Impact of warming temperatures on planting progress: Evidence from US corn

by

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Abstract

The impact of climate change, and the associated warming temperatures, on agricultural production has been a focus of researchers in recent years. The primary focus of many of these studies includes estimating yield losses stemming from anticipated warming temperatures. This paper quantifies the extent to which farmers adapt to warming temperatures, which leaves the door open to an extension investigating whether said adaptation could mitigate yield losses.

Using USDA Crop Progress Reports, this paper analyses how planting time in US corn, specifically the median planting date, has changed over the last few decades. We find that seven of the sixteen states in our sample exhibit a statistically significant shift towards an earlier median planting date. After incorporating PRISM weather data into our models, we find a one-degree Celsius increase in average April temperature is associated with, on average, a median planting date that is 1.82 days earlier.

This paper then builds upon the median planting date models by using weekly first differences in planting progress as the dependent variable, yielding a more dynamic analysis of the planting season. We allow for temporal and spatial heterogeneity in weekly weather coefficient estimates and control for realized cumulative planting progress made in previous weeks. The results indicate that warmer weekly temperatures have a positive, statistically significant impact on planting progress for the first six weeks of the planting season. Using prediction analysis, we quantify the expected impact of warmer weekly temperatures on planting progress. Results show that a one-degree Celsius increase in weekly average temperature is associated with, on average, a predicted median planting date that ranges from 0.51 days earlier in Texas to 2.08 days earlier in Kentucky.

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Dedication

I dedicate this thesis to those who piqued my interest in agriculture from a young age and sent me on a path towards a Master's degree in agricultural economics. They include my parents, James and Doris Green, and my grandfathers, John Green and Peter Schaefer.

Chapter 1 - Introduction

Climate change, and the warming temperatures associated with it, has been a primary focus of many researchers in recent years. Research regarding row crop agriculture has attempted to get a clearer picture of the potential future impact of climate change on those crops. Several studies have found that warming temperatures, and the associated extreme heat, have large, negative impacts on crop yields for several different crops throughout the world, (e.g., Schlenker and Roberts 2009; Tack, Barkley, and Nalley 2015; Chen, Chen, and Xu 2016; Gammans, Mérel, and Ortiz-Bobea 2017).

When quantifying the impact of warming temperatures and climate change on crop yields, it is important to consider producer behavior. Specifically, do farmers adapt to changing weather patterns, and if so, by how much? In US corn, several studies by Kucharik find evidence of a shift towards earlier corn planting between the 1980's and the mid 2000's (Kucharik 2006; Kucharik 2008; Sacks and Kucharik 2011). While the shift earlier is quite apparent, the cause for said shift is not. During the 1980's and the mid 2000's, there were several technological advances, changing agronomic practices, and changing weather patterns with the potential to contribute to earlier planting dates.

The purpose of this paper is to analyze how temperatures during the planting season impact planting progress in US corn. Using USDA crop progress report data, we identify the median planting date for a given region and examine how that median planting date has changed over time. We find that the majority of the states in our sample experienced a shift towards an earlier median planting date. States experiencing the largest shifts, on average, towards an earlier median planting date between 1981 and 2020 include Missouri (14.87 days), Kentucky (9.22 days), and Kansas (9.18 days).

Using PRISM weather data, we calculate the average temperature and precipitation during the month of April and use fixed effects linear regression analysis to quantify the impact of April weather on the median planting date. We find that a one-degree Celsius increase in average temperature during the month of April is associated with a median planting date that is, on average, 1.82 days earlier.

In order to more dynamically analyze the planting season, we calculate the weekly first differences in the percent of corn acres planted. Again using PRISM weather data, we use Poisson regression analysis to estimate the impact of weekly temperature and precipitation on planting progress. Results indicate that warmer temperatures in the week preceding a crop progress report have a positive, statistically significant relationship with planting progress for the first six weeks of the planting season.

Using prediction analysis, we calculate the predicted impact, on average, that a one-degree Celsius increase in weekly average temperature would have on planting progress. We find that a one-degree increase in average weekly temperature is predicted to increase the cumulative percent of acreage planted, on average, by 5.14 percentage points by the end of the sixth week, across all states. States experiencing higher than average predicted increases in acreage planted by the end of the sixth week include Wisconsin (6.80), Kentucky (6.16), and Kansas (6.01).

Finally, using the aforementioned predicted weekly increase in planting progress, we calculate the implied shift in median planting date if weekly temperatures were indeed one-degree Celsius higher. We find a one-degree increase in weekly temperature is predicted to shift median planting date, on average, 1.03 days earlier across all states. States with above average predicted shifts in median planting date include Kentucky (2.08 days), Missouri (1.27 days), Kansas (1.26 days), and North Carolina (1.24 days), South Dakota (1.24 days).

Chapter 2 - Background & Literature Review

When making the decision whether or not to initiate planting, there are many factors a producer must consider. Realized weather, crop insurance restrictions, weather risk, and forecasted weather are all among these factors. Field suitability and soil temperatures both influence the planting decision-making process, while being functions of weather. Field conditions that are either too wet or too cold can hamper seed germination and negatively impact crop yields and producer profitability. Additionally, lower temperatures can be associated with a higher freeze risk, which has the potential to devastate crop production. Therefore, a farmer must be aware of weather patterns and forecasts if he or she hopes to choose a planting date that optimizes production.

The changes in temperature and precipitation patterns associated with climate change are another aspect of weather that a producer might consider when making planting decisions. In US corn, several studies by Kucharik find evidence of a shift towards earlier corn planting between the 1980's and the mid 2000's. These studies, however, argue that this shift towards earlier planting was driven by technological advances and changing agronomic practices, rather than by climate change and warming temperatures (Kucharik 2006; Kucharik 2008; Sacks and Kucharik 2011). Nonetheless, Kucharik (2011) noted that farmer adaptation towards longer maturity corn varieties helped contribute to yield growth in that same time frame. While there is little doubt of adaptation by farmers over time, the driver of said adaptation in both the past and future is up for debate. It does seem likely that farmers adapt accordingly in an attempt to mitigate yield losses or maximize yields.

A potential shortcoming of recent studies seeking to quantify the impact of climate change on crop yields is the extent in which they control for farmer adaptation in the long run.

Much of the literature implicitly assumes that little or no adaptation occurs in response to rising temperatures. There have been recent studies that attempt to quantify the extent to which farmers adapt in the long run. Burke and Emerick (2016) find little evidence of adaptation to warming temperatures while Keane and Neal (2017) find evidence in favor of adaptation.

Another study worthy of mention is by Ortiz-Bobea and Just (2013). In this study, they examine how shifting planting earlier might help to mitigate yield losses stemming from climate change and warming temperatures. However, rather than measure this directly, they simulate how those yield losses would be mitigated in a scenario where farmers do indeed adapt. As a result, this study offers more of a hypothetical, optimal adjustment with regard to mitigating yield losses. While there is value in this, there are also shortcomings, as reality would likely hamper the extent to which farmers would be able to actually adapt to that optimal point.

Several of these studies tend to measure adaptation in a more indirect fashion by analyzing the relationship between crop yields and temperature over time. A more direct approach would include looking at a mode of adaptation, such as earlier planting dates, and examining how that varies in response to changes in temperature. While there has been some recent work using this direct approach to measure the extent in which weather impacts the planting season (e.g., Cui and Xie 2021), there remains value in fleshing out this approach, especially for US corn.

Cui and Xie (2021) use novel panel data, spanning from 1993 to 2013, from 778 agro-climatic monitoring sites in China. These data contain information on crop planting and growth progress. After incorporating weather data, Cui and Xie analyze the impact of temperature and precipitation on corn planting and growing season length. They find that a one-degree Celsius increase in average temperature during the four weeks preceding the median planting date is associated with a median planting date that is 0.75 days earlier. If this average temperature increase occurs during the 8 weeks preceding the median planting date, the associated shift in the median planting date is 1.21 days. These estimates provide insight regarding short run adaptation. They find little evidence of long run adaptation but note that data limitations may contribute to this. This paper will build upon the work done by Cui and Xie by quantifying the extent to which US corn producers adapt to warming temperatures in the short and long run.

Chapter 3 - Data, Variable Description, & Summary Statistics

Data Description

Analyzing the impact of weather, specifically temperature, on planting progress for corn grown in the United States requires two different types of data: weather data and crop progress data.

Crop Progress Data

Weekly crop progress reports for each state are released by the United States Department of Agriculture (USDA) during the growing season. Within each crop progress report, data highlighting the cumulative percentage of acreage at a given growth stage for a given crop is available. With this project focusing on corn planting progress, we compile corn planting data for sixteen of the top corn-growing states.

Depending on the state, the corn planting progress data are either available at the state level or at the crop reporting district (CRD) level. Accessing state level data is as simple as downloading the data from the Quick Stats database on the USDA, NASS website. Acquiring CRD level data requires contact with the USDA regional field offices or manually referencing individual weekly crop progress reports. Generally speaking, major corn-producing states, such as Iowa and Illinois, tend to be the states that have data available at the CRD level. CRD level data availability is subject to change, however. In recent years, the states of Illinois, Indiana, and Missouri have ceased publishing corn planting progress data at the CRD level. Table 3.1 summarizes the structure of the crop progress data used throughout this paper.

In our analysis, we use CRD level data when available. For a given state in a given year, if both CRD and state level data are available, we drop the state level data from our dataset. If no CRD level data is available, we use the state level data. For some states, we end up with mixed data levels across our sample. For example, with the state of Nebraska, we use CRD level data from 1991 to 2003 and state level data from 1979 to 1990 and from 2004 to 2020.

Table 3.1 Summary of Crop Progress Data

State	Observations	Data Level	First Year	Final Year
CO	350	State	1979	2020
IL*	2,094	CRD	1980	2017
	383	State	1980	2020
IN*	2,943	CRD	1975	2018
	360	State	1979	2020
IA**	2,358	CRD	1974	2020
KS	3,037	CRD	1979	2020
KY	363	State	1979	2020
MI	330	State	1979	2020
MN	326	State	1979	2020
MO*	5,643	CRD	1977	2017
	378	State	1977	2020
NE*	672	CRD	1991	2003
	341	State	1979	2020
NC	373	State	1979	2020
OH	356	State	1979	2020
PA	342	State	1979	2020
SD	306	State	1979	2020
TX	358	State	1985	2020
WI*	1,700	CRD	1987	2020
	356	State	1979	2020
Total	23,369			

*Mixed Data Level Used for Analysis
**No CRD Level Data in 1992, State Level Data Used that Year

Weather Data

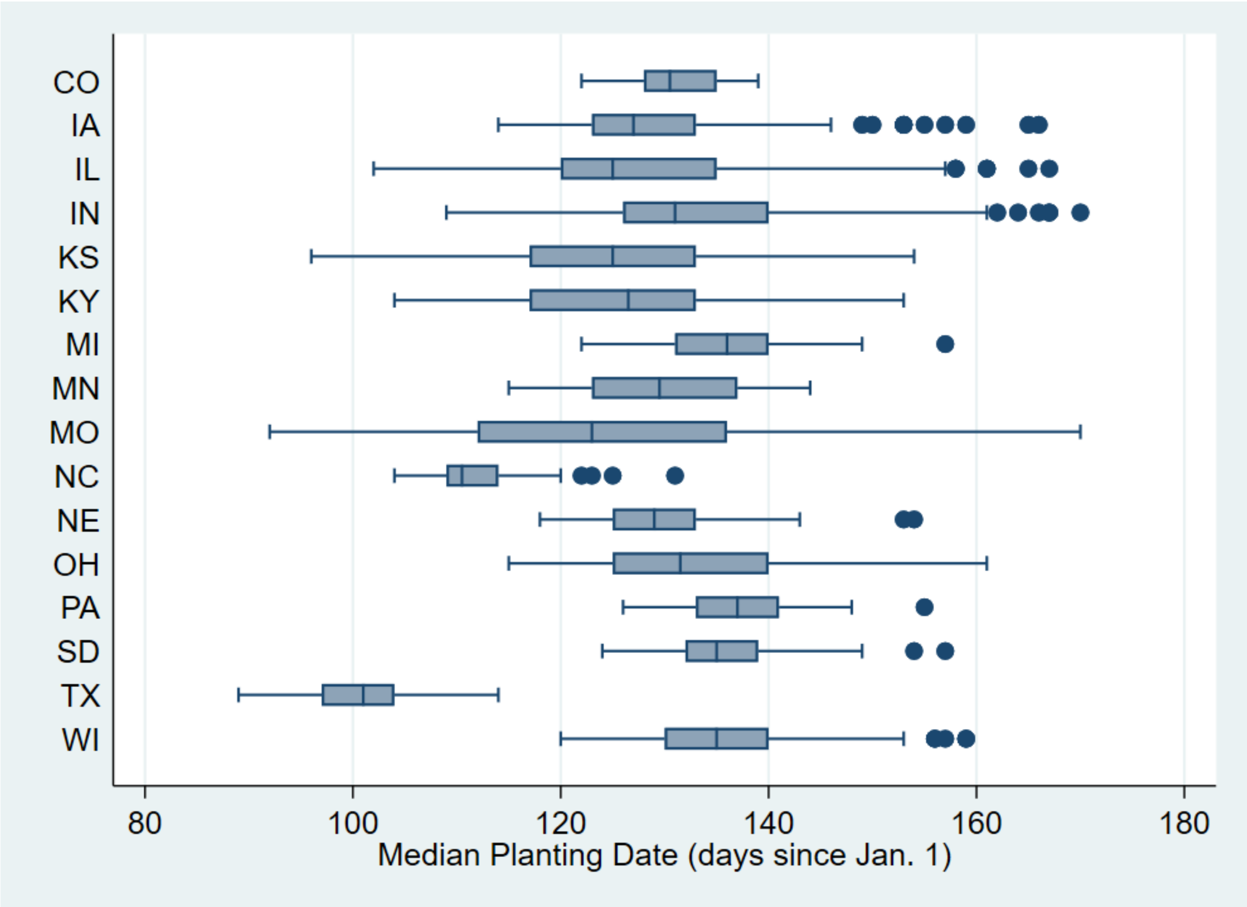
The weather data comes from Wolfram Schlenker’s website, which is based on the PRISM weather dataset. The raw data provides daily precipitation (mm), minimum temperature (°C), and maximum temperature (°C) values for 2.5 x 2.5 mile grids across the United States. A simple average of the maximum and minimum daily temperatures provides an average daily temperature value. Additionally, using code from Schlenker's website, we aggregate this grid data up to the CRD or state level using a weighted average of total crop acreage in a given region. The result is average daily temperature and total daily precipitation values at the CRD and state level for a time period ranging from 1950 to 2019.

Median Planting Date

We define the median planting date as the first day in which at least 50% of corn acres in a given region have been planted. The median planting date summarizes and provides a glimpse of what the corn planting season looks like in a particular region. In order to identify the median planting date, we convert the weekly planting progress data into daily planting progress via linear interpolation. Once we have daily corn planting progress, we identify the first day of the year where the percentage of corn planted surpasses 50%. Figure A.1 in Appendix A provides a visual example of how the linear interpolation process and median planting date identification occurs. The median planting date value is relative to January 1st. For example, if the median planting date in a given region is determined to be April 29th, this variable takes a value of 120, as this day is 120 days after January 1st.

Figure 3.1 provides box plots of the median planting date for each of the sixteen states in our sample from 1979 and 2020. From the box plots, we are able to compare among states when median planting tends to occur, on average, and how consistent the median planting date has been over time by inspecting the range. With regard to those two factors, we are able to draw the following conclusions. As one would expect, southern states tend to plant earlier, as evidenced by the early median planting dates for the states of Texas and North Carolina. Conversely, northern states tend to plant later, as evidenced by the later median planting dates of Wisconsin, Pennsylvania, Minnesota, and Michigan. The range of median planting dates doesn't appear to be as closely associated with geographic location. Missouri, Indiana, Illinois, Kansas, and Kentucky are among the states with a larger range of median planting dates. One commonality among these states is that they are neither the northern-most nor the southern-most states.

Figure 3.1 Median Planting Date Box Plots by U.S. State, 1979-2020



Median Planting Date & Weather

In order to quantify the impact of changing weather patterns on the planting of U.S. corn, and specifically on the median planting date, we incorporate PRISM weather data into the forthcoming models. *Median planting date* offers only one observation per year in a given region, and we find that the majority of corn planting preceding the median planting date occurs in the month of April. Therefore, we consider weather throughout the entire month of April to be impactful on the median planting date. Using the aforementioned PRISM daily weather data from Wolfram Schlenker's website, we calculate the average April daily temperature in degrees Celsius and average April daily precipitation in millimeters.

Figure 3.2 Median Planting Date and April Weather Scatter Plots by State

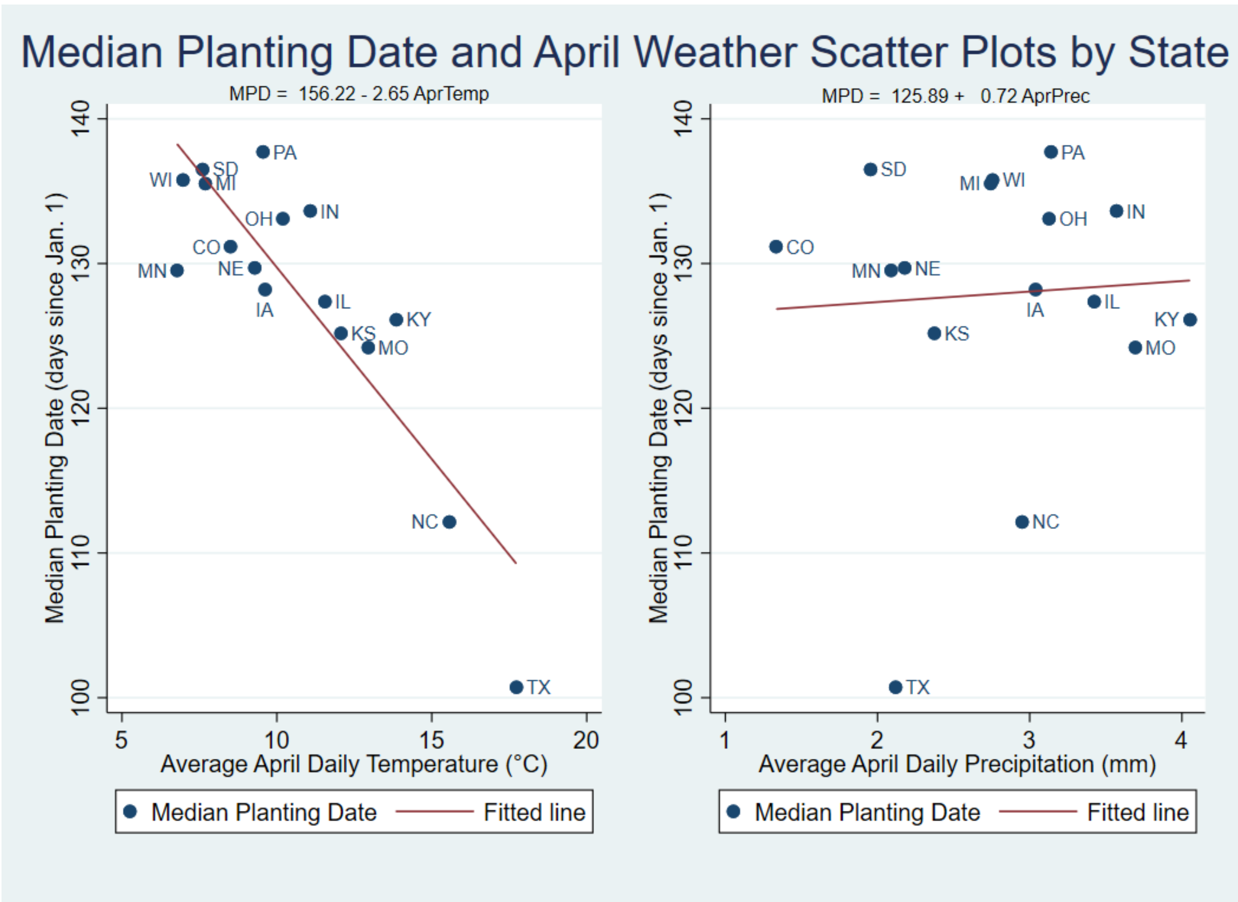


Figure 3.2 presents a two-way scatter plot, with a fitted line, of median planting date (MPD) and average April weather by state. Table A.1 in the appendix provides the numerical values for these data. The left scatter plot shows a strong, negative relationship between median planting date and average April temperature, while the right scatter plot shows the relationship between median planting date and average April precipitation that is slightly positive but not as strong. The left scatter plot shows that the states with warmer springtime (April) temperatures tend to have earlier median planting dates. This is evidenced by the fact that the six warmest

states – Texas, North Carolina, Missouri, Kansas, Kentucky, and Illinois – also have the six earliest median planting dates. There are two states – Indiana and Ohio – that have above average April temperatures but do not achieve median planting date as early. Looking at the right scatter plot, we find Ohio and Indiana have above average April precipitation, which may contribute to their later median planting date. There, of course, may exist other factors besides temperature and precipitation that could be impacting median planting date as well. We will quantify the impact of precipitation and temperature on median planting date, with multivariate regression analysis, in the next chapter.

Median Planting Date Over Time

It has been documented in the literature that over the last four decades, median planting dates have shifted earlier throughout the United States (Kucharik 2006). We measure this shift in median planting date over time with a state-specific, linear trend. From this, we are able to estimate the trend coefficient, which indicates how many days earlier per year, on average, the median planting date has shifted between 1981 and 2020. Table 3.3 presents this shift in median planting date in terms of days per year and in total days. For example, between 1981 and 2020, Iowa's median planting date shifted earlier at a rate of, on average, 0.175 days per year. Therefore, the predicted median planting date for Iowa in 2020 is about 6.83 days earlier than the predicted median planting date in 1981. As evidenced in the literature, most states experienced a shift towards early planting over the last four decades, though not all were statistically significant. The states with the most significant shift towards earlier median planting dates include Missouri (14.87 days), Nebraska (9.63 days), Kentucky (9.22 days), and Kansas (9.18 days). States that did not experience a statistically significant shift in median planting date include Michigan, Wisconsin, Colorado, and Minnesota.

Table 3.2 State Specific Median Planting Date Trends, 1981-2020

	------ Median Planting Date ------	
State	Days/Year	Days Earlier†
MO	-0.381***	-14.87
NE	-0.247**	-9.63
KY	-0.236**	-9.22
KS	-0.235***	-9.18
IL	-0.219***	-8.52
MN	-0.211	-8.24
SD	-0.186	-7.25
IA	-0.175***	-6.83
TX	-0.165	-6.44
IN	-0.099**	-3.86
OH	0.088	3.43
NC	-0.085	-3.32
PA	-0.084	-3.27
WI	-0.069	-2.68
CO	0.058	2.27
MI	0.044	1.71

Note: State fixed effects omitted from output
* p < 0.10, ** p<0.05, *** p<0.01
†Change in median planting date between 1981 and 2020

Planting Progress

As previously mentioned, when a region's median planting date is calculated, there is only one value for a given region in a given year. While knowing the median planting date provides some insight into the planting season for that particular region, not as much is known about what happened in the days and weeks preceding and succeeding the median planting day. To get a better understanding of the entire planting season, we calculate planting progress, or simply progress, which is define as how much corn planting progressed from one week to the next. Equation (3.1) presents how this *progress* variable is calculated for a given week *w*. As the equation shows, progress in week *w* is equal to the difference between percent corn planted in week *w* and week *w-1*. Figure A.2 in Appendix A presents a numerical example of how this progress variable is calculated for a given region in a given year.

$$(3.1)\ Progress_{week\ w} = PctPlanted_{week\ w} - PctPlanted_{week\ w-1}$$

The *progress* variable is bounded between 0 percent and 100 percent, with a value of 100 implying that a given region planted 100 percent of its corn acres in a single week. We store this variable value in decimal form, giving it a range of 0.00 to 1.00.

Planting Progress & Weather

As is the case with median planting date, we will incorporate the PRISM weather data from Wolfram Schlenker's website. While the median planting date offers one observation per year in a given region, the *progress* variable is more dynamic, containing weekly observations throughout the planting season. As a result, the weather data used for the forthcoming analysis must be aggregated differently.

The *progress* variable is essentially how much corn planting progresses from one week to the next. Therefore, it seems logical that the weather during the week preceding a given crop progress update, between periods *w* and *w-1*, would be most impactful on planting progress. Wielding this intuition, we find the weekly average daily temperature (°C), denoted *WeeklyTemp,* and weekly total precipitation (mm), denoted *WeeklyPrec*, for the week before a crop progress update. This is the weather data that will be incorporated into the forthcoming progress models. Equations A.1 and A.2 in Appendix A define generally how *WeeklyTemp* and *WeeklyPrec* are calculated for a crop progress report released on a given day, d.

Summary Statistics

The forthcoming chapter will outline the methodology and models used when quantifying the impact of weather, temperature, and precipitation on planting progress in U.S. corn. Some models will use the *median planting date* variable in conjunction with April weather data. There will be additional models that use the *progress* variable in conjunction with weekly weather data. Summary statistics for *median planting date*, *progress,* and the associated April weather data and weekly weather data are presented in Table A.1 of Appendix A.

Chapter 4 - Methodology & Models

Median Planting Date Models

This section of the paper outlines the general form of the OLS regression models used to quantify the impact of weather on the median planting date and the intuition used when designing those models. In the forthcoming equations, median planting date is denoted as *Plant50*, with *i* representing a given region, *t* representing a given year, and ε denoting the error term. As discussed in the previous chapter, median planting date has shifted earlier throughout the U.S. over the last four decades. This first model includes a simple trend that captures the yearly change in median planting date.

$$(4.1)\ Plant50_{it} = \beta_0 + \beta_1 Year_t + \varepsilon_{it}$$

Building upon this trend model, we incorporate average April daily precipitation and temperature in order to quantify the impact of springtime temperature and precipitation on the median planting date, as is shown below. This model will henceforth be referred to as the no fixed effects model.

$$(4.2)\ Plant50_{it} = \beta_0 + \beta_1 AprTemp_{it} + \beta_2 AprPrec_{it} + \beta_3 Year_t + \varepsilon_{it}$$

As the name of the previous model may foreshadow, the next model includes region fixed effects, denoted by τ. This allows us to control for confounding factors, such as soil type, that may be specific to a certain region. This model will henceforth be referred to as the fixed effects model.

$$(4.3)\ Plant50_{it} = \beta_0 + \beta_1 AprTemp_{it} + \beta_2 AprPrec_{it} + \beta_3 Year_t + \tau_i + \varepsilon_{it}$$

As shown in Table 2.2, median planting date shifts have been more pronounced and statistically significant in some states, relative to others. To account for this heterogeneity, we incorporate a state-specific, quadratic trend for each state, j, into our model. This model, which we refer to as the state quadratic trend model, is given by:

$$(4.4)\ Plant50_{it} = \beta_0 + \beta_1 AprTemp_{it} + \beta_2 AprPrec_{it} + \beta_{3j} Trend_j + \beta_{4j} Trend_j^2 + \tau_i + \varepsilon_{it}$$

The aforementioned models utilize panel data and its associated year-to-year variation to estimate how warming temperatures would impact the median planting date. This results in estimates that adequately capture short run adjustment to changing weather patterns. In order to estimate how these changing weather patterns would impact long run expectations and adaptation, we include a cross-sectional model as our final median planting date model iteration. For each region in the sample, we average the median planting date and April weather data across all years. After doing this, we regress median planting date on average precipitation and temperature in the month of April, as is shown below. With this model no longer having any year-to-year variation, the results can be interpreted as the long run adaptation to a shift in weather expectations.

$$(4.5)\ Avg(Plant50_i) = \beta_0 + \beta_1 Avg(AprTemp_i) + \beta_2 Avg(AprPrec_i) + \varepsilon_i$$

Planting Progress Models

This section of the paper outlines the general form of the models that will be used to quantify the impact of weekly weather on weekly planting progress for U.S. corn. From the weekly planting progress data, we create a variable, *weeks-in*, identifying how many weeks into the planting season a given observation is. Since different areas plant corn at different times, the timing of the first week of planting varies by state. For example, in a given year, the first week of planting in Texas may occur at the beginning of March while the first week of planting in Michigan doesn't occur until the end of April. Nonetheless, the *weeks-in* value for these first week observations would be the same, even though they take place at different times. In the forthcoming models, γ_w is used to denote a fixed effect for the number of weeks in an observation is. As in the median planting date models, τ_i represents region fixed effects for a given region, *i*. Finally, we once again use *t* to denote a given year and ε to symbolize the error term.

The weekly fixed effects (WFE) model, which is defined by equation (4.6) is the first planting progress model iteration. After controlling for region and weeks-in fixed effects, and incorporating an annual linear trend, we are able to quantify the impact that average daily temperature and total precipitation in the week preceding a report have on corn planting progress.

$$(4.6)\ Progress_{iwt} = \beta_0 + \beta_1 WeeklyPrec_{iwt} + \beta_2 WeekTemp_{iwt} + \beta_3 Year_t + \gamma_w + \tau_i + \varepsilon_{iwt}$$

The weekly fixed effects model implies that the impact of weekly temperature and precipitation on planting progress does not vary spatially. In other words, it does not allow for heterogeneity of weekly weather coefficient estimates by geographic region. Consider the states of Michigan and Wisconsin, which are located in the northern United States where springtime temperatures tend to be cooler and risk of freezing temperatures higher. Next, consider the states of Texas and North Carolina, which are further south and tend to have warmer springtime temperatures. Would the marginal impact of weekly temperature on planting progress be higher in northern states, where temperature may be more of a limiting factor, than in southern states? Imposing heterogeneity of coefficient estimates by latitudinal location allows for differing weekly weather coefficient estimates in different parts of the United States.

We allow for heterogeneity by dividing the sixteen states in our sample into four different regional groups: north, mid-north, mid-south, and south, based on latitudinal location. The mid-north region, for example, includes the states of Nebraska, Iowa, Illinois, Indiana, Ohio, and Pennsylvania. Figure A.3 of Appendix A provides a map depicting which states are in which latitudinal region groups. Then, we interact weekly weather with latitudinal region indicator variables, which are denoted by *r*. This regional fixed weather effects (RFWE) model produces different weekly weather coefficient estimates for different latitudinal region groups and is defined below.

$$(4.7)\ Progress_{iwt} = \beta_0 + \beta_{1r}WeeklyPrec_{iwt} + \beta_{2r}WeeklyTemp_{iwt} + \beta_3 Year_t + \gamma_w + \tau_i + \varepsilon_{iwt}$$

A notable shortcoming of both the weekly fixed effects (WFE) and regional fixed weather effects (RFWE) models is that they do not allow for weather impacts to vary throughout the planting season. Rather, they imply that the impact of temperature and precipitation on planting progress remains the same throughout the planting season. Consider a one-degree Celsius increase in weekly average temperature. In early April, when temperatures are expected to be colder, this temperature increase could be more impactful on planting progress than in mid-May when temperatures, on average, are expected to be warmer. For this reason, we build upon the weekly fixed effects model by interacting the weekly weather variables with the weeks-in indicator variables, thereby allowing the estimated impact of weekly temperature and precipitation to change throughout the planting season. This modified model, which we call the weekly fixed weather effects (WFWE) model, is given by:

$$(4.8)\ Progress_{iwt} = \beta_0 + \beta_{1w}WeeklyPrec_{iwt} + \beta_{2w}WeeklyTemp_{iwt} + \beta_3 Year_t + \gamma_w + \tau_i + \varepsilon_{iwt}$$

This general weekly fixed weather effects model doesn't allow for heterogeneity by latitudinal regional group, as was done in the regional fixed weather effects model. So, we allow for heterogeneity of weekly weather coefficient estimates by latitudinal region using sample restrictions during regression analysis. Specifically, we estimate equation (4.8) using a sample that includes all sixteen states. To allow for spatial heterogeneity, we re-estimate equation (4.8) four separate times, in each case using only observations from a given latitudinal region group. This results in four, region-specific weekly fixed weather effect (RSWFWE) model outputs. The RSWFWE model combines the strengths of the RSWE and WFWE models by allowing for heterogeneity by latitudinal region group while also allowing for different weekly weather coefficient estimates in different weeks.

With our final model, we consider how we can observe and control for the planting decisions that have been made during previous weeks of the planting season. In the previous models, we impose heterogeneity temporally and spatially. First, we include *weeks-in* indicator variables to account for the fact that, on average, different weeks tend to see different levels of planting progress. For example, early on in the planting season, farmers may be more hesitant to begin planting due to freeze risk or poor field conditions while planting progress in later weeks may be limited by the proportion of acres already planted. We then interact *weeks-in* with weekly weather variables, to account for the fact that weather impacts planting progress differently at different points in the planting season. Spatial heterogeneity is permitted by separating the sample by latitudinal region group. These features provide a more accurate picture of the planting season across space and time. In this dynamic planting progress framework, however, there is another valuable consideration yet to be introduced: past planting decisions. Specifically, what planting decisions did farmers make in the preceding weeks?

Recall that the *progress* variable measures the increase in percentage of corn acres planted from week *w-1* to week *w* in a given region. Consider a case where at the end of week *w-1*, only ten percent of corn acres have been planted in a given region. Next, consider a case where at the end of week *w-1*, 60 percent of acres in a given region have been planted. In the first scenario, $Progress_{iwt}$ could theoretically take on a value as high as 90, while in the second scenario, $Progress_{iwt}$ cannot take on a value above 40. Therefore, it seems probable that, given similar weekly weather, there will be more planting progress made during week w in the first scenario. Given this, our final planting progress model builds upon the RSWFWE and WFWE models to include a lagged percent planted value, or the total percentage of corn planted in a given region at the end of the previous week. This percent planted variable is also interacted with the weeks-in indicator variables, allowing the coefficient estimates to vary by week. This model allows us to control for realized decisions made by producers during previous weeks of the planting season. The general form for this final planting progress model is shown below.

$$(4.9)\ Progress_{iwt} = \beta_0 + \beta_{1w} WeeklyPrec_{iwt} + \beta_{2w} WeeklyTemp_{iwt} + \beta_3 Year_t + \beta_4 PctPlanted_{w-1} + \beta_{5w} PctPlanted_{w-1} + \gamma_w + \tau_i + \varepsilon_{iwt}$$

Two different types of regression analysis are used for the planting progress models: OLS and Poisson. There is discussion in the literature regarding whether an OLS or Poisson estimator would yield the best estimates with a dependent variable such as ours. As noted by Möhring et al. (2020), there are two prevailing schools of thought. Wooldridge (2010) suggests that a model such as the Poisson model can effectively yield consistent estimators. Conversely, it is also argued that a standard OLS model can adequately provide coefficient estimates (Angrist and Pischke, 2008; Angrist, 2001).

This paper prescribes to Wooldridge's reasoning and prioritizes the fixed effects Poisson estimator for a number of reasons. Using an OLS estimator, dependent variables can take on negative and non-negative values. The values of our dependent variable, *progress*, however, are bounded by 0 and 1. The Poisson estimator is traditionally used to model count variables, such as number of regions that have attained median planting date by the end of the first week of May in a given year. A resulting characteristic of the Poisson estimator is non-negative dependent variable values. Therefore, when we predict progress values using Poisson coefficient estimates later on in this paper, there will be no predicted progress values less than zero. Additionally, since the Poisson model is traditionally used for count variables, it is effective at modeling distributions with a right skew and a high proportion of zero values (Wu and Little, 2011). Figure A.4 of Appendix A is a histogram of the *progress* variable, which visualizes the distribution and skewness of our dependent variable. The histogram shows a high proportion of zero values, right skew, and distribution that resembles a Poisson distribution, all of which motivate the use of the Poisson estimator.

The Poisson estimator is in the family of log-linear regression estimators. As a result, when using Poisson regression analysis, the aforementioned models would be defined as follows, where θ is the vector of independent variables, including fixed effects, used in a given model iteration.

$$(4.10)\ Progress_{iwt} = e^{(\beta_0 + \beta'\theta + \varepsilon_{iwt})}$$

Another model considered during this project was the fractional logit regression model, which bounds the dependent variable between 0 and 1. However, failure to achieve consistent convergence resulted in the exclusion of this model from the analysis. Given the outlined strengths of the Poisson estimator, it will be our preferred regression estimator used for the weekly planting progress models. Additionally, we use robust standard errors for all Poisson model regressions. While not presented in the body of the paper, OLS regression results will be provided in the appendix and are available for robustness checks.

Chapter 5 - Results & Discussion

Median Planting Date Model Results

Table 5.1 presents the median planting date OLS regression results. Regardless of model or variable, coefficient estimates are consistently statistically significant. Additionally, the signs of the coefficient estimates align with intuition. Ceteris paribus, higher temperatures in the month of April are associated with an earlier median planting date, higher levels of precipitation in the month of April are associated with a later median planting date, and over time, the median planting date has shifted earlier. The state quadratic trend model is our preferred model since we control for weather, region fixed effects, and state-specific quadratic trends. This model has an R-squared value of 0.629, meaning 62.9% of the variation in median planting date can be explained by our independent variables. The April precipitation coefficient can be interpreted as follows: holding all else constant, an additional millimeter of average daily precipitation during the month of April is, on average, associated with a median planting date that is 3.39 days later. In this paper, the primary focus is on the implications of a warming scenario. We find that a one-degree Celsius increase in average daily temperature during the month of April is, on average, associated with a median planting date that is 1.82 days earlier, holding all else constant.

As noted earlier, the cross-sectional model results can be interpreted as the long run adaptation to a shift in weather expectations. We find that if producers expect average April temperatures to be one degree Celsius warmer, that would be associated with a long run median planting date that is 2.07 days earlier, ceteris paribus. Finally, it is worth noting that this statistically significant, coefficient estimate is similar in magnitude to the short run coefficient estimate discussed earlier, which indicated a 1.82-day shift in the median planting date.

Table 5.1 Median Planting Date Model Results

Median Planting Date	Trend Only	No Fixed Effects	Fixed Effects	State Quadratic Trends	Cross-Sectional
April Temp. (°C)		-2.102^{***} (0.061)	-1.721^{***} (0.091)	-1.815^{***} (0.089)	-2.070^{***} (0.262)
April Precip. (mm)		3.111^{***} (0.118)	3.390^{***} (0.113)	3.391^{***} (0.110)	2.176^{**} (0.878)
Year	-0.161^{***} (0.019)	-0.293^{***} (0.016)	-0.305^{***} (0.014)		
Constant	450.23^{***} (38.684)	727.671^{***} (31.521)	746.505^{***} (27.630)	145.564^{***} (1.168)	144.437^{***} (2.918)
Observations	2684	2597	2597	2597	76
R^2	0.025	0.422	0.595	0.629	0.465
Fixed Effects	-	-	Region	Region	-

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Planting Progress Model Results

Table 5.2 presents the Poisson regression results for the weekly fixed effects model. The signs of the coefficient estimates indicate that warmer average weekly temperatures are associated with higher levels of planting progress, holding all else constant. Additionally, higher levels of weekly precipitation are associated with a less productive week of planting, holding all else constant. Both weekly weather variables are statistically significant at a 1% percent level of significance. In order to correctly interpret the coefficient estimates, we use the margins command in *Stata* and find that a one-degree Celsius increase in the average weekly temperature is associated with, on average, 0.62 percent more corn acres planted in a given week, holding all else constant.

Table 5.2 Poisson Weekly Fixed Effects Model Results

Progress	Weekly Fixed Effects
Weekly Average Temperature (°C)	0.055^{***} (0.000)
Weekly Total Precipitation (mm)	-0.014^{***} (0.000)
Year	0.002 (0.264)
Constant	-8.716^{**} (0.010)
Observations	23276
LR Chi²	1112.83
Fixed Effects	Region Weeks In

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The regression results of the Poisson regional fixed weather effects model are presented in Table 5.3. While temperature and precipitation impacts do not yet vary by week with this model, we are able to see how weekly weather impacts different latitudinal region groups. Table 5.3 shows that weekly temperature and weekly precipitation have a statistically significant impact on planting progress in all four latitudinal region groups. Further examination of the coefficient magnitudes shows that weekly temperature appears to have the largest positive impact on planting progress in the mid-north and mid-south regions. The impact of weekly temperature on *progress* in the north and south regions is smaller in magnitude and, in the south, less statistically significant. Reasons for this might include more extreme temperatures early in the planting season that limit planting progress or a generally longer planting season that results in a coefficient estimate of a smaller magnitude.

Table 5.3 Poisson Regional Fixed Weather Effects Model Results

Progress	Regional Fixed Weather Effects	
Year	0.002^{***}	
	(0.001)	
Region	Temp	Prec.
North	0.033^{***}	-0.013^{***}
Mid-North	0.051^{***}	-0.016^{***}
Mid-South	0.077^{***}	-0.012^{***}
South	0.022^{**}	-0.008^{***}
Constant	-9.317^{***}	
	(1.174)	
Observations	23276	
Fixed Effects	Region Weeks In	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The coefficient estimates from the Poisson weekly fixed weather effects models are presented in Table 5.4. The left-most column contains coefficient estimates for the model without any sample restrictions. The other four columns contain the region-specific model results where we allow for heterogeneity by latitudinal region group. The key takeaway from these results is that weekly average temperature has a positive, statistically significant impact on planting progress throughout the first six weeks of the planting season. This holds true for the homogeneous model, as well as for the region-specific models for the north, mid-north, and mid-south. In the southern states, the impact of weekly temperature on planting progress is not as consistently statistically significant. While the impact of precipitation is not the primary focus of this paper, it is worth noting that, as expected, higher levels of precipitation are associated with diminished planting progress throughout the entire planting season in most regions. As was the case with temperature, weekly precipitation also appears to be less impactful on planting progress in the states of Texas and North Carolina.

Table 5.4 Poisson Weekly Fixed Weather Effects Model Results

Progress	WFWE		Region Specific Weekly Fixed Weather Effects (RSWFWE)							
			North (0)		Mid-North (1)		Mid-South (2)		South (3)	
Year	0.002***		0.003*		0.002**		0.004***		-0.001	
	(0.000)		(0.000)		(0.006)		(0.000)		(0.579)	
Weeks In	Temp	Prec.	Temp	Prec.	Temp	Prec.	Temp	Prec.	Temp	Prec.
2	0.221***	-0.033***	0.203***	-0.018**	0.198***	-0.055***	0.289***	-0.019**	0.200*	-0.011
3	0.156***	-0.021***	0.144***	-0.015**	0.142***	-0.025***	0.245***	-0.017***	0.181***	-0.017
4	0.119***	-0.013***	0.142***	-0.014***	0.113***	-0.015***	0.142***	-0.012***	0.101***	-0.004
5	0.074***	-0.012***	0.075***	-0.009***	0.076***	-0.016***	0.084***	-0.010***	0.108***	0.001
6	0.049***	-0.016***	0.063***	-0.009***	0.036***	-0.018***	0.066***	-0.015***	0.065	0.002
7	0.005	-0.015***	-0.019*	-0.014***	-0.006	-0.017***	0.031***	-0.012***	-0.045**	-0.011
8	-0.013**	-0.014***	-0.048***	-0.018***	0.002	-0.013***	-0.014	-0.014***	-0.099**	-0.027*
9	-0.004	-0.014***	-0.089***	-0.012***	0.012	-0.010***	0.006	-0.017***	-0.034	-0.027**
10	-0.012	-0.016***	-0.079***	-0.012**	0.051***	-0.011***	-0.060***	-0.020***	-0.123***	-0.018***
Constant	-10.498***		-11.924***		-9.224***		-15.869***		-4.441	
Observations	23276		3563		10505		8341		867	
Fixed Effects	Region Weeks In		Region Weeks In		Region Weeks In		Region Weeks In		Region Weeks In	

Coefficient estimates for fixed effects excluded from table
p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Coefficient estimates from the Poisson weekly fixed weather effects regressions, where we also control for previous planting decisions, are presented in Table 5.5. As was the case with the previous table, the left-most of the five regression outputs presents coefficient estimates when observations from all sixteen states in our sample are included. In the other four iterations, we allow for heterogeneity by latitudinal region group.

We find that once we control for previous planting decisions with the inclusion of the $PctPlanted_{w-1}$ variable, weekly temperature coefficient estimates tend to be positive and statistically significant further into the planting season. Recall that in the standard WFWE and RSWFWE models without planting lags, we found weekly temperature coefficient estimates tended to be positive and statistically significant for the first six weeks of the planting season. After controlling for realized cumulative planting decisions in preceding weeks, weekly temperature coefficient estimates tend to be statistically significant and positive for at least the first seven weeks of the planting season, with some regions having statistical significance through nine weeks. The magnitude of said coefficient estimates consistently wane by week, and the southern region, yet again, experiences negligible statistical significance with regard to weekly temperature coefficient estimates.

OLS regression results for all planting progress models can be found in Appendix B. Table B.1 presents the weekly fixed effects model results. Similarly, Table B.2 presents the regional fixed weather effect model results. Table B.3 contains all five weekly fixed weather effects model results, and Table B.4 presents weekly fixed weather effect model results when we also include planting lags in our models. Relative to the Poisson coefficient estimates, the OLS regression results are more easily interpretable

Table 5.5 Poisson Weekly Fixed Weather Effects with Planting Lags Model Results

---------- With Planting Lags ----------										
Progress	WFWE		Region Specific Weekly Fixed Weather Effects (RSWFWE)							
			North (0)		Mid-North (1)		Mid-South (2)		South (3)	
Year	0.005***		0.001		0.002***		0.009***		-0.001	
	(0.000)		(0.482)		(0.008)		(0.000)		(0.824)	
Weeks In	Temp	Prec.	Temp	Prec.	Temp	Prec.	Temp	Prec.	Temp	Prec.
2	0.218***	-0.031***	0.194***	-0.020**	0.200***	-0.054***	0.280***	-0.015**	0.203*	-0.018
3	0.148***	-0.023***	0.127***	-0.024***	0.143***	-0.029***	0.227***	-0.017***	0.108	-0.033**
4	0.110***	-0.017***	0.113***	-0.017***	0.112***	-0.020***	0.129***	-0.013***	0.065**	-0.007
5	0.071***	-0.013***	0.058***	-0.011***	0.079***	-0.015***	0.071***	-0.012***	0.042	-0.007
6	0.065***	-0.015***	0.073***	-0.010***	0.058***	-0.018***	0.072***	-0.015***	0.030	-0.001
7	0.038***	-0.014***	0.031***	-0.011***	0.028***	-0.016***	0.053***	-0.012***	0.045	-0.002
8	0.027***	-0.013***	0.007	-0.014***	0.034***	-0.013***	0.021**	-0.014***	0.073*	-0.001
9	0.024***	-0.017***	-0.022	-0.009***	0.014*	-0.014***	0.057***	-0.021***	0.081**	-0.007
10	0.012	-0.016***	-0.046**	-0.014***	0.030***	-0.014***	-0.003	-0.019***	-0.047	-0.013**
Constant	-15.528***		-8.119***		-9.795***		-25.219***		-5.363	
Observations	23276		3563		10505		8341		867	
Fixed Effects	Region Weeks In Weeks In # Planted		Region Weeks In Weeks In # Planted		Region Weeks In Weeks In # Planted		Region Weeks In Weeks In # Planted		Region Weeks In Weeks In # Planted	

Coefficient estimates for fixed effects and percent planted lag excluded from table
p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Planting Progress Model Implications

The weekly fixed weather effects model, specifically the region-specific weekly fixed weather effect model, with and without lagged percent planted controls, is our preferred planting progress model. Regression results from said iterations yield different weekly weather coefficient estimates for different weeks-in values during the planting season. Additionally, when we allow for heterogeneity by latitudinal region group, each group of states will have its own coefficient estimate for a given weekly weather variable in a given week. The sheer number of coefficient estimates could prove overwhelming and challenging to interpret, an issue exacerbated by the use of the log-linear Poisson estimator. With the impact of a warming scenario on planting progress being our primary interest, we use prediction analysis to more easily interpret the effect of an average weekly temperature increase on planting progress.

Using the RSWFWE and WFWE coefficient estimates, we generate predicted progress values. Since the Poisson estimator is a log-linear model, Poisson and OLS estimators have different prediction equations which are denoted by $\widehat{Progress}_{iwt}^{POI}$ and $\widehat{Progress}_{iwt}^{OLS}$ below. After generating the original predicted progress values, we manually increase the value of weekly average temperature by one to mimic a one-degree Celsius increase in average weekly temperature. We then re-predict the values of progress. These new prediction values are denoted by $\widetilde{Progress}_{iwt}^{POI}$ and $\widetilde{Progress}_{iwt}^{OLS}$. $ProgressDifference_{iwt}$ is defined as the difference between these two predictive values for a given estimator, as shown below, and can be interpreted as the predicted change in weekly planting progress as a result of a one-degree Celsius temperature increase. Finally, we can calculate the cumulative value of the planting progress difference w weeks into the planting season in a given region and year, denoted by $CumProgressDiff_{iwt}$. Figure A.5 in Appendix A presents a numerical example of this process.

$$(5.1)\ \widehat{Progress}_{iwt}^{OLS} = \widehat{\beta_0} + \widehat{\beta_{1w}}WeeklyPrec_{iwt} + \widehat{\beta_{2w}}WeeklyTemp_{iwt} + \widehat{\beta_3}Year_t + \widehat{\gamma_w} + \widehat{\tau_i}$$

$$(5.2)\ \widehat{Progress}_{iwt}^{POI} = e^{(\widehat{\beta_0} + \widehat{\beta_{1w}}WeeklyPrec_{iwt} + \widehat{\beta_{2w}}WeeklyTemp_{iwt} + \widehat{\beta_3}Year_t + \widehat{\gamma_w} + \widehat{\tau_i})}$$

$$(5.3)\ \widetilde{Progress}_{iwt}^{OLS} = \widehat{\beta_0} + \widehat{\beta_{1w}}WeeklyPrec_{iwt} + \widehat{\beta_{2w}}(WeeklyTemp + 1)_{iwt} + \widehat{\beta_3}Year_t + \widehat{\gamma_w} + \widehat{\tau_i}$$

$$(5.4)\ \widetilde{Progress}_{iwt}^{POI} = e^{(\widehat{\beta_0} + \widehat{\beta_{1w}}WeeklyPrec_{iwt} + \widehat{\beta_{2w}}(WeeklyTemp+1)_{iwt} + \widehat{\beta_3}Year_t + \widehat{\gamma_w} + \widehat{\tau_i})}$$

$$(5.5)\ ProgressDifference_{iwt} = \widetilde{Progress}_{iwt} - \widehat{Progress}_{iwt}$$

$$(5.6)\ CumProgressDiff_{iwt} = \sum^{w} ProgressDifference_{iwt}$$

Implied Median Planting Date Change

Finally, we consider what implied impact this increase in weekly average temperature has on median planting date. With $CumProgressDiff_{iwt}$, the predicted cumulative increase in planting progress in week *w* has already been calculated. Using the original percent planted values from the crop progress reports, we calculate $\widehat{Planted}_{iwt}$ by summing the observed percent planted value and the cumulative planting progress difference, as is shown below and visualized in Figure A.6 from Appendix A. After which, this weekly data is once again linearly interpolated to yield daily crop progress observations.

$$(5.7)\ \widehat{Planted}_{iwt} = Planted_{iwt} + CumProgressDiff_{iwt}$$

As was done earlier in this paper, we identify the day in which at least fifty percent of corn acres have been planted in a region and let this day be the median planting date. With this, we have the original median planting date values, $Plant50_{it}$, along with new median planting dates that account for a one-degree Celsius increase in weekly average temperature and its impact on median planting date. The predicted median planting date from the Poisson model is denoted as $\widehat{Plant50}_{it}^{POI}$, while the predicted OLS median planting date is denoted as $\widehat{Plant50}_{it}^{OLS}$. The difference between predicted median planting date and original median planting date, denoted $\triangle\ Plant50_{it}^{POI}$ and defined below, can be interpreted as the implied shift in median planting date as a result of, on average, weekly temperatures that are one-degree Celsius warmer. Finally, we average $\triangle\ Plant50_{it}^{POI}$ for each state, *j*, which yields $\overline{\triangle\ Plant50_{j}^{POI}}$, the implied median planting date shift in days.

$$(5.8)\ \triangle\ Plant50_{it}^{POI} = \widehat{Plant50}_{it}^{POI} - Plant50_{it}$$

Predicted Cumulative Progress Difference

The results from the region-specific weekly fixed weather effects model, the preferred model in this paper, indicate that warmer weekly temperatures tend to have a statistically significant impact on *progress* for <u>at least</u> the first six weeks of the growing season in most regions. Some regions and models indicate statistical significance beyond six weeks while the southern region states tend to have negligible statistical significance in general. Nonetheless, we assume a six-week cutoff in statistical significance, which allows for comparison across different model iterations. Using the methods previously outlined, we calculate $ProgressDifference_{iwt}$ by subtracting $\widehat{Progress}_{iwt}$ from $\widetilde{Progress}_{iwt}$. $ProgressDifference_{iwt}$ is the predicted increase in *progress* as a result of a one-degree Celsius increase in weekly average temperature. We cumulatively add the progress difference values together for the first six weeks of the growing season, $\sum_{w=1}^{6} ProgressDifference_{iwt}$, to calculate the impact of this warming scenario and average those values by state. Table 5.6 presents the predicted cumulative progress differences six weeks into the growing season using four different Poisson model iterations: the general, non-sample restricted weekly fixed weather effect model and the region-specific weekly fixed weather effects models, both with and without percent planted lags included. Table B.5 in Appendix B presents these same results when we use the OLS estimator rather than the Poisson.

Table 5.6 Predicted Cumulative Progress Difference Six Weeks into the Planting Season by State Using Poisson Models

	-- Without Planting Lags --		-- With Planting Lags --	
State	WFWE*	RSWFWE†	WFWE#*	RSWFWE#†
WI	0.0523	0.0680	0.0580	0.0605
KY	0.0495	0.0616	0.0483	0.0567
KS	0.0518	0.0601	0.0526	0.0583
NC	0.0535	0.0574	0.0599	0.0373
IA	0.0581	0.0540	0.0629	0.0638
SD	0.0386	0.0514	0.0353	0.0356
Average	0.0486	0.0514	0.0486	0.0501
MN	0.0381	0.0507	0.0420	0.0435
IL	0.0532	0.0492	0.0538	0.0543
IN	0.0496	0.0460	0.0470	0.0467
MI	0.0326	0.0443	0.0287	0.0290
NE	0.0446	0.0430	0.0441	0.0442
CO	0.0407	0.0425	0.0446	0.0547
MO	0.0369	0.0405	0.0290	0.0335
OH	0.0398	0.0384	0.0332	0.0327
TX	0.0353	0.0341	0.0269	0.0074
PA	0.0343	0.0336	0.0282	0.0282

*Weekly Fixed Weather Effects Model
† Region-Specific Weekly Fixed Weather Effects Model
# Using models with percent planted lag (See Equation 4.9)

The findings show that, using the general region-specific models, a consistent increase in average weekly temperature during the first six weeks of the planting season by one-degree Celsius is associated with, on average, a 5.14 percentage point increase in corn acres planted at the end of the sixth week. States experiencing higher predicted cumulative progress differences include Wisconsin (6.80), Kentucky (6.16), and Kansas (6.01). States predicted to be less impacted by warming temperatures include Pennsylvania (3.36), Texas (3.41), and Ohio (3.84).

When we also control for previous planting decision-making using lagged cumulative progress, a consistent increase in average weekly temperature during the first six weeks of the planting season by one-degree Celsius is associated with, on average, a 5.01 percentage point increase in corn acres planted by the end of the sixth week. States experiencing the highest predicted cumulative progress difference are Iowa (6.38), Wisconsin (6.05), and Kansas (5.83). The states with the lowest predicted cumulative progress difference increase include Texas (0.74), Pennsylvania (2.82), and Michigan (2.90).

Implied Shift in Median Planting Date

Using the methods described above, $\widehat{Planted}_{iwt}$ is calculated by adding $CumProgressDiff_{iwt}$ from the Poisson region-specific weekly fixed weather effects model to the original percent planted values, $Planted_{iwt}$, from the crop progress reports. $\widehat{Planted}_{iwt}$ can be interpreted as the predicted percent of corn acres planted by week *w* in region *i* during year *t* as a result of average weekly temperatures being one-degree Celsius warmer. We then, once again, transform this weekly data into daily data using linear interpolation and identify the median planting date, denoted $Plant50_{it}^{POI}$. Finally, after taking the difference between the original median planting date and the temperature-adjusted median planting date to calculate the implied shift in median planting date, we average said median planting date shift by state.

Table 5.7 reports the implied shift in median planting date, by state, as a result of a one-degree Celsius increase in weekly average temperature. We also include the implied median planting date shift stemming from the non-sample-restricted weekly fixed weather effects model. The findings indicate that, on average, warmer weekly temperatures imply a median planting date that is 1.03 days earlier. Some states have more pronounced predicted median planting date shifts than others, including Kentucky (2.00 days), Missouri (1.27 days), South Dakota (1.24 days), and North Carolina (1.24 days). The states with a median planting date that isn't predicted to be impacted as much by warmer temperatures include Texas (0.51 days), Illinois (0.75 days), and Iowa (0.76 days). Table B.6 in Appendix B presents these same results when we use the OLS estimator rather than the Poisson.

Table 5.7 Implied Median Planting Date Shift in Days by State Using Poisson Models

	-- Without Planting Lags --		-- With Planting Lags --	
State	WFWE*	RSWFWE†	WFWE#*	RSWFWE#†
KY	-1.6500	-2.0750	-1.7750	-2.0250
MO	-1.1536	-1.2749	-1.1563	-1.3585
KS	-1.0347	-1.2640	-1.0796	-1.2739
PA	-1.1951	-1.1707	-1.2683	-1.2439
CO	-1.1707	-1.1463	-1.2439	-1.2195
IN	-1.2133	-1.1163	-1.2216	-1.1939
Average	-0.9845	-1.0340	-1.0473	-1.0866
WI	-0.8889	-1.1044	-0.9562	-1.0269
SD	-1.0000	-1.2439	-1.0732	-1.0244
NE	-0.8409	-0.8258	-1.0079	-0.9848
OH	-0.9512	-0.9024	-1.0488	-0.9512
NC	-1.1707	-1.2439	-1.2927	-0.9024
IA	-0.8141	-0.7613	-0.9095	-0.8920
IL	-0.8169	-0.7500	-0.8605	-0.8401
TX	-1.2286	-0.5882	-1.2857	-0.8000
MN	-0.6098	-0.7805	-0.7317	-0.7805
MI	-0.7561	-0.9512	-0.9268	-0.7805

*Weekly Fixed Weather Effects Model

† Region-Specific Weekly Fixed Weather Effects Model

Using models with percent planted lag (See Equation 4.9)

When we also control for previous planting decision-making using a cumulative progress lag, a one-degree Celsius increase in average weekly temperature is associated with a median planting date that is, on average, 1.09 days earlier. States with more extreme predicted median planting date shifts include Kentucky (2.03 days), Missouri (1.36 days), and Kansas (1.27 days). Conversely, Texas (0.80 days), Illinois (0.84 days), and Iowa (0.89 days) have the smallest predicted shift in median planting date. While Table 5.7 only reports values for the Poisson models, similar results for the standard OLS regression models can be found in Table B.5.

General Implications and Future Extension Opportunities

A key takeaway from this project is a quantified estimate of how farmers adjust to warming temperatures. Specifically, we predict that if temperatures were to increase, on average, by one-degree Celsius, US farmers would be expected to plant corn earlier or at a faster pace. As a result, regions reach cumulative corn planting thresholds, such as median planting day, earlier.

We find statistically significant evidence that US farmers adapt to changing weather patterns. It is unclear if this farmer adaption might help to mitigate potential yield reductions as a result of warming temperatures. Therefore, factoring said farmer adaptation into a weather-based yield model is an expected extension of this project. This would help to show if, and by how much, farmers might be able to mitigate potential climate change associated yield losses through planting adaptation.

In this paper, we look only at planting progress in corn. However, the USDA Crop Progress Reports offer data on the progress of other corn growth stages, including emergence, silking, dough, dent, maturity, and harvesting. This offers potential extensions looking at different corn growth stages. USDA Crop Progress Reports also publish data on the growth progress of other crops, opening the door to extensions that quantify the impact of warming temperatures on different growth stages for different crops, such as soybeans, sorghum, or wheat.

With regard to weather, there are variables besides temperature and precipitation that could be included in future projects. The USDA Crop Progress Reports release data on days suitable for fieldwork and moisture levels of the topsoil and subsoil in a given week. These two variables, however, likely proxy for precipitation and temperature in a given region. Therefore, including them in a model with temperature and precipitation opens up the potential for a "bad controls" issue. There are, however, variables, such as growing degree days, that could be incorporated into the existing methodology and models. Therefore, it may be worth pursuing future projects that look at other variables that may better capture the weather impact on corn planting.

Chapter 6 - Conclusion

This project explores the impact of warming temperatures on planting progress in US corn in an effort to quantify how US corn farmers might adapt planting habits in the event of a warming scenario. Using data from USDA Crop Progress Reports that publish the percent of corn planted in a given region for a given week, these weekly observations are converted to daily observations via linear interpolation. From that, the median planting date can be generated by identifying the first day in which at least 50 percent of acres in a given region are planted.

Further analysis of the median planting date using state specific trends shows that over the last four decades, median planting date has shifted earlier in 13 of the 16 states in our sample, though only seven of those shifts were found to be statistically significant. States witnessing the most pronounced shifts towards earlier median planting date include Missouri, Nebraska, Kentucky, and Kansas. Between 1981 and 2020, the median planting date for these four states shifted 14.87, 9.63, 9.22, and 9.18 days earlier, respectively.

Using PRISM weather data, we compute the average daily temperature and precipitation during the month of April for a given region. After controlling for state-specific quadratic trends, region fixed effects, and average daily precipitation during the month of April, we find a one-degree Celsius increase in average April temperature is associated with, on average, a median planting date that is 1.82 days earlier.

When median planting date is calculated, only one observation is offered for a given region in a given year. To allow for a more dynamic analysis of the planting season, we take the first differences of the percent planted values in the crop progress reports, defined as *Progress*. *Progress* reveals the percentage point increase in acres planted from one week to the next.

PRISM weather data outlining the average temperature and total precipitation during the week preceding an observation is then incorporated into planting progress models.

The weekly fixed weather effects model outlined in this paper controls for a simple annual linear trend, weekly fixed effects, and region fixed effects. We also interact the weekly weather variables with weekly indicator variables, allowing the impact of temperature and precipitation on planting progress to vary throughout the planting season. Additionally, splitting up states into four different latitudinal groups allows for spatial heterogeneity. Finally, we control for planting decision and progress made in previous weeks by incorporating a lagged percent planted value into our model. Using Poisson regression analysis, the findings show that temperatures have a statistically significant impact on planting progress during *at least* the first six weeks of the planting season in three of the four latitudinal groups.

Using prediction analysis with coefficient estimates from the general RSWFWE model, we analyze the impact of warming temperatures on planting progress. Specifically, we find a one-degree Celsius increase in average weekly temperature during the planting season is predicted to result in, on average, a 5.14 percentage point increase in corn acres planted six weeks into the planting season. Utilizing the predicted weekly change in planting progress as a result of the weekly temperature increase, we calculate the implied shift in median planting date by state. Across all states, it is predicted that a one-degree increase in weekly temperature would shift median planting date earlier by an average of 1.03 days. States with more pronounced predicted shifts in median planting date include Kentucky (2.08 days), Missouri (1.27 days), Kansas (1.26 days), South Dakota (1.24 days), and North Carolina (1.24 days).

This project leaves ample opportunities for further research and other extensions. One such possibility would include research looking at other growth stages or different crops.

Another possibility is delving further into other weather-related variables that might be impactful on the planting season, such as days suitable for fieldwork, topsoil moisture levels, or growing degree days. Most importantly, findings from this project show statistically significant adaptation by farmers when faced with a warming scenario. As a result, factoring this implied farmer adaptation into a weather-based yield model is an intriguing, and expected, extension that would quantify the extent to which this adaptation by farmers would mitigate potential climate change induced yield losses.

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Appendix A - Supplemental Figures, Tables, & Equations

Figure A.1 Linear Interpolation of Weekly Data and Median Planting Date Identification

- From Weekly Percent Planted Data:
  - Linearly interpolate data to go from weekly to daily.
  - By CRD, year: identify day where percent planted reaches 50%

Date	Planted
Mon, 4/27/1997	42
4/28/1997	-
4/29/1997	-
4/30/1997	-
5/1/1997	-
5/2/1997	-
5/3/1997	-
Mon, 5/4/1997	73

Date	Planted
Mon, 4/27/1997	42
4/28/1997	46.4
4/29/1997	50.9
4/30/1997	55.3
5/1/1997	59.7
5/2/1997	64.1
5/3/1997	68.6
Mon, 5/4/1997	73

Table A.1 Median Planting Date, Mean Temperature, and Mean Precipitation by State

State	Median Planting Date	Mean April Temperature (°C)	Mean April Precipitation† (mm)
TX	100.72	17.73	2.12
NC	112.14	15.57	2.95
MO	124.20	12.95	3.69
KS	125.18	12.07	2.37
KY	126.12	13.86	4.05
IL	127.37	11.55	3.42
IA	128.20	9.62	3.04
Average	128.66	10.75	3.03
MN	129.52	6.78	2.09
NE	129.70	9.29	2.18
CO	131.17	8.51	1.33
OH	133.10	10.19	3.13
IN	133.64	11.08	3.57
MI	135.52	7.69	2.74
WI	135.77	6.97	2.76
SD	136.5	7.60	1.95
PA	137.71	9.55	3.14

†Average daily precipitation throughout the month of April

Figure A.2 Progress Variable Numerical Example

Date	Percent Planted	Progress
4/7/1997	0	-
4/13/1997	0	0
4/20/1997	3	3
4/27/1997	42	39
5/4/1997	73	31
5/11/1997	77	4
5/18/1997	90	13
5/25/1997	99	9
6/1/1997	99	0
6/8/1997	99	0
6/15/1997	100	1

Equation A.1

$$WeeklyAvgTemp_d = \frac{\sum_{i=0}^{6} AvgTemp_{d-i}}{7}$$

Equation A.2

$$WeeklyPrec_d = \sum_{i=0}^{6} Prec_{d-i}$$

Table A.2 Summary Statistics

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Median Planting Date	2,684	128.66	12.05	89	170
Mean April Temp. (°C)	2,556	10.75	2.93	1.63	20.49
Mean April Prec. (mm)	2,556	3.03	1.56	0.21	12.13
Progress	23,666	0.11	0.13	0	0.99
WeeklyTemp (°C)	25,947	13.39	5.25	-9.24	28.33
WeeklyPrec (mm)	25,947	23.25	20.92	0.44	226.14

Figure A.3 Latitudinal Region Groups

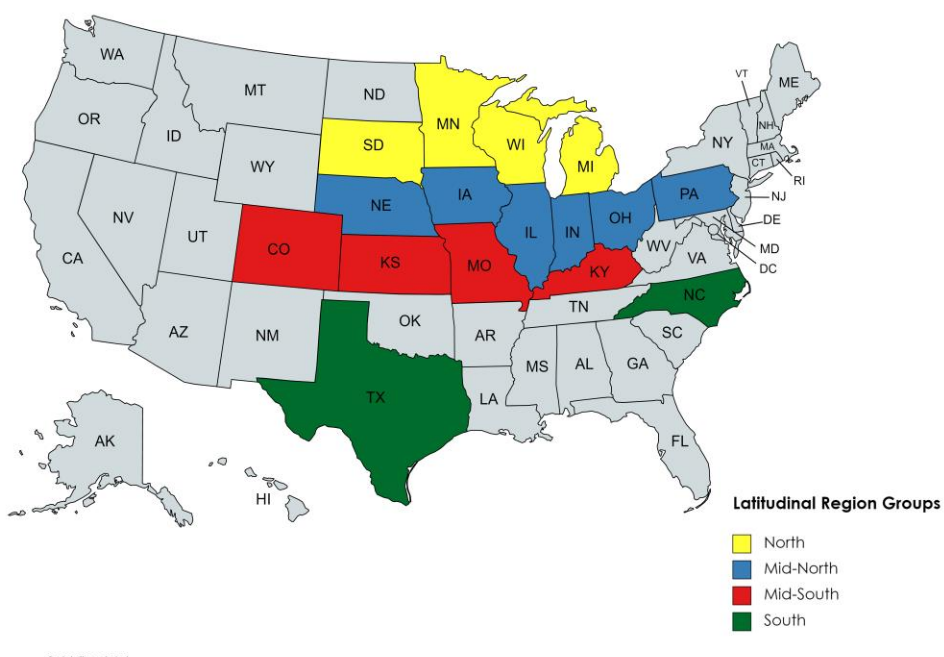

Figure A.4 Progress Variable Histogram

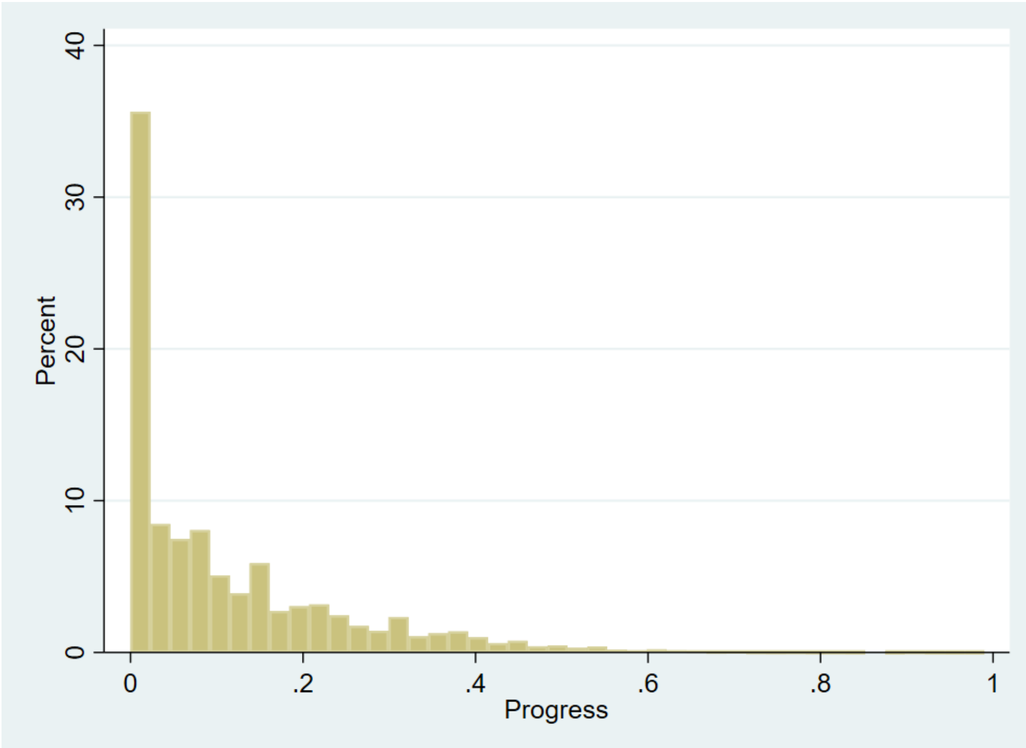

Figure A.5 Prediction Analysis Numerical Example

Date	$\widehat{Progress}_{iwt}$	$\widetilde{Progress}_{iwt}$	$ProgDiff_{iwt}$	$CumProgDiff_{iwt}$
4/7/1997	3.62	4.21	0.59	0.59
4/13/1997	2.37	3.29	0.92	1.51
4/20/1997	1.69	2.90	1.21	2.72
4/27/1997	7.32	8.64	1.31	4.03
5/4/1997	9.82	10.63	0.81	4.84
5/11/1997	19.66	19.84	0.18	5.02

Figure A.6 Numerical Example of Temperature-Adjusted Planted Values

Date	Planted	$CumShareDiff_{imt}$	$\widehat{Planted}$
4/7/1997	0	0.59	0.59
4/13/1997	0	1.51	1.51
4/20/1997	3	2.72	5.72
4/27/1997	42	4.03	46.03
5/4/1997	73	4.84	77.84
5/11/1997	77	5.02	82.02

Figure A.7 Shift In Median Planting Date Numerical Example

- From New Weekly Percent Planted Data:
  - Linearly interpolate data and identify day where percent planted reaches 50%.
  - For this CRD & Year, a temperature increases implies a median planting date one day earlier.

Date	$\widehat{Planted}$
Mon, 4/27/1997	46.03
4/28/1997	-
4/29/1997	-
4/30/1997	-
5/1/1997	-
5/2/1997	-
5/3/1997	-
Mon, 5/4/1997	77.84

Date	$\widehat{Planted}$	Planted
Mon, 4/27/1997	46.03	42
4/28/1997	50.57	46.4
4/29/1997	55.11	50.9
4/30/1997	59.66	55.3
5/1/1997	64.21	59.7
5/2/1997	68.75	64.1
5/3/1997	73.30	68.6
Mon, 5/4/1997	77.84	73

Appendix B - Additional Models & Results

Table B.1 OLS Weekly Fixed Effects Model Results

Progress	Weekly Fixed Effects
Weekly Average Temperature (°C)	0.006^{***} (0.000)
Weekly Total Precipitation (mm)	-0.001^{***} (0.000)
Year	0.000^{**} (0.049)
Constant	-0.284^{**} (0.033)
Observations	23276
R^2	0.247
Fixed Effects	Region Weeks-in

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2 OLS Regional Fixed Weather Effects Model Results

Progress	Regional Fixed Weather Effects	
Year	0.000^{**} (0.034)	
Region	Temp	Prec.
North	0.004^{***}	-0.001^{***}
Mid-North	0.006^{***}	-0.002^{***}
Mid-South	0.007^{***}	-0.001^{***}
South	0.003^{***}	-0.001^{**}
Constant	-0.320^{**} (0.016)	
Observations	23276	
R^2	0.250	
Fixed Effects	Region Weeks In	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.3 OLS Weekly Fixed Weather Effects Model Results

Progress	WFWE		Region Specific Models							
			North (0)		Mid-North (1)		Mid-South (2)		South (3)	
Year	0.000***		0.000**		0.000*		0.000***		-0.000	
	(0.000)		(0.023)		(0.075)		(0.000)		(0.621)	
Weeks In	Temp	Prec.	Temp	Prec.	Temp	Prec.	Temp	Prec.	Temp	Prec.
2	0.002***	-0.000***	0.002***	-0.000***	0.002***	-0.000***	0.002**	-0.000	-0.000	-0.000
3	0.008***	-0.001***	0.009***	-0.001**	0.008***	-0.001***	0.009***	-0.001**	0.006	-0.001
4	0.014***	-0.001***	0.020***	-0.002***	0.015***	-0.002***	0.013***	-0.001***	0.013**	-0.000
5	0.013***	-0.002***	0.015***	-0.002***	0.016***	-0.003***	0.011***	-0.001***	0.015*	0.000
6	0.009***	-0.002***	0.012***	-0.002***	0.007***	-0.003***	0.010***	-0.002***	0.008	0.000
7	0.001	-0.002***	-0.003	-0.002***	-0.001	-0.002***	0.006*	-0.001***	-0.006	-0.001*
8	-0.002*	-0.001***	-0.006***	-0.002***	0.000	-0.001***	-0.001	-0.001***	-0.012	-0.003
9	-0.000	-0.001***	-0.008***	-0.001***	0.002	-0.001***	0.001	-0.001***	-0.003	-0.002
10	-0.001	-0.001***	-0.005**	-0.001*	0.005***	-0.001***	-0.005***	-0.001***	-0.009	-0.001
Constant	-0.402***		-0.547**		-0.294*		-0.851***		0.261	
Observations	23276		3563		10505		8341		867	
R^2	0.275		0.353		0.301		0.245		0.215	
Fixed Effects	Region Weeks In		Region Weeks In		Region Weeks In		Region Weeks In		Region Weeks In	

Coefficient estimates for fixed effects excluded from table
p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.4 OLS Weekly Fixed Weather Effects with Planting Lags Model Results

---------- With Planting Lags ----------										
Progress	WFWE		Region Specific Weekly Fixed Weather Effects (RSWFWE)							
			North (0)		Mid-North (1)		Mid-South (2)		South (3)	
Year	0.000***		0.000		0.000		0.001***		-0.001	
	(0.000)		(0.893)		(0.247)		(0.000)		(0.108)	
Weeks In	Temp	Prec.	Temp	Prec.	Temp	Prec.	Temp	Prec.	Temp	Prec.
2	0.002***	-0.000***	0.001**	-0.000***	0.003***	-0.000***	0.001***	0.000	-0.004*	-0.001***
3	0.007***	-0.001***	0.006***	-0.001***	0.007***	-0.001***	0.007***	-0.000***	-0.001	-0.002***
4	0.012***	-0.002***	0.015***	-0.002***	0.013***	-0.002***	0.011***	-0.001***	0.010**	-0.001
5	0.012***	-0.002***	0.012***	-0.002***	0.016***	-0.002***	0.009***	-0.001***	0.006	-0.001
6	0.011***	-0.002***	0.016***	-0.001***	0.011***	-0.002***	0.011***	-0.002***	0.004	-0.000
7	0.007***	-0.002***	0.006***	-0.001***	0.005***	-0.002***	0.009***	-0.001***	0.009	-0.000
8	0.005***	-0.002***	0.002*	-0.001***	0.006***	-0.002***	0.004***	-0.001***	0.012**	0.000
9	0.004***	-0.001***	0.001	-0.001***	0.002***	-0.001***	0.008***	-0.001***	0.009***	-0.001*
10	0.002***	-0.001***	-0.002	-0.001***	0.004***	-0.001***	0.000	-0.001***	-0.002	-0.001*
Constant	-0.833***		-0.075		-0.203		-1.690***		1.161*	
Observations	23276		3563		10505		8341		867	
R^2	0.416		0.518		0.455		0.370		0.517	
Fixed Effects	Region Weeks In Weeks In # Planted		Region Weeks In Weeks In # Planted		Region Weeks In Weeks In # Planted		Region Weeks In Weeks In # Planted		Region Weeks In Weeks In # Planted	

Coefficient estimates for fixed effects and percent planted lag excluded from table
p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.5 Predicted Cumulative Progress Difference Six Weeks into the Planting Season by State Using OLS Models

	-- Without Planting Lags --		-- With Planting Lags --	
State	WFWE*	RSWFWE†	WFWE#*	RSWFWE#†
CO	0.0466	0.0455	0.0434	0.0387
IL	0.0466	0.0476	0.0434	0.0500
IN	0.0466	0.0476	0.0434	0.0500
IA	0.0466	0.0474	0.0434	0.0488
KS	0.0466	0.0455	0.0434	0.0387
KY	0.0466	0.0455	0.0434	0.0387
MI	0.0466	0.0581	0.0434	0.0489
MN	0.0466	0.0581	0.0434	0.0489
MO	0.0466	0.0455	0.0434	0.0387
NE	0.0466	0.0476	0.0434	0.0498
NC	0.0466	0.0421	0.0434	0.0145
OH	0.0466	0.0476	0.0434	0.0489
PA	0.0466	0.0476	0.0434	0.0489
SD	0.0466	0.0581	0.0434	0.0489
TX	0.0466	0.0421	0.0434	0.0145
WI	0.0466	0.0581	0.0434	0.0489
Average	0.0466	0.0486	0.0434	0.0451

*Weekly Fixed Weather Effects Model

† Region-Specific Weekly Fixed Weather Effects Model

Using models with percent planted lag (See Equation 4.9)

Table B.6 Implied Median Planting Date Shift in Days by State Using OLS Models

State	-- Without Planting Lags -- WFWE*	RSWFWE†	-- With Planting Lags -- WFWE#*	RSWFWE#†
PA	-1.5610	-1.5366	-1.8293	-1.9756
MO	-1.4960	-1.5526	-1.7412	-1.6819
KY	-1.5750	-1.6250	-1.5750	-1.4000
SD	-1.2195	-1.3415	-1.3171	-1.3902
OH	-1.0732	-1.1220	-1.1707	-1.3902
MI	-1.1220	-1.3415	-1.2683	-1.3659
IN	-1.1025	-1.1440	-1.1579	-1.2881
TX	-1.7429	-0.9714	-1.9143	-1.1143
NE	-0.8636	-0.9394	-0.9697	-1.0985
CO	-1.1951	-1.1707	-1.1707	-1.0488
KS	-0.9573	-1.0160	-0.9920	-0.8827
MN	-0.8293	-1.0244	-0.8049	-0.8780
WI	-0.8418	-1.0236	-0.8081	-0.8418
IL	-0.7035	-0.7413	-0.7267	-0.8227
IA	-0.6834	-0.7060	-0.6633	-0.7337
NC	-1.0976	-0.8780	-0.9756	-0.3415
Average				

*Weekly Fixed Weather Effects Model

† Region-Specific Weekly Fixed Weather Effects Model

Using models with percent planted lag (See Equation 4.9)