Tobit Insurance claims for Hail	(11) Tobit Insurance claims for Irrigation supply Failure
Bt crops adoption rate (Bt corn and cotton planted area /field crops planted area)	-6.065***	1.130	1.031**	-1.135***	0.688**	0.287	-0.027	0.029	0.175	-0.173	-0.043
	(1.210)	(1.047)	(0.503)	(0.171)	(0.331)	(0.297)	(0.152)	(0.119)	(0.146)	(0.140)	(0.044)
Z-index in June	-0.499***	0.649***	-0.200***	0.051***	-0.044	0.047	0.007	-0.037**	-0.030*	0.021	-0.013**
	(0.128)	(0.122)	(0.054)	(0.015)	(0.045)	(0.038)	(0.021)	(0.018)	(0.017)	(0.019)	(0.005)
Z-index in July	-1.179***	0.177	-0.311***	0.019	-0.093**	-0.008	-0.055**	0.040**	0.025*	-0.017	-0.008*
	(0.171)	(0.134)	(0.066)	(0.017)	(0.044)	(0.032)	(0.024)	(0.015)	(0.014)	(0.017)	(0.005)
Z-index in August	-0.869***	0.443***	-0.086*	0.051***	-0.043	-0.023	0.044*	0.003	0.006	-0.020	-0.007
	(0.127)	(0.118)	(0.052)	(0.016)	(0.033)	(0.031)	(0.023)	(0.013)	(0.013)	(0.018)	(0.005)
Z-index in September	-0.209**	0.534***	-0.115***	-0.000	-0.019	-0.030	0.015	0.007	0.009	-0.009	-0.010**
	(0.101)	(0.094)	(0.038)	(0.012)	(0.028)	(0.025)	(0.018)	(0.011)	(0.013)	(0.014)	(0.005)
Z-index in October	0.131	0.892***	0.067	0.012	0.068*	0.012	0.029*	0.024*	0.010	0.045	-0.011**
	(0.106)	(0.105)	(0.042)	(0.015)	(0.038)	(0.026)	(0.017)	(0.013)	(0.012)	(0.028)	(0.005)

Table 4.4 (cont'd)

Variables	(1) Tobit Insurance claims for Drought	(2) Tobit Insurance claims for Extra moist	(3) Tobit Insurance claims for Heat	(4) Tobit Insurance claims for Plant disease	(5) Tobit Insurance claims for Hot wind	(6) Tobit Insurance claims for Wildlife	(7) Tobit Insurance claims for Wind	(8) Tobit Insurance claims for Cold wet	(9) Tobit Insurance claims for Freeze	(10) Tobit Insurance claims for Hail	(11) Tobit Insurance claims for Irrigation supply Failure
Proportion of days with temperature range between 36 and 42°C in June (%)	-8.020***	1.197	-2.428***	-0.166	0.055	-0.744	-0.003	-0.696**	-0.018	-0.203	-0.088
	(2.467)	(1.934)	(0.863)	(0.272)	(0.444)	(0.561)	(0.247)	(0.270)	(0.208)	(0.272)	(0.070)
Proportion of days with temperature range between 36 and 42°C in July (%)	1.412	3.516**	2.557***	0.303	-0.221	0.285	-0.165	0.301**	-0.256	0.290	-0.091**
	(2.070)	(1.748)	(0.668)	(0.212)	(0.401)	(0.365)	(0.180)	(0.152)	(0.175)	(0.203)	(0.047)
Proportion of days with temperature range between 36 and 42°C in August (%)	11.488***	-8.702***	1.461*	-0.642***	0.709	0.604	0.033	0.010	0.034	-0.135	0.178***
	(2.246)	(2.199)	(0.812)	(0.234)	(0.453)	(0.515)	(0.212)	(0.187)	(0.158)	(0.215)	(0.060)

Table 4.4 (cont'd)

Variables	(1) Tobit Insurance claims for Drought	(2) Tobit Insurance claims for Extra moist	(3) Tobit Insurance claims for Heat	(4) Tobit Insurance claims for Plant disease	(5) Tobit Insurance claims for Hot wind	(6) Tobit Insurance claims for Wildlife	(7) Tobit Insurance claims for Wind	(8) Tobit Insurance claims for Cold wet	(9) Tobit Insurance claims for Freeze	(10) Tobit Insurance claims for Hail	(11) Tobit Insurance claims for Irrigation supply Failure
Proportion of days with temperature range between 3 and 42°C in September (%)	7.393	2.138	1.307	-0.113	1.221	-1.861*	0.070	-0.442	-0.106	0.161	-0.092
	(4.961)	(4.892)	(2.117)	(0.552)	(0.939)	(0.980)	(0.704)	(0.461)	(0.383)	(0.314)	(0.125)
Proportion of days with temperature range between 36 and 42°C in October (%)	-64.245	-13.705	-10.673	3.674	-4.365	2.147	1.200	-2.017	-3.980	-63.689***	-0.271
	(39.504)	(29.724)	(12.542)	(5.772)	(4.632)	(6.025)	(2.149)	(2.789)	(3.443)	(6.314)	(0.570)
Yearly maximum temperature in June-October	11.028***	-0.435	0.410	1.146***	-1.675***	1.548***	-0.459***	-0.174*	-0.240**	-0.251**	0.068**
	(1.043)	(0.942)	(0.339)	(0.154)	(0.424)	(0.365)	(0.169)	(0.094)	(0.104)	(0.120)	(0.032)
Yearly precipitation in June-October	0.170	-0.048	-0.621***	-0.119**	-0.245**	-0.155	-0.194***	-0.110**	-0.157***	-0.071	-0.005
	(0.479)	(0.399)	(0.173)	(0.057)	(0.118)	(0.113)	(0.071)	(0.047)	(0.048)	(0.051)	(0.014)

Table 4.4 (cont'd)

Variables	(1) Tobit Insurance claims for Drought	(2) Tobit Insurance claims for Extra moist	(3) Tobit Insurance claims for Heat	(4) Tobit Insurance claims for Plant disease	(5) Tobit Insurance claims for Hot wind	(6) Tobit Insurance claims for Wildlife	(7) Tobit Insurance claims for Wind	(8) Tobit Insurance claims for Cold wet	(9) Tobit Insurance claims for Freeze	(10) Tobit Insurance claims for Hail	(11) Tobit Insurance claims for Irrigation supply Failure
Yearly minimum temperature	-18.977***	-1.055	5.833***	2.084***	2.363***	-2.724***	0.622*	0.743***	0.537	0.936*	0.402***
in June-October	(3.378)	(3.648)	(1.399)	(0.357)	(0.814)	(0.907)	(0.330)	(0.251)	(0.333)	(0.490)	(0.103)
Piedmont dummy	-0.283	-6.197***	0.504**	-0.245***	0.406**	-0.025	0.019	-0.055	-0.079	-0.050	0.045**
which is 1 if state is AL, GA, SC, NC, VA	(0.588)	(0.604)	(0.200)	(0.075)	(0.178)	(0.140)	(0.087)	(0.069)	(0.066)	(0.091)	(0.022)
Missing dummy	-0.433***	-0.570***	-0.033	-0.068***	0.043*	0.008	-0.013	0.005	-0.007	-0.006	0.006*
	(0.091)	(0.083)	(0.032)	(0.013)	(0.024)	(0.022)	(0.012)	(0.010)	(0.009)	(0.010)	(0.003)
Irrigation	2.908***	8.652***	0.755**	0.521***	-0.411	-0.171	0.075	-0.063	-0.258***	0.169	-0.096***
(time average, range 0-1)	(0.780)	(0.802)	(0.325)	(0.112)	(0.257)	(0.202)	(0.112)	(0.094)	(0.094)	(0.124)	(0.032)
Observations	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248	2,248

Table 4.5 shows the economic loss caused by aflatoxin in peanuts and the estimated economic loss averted (benefits of Bt). The loss caused by aflatoxin amounts to between US $ 0.18 million and US $ 0.36 million per year. The estimated loss averted due to Bt crops amounts to between US $ 0.23 million and US $0.45 million per year. If there had been no area-wide suppression of Bt, aflatoxin would have caused twice the loss that occurred in past sixteen years. Bt corn and cotton averted 0.02-0.04% of the economic value of peanut production (US $1,000 million per year) by reducing the incidence of aflatoxin.

Table 4.5 Economic loss caused by aflatoxin in peanuts and the economic benefits of Bt crops by reducing aflatoxin-related damage

Year	Value of Peanut production [a]	Loss due to the Aflatoxin [b]	Benefit of Bt adoption using aflatoxin indemnities per acres	
	($1,000)	($1,000)	Million $	Benefit of Bt over Value of production (%)
2001	1,000,512	841.9 - 1613.2	175.6-336.4	0.02-0.03
2002	599,714	182 - 348.8	16.2-31.1	0-0.01
2003	799,428	0 - 0	13.5-25.9	0-0
2004	813,551	31.5 - 60.4	3-5.8	0-0
2005	843,435	37.7 - 72.1	173.4-332.3	0.02-0.04
2006	612,798	121 - 231.8	281.6-539.5	0.05-0.09
2007	758,626	56.7 - 108.5	144.4-276.6	0.02-0.04
2008	1,193,617	9.8 - 18.8	123.9-237.3	0.01-0.02
2009	793,147	0 - 0	30.4-58.3	0-0.01
2010	938,611	1536.5 - 2944.1	1298-2487.2	0.14-0.26
2011	1,168,587	37.7 - 72.2	750-1437.1	0.06-0.12
2012	2,026,326	0 - 0	88-168.7	0-0.01
2013	1,055,095	0 - 0	2.1-4.1	0-0
2014	1,158,251	38.3 - 73.5	77.7-148.8	0.01-0.01
2015	1,160,560	39.6 - 75.9	235.6-451.4	0.02-0.04
2016	1,088,165	34.9 - 66.9	316.8-607.1	0.03-0.06
Average per year	1,000,651	185.5 - 355.4	233.1-446.7	0.02-0.04

4.6 Robustness Check

I also looked at the Bt corn and Bt cotton effect separately. Columns 1 and 2 in Table 4.6 indicate the Bt corn and Bt cotton effects on aflatoxin-related insurance claims respectively. Whereas the Bt corn effect is not statistically significant, the Bt cotton effect is significant. The Bt cotton effect is stronger than the Bt corn effect because cotton shares more areas with peanuts than corn does. For counties that have peanut insurance, the average cotton-planted area (13,631 hectare) is much larger than the average corn area (3,912 hectare). The cotton-planted area accounts for 46% of the total field crops area on average, but the corn-planted area accounts for 21% of the total crop area within peanut planted counties. The results imply that the Bt effect depends mainly on Bt cotton rather than Bt corn. Also, the Bt cotton adoption rate is higher (36.1%) than the Bt corn adoption rate (8.8%) within peanut planted counties.

Table 4.6 Marginal effect of Bt corn and Bt cotton on aflatoxin-related insurance claims in peanuts estimated by Tobit models

Variables	(1) Tobit Aflatoxin-related insurance claims (%)	(2) Tobit Aflatoxin-related insurance claims (%)	(3) Tobit Aflatoxin-related insurance claims (%)
Bt crops adoption rate *alternative* (Bt corn and cotton planted area/field crops planted area)			-0.122**
			(0.058)
Bt cotton adoption rate (Bt cotton planted area /field crops planted area)		-0.087**	
		(0.039)	
Bt corn adoption rate (Bt corn planted area /field crops planted area)	0.065		
	(0.065)		
Z-index in June	0.004	0.005**	0.007**
	(0.003)	(0.002)	(0.003)
Z-index in July	-0.001	0.002	-0.000
	(0.003)	(0.002)	(0.003)
Z-index in August	-0.002	0.001	-0.000
	(0.003)	(0.002)	(0.002)
Z-index in September	-0.002	-0.011***	-0.008***
	(0.002)	(0.003)	(0.003)
Z-index in October	0.010**	0.005**	0.010**
	(0.004)	(0.002)	(0.004)
Proportion of days with temperature range between 36 and 42°C in June (%)	-0.048	-0.009	-0.028
	(0.044)	(0.026)	(0.043)

Table 4.6 (cont'd)

Variables	(1) Tobit Aflatoxin-related insurance claims (%)	(2) Tobit Aflatoxin-related insurance claims (%)	(3) Tobit Aflatoxin-related insurance claims (%)
Proportion of days with temperature range between 36 and 42°C in July (%)	-0.021	0.031	-0.006
	(0.038)	(0.031)	(0.046)
Proportion of days with temperature range between 36 and 42°C in August (%)	-0.033	0.003	-0.025
	(0.041)	(0.025)	(0.040)
Proportion of days with temperature range between 36 and 42°C in September (%)	0.203**	0.121	0.141
	(0.094)	(0.088)	(0.109)
Proportion of days with temperature range between 36 and 42°C in October (%)	1.003**	0.739***	0.557*
	(0.493)	(0.265)	(0.297)
Yearly maximum temperature in June-October	0.053**	0.058***	0.095***
	(0.022)	(0.017)	(0.030)
Yearly precipitation in June-October	-0.002	0.002	0.003
	(0.002)	(0.002)	(0.003)
Yearly minimum temperature in June-October	-0.008	-0.035**	-0.043**
	(0.021)	(0.014)	(0.022)
Piedmont dummy	0.041	0.057**	0.111**
which is 1 if state is AL, GA, SC, NC, VA	(0.027)	(0.023)	(0.044)
Missing dummy	-0.010	0.006	-0.000
	(0.018)	(0.009)	(0.014)
Irrigation	-0.153*	-0.015	-0.034
(time average, range 0-1)	(0.084)	(0.056)	(0.068)
Observations	1,726	1,576	1,637

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Column 3 in Table 4.6 indicates the alternative Bt crops adoption rate (Bt crops adoption rate *alternative*) on aflatoxin-related insurance claims in peanut (%). This adoption rate was calculated as Bt corn- and cotton-planted areas over field crops-planted areas. Bt corn- and cotton-planted areas were regarded as missing when at least one of Bt corn- or Bt cotton-planted area information was missing. The result is consistent with the main results (column 1 in Table 4.3). Regarding missing of Bt corn or Bt cotton data as a zero value does not qualitatively change the results.

Table 4.7 presents the results of alternative temperature ranges on aflatoxin-related insurance claims. The columns 1, 2, and 3 indicate the effect of temperature ranges of 30 to 36°C, 32 to 38°C, and 34 to 40°C, respectively. The range 30 to 36°C in September represents a negative effect of the temperature on aflatoxin. It means that a temperature of 30 to 36°C is not warm enough to increase aflatoxin-related claims in peanuts. However, the temperature ranges of 32 to 38°C and 34 to 40°C in September and October have positive effects on aflatoxin, as in the main result (column 1 in Table 4.3). Therefore, warm temperatures above 32°C are associated with a high incidence of aflatoxin. This temperature range is higher than the literature suggests; the optimum temperature for aflatoxin production is between 28 and 30°C, and the production is decreased as the temperature reaches 37°C (OBrian et al. 2007; Smith et al. 2008). However, I believe my results are consistent with the literature, because aflatoxigenic mold in pods is likely to occur under lower temperatures than the air temperatures (I used for variables), because the soil temperature is lower than the air temperature.

Table 4.7 The marginal effect of alternative temperature ranges on aflatoxin-related insurance claims in peanuts estimated by Tobit models

Variables	(1) Tobit Aflatoxin-related insurance claims (%)	(2) Tobit Aflatoxin-related insurance claims (%)	(3) Tobit Aflatoxin-related insurance claims (%)
Bt crops adoption rate (Bt corn and cotton planted area /field crops planted area)	-0.079**	-0.058*	-0.060*
	(0.040)	(0.035)	(0.034)
Z-index in June	0.005**	0.003	0.002
	(0.002)	(0.003)	(0.002)
Z-index in July	-0.003	-0.002	0.000
	(0.003)	(0.003)	(0.003)
Z-index in August	0.001	-0.004	-0.003
	(0.002)	(0.002)	(0.003)
Z-index in September	-0.006**	-0.003	-0.003
	(0.003)	(0.002)	(0.002)
Z-index in October	0.009***	0.009***	0.008***
	(0.003)	(0.003)	(0.003)
Proportion of days with temperature range of 30 to 36°C in June (%)	0.021		
	(0.031)		
Proportion of days with temperature range of 30 to 36°C in July (%)	-0.019		
	(0.031)		
Proportion of days with temperature range of 30 to 36°C in August (%)	0.005		
	(0.029)		
Proportion of days with temperature range of 30 to 36°C in September (%)	-0.062*		
	(0.037)		
Proportion of days with temperature range of 30 to 36°C in October (%)	0.018		
	(0.032)		
Proportion of days with temperature range of 32 to 38°C in June (%)		-0.003	
		(0.027)	
Proportion of days with temperature range of 32 to 38°C in July (%)		0.013	
		(0.026)	
Proportion of days with temperature range of 32 to 38°C in August (%)		-0.033	
		(0.025)	

Table 4.7 (cont'd)

Variables	(1) Tobit Aflatoxin-related insurance claims (%)	(2) Tobit Aflatoxin-related insurance claims (%)	(3) Tobit Aflatoxin-related insurance claims (%)
Proportion of days with temperature range of 32 to 38°C in September (%)		0.098***	
		(0.034)	
Proportion of days with temperature range of 32 to 38°C in October (%)		-0.059	
		(0.072)	
Proportion of days with temperature range of 34 to 40°C in June (%)			-0.001
			(0.028)
Proportion of days with temperature range of 34 to 40°C in July (%)			0.012
			(0.024)
Proportion of days with temperature range of 34 to 40°C in August (%)			-0.035
			(0.027)
Proportion of days with temperature range of 34 to 40°C in September (%)			0.133***
			(0.042)
Proportion of days with temperature range of 34 to 40°C in October (%)			0.777*
			(0.413)
Yearly maximum temperature in June-October	0.054***	0.044**	0.043**
	(0.018)	(0.018)	(0.018)
Yearly precipitation in June-October	-0.002	0.000	-0.000
	(0.002)	(0.002)	(0.002)
Yearly minimum temperature in June-October	0.008	-0.035*	-0.032*
	(0.016)	(0.018)	(0.017)
Piedmont dummy	0.022	0.066**	0.052**
which is 1 if state is AL, GA, SC, NC, VA	(0.022)	(0.029)	(0.024)
Missing dummy	-0.004	-0.006	-0.002
	(0.018)	(0.018)	(0.016)
Irrigation	-0.117*	-0.054	-0.035
(time average, ranges 0-1)	(0.067)	(0.074)	(0.050)
Observations	2,248	2,248	2,248

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

4.7 Discussion

These results suggest that there is a spillover effect of Bt crops on aflatoxin in peanuts. This is the first study that examines the Bt crops effect on reducing aflatoxin in a non-Bt crop. The effect means that the spillover effect of Bt plants that is known to benefit non-Bt farmers by saving insecticide costs can benefit non-adopters by reducing aflatoxin-related damage and thereby providing safe food, i.e.,- aflatoxin-free peanuts in the market. I estimated that the economic benefits of Bt crops by reducing aflatoxin-related damage in peanuts are approximately US $ 0.23 million to US $0.45 million per year. This provides market-level confirmation of an economic and health benefit from Bt crops by reducing aflatoxin in peanut (a non-Bt crop).

The spillover effect of Bt crops on aflatoxin in peanuts has policy implications. Currently, the Insect Resistance Management (IRM) allows the Bt corn adoption rate to be as high as 80% in the Corn Belt area to control the insect resistance against Bt. However, the spillover effect means that a policy should be enacted to consider the ecological relationship of using Bt and non-Bt crops, such as peanuts and vegetables for resistance control instead of considering only Bt crops (corn and cotton).

On the other hand, the spillover effect of Bt plants means insects that already have resistance against Bt can move to peanut fields as well. In that case, the Bt effect will be reduced in both Bt and non-Bt fields. It means that if Bt is commercialized in peanuts seed market, it may not have enough effect to control insects and aflatoxin as Bt corn and cotton did. Therefore, more research is needed on the spillover effect of Bt to control insects and aflatoxin considering resistance.

This effect raises an interesting question about the management of decisions about crop choices and insect management between neighboring farms. For instance, biocontrol management can be effective if Bt crops are planted in the neighborhood (Lu et al. 2012). Through consideration of how the Bt seed trait can protect against damage, my analysis will also shed light on the unintended benefits of Bt crops to afford protection in countries where genetically modified seeds are not currently in use.

REFERENCES

REFERENCES

Brookes G, Barfoot P. 2013. Gm crops: Global socio-economic and environmental impacts 1996–2011. Dorchester, UK: PG Economics Ltd 187.

Cotty PJ, Jaime-Garcia R. 2007. Influences of climate on aflatoxin producing fungi and aflatoxin contamination. International Journal of Food Microbiology 119:109-115.

Diener UL, Davis ND. 1970. Limiting temperature and relative humidity for aflatoxin production byaspergillus flavus in stored peanuts. Journal of the American Oil Chemists' Society 47:347-351.

Diener UL, Davis ND. 1977. Aflatoxin formation in peanuts by aspergillus flavus.

Dively GP, Venugopal PD, Bean D, Whalen J, Holmstrom K, Kuhar TP, et al. 2018. Regional pest suppression associated with widespread bt maize adoption benefits vegetable growers. Proceedings of the National Academy of Sciences 115:3320-3325.

Dorner J. 2008. Management and prevention of mycotoxins in peanuts. Food Additives and Contaminants 25:203-208.

Hutchison W, Burkness E, Mitchell P, Moon R, Leslie T, Fleischer SJ, et al. 2010. Areawide suppression of european corn borer with bt maize reaps savings to non-bt maize growers. Science 330:222-225.

Kathage J, Qaim M. 2012. Economic impacts and impact dynamics of bt (bacillus thuringiensis) cotton in india. Proceedings of the National Academy of Sciences 109:11652-11656.

Klich MA. 2007. Aspergillus flavus: The major producer of aflatoxin. Molecular plant pathology 8:713-722.

Liu Y, Wu F. 2010. Global burden of aflatoxin-induced hepatocellular carcinoma: A risk assessment. Environmental Health Perspectives 118:818.

Lu Y, Wu K, Jiang Y, Guo Y, Desneux N. 2012. Widespread adoption of bt cotton and insecticide decrease promotes biocontrol services. Nature 487:362.

Masoero F, Moschini M, Rossi F, Prandini A, Pietri A. 1999. Nutritive value, mycotoxin contamination and in vitro rumen fermentation of normal and genetically modified corn (cry1a(b)) grown in northern italy. Maydica 44:205-209.

OBrian G, Georgianna D, Wilkinson J, Yu J, Abbas H, Bhatnagar D, et al. 2007. The effect of elevated temperature on gene transcription and aflatoxin biosynthesis. Mycologia 99:232-239.

Perry ED, Ciliberto F, Hennessy DA, Moschini G. 2016. Genetically engineered crops and pesticide use in us maize and soybeans. Science Advances 2:e1600850.

Pettit RE, Taber RA, Schroeder HW, Harrison AL. 1971. Influence of fungicides and irrigation practice on aflatoxin in peanuts before digging. Applied and Environmental Microbiology 22:629-634.

Sanders TH, Blankenship PD, Cole RJ, Hill RA. 1984. Effect of soil temperature and drought on peanut pod and stem temperatures relative to aspergillus flavus invasion and aflatoxin contamination. Mycopathologia 86:51-54.

Smith CA, Robertson D, Yates B, Nielsen DM, Brown D, Dean RA, et al. 2008. The effect of temperature on natural antisense transcript (nat) expression in aspergillus flavus. Current Genetics 54:241-269.

Wiatrak P, Wright D, Marois J, Wilson D. 2005. Influence of planting date on aflatoxin accumulation in bt, non-bt, and tropical non-bt hybrids. Agronomy Journal 97:440-445.

Wu F, Khlangwiset P. 2010. Health economic impacts and cost-effectiveness of aflatoxin-reduction strategies in africa: Case studies in biocontrol and post-harvest interventions. Food Additives and Contaminants 27:496-509.

Wu F, Bhatnagar D, Bui-Klimke T, Carbone I, Hellmich R, Munkvold G, et al. 2011. Climate change impacts on mycotoxin risks in us maize. World Mycotoxin Journal 4:79-93.

Xu Z, Hennessy DA, Sardana K, Moschini G. 2013. The realized yield effect of genetically engineered crops: Us maize and soybean. Crop Science 53:735-745.

CHAPTER 5

Discussion

This dissertation study contributes to filling a knowledge gap between aflatoxin, Bt crops, and climate conditions. It is the first study to show Bt corn effects that reduce aflatoxin-related damage in a natural field setting. By using crop insurance data, I was able to estimate the actual loss of aflatoxin that has historically occurred in corn in the United States.

The findings of this research indicate that higher Bt planting causes lower aflatoxin-related insurance claims, which has health and economic implications. Because aflatoxin-contaminated crops are discounted or destroyed by FDA regulations in the United States, Bt corn benefits farmers by avoiding the economic loss caused by aflatoxin. The use of Bt corn also has implications in terms of health for countries that do not have regulations for aflatoxin. Reduced consumption of aflatoxin-contaminated food decreases the risk of childhood stunting and liver cancer. Additionally, the effect of Bt on aflatoxin can improve food security by reducing the number of crops destroyed by aflatoxin.

The finding that the effect of drought on aflatoxin varies in the crop growing stage means that drought affects areas differently depending on crops and time. For instance, drought in September was shown to reduce aflatoxin damage in corn, but it was simultaneously associated with high aflatoxin related loss in peanuts. By dividing fungal infection and toxin production by periods of corn progress, a hypothesis was set and confirmed that drought increases aflatoxin in fungal invasion, which mainly occurs in the corn silking stage. However, drought also was shown to decrease aflatoxin after fungal invasion. This study also demonstrates how this drought effect varies in crop progress and that it occurred in peanuts as well.

The estimated county specific risk of aflatoxin under climate change can be useful for crop choice decisions. This research predicted aflatoxin risk in 2031-2040 using 16 climate change models. The estimated risk is expected to increase in the corn belt area and decrease in southern areas. This estimated risk will be useful for calculating the expected profits that decrease and increase from aflatoxin depending on the county. Consequently, knowing this risk is useful for farmers' future crop choice decisions in the face of climate change.

Lastly, the spillover effect of Bt on aflatoxin in peanuts has implications for Bt crops in that Bt crops can improve food safety by enabling the growth of aflatoxin free peanuts in the market. The results presented here indicate that Bt crops unintentionally reduce aflatoxin in non-Bt crops (peanut) as well as in Bt planted crops. Indeed, as more Bt crops are adopted in a county, aflatoxin-related insurance claims in peanuts were shown to decrease. This spillover effect means that peanut farmers are benefiting from their neighbors' Bt planting via reduced aflatoxin-related damage to their own crops. This spillover effect increases the importance of interdependence in decision making, such as Bt planting and biocontrol management decisions associated with Bt between Bt planted farmers and their neighbors.

In conclusion, Bt corn and other Bt crops may be a highly effective and economic tool to protect against aflatoxin not just in corn, but in other crops. This may become increasingly important with near-term future climate change, when problems of aflatoxin are likely to spread to the Corn Belt states on a more regular basis.