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## Adaptation to Climate Change: Evidence from US Acreage Response

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*Recent studies of climate change impacts on agriculture have predominantly focused on crop yields. However, climate change has heterogeneous effects across crops, so growers can adapt to climate change by adjusting planted acres. This paper measures how corn and soybean planted acres have responded to climate change in the United States since 1980. A county-level panel is formed with agricultural and high-resolution climatological data. To identify long-run effects of climate change, a “rolling-panel” approach is used, in which annual climatic variables are constructed by averaging growing-season temperature and precipitation over the past 30 years. Planted acres of corn and soybeans are positively affected by increases in temperature and precipitation in cool and dry areas, but negatively affected in warm and moist areas.*

*Acknowledgment:*

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#897



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## **Abstract**

Recent studies of climate change impacts on agriculture have predominantly focused on crop yields. However, climate change has heterogeneous effects across crops, so growers can adapt to climate change by adjusting planted acres. This paper measures how corn and soybean planted acres have responded to climate change in the United States since 1980. A county-level panel is formed with agricultural and high-resolution climatological data. To identify long-run effects of climate change, a “rolling-panel” approach is used, in which annual climatic variables are constructed by averaging growing-season temperature and precipitation over the past 30 years. Planted acres of corn and soybeans are positively affected by increases in temperature and precipitation in cool and dry areas, but negatively affected in warm and moist areas.

# 1 Introduction

Agriculture is an industry highly sensitive to climate change (IPCC, 2014). The impacts of climate change on crop yields have been examined in various contexts, and yield losses are predicted to be as high as 82% by the end of this century for some crops (Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Welch et al., 2010; Chen et al., 2015; Gammans et al., 2017; Schauburger et al., 2017). This yield-loss concern is important in the discussion of global food security given that recent studies have found minimal adaptability of crop yields to climate change (e.g., Schlenker and Roberts, 2009; Burke and Emerick, 2016). However, using yield-response estimates to predict future crop production implicitly assumes a constant cropping pattern and rules out the possibility of geographical expansion or migration of crops. Failure to account for acreage changes and crop substitution likely leads to overestimation of climate change impacts on agriculture (Beddow and Pardey, 2015; Costinot et al., 2016).

From 1980 to 2016, the planted acres of corn and soybeans in the US increased by 11.9% and 19.3%, respectively. Over the same period, wheat experienced a 43.2% reduction in its planted acres (USDA, 2016).<sup>1</sup> The shift in acres was substantial in the Northern Plains and the Upper Midwest, where both temperature and precipitation have increased (Melillo et al., 2014). While favorable market conditions and technological improvements, such as advances of biotechnology, have been recognized as leading factors driving the changing acres (e.g., Olmstead and Rhode, 2011a; Roberts and Schlenker, 2013; Barrows et al., 2014), the contribution of climate change is not well understood.

This paper addresses the question of how agriculture adapts to climate change through changes in acreage patterns. I measure climate change impacts on sown acres of corn and soybeans in the United States, and analyze acreage substitution across various crops.

Human adaptation to environmental change has been examined under various con-

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<sup>1</sup>In 2016, the planted acres of corn, soybeans, and wheat were 94, 83, and 50 million acres, respectively. In 1980, they were 84, 69, and 88 million acres, respectively.

texts (e.g., Deschênes and Greenstone, 2011; Hornbeck, 2012; Hornbeck and Keskin, 2014; Barreca et al., 2015). The dire prediction on climate change impacts on agriculture has prompted emerging research on agricultural adaptation to climate change over the past decade (e.g., Howden et al., 2007; Lobell et al., 2008; Olmstead and Rhode, 2011a; Di Falco et al., 2011; Moore and Lobell, 2014; Fezzi et al., 2015; Burke and Emerick, 2016; Taraz, 2017).

The idea of crop switching as an adaptation to climate change has been motivated in many studies (e.g., Mendelsohn et al., 1994; Zilberman et al., 2004; Costinot et al., 2016).<sup>2</sup> Induced shifts in crop acreage have also been implicitly accounted for in the *Ricardian* estimation of the capitalization of climatic factors into farmland values. (e.g., Mendelsohn et al., 1994; Mendelsohn and Dinar, 2003; Schlenker et al., 2006). However, omitted variable bias is a critical issue in the Ricardian approach (Nickerson et al., 2014). Neglecting the endogeneity in land use decisions further biases these results (Timmins, 2006).

Closely related to the Ricardian approach, a group of studies estimates how local climate affect micro-level crop-choice decisions using a revealed preference approach (e.g., Kurukulasuriya et al., 2007; Hassan et al., 2008; Seo and Mendelsohn, 2008; Wang et al., 2010). Data for these analyses are cross-sectional, so that the empirical identification does not rely on actual changes in the local climate. Using time-series data, Lee and Sumner (2015) estimate the evolving effect of climate change on crop acreage, but the results are specific to a small area, Yolo county in California. Some attempts have been made to estimate acreage response to climate change by using year-to-year variation in weather under a panel-data framework (Miao et al., 2016; Cohn et al., 2016). However, planting decisions are also influenced by knowledge of weather realizations over a long period of time. Farmers choose a crop to grow if they believe it is profitable under their local climate.

The empirical challenge associated with estimating climate change impacts on crop acres centers around how to summarize climate information relevant to the growers' cropping

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<sup>2</sup>The shift in crop acreage induced by climate change has also been predicted in early work based on integrated simulation models and highly aggregated data (e.g., Adams et al., 1990).

decisions. To deal with this, I construct a county-level panel of “climate normals”, defined by NOAA as “three-decades averages of climatological variables including temperature and precipitation.” The year-to-year change in a county’s climate normals reflects gradually updated knowledge on the local climate. The acreage variables are regressed on the climate normals in a fixed-effects panel estimation, controlling for flexible trends and time effects to avoid spurious correlation between climate trends and crop acres.

I find that rising temperature and precipitation have increased the planted acres of corn and soybeans in cool and dry areas, but decreased acres in warm and moist areas. Results are robust to various specifications. Climate change over the past 30 years is found to increase the total planted acres of rain-fed corn and soybeans by 11.7 million acres, accounting for 30-40% of the observed acreage expansion. Significant acreage substitution effects are found with respect to barley, sorghum, wheat, and cotton.

This paper makes three main contributions. First, as an initial rigorous empirical analysis of acreage response to climate change, it extends the knowledge on climate change impacts on agriculture, and highlights the importance of considering acreage shifts in projections of future climate change impacts. Second, the findings contribute to the understanding of factors driving land-use changes. Third, by providing evidence of adaptation when the environmental change occurs gradually rather than abruptly, the paper also builds on the economic literature of environmental adaptation.

The paper is organized as follows. The next section presents a theoretical model that characterizes the incentives for acreage substitution and discusses the role of irrigation. The third and fourth sections discuss empirical estimates of how climate change affects corn and soybean expansion and acreage substitution in rain-fed agriculture. The last section concludes.

## 2 Theoretical Framework

A representative grower in a small area, for example, a county, maximizes her total profit by allocating a fixed amount of land to planting two crops. Production ( $y_k$ ,  $k = 1, 2$ ) is a concave function of land ( $A_k$ ,  $k = 1, 2$ ) for each crop, and it also depends on the climate ( $C$ ) and a pre-determined irrigation capacity ( $x$ ). Without loss of generality, the total amount of land is scaled to be 1.<sup>3</sup> The grower is a price taker ( $p_1$  and  $p_2$ ), and production is associated with a constant marginal cost on each unit of land ( $c$ ). The maximization problem is formally expressed as

$$\max_{A_1, A_2} p_1 y_1(A_1, C, x) + p_2 y_2(A_2, C, x) - c \quad \text{s.t.} \quad A_1 + A_2 = 1. \quad (1)$$

The optimal acreage for crop 1 ( $A_1^*$ ) is achieved by equating the marginal values of land, i.e.,

$$p_1 \frac{\partial y_1(A_1^*, C, x)}{\partial A_1} = p_2 \frac{\partial y_2(1 - A_1^*, C, x)}{\partial A_2}. \quad (2)$$

The marginal effect of climate change on the optimal acres of crop 1 is

$$\frac{\partial A_1^*}{\partial C} = - \frac{p_1 \frac{\partial^2 y_1}{\partial A_1 \partial C} - p_2 \frac{\partial^2 y_2}{\partial A_2 \partial C}}{p_1 \frac{\partial^2 y_1}{\partial A_1^2} + p_2 \frac{\partial^2 y_2}{\partial A_2^2}}. \quad (3)$$

The denominator is negative by concavity of the production function. The impacts of climate change on acreage allocation depends on the relative changes in the marginal values of land (MVL) affected by climate change, which is essentially determined by the relative changes in marginal products of land (MPL) under the price-taking assumption.

The following discussion is based on the situation that climate change negatively affects the MVL for both crops, and the effect is larger on crop 1 than on crop 2, i.e.,  $p_1 \frac{\partial^2 y_1}{\partial A_1 \partial C} < p_2 \frac{\partial^2 y_2}{\partial A_2 \partial C} < 0$ . In reality, this can be realized when excessive warming damages yields for

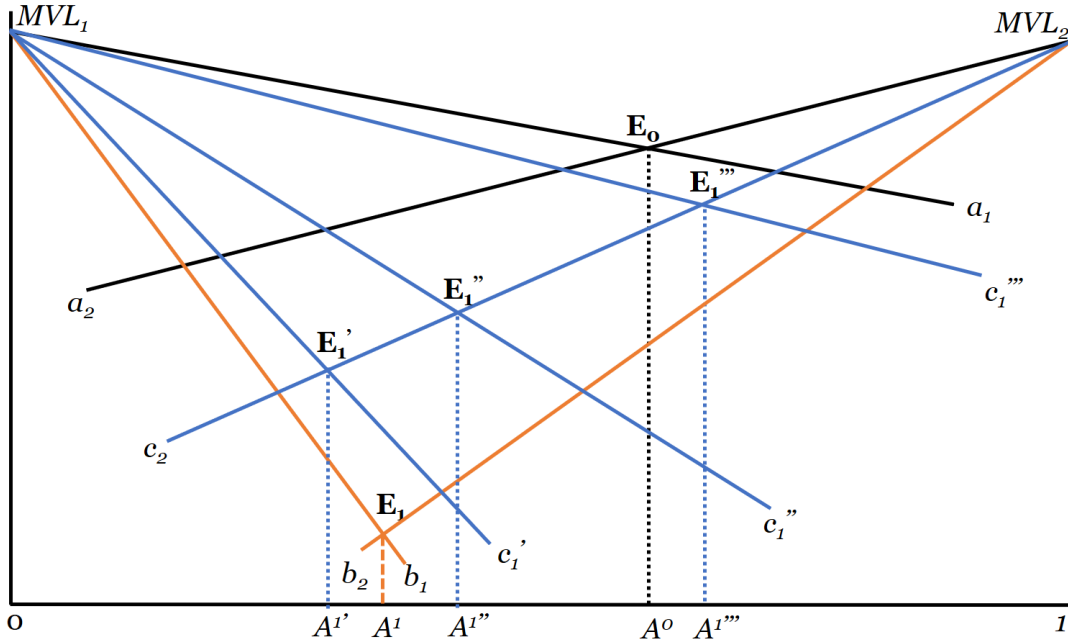
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<sup>3</sup>This stylized model assumes away land abandonment and land transfer to non-crop uses.

many crops, but some crops are more heat-resistant than others. However, similar derivations can be made under the situation where climate change benefits both crops but to different extents, which likely happens when warming occurs in a cold place.<sup>4</sup>

In Figure 1, the shift from  $\mathbf{E}_0$  to  $\mathbf{E}_1$  illustrates the equilibrium displacement when climate change negatively affects both crops, and more so for crop 1 than crop 2. The initial equilibrium  $\mathbf{E}_0$  is achieved before climate change. Holding irrigation constant, a change in climate shifts the MVL curves downward, more for crop 1 than for crop 2 (from  $a_1, a_2$  to  $b_1, b_2$ ). The new equilibrium is at  $\mathbf{E}_1$ . The optimal acreage of crop 1 falls from  $A^0$  to  $A^1$ .

Figure 1: Graphical Representation of the Economic Model



Note: The two vertical axes represent marginal values of land (MVL) of the two crops. The horizontal axis represents the amount of land allocated to the two crops, with the total amount of land is scaled to unity. Before climate change, the MVL for the two crops are  $a_1$  and  $a_2$ . The equilibrium is  $\mathbf{E}_0$  with the optimal acreage for crop 1 as  $A^0$ . After climate change, the MVL shift down from  $a_1, a_2$  to  $b_1, b_2$ , and the equilibrium is  $\mathbf{E}_1$  with the optimal acreage for crop 1 as  $A^1$ . More irrigation can potentially lead to three scenarios under climate change. (1) Exacerbating acreage shift: MVL become  $c'_1$  and  $c_2$ , new equilibrium at  $\mathbf{E}'_1$  with crop 1's acreage as  $A^{1'}$  such that  $A^{1'} < A^1 < A^0$ . (2) Mitigating acreage shift: MVL become  $c''_1$  and  $c_2$ , new equilibrium at  $\mathbf{E}''_1$  with crop 1's acreage as  $A^{1''}$  such that  $A^1 < A^{1''} < A^0$ . (3) Reversing acreage shift: MVL become  $c'''_1$  and  $c_2$ , new equilibrium at  $\mathbf{E}'''_1$  with crop 1's acreage as  $A^{1'''}$  such that  $A^1 < A^0 < A^{1'''}$ .

<sup>4</sup>For example, warming in northern Montana will make it possible to plant corn for grain, so that the marginal value increase for corn is much higher than for crops used for a colder environment, like barley.



Irrigation likely mitigates the effect of climate change. Irrigation replaces the water evaporation of crops when temperature is high and rainfall is inadequate. However, the mitigating effects can be heterogeneous across crops because crops differ in their water-use efficiencies. By obtaining comparative statics under additional assumptions, the role of irrigation can be described as

$$\frac{\partial^2 A_1^*}{\partial C \partial x} = - \left( p_1 \frac{\partial \left( \frac{\partial^2 y_1}{\partial A_1 \partial C} \right)}{\partial x} - p_2 \frac{\partial \left( \frac{\partial^2 y_2}{\partial A_2 \partial C} \right)}{\partial x} \right) / \left( p_1 \frac{\partial^2 y_1}{\partial A_1^2} + p_2 \frac{\partial^2 y_2}{\partial A_2^2} \right), \quad (4)$$

which depends on how irrigation influences the relative effects of climate change on the MVL of the two crops.

If the mitigating effect of irrigation is smaller on crop 1 than on crop 2 (i.e.,  $p_2 \frac{\partial \left( \frac{\partial^2 y_2}{\partial A_2 \partial C} \right)}{\partial x} > p_1 \frac{\partial \left( \frac{\partial^2 y_1}{\partial A_1 \partial C} \right)}{\partial x} > 0$ ), irrigation can exacerbate the climate change effect on acreage shift (i.e.,  $\frac{\partial^2 A_1^*}{\partial C \partial x} < 0$ ). In this scenario, MVL curves under more irrigation are depicted as  $c'_1$  and  $c_2$  in Figure 1, and the new equilibrium is at  $\mathbf{E}'_1$ . The optimal acreage of crop 1 is even smaller than that with less irrigation, shown as  $A^{1'} < A^1 < A^0$  in Figure 1.

If the mitigating effect of irrigation is larger on crop 1 than on crop 2 (i.e.,  $p_1 \frac{\partial \left( \frac{\partial^2 y_1}{\partial A_1 \partial C} \right)}{\partial x} > p_2 \frac{\partial \left( \frac{\partial^2 y_2}{\partial A_2 \partial C} \right)}{\partial x} > 0$ ), irrigation reduces the acreage shift induced by climate change (i.e.,  $\frac{\partial^2 A_1^*}{\partial C \partial x} > 0$ ). In this scenario, MVL curves under more irrigation are depicted as  $c''_1$  and  $c_2$  in Figure 1. The new equilibrium with more irrigation ( $\mathbf{E}''_1$ ) is between the pre-change equilibrium ( $\mathbf{E}_0$ ) and the post-change equilibrium with less irrigation ( $\mathbf{E}_1$ ). The optimal acreage of crop 1 is still smaller than the pre-change level, but larger than the post-change acreage with less irrigation, shown as  $A^1 < A^{1''} < A^0$  in Figure 1.

If the mitigating effect of irrigation is much larger on crop 1 than on crop 2, it could increase the acres of crop 1 even compared with the optimal acres before climate change. In this scenario, MVL curves under more irrigation are depicted as  $c'''_1$  and  $c_2$  in Figure 1. The new equilibrium with more irrigation is at  $\mathbf{E}'''_1$ , and the optimal acreage of crop 1 is larger than before climate change, shown as  $A^1 < A^0 < A^{1'''}$  in Figure 1. In this situation, a similar

change in climate induces acreage shifts in opposite directions for less irrigated versus more irrigated situations.

### 3 Corn and Soybean Acreage Response

This section empirically examines the marginal effects of climate change on rain-fed corn and soybean acres. I exclude counties in the western region of the United States.<sup>5</sup> A county is categorized as rain-fed if its irrigated acres are below 10% of its total cropland according to the US Census of Agriculture. This selection criterion is preferable over the conventional approach of dividing farmland on the two sides of the 100th meridian, which misclassifies some irrigated areas, like the Mississippi Delta region, as rain-fed.

#### Empirical Strategy

The empirical strategy relies on using a panel fixed-effects model to identify the marginal effects of climate change on the total planted acres of corn and soybeans at the county level. A “rolling-panel” approach is used to approximate climate change, whereby climate normals are defined as three-decades rolling averages of weather realizations. Formally, the regression equation is

$$\log(A_{it}^{cs}) = W_{it}'\beta + \alpha_i + \delta_t + f_s(t) + \epsilon_{it}. \quad (5)$$

$A_{it}^{cs}$  is the total planted acres of corn plus soybeans in county  $i$  in year  $t$ ,  $W_{it}$  is a vector characterizing climate normals over the growing season,  $f_s(t)$  characterizes the state-level quadratic trend,  $\alpha_i$  and  $\delta_t$  represent the county and year fixed effects, respectively, and  $\epsilon_{it}$  is the error term. The estimation addresses potential spatial and temporal correlation in the error structure by employing an estimation routine robust to spatial correlation, heteroskedasticity, and autocorrelation.<sup>6</sup>

<sup>5</sup>Specifically, all counties in WA, OR, ID, WY, CA, NV, UT, and AZ are excluded. I also exclude counties in CO and NM that are on the western side of the 106th meridian (the west of the Rocky Mountains). These counties are fundamentally different from the others due to their size and agricultural characteristics. The production of corn and soybeans in these regions accounts for less than one percent of the total national production.

<sup>6</sup>Specifically, a linear Bartlett kernel with the distance of 300 km is used to account for spatial correlation, and serial correlation is allowed for all periods within a county. This estimation procedure follows Hsiang

Corn and soybean acres are aggregated to form the dependent variable for the following reasons. As identified in Schlenker and Roberts (2009), corn and soybeans have similar biophysical responses to temperature and precipitation changes. Their cropping practices also share substantial similarities, and farm machines are commonly shared between these two crops. More importantly, the “corn-soybean” rotation is predominant. Growers can save nitrogen fertilizer and improve yields by planting corn right after a soybean year. Whether to plant corn or soybeans largely depends on which crop was planted in the previous year (Hennessy, 2006; Hendricks et al., 2014). Regressing corn and soybean acres separately would therefore introduce dynamics into the estimation model and confound the identification of marginal effects.

The climate normals characterize the means of climatological factors including temperature and precipitation. I use 30-year as the time length for constructing the moving averages because it has been widely accepted as a benchmark for representing climate by the scientific groups.<sup>7</sup> This time length has also been used in economic studies of climate change impacts since the seminal work of Mendelsohn et al. (1994). In a recent work, Henderson et al. (2017) used moving averages over 3-5-years, which more likely captures short-run weather effects rather than long-run effects in climate.

Perceiving the mean changes in climate, economic agents are induced to adjust their behaviors accordingly to maximize potential gains or to minimize potential losses. These induced responses are not limited to growers’ proactive adjustments in crop acreage because of observing climate change. The development of a new technology that incentivizes acreage change should also be considered as an induced adjustment if its emergence is a result of climate change.<sup>8</sup>

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(2010), which is adapted from Conley’s method (Conley, 1999). While Conley uses a uniform spatial kernel, this routine allows spatial dependence to decay over space, i.e., a Bartlett kernel.

<sup>7</sup>In addition to NOAA, the World Meteorological Organization and some other scientific groups also recognize the 30-year average as the benchmark for characterizing climate.

<sup>8</sup>This relates to the literature on induced technological change in agriculture. Many agricultural innovations are developed under the incentive to combat with environmental challenges, like weather risks. Just et al. (1979) acknowledged that farmers, private corporations, and public research institutions are all sources of technology developments.

Two specifications are used for constructing climate normals. The first specification uses 30-year moving averages of growing-season average temperature and total precipitation as directly in line with NOAA's definition. To characterize the nonlinear relationship, squared terms of the 30-year moving averages are included as in the general case in Burke et al. (2015). The second specification replaces the temperature variables with 30-year moving averages of growing and heat degree days, where growing degree days (GDD) accumulate moderate heat between 8-29°C and heat degree days (HDD) accumulate excessive heat above 29°C over the growing season. Growing and heat degree days are effective in explaining the nonlinear response of U.S. corn and soybean yields to heat accumulation within the growing season (Schlenker et al., 2006; Schlenker and Roberts, 2009; Miao et al., 2016).

The underlying identification assumption is that a county experiencing climate change would have changed its planted acres of corn and soybeans differently from a county not experiencing any climate change, after purging off state-level trends and nation-level shocks. By including state-level trends in the regression, the identification relies on within-state variation in the changes of climate normals, because co-movements at the state level will be soaked up by state-level trends.

Improved technology and favorable prices are commonly considered as two leading factors driving corn and soybean area expansion. These factors do not confound the identification strategy even if they are not directly controlled for. As in Schlenker and Roberts (2009) and others, it is reasonable to assume that technology advances are relatively smooth and have the same pace within a state, implying that these effects will be captured by state-level trends. Price shocks, given that the commodity market is highly integrated, transmit smoothly across regions so that their effects will be absorbed by year fixed effects.<sup>9</sup> A more conservative specification replaces state-level trends and year fixed effects with state-by-year fixed effects, which absorbs any shock that is specific to a state in a given year.

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<sup>9</sup>The effective price signal for planting decision is the futures prices maturing at the harvest time. Price changes over the growing season have no direct impact on the planting decision made at the beginning of the season. Although cash prices differ for different locations, the within-variation of prices is mostly homogeneous as the calculation of basis is largely tied to geographical distances.

## Results

Column (1.1) in Table 1 shows baseline estimation results under the first specification. The estimated coefficients on moving-average temperature and precipitation are positive, while the coefficients on their squared terms are negative. The estimated relationship implies that rising temperature and precipitation increases corn and soybean acres in cool and dry areas, but decreases the acres in warm and moist areas. Evaluated at the sample means, a 1°C temperature rise is associated with a 7.46% reduction in the planted acres of corn and soybeans, and a 1cm precipitation increase is associated with a 2.73% expansion in the planted acres of corn and soybeans.

Column (2.1) in Table 1 presents baseline estimation results under the second specification. Consistent with the estimated yield responses in Schlenker and Roberts (2009) and Burke and Emerick (2016), the acreage of corn and soybeans increases with moderate heat but decreases with excessive heat. A one-hundred additional GDD is associated with about 10% increase in corn and soybean acres, while one additional HDD is associated with about 5% decrease in corn and soybean acres. Some similar results have also been suggested in Burke and Emerick (2016), where their long-differences approach finds the share of corn acreage to be positively affected by GDD but negatively affected by HDD.

Although measuring different aspects of the effects, results from the second specification are qualitatively consistent with the prediction based on the first specification. Warming in cool areas is expected to increase more growing degree days and encourage more corn and soybeans, but warming in warm areas is expected to increase more heat degree days and lead to less corn and soybeans.

Columns (1.2) and (2.2) in Table 1 correspond to the alternative specification that replaces state-level quadratic trends and year fixed effects with state-by-year fixed effects. State-by-year fixed effects absorb any shock that is specific to a state in a given year. Hence, even if the effects associated with changes in market condition, technology, and price are non-parametric functions of time at the state level, these effects do not confound the identi-

fication of climate change effects on crop acreage. The results show that regressions using state-by-year fixed effects produce very similar estimates with the baseline regressions.<sup>10</sup>

Table 1: Corn and Soybean Acreage Response to Climate Change

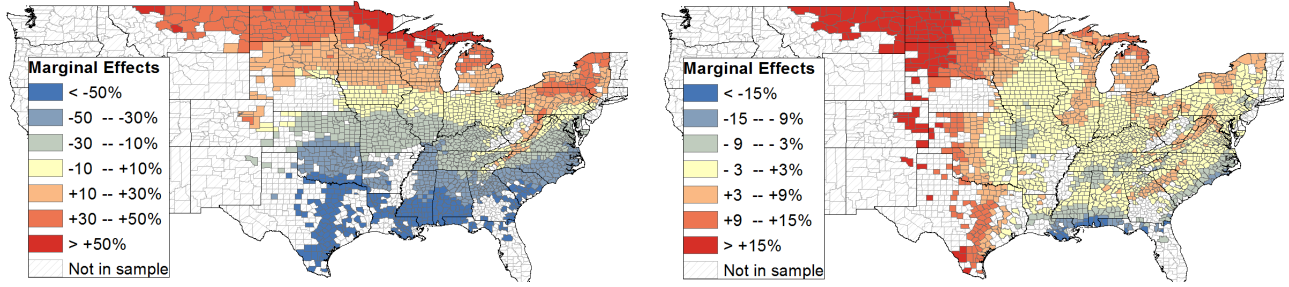
	Specification (1)		Specification (2)	
	(1.1)	(1.2)	(2.1)	(2.2)
<i>30-year M.A. of</i>				
Avg. Temp. (°C)	1.990*** (0.3096)	1.760*** (0.3010)		
Avg. Temp., squared	-0.053*** (0.0082)	-0.046*** (0.0081)		
GDD <sub>(8,29)</sub> (100°C)			0.102*** (0.0262)	0.114*** (0.0250)
HDD <sub>29+</sub> (°C)			-0.049*** (0.0050)	-0.054*** (0.0053)
Total Prec. (cm)	0.370*** (0.0221)	0.402*** (0.0211)	0.343*** (0.0219)	0.375*** (0.0206)
Total Prec., squared	-0.003*** (0.0002)	-0.003*** (0.0002)	-0.003*** (0.0002)	-0.003*** (0.0002)
<i>Controls</i>				
Fixed effects	cty & yr	cty & state×yr	cty & yr	cty & state×yr
State quad. trends	yes	no	yes	no
Observations	59,173	59,173	59,173	59,173

Note: The dependent variable is the total planted acres of corn and soybeans in logarithm. The growing season is defined as Apr 1st - Sep 30th. GDD and HDD represent growing degree days and heat degree days, respectively. A county is included in the regression if its average share of irrigated acres is below 10%. Standard errors (in parentheses) are robust to spatial correlation, heteroskedasticity and autocorrelation. A linear Bartlett kernel with the distance of 300 km is used to account for spatial correlation, and the serial correlation is allowed for all periods within a county. Significance: \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), \*\*\* ( $p < 0.001$ ).

One convenience provided by the first specification is that the marginal effects of both temperature and precipitation are dependent on where these effects are evaluated at. Given the geographical differences in temperature and precipitation normals, exploring the spatial heterogeneity in marginal effects is meaningful for understanding the spatial dynamics in corn and soybean acreage under climate change. For this reason, the following discussions focus on results based on the first specification. Using the second specification also leads to qualitatively similar interpretation on the spatial patterns.

<sup>10</sup>I do not use the alternative specification as the baseline because using state-by-year fixed effects can potentially magnify measurement errors (Fisher et al., 2012).

Figure 2: Marginal Effect of Climate Change on Rain-fed Corn and Soybeans Acres  
Panel A: Temperature Effects      Panel B: Precipitation Effects



Note: Marginal effects are calculated based on point estimates in column (1.1) in Table 1 and county-level temperature and precipitation normals over the latest 30 years (1985-2014). The units are degree Celsius for temperature and centimeters for precipitation.

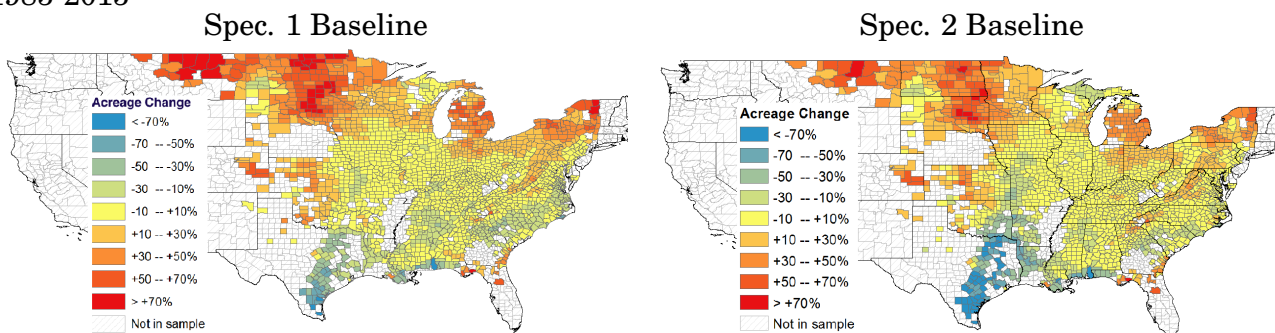
Based on the estimates from column (1.1) in Table 1, Figure 2 demonstrates the spatial pattern of the marginal effects of temperature and precipitation on rain-fed corn and soybean acres, evaluated at temperature and precipitation normals for 2015. A higher temperature will induce more planting in the northern region, including the Dakotas, southern Minnesota and Wisconsin, Michigan, and the northern part of the traditional Corn Belt. The warming effects are very limited for most of Iowa, Illinois, and Indiana. Areas south of  $40^{\circ}$  N will largely experience corn and soybean contraction if warming occurs. The more southern the county, the more reduction in acreage due to an additional one-degree increase in the temperature normal.

The spatial pattern of precipitation effects is less monotone. The Plains, especially the Dakotas, will significantly increase corn and soybean acres in the rain-fed counties if they receive more rainfall, largely due to the region's relatively low precipitation to begin with. The regions around Tennessee, northern Mississippi and Alabama, as well as the Carolina coast will reduce corn and soybean acres if precipitation normals rise.

Combining the estimated effects with actual changes in climate, a back-of-the-envelope calculation suggests that climate change has induced an increase of 11.7 million acres in the planted acres of rain-fed corn and soybeans over the past 30 years. As shown in Figure 3, the most significant increase was induced around the northernmost region, especially the

Northern Plains. The southernmost region and the Appalachia were induced to decrease corn and soybean acreage. These results also echo the historical movements of corn location discussed in Olmstead and Rhode (2011b) and Beddow and Pardey (2015).

Figure 3: County-level Changes in Corn and Soybean Acreage Induced by Climate Change: 1985-2015



Note: County-level percentage changes are calculated by combining baseline estimates with 30-year averaged climatic variables at 1985 and 2015.

## Robustness Checks

Using 30-year moving averages may raise concern about the exogeneity of the climatic variables. Specifically, if there is a county-level omitted variable correlated with climate normals and at the same time influencing planted acres, it would confound the identification. This endogeneity concern is tested by including county population into the regression.<sup>11</sup> An increasing population may reflect urban expansion, which changes land use, for instance, by contracting planted acres of certain crops. Population and urban growth could also correlate with the local climate.<sup>12</sup> Column (1) in Table 2 correspond to adding logarithmic population to the preferred specification. The result shows that adding population does not influence the estimates of climatic variables, which largely alleviates the endogeneity concern.

<sup>11</sup>Data on county-level population estimates were obtained from the Census Bureau's Population Estimates Program.

<sup>12</sup>On one hand, cities may attract more population as their climate becomes more favorable. On the other hand, increased human activities can affect local climate. A typical example is the "heat-island" effect, which refers to the situation where the built-up region becomes significantly warmer than the surroundings.



Table 2: Robustness: Corn and Soybean Acreage Response to Climate Change

	(1)	(2)	(3)	(4)	(5)
<i>30-year M.A. of</i>					
Avg. Temp. (°C)	1.914*** (0.3086)	2.089*** (0.6201)	2.023*** (0.3242)	2.053*** (0.5322)	1.382** (0.4683)
Avg. Temp., squared	-0.050*** (0.0082)	-0.053*** (0.0166)	-0.052*** (0.0085)	-0.055*** (0.0148)	-0.037** (0.0130)
Total Prec. (cm)	0.362*** (0.0220)	0.332*** (0.0430)	0.360*** (0.0232)	0.172*** (0.0250)	0.220*** (0.0295)
Total Prec., squared	-0.003*** (0.0002)	-0.003*** (0.0004)	-0.003*** (0.0002)	-0.001*** (0.0002)	-0.002*** (0.0002)
<i>Controls</i>					
log(population)	-0.259*** (0.0241)				
log(lagged corn price)			0.106*** (0.0287)		
log(lagged soy price)			-0.091* (0.0333)		
Fixed effects	cty & yr	cty & yr	cty	cty & yr	cty & yr
Quadratic trends	state	state	state	state	state
Sample	full	census	full	major areas	1981-95
Observations	59,173	12,097	59,173	16,409	28,083

Note: The dependent variable is the total planted acres of corn and soybeans in logarithm. The growing season is defined as Apr 1st - Sep 30th. A county is included in the regression if its average share of irrigated acres is below 10%. Major areas contain counties with more than 100,000 acres of corn and soybean in 1981. Standard errors (in parentheses) are robust to spatial correlation, heteroskedasticity and autocorrelation. A linear Bartlett kernel with the distance of 300 km is used to account for spatial correlation, and the serial correlation is allowed for all periods within a county. Significance: \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), \*\*\* ( $p < 0.001$ ).

Another concern regarding the use of 30-year moving averages is that the annual variation in 30-year temperature and precipitation is too slim to properly identify the marginal effects. To address this concern, the baseline specification is run on a sub-sample consisting of only census years, so that the within-county variation reflects changes in climate normals over every five years. The results presented in column (2) in Table 2 are still very similar with the baseline results. As expected, the standard errors from this sub-sample regression are larger because only parts of the available information are used.

Column (3) in Table 2 corresponds to the regression that controls for corn and soybean prices directly, rather than relying on year fixed effects. Specifically, I control for received prices of corn and soybeans (GDP deflated) in the previous year in logarithm. This specifica-

tion produces similar results with the baseline estimation. Because corn and soybean acres have been aggregated to form the dependent variable, the price coefficients are not directly interpretable. A linear combination of the price coefficients using the weights of  $3/4$  and  $1/4$  yields a point estimate of 0.26 with a 95% confidence interval of (0.14, 0.37), suggesting that, as expected, corn and soybean acres are positively influenced by lagged prices of corn and soybeans.<sup>13</sup>

Columns (4) and (5) in Table 2 report results estimated on two sub-samples. Column (4) corresponds to the sub-sample of major areas that planted at least 100,000 acres of corn and soybeans in 1981. This regression is to check if the estimated climate change effects are entirely driven by counties on the peripheral of the Corn Belt, where the planted acres were low to begin with but grew rapidly. Column (5) corresponds to the sub-sample only covering the period of 1981-1995, before the commodity price booming, the commercialization of genetically modified seeds, and the 1996 Farm Bill reform have taken place. Results based on the two sub-samples are qualitatively similar to the baseline, despite that some coefficients have smaller magnitudes partly due to less variation in the sub-samples.

## 4 Acreage Substitution Induced by Climate Change

The theoretical model predicts that climate change will affect acreage allocation among crops given the heterogeneous effects of climate change on different crops. Knowing what crops are substituted at where will provide a more comprehensive understanding on the induced acreage response of corn and soybeans to climate change.

An ideal examination would be to establish the relationship between field-level land-use and changes in the local climate. However, this is not feasible given data limitations. Alternatively, I infer how climate change affects the acres of corn and soybeans relative to other field crops at the county level. The empirical strategy rests on the underlying assumption that a county's relative acres of corn and soybeans with respect to an alternative crop

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<sup>13</sup>The weights are  $3/4$  and  $1/4$  for the linear combination because per-acre corn yield is approximately three times of soybean yield.

would have changed in a similar way, had it experienced the same changes in temperature and precipitation normals as in other counties, after controlling for state-level trends and nation-level shocks.

Following the empirical strategy in the last section, the revised regression model is

$$\frac{A_{it}^{cs}}{A_{it}^{cs} + A_{it}^k} = W_{it}'\beta + \alpha_i + \delta_t + f_s(t) + \epsilon_{it}, \quad (6)$$

where  $A_{it}^{cs}$  is the total planted acres of corn and soybeans,  $A_{it}^k$  is the planted acres of an alternative crop  $k$ . I only use the 30-year averages of average temperature and total precipitation with their squared terms in this analysis for the ease of discussing spatial heterogeneous effects. Other terms in the equation are defined in the same way as in equation (5). Five alternative crops are considered: barley, sorghum, spring wheat, winter wheat, and cotton. These crops, plus corn and soybeans, take about 75% of the total cropland acreage in the United States.

The dependent variable is a ratio metric, in which the numerator is the planted acres of corn and soybeans and the denominator is the planted acres of corn and soybeans plus the alternative crop. The regression model only considers one alternative crop so that the relative acreage of corn and soybeans can be studied with respect to a specific alternative crop at the location that alternative crop has been planted. The sample is restricted to rain-fed counties. Including the planted acres of corn and soybeans into the denominator guarantees that the ratio metric is bounded between zero and one, and the estimated marginal effects can be interpreted as proportional changes.

Rather than examining the acreage response of each crop, the analysis intends to infer how the comparative advantage of corn and soybeans has been changed due to climate change. The empirical strategy measures the reduced-form relationship between climate normals and the advantage of planting corn and soybeans relative to five specific alternative crops. It neither assumes away conversion between cropland and non-cropland, nor

precludes acreage shifts among the alternative crops.

Table 3: Response of Corn and Soybean Acres Relative to An Alternative Crop

	Corn and Soybean Acres Relative to				
	Barley	Sorghum	Spr. Wheat	Wtr. Wheat	Cotton
30-year M.A. Avg. Temp. ( $^{\circ}\text{C}$ )	1.0952*** (0.1016)	0.3985*** (0.1171)	-0.0401 (0.2951)	0.5020*** (0.0714)	1.2967* (0.5652)
30-year M.A. Avg. Temp., squared	-0.0279*** (0.0026)	-0.0119*** (0.0028)	0.0088 (0.0092)	-0.0125*** (0.0018)	-0.0281* (0.0123)
30-year M.A. Total Prec. (cm)	0.0562*** (0.0096)	-0.0030 (0.0062)	0.1835*** (0.0131)	-0.0055 (0.0064)	0.0262 (0.0158)
30-year M.A. Total Prec., squared	-0.0005*** (0.0001)	0.0000 (0.0001)	-0.0017*** (0.0001)	0.0001 (0.0001)	-0.0002 (0.0001)
	24,669	32,415	8,958	55,760	11,781

Note: The dependent variable is the planted acres of corn and soybeans over the total planted acres of corn, soybeans, and the alternative crop. Each regression includes county fixed effects, year fixed effects, and state-level quadratic trends. The growing season is defined as Apr 1st - Sep 30th. Regressors are constructed based on a moving average of weather variables over the previous 30 years. A county is included in the regression if its irrigation ratio is below 10%. Standard errors (in parentheses) are robust to spatial correlation, heteroskedasticity, and autocorrelation. A linear Bartlett kernel with the distance of 300 km is used to account for spatial correlation, and the serial correlation is allowed for all periods within a county.

Significance: \* ( $p < 0.05$ ), \*\* ( $p < 0.01$ ), \*\*\* ( $p < 0.001$ ).

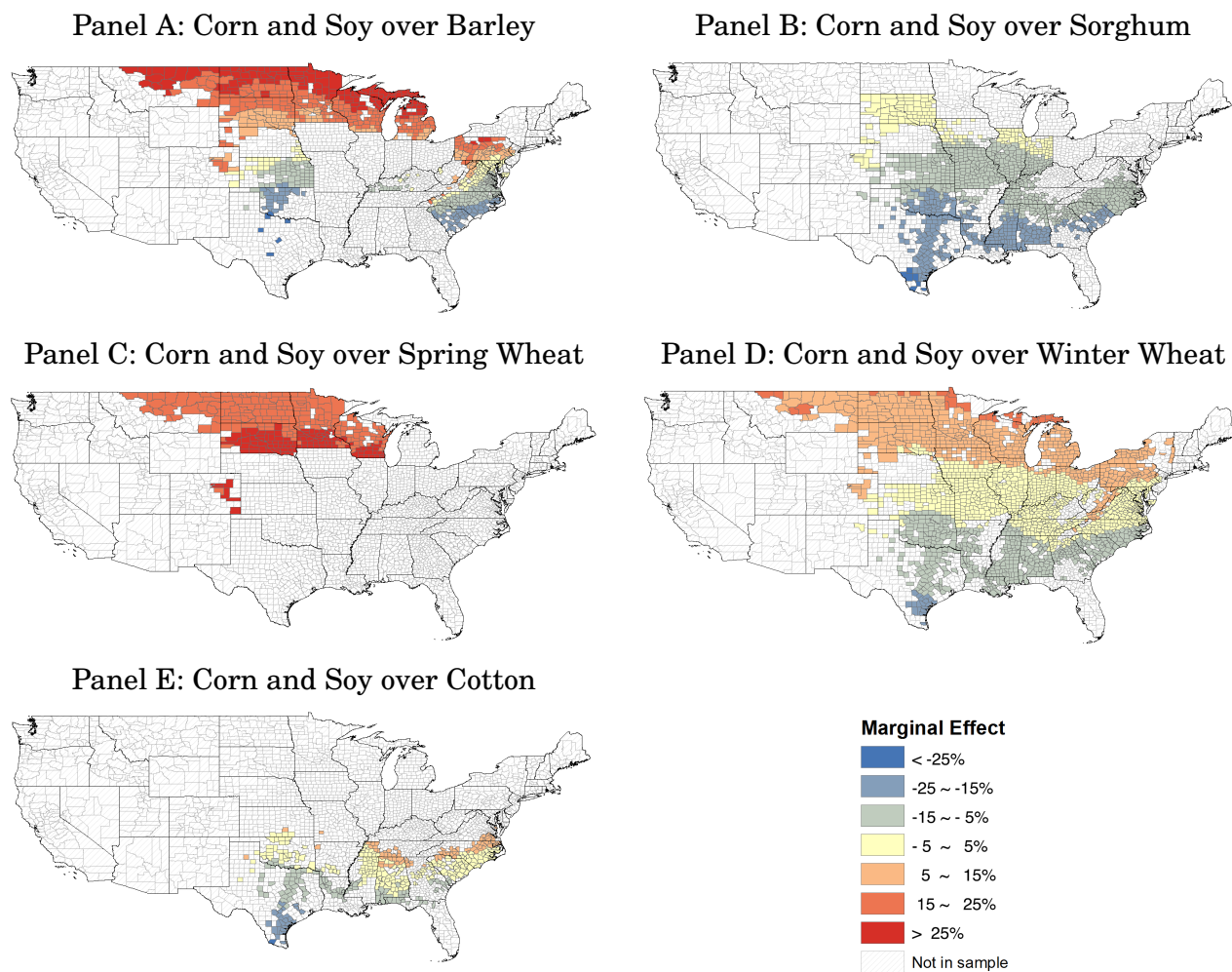
Estimated coefficients are presented in Table 3, in which each column corresponds to the relative acres of corn and soybeans with respect to a specific alternative crop. Standard errors are robust to spatial and temporal correlation under the same estimation procedure as before.

The relative acreage of corn and soybeans responds to climate change differently with respect to different alternative crops. Regarding barley, sorghum, winter wheat, and cotton, warming increases the relative acres of corn and soybeans if the temperature normal is low to begin with, but additional warming in a warm region will induce reductions in the relative acres of corn and soybeans. The relative acres of corn and soybeans always increase with respect to spring wheat when warming occurs in a reasonable temperature range.

Figure 4 plots the marginal temperature effects on the relative acres of corn and soybeans evaluated at the temperature normals for 2015. For the northernmost part of the United States, warming favors corn and soybeans over barley and wheat (Panels A, C, and

D of Figure 4). The increase in the relative acres of corn and soybeans associated with one more degree Celsius can be more than 25%.

Figure 4: Effects of a 1°C Increase in Temperature on Relative Acres of Corn and Soybeans



Note: Marginal effects are calculated based on point estimates in Table 3 and county-level temperature normals over the latest 30 years (1985-2014).

A warmer climate allows for a prolonged growing season for corn and soybeans so that adequate heat can be accumulated. The cost and revenue studies by USDA report that the per-acre revenue for corn and soybeans has been consistently higher than barley and wheat in the Northern Plains, ranging from 1.5 to 2.5 times. Given the relative profitability of corn and soybeans, persistent temperature rising, as a signal, can therefore incentivize growers and firms to adjust planting decisions and breeding developments to take advantage of the

warming and induce more acreage of corn and soybeans.

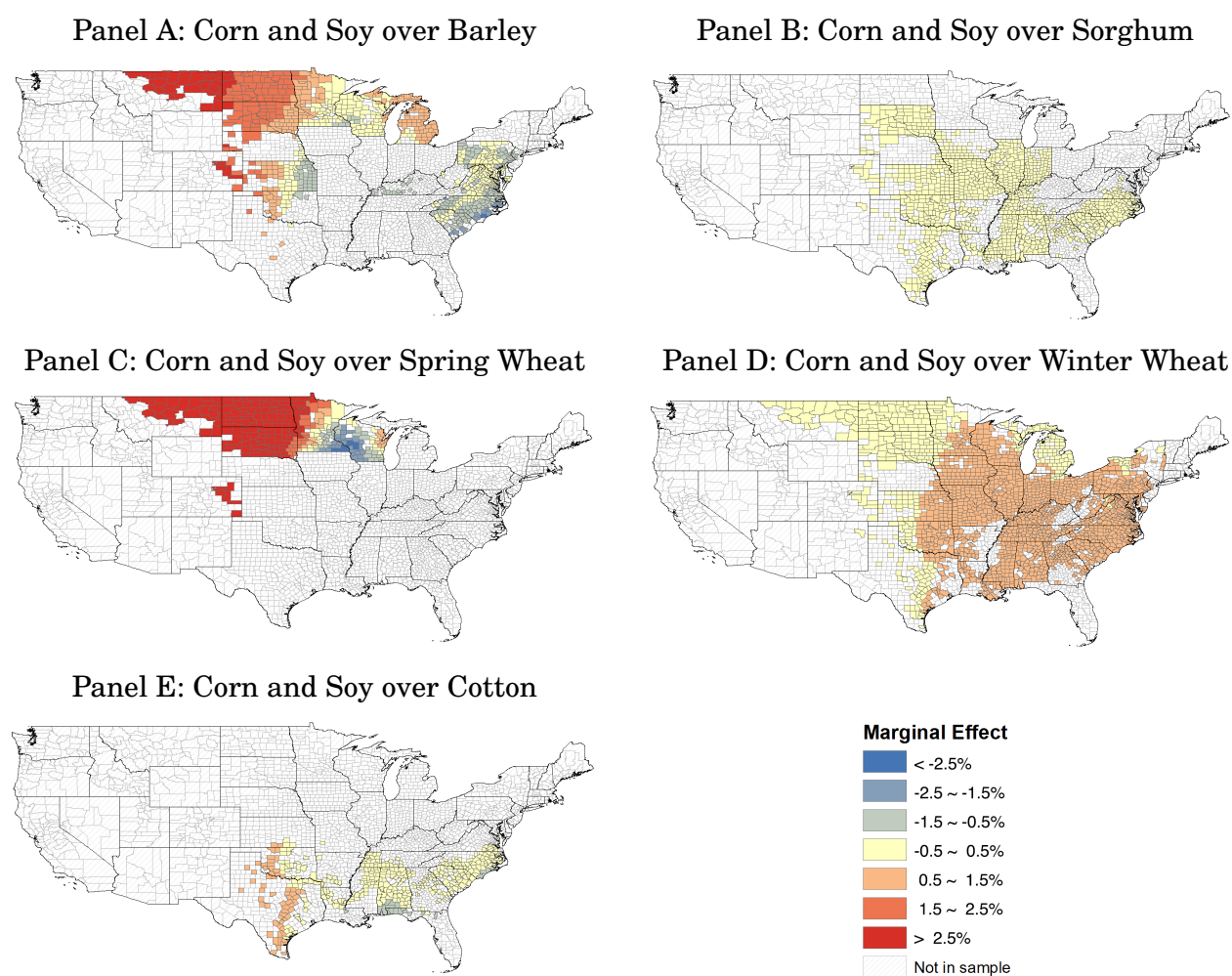
Moving toward the south, warming generally induces less corn and soybean acres relative to sorghum, winter wheat, and cotton (Panels B, D, and E of Figure 4). Both sorghum and cotton are more heat-tolerant than corn and soybeans. Warming in the southern region is expected to have higher yield-damaging effects on corn and soybeans than sorghum and cotton, and therefore, all else equal, reduces the relative profitability of planting corn and soybeans. The marginal effects on the relative acreage of corn and soybeans are positive but modest on the northern rim of the cotton region, where the temperature normals have not reached the level such that an additional degree will do more harm on corn and soybeans than on cotton.

The warming-induced decrease in corn and soybean acres relative to winter wheat in warm areas relates to the unique growing season of winter wheat. Winter wheat likely avoids the most yield-damaging summer heat compared to corn and soybeans because its growing season typically ends in August or earlier. A warming climate in the southern region will therefore put more pressure on the productivity of corn and soybeans than on winter wheat, inducing more acres of corn and soybeans to be substituted into winter wheat, *ceteris paribus*.

Figure 5 plots the marginal precipitation effects on the relative acres of corn and soybeans evaluated at the precipitation normals for 2015. The marginal effects on corn and soybean acreage relative to barley and spring wheat generally follow a west-to-east spectrum (Panels A and C of Figure 5). Over a growing season, corn and soybeans typically use more water than barley and spring wheat. In dry areas, the yield boost triggered by more rainfall pushes up the relative profitability of corn and soybeans over barley and spring wheat. Moving toward the east, this precipitation-induced boosting effect diminishes as the original precipitation has been sufficient for corn and soybeans in most rain-fed areas east of the 100th meridian. For these regions, the relative increase in corn and soybean acreage is very marginal, and even slightly reversed in some places.

The relative acres of corn and soybeans compared to sorghum and cotton are generally not influenced by precipitation changes (Panels B and E of Figure 5). The positive effects regarding winter wheat are modest in magnitude and statistically insignificant for most areas (Panel D of Figure 5). These findings suggest that the partial effects of precipitation changes are limited in influencing the profitability of corn and soybeans relative to sorghum, cotton, and winter wheat in rain-fed areas.

Figure 5: Effects of a 1cm Increase in Precipitation on Relative Acres of Corn and Soybeans



Note: Marginal effects are calculated based on point estimates in Table 3 and county-level temperature normals over the latest 30 years (1985-2014).

## 5 Conclusion

Much has been written on climate change impacts on crop yields. All else equal, the heterogeneity of yield responses across crops also implies a change in relative profitability per acre. As climate change persists, this will slowly alter cropping patterns. This paper examines how climate change, represented by decades-long weather averages, has affected corn and soybean acreage in the United States. In rain-fed agriculture where crop yields are sensitive to climate change, adjustments in planted acres are significant. When a region becomes warmer and wetter, corn and soybeans expand in cool and dry areas, and contract in warm and moist areas. Over the past 30 years, a significant portion of the observed change in corn and soybean acreage can be explained by climate change.

In contrast to recent findings on the lack of adaptation to climate change (Schlenker and Roberts, 2009; Burke and Emerick, 2016), this paper finds robust evidence of agricultural adaptation on crop acreage, which is consistent with the historical observation on the strong adaptability in crop planting (Olmstead and Rhode, 2011a). This study highlights the importance of taking acreage changes into consideration when evaluating climate change impacts on agriculture. Neglecting adjustment and adaptation in crop acreage may lead to imprecise and even unrealistic projections of future crop losses due to climate change.

This study has a few limitations. First, rather than fully decomposing the environmental, technological, and socioeconomic drivers of the changing cropping patterns, this analysis focuses on the reduced-form relationship between climate change and crop acres. To understand the relative importance of different drivers requires imposing more structure on the estimation. Second, the nature of the data determines that acreage shifts are not directly observed at the field level, and the inference on acreage substitution relies on examining county-level acreage shares. Future research is needed to incorporate more disaggregated data. Third, this paper only considers a selected number of field crops other than corn and soybeans. The acreage effects on other crops as well as grazing and Conservation Reserve Program land are still to be studied. Finally, it is worth noting that the adaptive mecha-



nisms are not restricted to behavioral responses regarding crop yield and acreage. Though not addressed in this paper, changes in plant characteristics, cultivation practices, farm management strategies and such are also important margins for climate change adaptation.

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