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Climate change and adaptation in agriculture: Evidence from US cropping patterns☆

Xiaomeng Cui

Jinan University, Institute for Economic and Social Research, 601 West Huangpu Road, Guangzhou, 510632, China

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ABSTRACT

Understanding how a changing climate alters regional comparative advantage is crucial for evaluating the economic impacts of climate change. I exploit temporal variation in decades-long averages of weather and estimate crop acreage elasticities with respect to climate change in the United States. I find substantial climate change adaptation through acreage adjustments in US agriculture. Climate change explains about 10–35% of the observed US corn and soybean expansion over the past 30 years, and climate-driven crop substitution has played an important role. The acreage response is heterogeneous across major and minor producing areas and across dryland and irrigated counties.

1. Introduction

Agriculture is an industry highly sensitive to climate change (IPCC, 2014). Focusing on crop yields, a vast literature has documented the negative impact of climate change on agriculture and its threat on future food security (Schlenker and Roberts, 2009; Schlenker and Lobell, 2010; Welch et al., 2010; Chen et al., 2016; Gammans et al., 2017; Schauberger et al., 2017). The concern becomes even more pressing as recent studies find minimal climate adaptability in crop yields (e.g., Schlenker and Roberts, 2009; Burke and Emerick, 2016). However, climate change will also change comparative advantage in agriculture, and the induced crop reallocation can potentially mitigate the overall impact of climate change (Costinot et al., 2016). How much

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E-mail address: cuixiaomeng@jnu.edu.cn.

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agriculture will adapt through changing cropping patterns is therefore very important for designing cost-effective policies for climate change adaptation.

This paper provides the first empirical estimate of acreage elasticities with respect to climate by examining how planted acres of US corn and soybeans respond to long-run climate change. As the largest producer of corn and soybeans in the world, the United States accounts for about 30–40% of the world's total exports of these two crops (USDA, 2017). Cropping patterns in the United States have also experienced substantial changes over the past few decades. From 1980 to 2016, the planted acres of corn and soybeans in the United States increased by 11.9% and 19.3%, respectively, while wheat acres experienced a 43.2% reduction (USDA, 2016).[1] 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 in biotechnology, have been recognized as leading factors driving the changing acres (e.g., Olmstead and Rhode, 2011; Roberts and Schlenker, 2013; Barrows et al., 2014), the contribution of climate change is not well understood.

In this paper, I estimate how climate change affects the planted acres of corn and soybeans using US county-level data by exploiting the temporal variation in long-run climate change rather than short-run weather fluctuations. Guided by the scientific literature, relevant climate information is summarized by *climate normals*, defined by the National Oceanic and Atmospheric Administration (NOAA) as "three-decade averages of climatological variables including temperature and precipitation." In a panel fixed effects estimation, the key variation comes from the within-county variation in climate normals that reflects the gradually updated local climate. Because the regional comparative advantage evolves differently as the regional climate endowments differ, I explicitly allow for spatially heterogeneous acreage response in the estimation.

I find that rising temperature and precipitation have increased the planted acres of corn and soybeans in cool and dry areas, but decreased their acres in warm and moist areas. The results are robust to a set of different specifications and not sensitive to the inclusion of additional socioeconomic and policy relevant controls. I also show that short-run weather fluctuation does not confound the effect of long-run climate change, and climate effects differ significantly from weather effects on acreage.

In terms of semi-elasticities of corn and soybean acreage with respect to climate, a uniform 0.1 °C increase in the 30-year average growing-season temperature would lead to a 0.9% acreage reduction, while a uniform 1 cm increase in the 30-year average of growing-season precipitation would induce a 4.0% acreage increase. Referring to the observed temporal variability of climate normals, the response to temperature change is less elastic than the response to precipitation change.

A comparison with price elasticities in the literature suggests that corn and soybean acreage is less responsive to changing climate than to changing prices. However, given the persistency in climate change over decades, the climate-driven acreage change is still substantial. Based on the preferred estimates, a back-of-the-envelope calculation shows that 10–35% of the observed US corn and soybean acreage expansion since 1980 can be explained by climate change. From another perspective, about 1.1–3.8% of the current US total corn and soybean outputs would not have been realized had no climate change over the past three decades, assuming average yields on the expanded acres. Bringing in additional acreage data, I also show that the acreage response of corn and soybeans is partly realized through acreage substitution with other major crops.

There is some heterogeneity in corn and soybean acreage response across major and minor producing areas. In particular, major areas in the cool region is much more responsive to warming, reflecting a lower adjustment cost relative to minor areas. Another dimension of response heterogeneity is related to irrigation. Using a subset of counties with detailed irrigation information, I show that the effect of climate change on irrigated acreage is very limited, especially for the precipitation effect. As irrigation breaks the linkage between crop growth and precipitation, more rainfall in dry areas no longer serves as a strong incentive for growers to expand their corn and soybean acres.

Previous studies on climate change impacts on agricultural supply largely focus on weather impacts on crop yields. On one hand, these estimated effects may only capture limited adaptability to long-run change in the climate, potentially biasing the predicted impacts of climate change (Hsiang, 2016; Blanc and Schlenker, 2017; Mendelsohn and Massetti, 2017; Carter et al., 2018).[2] On the other hand, crop acreage is typically assumed to be fixed, which precludes the potential mitigation effects associated with induced acreage adjustments.

An early strand of literature has related micro-level crop choice to different climatic characteristics (e.g., Kurukulasuriya and Mendelsohn, 2007; Seo and Mendelsohn, 2008; Wang et al., 2010). Due to the cross-sectional nature of these studies, their results are prone to the omitted variable bias. Recently, some attempts have been made to estimate acreage adjustments to climate change using panel estimation (Miao et al., 2016; Cohn et al., 2016). However, their identification is based on weather variation so that the results mostly reflect acreage response to short-run weather shocks rather than long-run climate change.[3]

By providing the first rigorous empirical estimation of acreage response to changing climate, this paper contributes to the understanding of climate change impacts in several ways. An innovation in this paper is to use long-average weather, as a proxy for climate, in a panel fixed effects estimation framework. This strategy permits identifying climate change effects directly. By demonstrating significant climate effects on crop acreage, this paper highlights an important adjustment margin that has been overlooked in the recent economics literature on climate change. The reduced-form estimates in this paper complement the

[1] In 2016, the US 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.

[2] Notable exceptions include Schlenker and Roberts (2009) and Burke and Emerick (2016). The former compares cross-sectional and time-series estimates and the latter compares annual panel and long-difference estimates. Both conclude that climate adaptability in US corn and soybeans are limited.

[3] Using time-series model, Lee and Sumner (2015) analyze acreage response to medium-run change in temperature in a specific county, but their results are hard to be generalized.

structural estimation of climate-induced crop reallocation in Costinot et al. (2016), strengthening the finding of agricultural adaptation to climate change through changing cropping patterns. The spatial pattern of the estimated acreage response also echoes the early predictions made under the production-function approach as well as the theoretical predictions in the Ricardian literature (Adams et al., 1990; Mendelsohn et al., 1994).

The heterogeneity in acreage response across major and minor producing areas illustrates that expanding crop production to new regions may face more obstacles. This finding also links to the recent discussion of high switching cost in the supply response literature (Scott, 2013; Gouel and Laborde, 2018).[4] The heterogeneous response found on irrigated acreage builds on the literature on the role of irrigation in climate change adaptation (e.g., Schlenker et al., 2005, 2006; Tack et al., 2012; Taraz, 2017). In particular, this paper finds that local yield adaptation supported by irrigation may provide disincentives for adaptation through acreage adjustments, linking to discussions of the effectiveness of water institutions in adapting to climate change (Libecap, 2011).

2. Conceptual model

I present a stylized model that characterizes the decision making of a representative grower on allocating planted acreage to crops that compete for land. The model highlights the mechanism of how climate change affects acreage allocation and leads to implications for the empirical design.

A representative grower in a small area (for example, a county) maximizes her total profit by allocating available land to planting two crops and an outside option. Crop production (y_k, $k = 1, 2$) is increasing in land (A_k, $k = 1, 2$) with a decreasing rate for each crop, and it also depends on the climate (C). The amount of available land not used for agricultural purposes is denoted as A_3. Without loss of generality, the total amount of land is scaled to be one. The grower is assumed to be a price taker. The crop prices are p_1 and p_2, and the unit return of non-agricultural land is r. For simplicity, I assume that crop production is associated with a constant marginal cost on each unit of land (s). The maximization problem is formally expressed as

$$\max_{A_1, A_2, A_3} \ p_1 y_1\left(A_1, C\right) + p_2 y_2(A_2, C) + rA_3 - s\left(A_1 + A_2\right) \ \text{ s.t. } \ A_1 + A_2 + A_3 = 1.$$

When adjustments can be made on non-agricultural land, the optimal acres for the two crops are determined by equating the marginal values of land (MVL) as

$$p_1 \frac{\partial y_1(A_1^*, C)}{\partial A_1} = p_2 \frac{\partial y_2(A_2^*, C)}{\partial A_2} = s + r.$$

The marginal effect of climate change on the optimal acres of the crops is therefore

$$\frac{dA_k^*}{dC} = -\frac{\partial^2 y_k}{\partial A_k \partial C} / \frac{\partial^2 y_k}{\partial A_k^2}, \text{for } k = 1, 2.$$

By definition, $\frac{\partial^2 y_k}{\partial A_k^2} < 0$, so how climate change affects a crop's acreage depends on its impact on the marginal productivity of land (MPL) for producing that crop. For example, if climate change benefits the MPL of crop 1, it will increase the acreage for crop 1 by bringing in available land used for non-agricultural purposes.

When the adjustments cannot be made on non-agricultural land (i.e., A_3 is fixed), the optimal acreage for a crop is determined by equating the MVL for the two crops. For example, the marginal effect of climate change on the optimal acres of crop 1 is characterized by the following expression:

$$\frac{dA_1^*}{dC} = -\frac{p_1 \frac{\partial^2 y_1}{\partial A_1 \partial C} - p_2 \frac{\partial^2 y_2}{\partial A_2 \partial C}}{p_1 \frac{\partial^2 y_1}{\partial A_1^2} + p_2 \frac{\partial^2 y_2}{\partial A_2^2}}.$$

The denominator is negative by the concavity of the production function. The impact of climate change on acreage allocation depends on the relative change in the MVL affected by climate change, which is determined by the climate-induced relative change in the MPL under the price-taking assumption.

Suppose both crops are adapted to certain environments, reflecting seed breeding efforts. Suppose climate C is a single dimensional object, the crop adaptation can be described as the MPL being an inverted U-shaped function of C. Specifically, I assume $\frac{\partial MPL_k}{\partial C} > 0$ if $C < C_k^*$ and $\frac{\partial MPL_k}{\partial C} < 0$ for $C > C_k^*$, $k = 1, 2$, where C_k^* reflects the optimal climate that crop k has adapted to. Without loss of generality, I assume $C_1^* < C_2^*$ to characterize different optima for the two crops.

If C increases within the range of $C < C_1^*$, the MVL for both crops increase with C. The direction of acreage change induced by climate change depends on the relative changing rate of MVL of the two crops. This qualitative conclusion also applies in the situation when C increases within the range of $C > C_2^*$, as the MVL for both crops decrease with C. However, if C increases within

[4] The supply response literature focuses more on estimating price elasticities of acreage. Examples include Nerlove (1958); Askari and Cummings (1977); Roberts and Schlenker (2013); Hendricks et al. (2014), etc.

the range between C_1^* and C_2^*, this change in climate will unambiguously lead to more acreage of crop 2, because $\frac{\partial MPL_1}{\partial C} < 0$ and $\frac{\partial MPL_2}{\partial C} > 0$ for $C \in (C_1^*, C_2^*)$. Intuitively, more land will be allocated to a crop as the climate moves towards its optimum and moves away from its competing crop's optimum.

The model has some important implications. Climate change may induce crop acreage change over the margin of non-agricultural land. When farmer cannot make adjustments on non-agricultural land, the ways in which climate change affects acreage change depend on the relative marginal impacts of climate on crop productivity, holding prices constant. A change in the climate that favors one crop therefore does not necessarily reduce the acreage of another crop, and *vice versa*. Moreover, a similar change in the climate could lead to different outcomes of acreage change at different locations, since the initial climate differs across space. The same change could bring the climate closer to a crop's optimal condition in one place, but moves away from it in another.

3. Data

3.1. Crop production data

County-level data on planted acres are used to construct dependent variables. The main crops of interest are corn and soybeans, and data for barley, spring wheat, winter wheat, sorghum, and cotton are collected for the analysis of crop substitution. Acreage data since the late 1970s are obtained from NASS annual surveys.[5] Two considerations determine that planted acres are preferable to harvested acres in the empirical analysis. First, planted acres reflect the intention of planting based on all relevant information prior to weather realizations of the current crop year. Compared to harvested acres, planted acres better characterize the behavioral response to long-run changes in climate. Second, harvested acres are influenced by both long-run climate and weather realizations in the current growing season. Using harvested acres to estimate climate effects thus brings additional difficulties as the contemporaneous weather effect has to be isolated.

Counties in the western region of the United States are excluded, including all counties in Washington, Oregon, Idaho, Wyoming, California, Nevada, Utah, and Arizona, and the counties in Colorado and New Mexico that are on the western side of the 106th meridian (the west of the Rocky Mountains). The above counties are fundamentally different from the others due to their size and agricultural characteristics. The total output of corn and soybeans in this western region accounts for less than one percent of the total national production.

The main analysis focuses on rain-fed agriculture, because the majority of corn and soybeans are non-irrigated in the United States. Data from the US Census of Agriculture are used to identify rain-fed counties. In line with Deschênes and Greenstone (2007), a county is categorized as rain-fed if its average irrigated acres are below 10% of its total cropland. This criterion successfully removes extensively irrigated counties on the Ogallala and the Mississippi River Valley aquifers.

The planted acres of corn and soybeans are combined in the empirical analysis. As identified in Schlenker and Roberts (2009), corn and soybeans have similar bio-physical responses to temperature and precipitation changes. Their cropping practices also bear 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. The decision is further complicated by price expectations over multiple periods (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.

Fig. 1 depicts the average annual rate of change in combined corn and soybean acres in rain-fed counties that have planted corn and/or soybeans for at least 20 years, from 1981 to 2015. It shows that the planted acres of corn and soybeans have increased substantially in the Dakotas, Upper Minnesota, and part of Kansas. However, in the southern region such as Louisiana, Mississippi, and Alabama, some counties have experienced a remarkable reduction in corn and soybean acres.

3.2. Climate data

Climate variables are constructed based on the PRISM historical weather data from 1951 to 2015. The raw data include daily average temperature and precipitation on 4 km-by-4km spatial pixels. The pixel-level data are aggregated to county-level, weighted by farmland areas, following the strategy in Schlenker and Roberts (2009).[6] Average temperature and cumulative precipitation, as well as other annual variables, are constructed over the growing season defined as April 1 to September 30. Referring to NOAA's definition of climate normals, the growing season weather in the preceding 30 years are averaged to form climate variables for each year.

As shown in Fig. 2, over the past 35 years, the 30-year average of growing-season average temperature (temperature normal, and hereafter) has gone up for most of the corn and soybean producing regions. Some northern counties have witnessed a more than 0.5 °C increase in temperature normals, while some parts of the lower Midwest have experienced modest cooling. The

[5] Data for the early 1970s are incomplete for some states.
[6] I thank Wolfram Schlenker and Michael Roberts for making the data and programs available at http://www.wolfram-schlenker.com/dailyData.html.

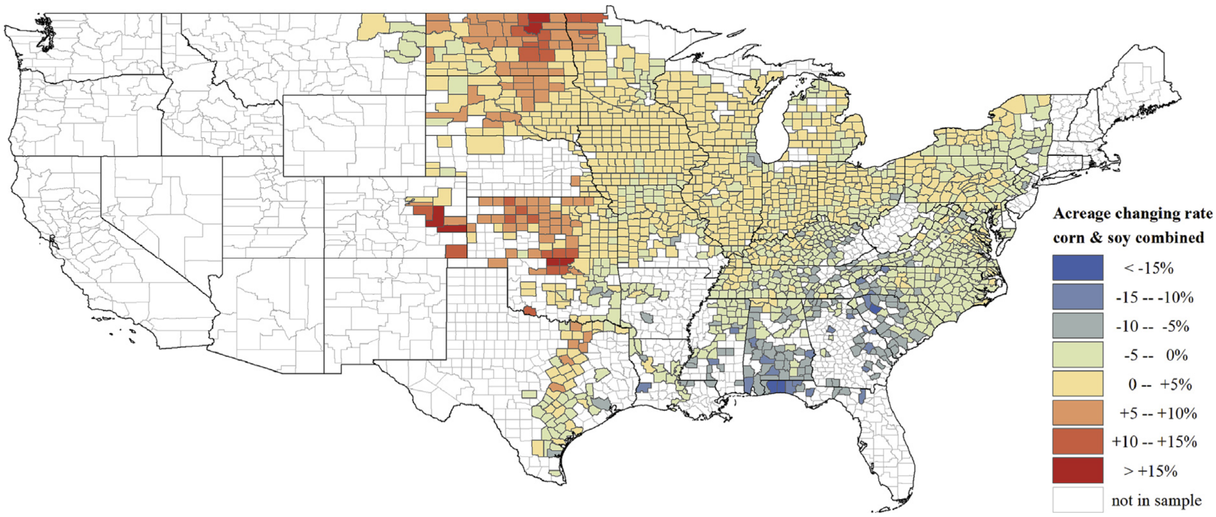

Fig. 1. Annual rate of change in combined corn and soybean acreage: 1981–2015. Notes: The annual changing rate is obtained by estimating the county-specific slope coefficients from $\log(y_{it}) = a_i + \beta_i \times t + \varepsilon_{it}$, where yit is the aggregate planted acres of corn and soybeans in county i in year t. The estimation is restricted to rain-fed counties that have planted corn and/or soybeans for at least 20 years, from 1981–2015.

30-year average of growing-season cumulative precipitation (precipitation normal, and hereafter) also features considerable variation both across space and over time. These maps show that the within-county change in climate normals features substantial spatial variation. More importantly, these spatial patterns do not coincide with the boundaries of administrative units like states, which provide useful variation for identification even after including state-level controls in the regression.

Comparing Figs. 1 and 2 provides some suggestive evidence on the correlation between climate change and crop acreage. The northern region used to be too cold for corn and soybeans. However, it has experienced a fast expansion of these crops, coinciding with a higher growing-season temperature and a modest increase in precipitation. The rain-fed area of the central Plain, featuring adequate heat but insufficient water, also shows high growth of corn and soybean acres, with the help of a significant increase in precipitation and negligible temperature changes. The summary statistics tabulated by regions and decades are shown in Appendix Table 1.

3.3. Other data

To evaluate the sensitivity of the results, I collect auxiliary information on relevant socioeconomic and policy variables, including county population, crop prices, crop insurance, conservation program enrollments, rental rates, and total cropland areas. I also use a subset of counties with detailed irrigation information to analyze the response of irrigated acreage. These data are discussed in details in Section 1 in Appendix.

4. Empirical strategy

The empirical strategy relies on a panel fixed-effects model to identify the partial effects of climate on the economic outcome,

$$y_{it} = f(\widetilde{T}_{it}; \beta) + g(\widetilde{P}_{it}; \gamma) + \alpha_i + \delta_t + h_r(t) + \varepsilon_{it}, \tag{1}$$

where y_{it} is the economic outcome in county i in year t. The outcome of most interest in this paper is crop acreage. $\widetilde{T}_{it}$ and $\widetilde{P}_{it}$ are temperature and precipitation normals, respectively. $f(\cdot)$ and $g(\cdot)$ denote flexible functional forms that allow for a complex relationship between the outcome and climatic variables. α_i and δ_t are county and year fixed effects, capturing time-invariant county characteristics and location-invariant yearly shocks, respectively. $h_r(t)$ characterizes flexible trends in the economic outcome at the state level. ε_{it} represents the idiosyncratic shock. The underlying identification assumption is that a county would have changed its economic outcome similarly to another county if they have experienced a similar change in climate, after purging the effects of state-level trends and nation-level shocks.

A distinguishing feature of this empirical framework is the utilization of change in climate directly, as opposed to using weather fluctuations to identify the causal effects of climate on economic outcomes. The within-county variation in climate normals reflects gradual changes in the local climate in a county, smoothing out drastic year-to-year fluctuations in weather realizations. Temperature and precipitation normals characterize growing-season average climate. This first-moment charac-

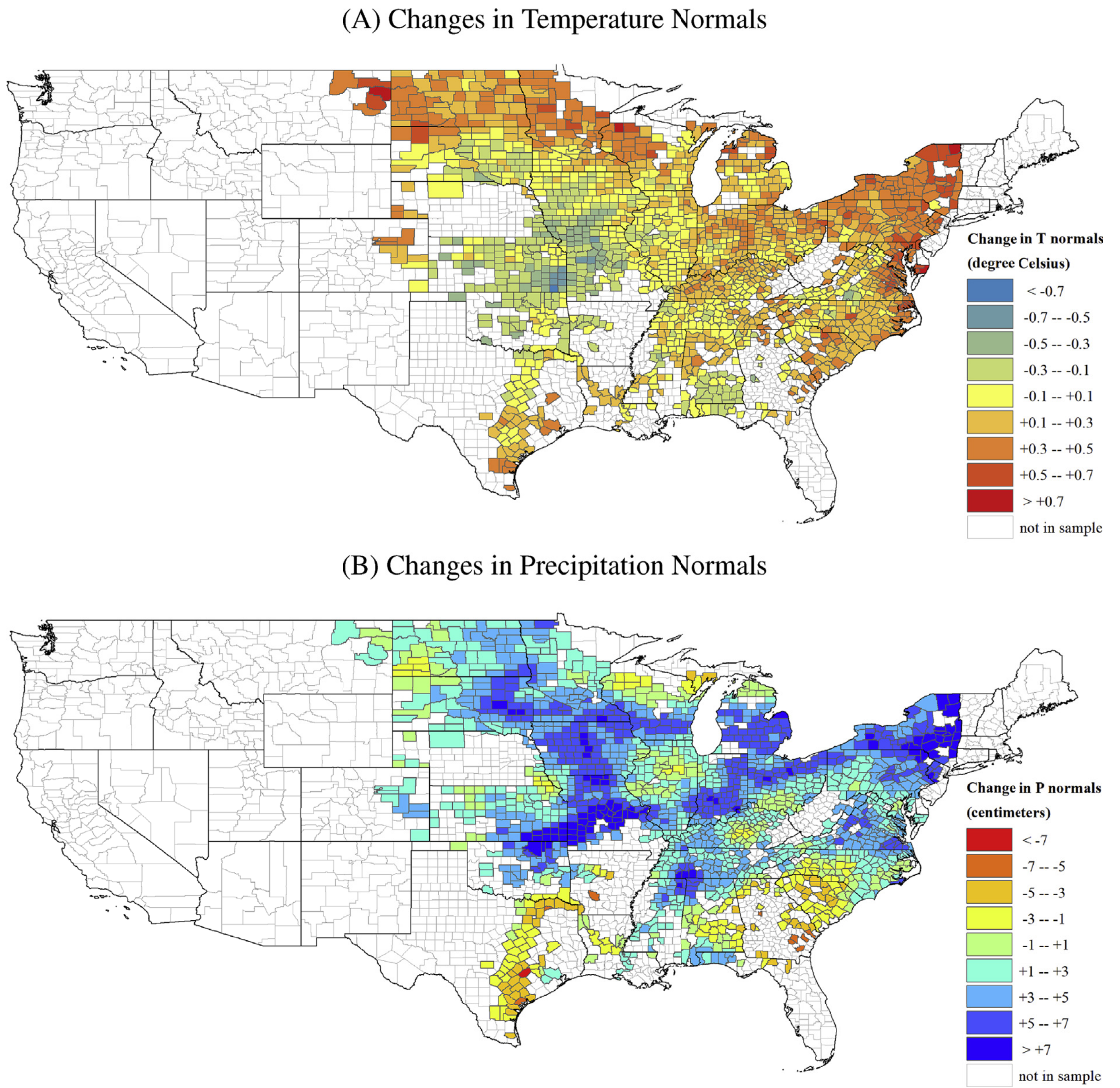

Fig. 2. Difference in climate normals (30-year averages): 1981–2015. *Notes:* Counties shown in colors are matched with counties presented in Figure 1. Maps are constructed by differencing 1985–2014 averages with the 1951–1980 averages of growing-season average temperature and total precipitation.

terization pertains to the main public discussion and perception of climate change.[7]

Perceiving the mean changes in climate, economic agents are induced to adjust their behavior accordingly to maximize potential gains or to minimize potential losses. At the county level, these induced responses are not limited to growers' proactive adjustments. The adjustments incentivized by new technologies should also be considered if their emergence would have not happened without climate change.[8] In this regard, the reduced-form estimates capture the total impacts of climate change on acreage that incorporate effects transmitted through all possible channels, given that the variation of changing climate is presumably exogeneous.

[7] The term "global warming" has been used interchangeably with "climate change" for a long time. Other aspects of climate change, like the change in weather volatility and the likelihood of weather extremes, have just received greater attention in recent years, but most discussion of climate change focuses on changes in mean temperature and precipitation. See Weber and Stern (2011) for a discussion of the American public's perception of climate change.

[8] As in the literature on induced technological change in agriculture, many agricultural innovations are developed under the incentive to combat environmental challenges, like weather risks. Just, Schmitz and Zilberman (1979) acknowledge that farmers, private corporations, and public research institutions are all sources of technology developments.

For inference, all regressions cluster standard errors at the state level to address potential spatial and temporal correlation and heteroskedasticity in the error structure. As discussed in Auffhammer et al. (2013), spatially correlated weather information that is not directly controlled for in the regression will be grouped in the error terms, and neglecting the spatial correlation generally underestimates standard errors. The chosen clustering at the state level is directly in line with recent work on climate impacts on agricultural production using US county-level data (e.g., Burke and Emerick, 2016).

5. Estimation and results

5.1. Baseline estimates and robustness checks

Climate change induces changes in regional comparative advantage. As discussed in the conceptual model, regional heterogeneity in the initial climate implies that a similar change in the climate could lead to different optimal production arrangements for different places. To characterize potential heterogeneous responses explicitly, temperature and precipitation coefficients are allowed to vary across groups, where groups are defined by referring to a county's initial temperature and precipitation normals.[9]

Specifically, I evenly divide the support of initial temperature and precipitation normals to form temperature and precipitation groups such that the group division is easily interpretable yet still allows for substantial spatial heterogeneity. Appendix Fig. 1 presents distributions of the initial temperature and precipitation normals. The temperature groups are defined over 2 °C bins with the following cutoffs: < 15 °C, 15–17 °C, 17–19 °C, 19–21 °C, 21–23 °C, 23–25 °C, and > 25 °C. Precipitation groups are defined over 10 cm bins using the following cutoffs: < 30 cm, 30–40 cm, 40–50 cm, 50–60 cm, 60–70 cm, 70–80 cm, and >80 cm. I report robustness checks using finer temperature and precipitation bins as well as an alternative sorting method based on plant hardiness categorization in Appendix Section 2.

The regression equation is written as

$$\log(A_{it}^{corn} + A_{it}^{soy}) = \beta_j \widetilde{T}_{it,j} + \gamma_k \widetilde{P}_{it,k} + \alpha_i + \delta_t + h_r(t) + \varepsilon_{it}, \tag{2}$$

where A_{it}^{corn} and A_{it}^{soy} represent planted acres of corn and soybeans, respectively, in county i in year t. $\widetilde{T}_{it,j}$ represents temperature normals in the jth temperature group, and $\widetilde{P}_{it,k}$ represents precipitation normals in the kth precipitation group. $h_r(t)$ represents state-level quadratic trends that characterize unobserved effects of macro economic factors and technological improvements at the state-level. δ_t represents year fixed effects, capturing year-to-year price fluctuations in the commodity markets and other unobserved countrywide policy shocks. α_i is the county fixed effects, and ε_{it} is the idiosyncratic shock. Referring to the magnitude of climate change shown in Fig. 2, the units of temperature and precipitation normals are scaled at 0.1 °C and centimeters, respectively. To avoid results being driven by counties in very marginal regions, the sample is restricted to counties that have planted corn or soybeans for at least 20 years, from 1981 to 2015. The sensitivity to this criteria is evaluated in Appendix Section 3.

The estimation results are plotted in black in Fig. 3 (model 1). The markers represent point estimates and the error bars show 95% confidence intervals. In the long run, rising temperature significantly increases corn and soybean acres in areas where the initial temperature is below 15 °C, but decreases corn and soybean acres when the initial temperature is above 25 °C. Specifically, for the coolest region of northern Minnesota and North Dakota, a 0.1 °C increase in temperature normals will induce a 7.1% increase in corn and soybean planted acres. However, for the warmest southern states, rising temperature normals by 0.1 °C can reduce corn and soybean acres by as much as 20.8%.

The relationship between corn and soybean acres and precipitation normals is also spatially heterogeneous. For dry regions normally receiving less than 40 cm precipitation over the growing season, a 1 cm increase in precipitation normals is associated with an increase in corn and soybean acres of more than 27.3%. The positive effects become very modest for more moist regions. For places with more than 70 cm rainfall, rising precipitation normals tend to reduce corn and soybean acres. A 1 cm increase can lead to a reduction as high as 10.0% when the initial precipitation normals have exceeded 80 cm.

A natural concern regarding the use of 30-year moving averages is that the annual variation in 30-year average temperature and precipitation is too slim, which may amplify measurement errors and invalidate the identification. To address this concern, the baseline regression is implemented on a sub-sample only consisting of years when US Census of Agriculture took place, so that the within-county variation reflects changes in climate normals over every five years.[10] As plotted in red in Fig. 3 (model 2), the results are very similar to the baseline estimates.

In the main specification, price effects are controlled at the national level by using year fixed effects. The effective price signal for the planting decision is the futures price maturing at 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 across locations, the within-location variation of prices is mostly homogeneous over space, as the calculation of basis is largely tied to geographical distances. Another way to control for prices explicitly at the state level is to replace year fixed effects with state-level received prices for the previous crop year. As shown in green in Fig. 3 (model 3), controlling for lagged received prices of corn and

[9] The initial climate normals are normals in 1981. Because the climate data starts from 1951, using a 30-year average to construct climate normals determines that the starting year of the sample is 1981.

[10] Census years include 1982, 1987, 1992, 1997, 2002, 2007, and 2012 within the sample period.

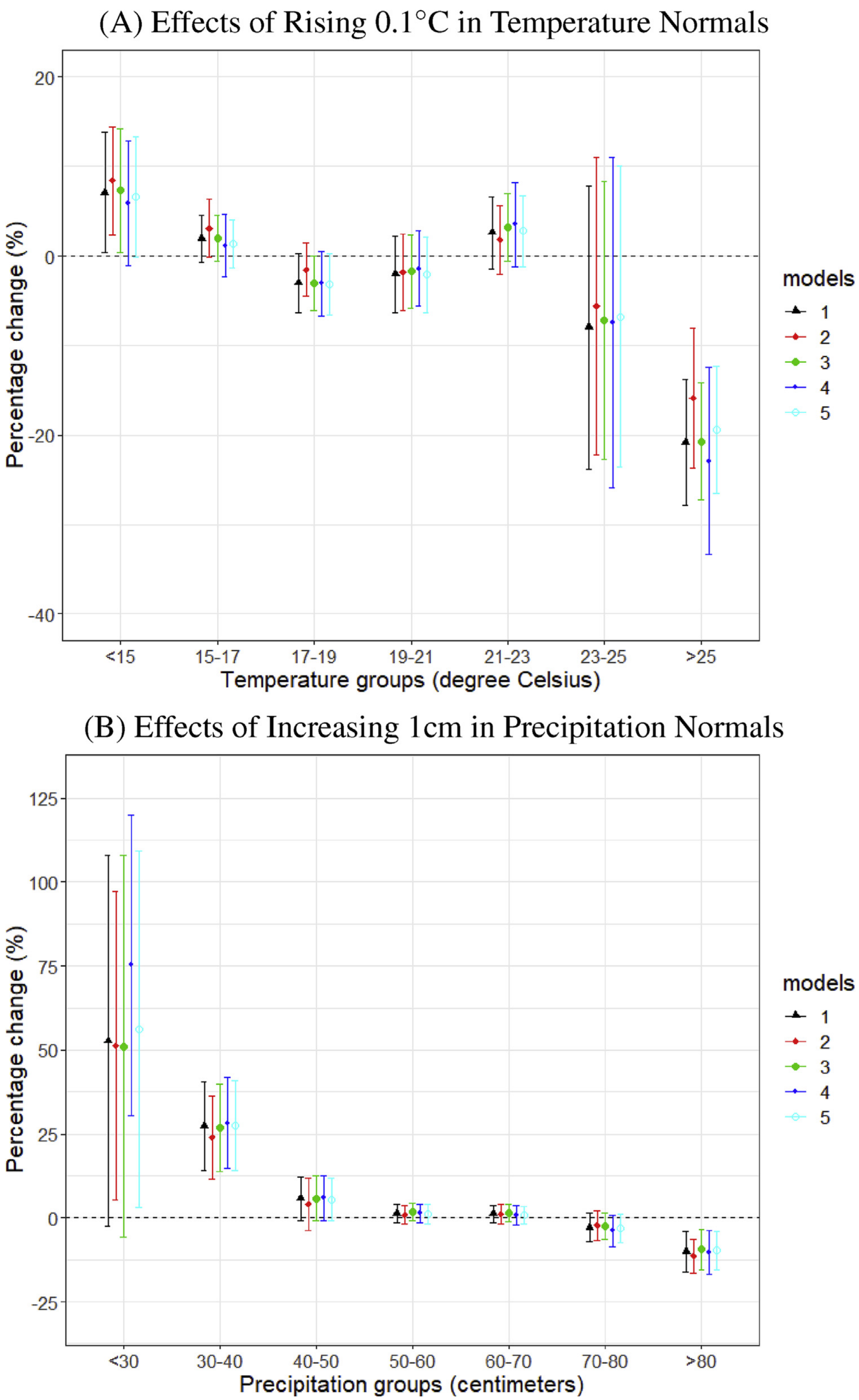

Fig. 3. Heterogeneous climate change impacts on corn and soybean acreage. *Notes:* Results are obtained from various specifications of equation (2): baseline specification (model 1), using census-year sample (model 2), replacing year fixed effects with price variables (model 3), replacing year fixed effects and state trends with state-by-year fixed effects (model 4), adding lagged weather realization to baseline specification (model 5). Markers represent point estimates and error bars represent 95% confidence intervals constructed based on state-clustered standard errors. See Appendix Table 2 for numerical results.

soybeans (GDP deflated and in logarithm) generates results very similar to the baseline.[11]

In addition to prices, improved technology and policy change that are unrelated to climate change could also confound the identification of climate impacts on crop acres. The baseline specification utilizes state trends and year fixed effects to control for these factors. State-level quadratic trends characterize the contribution of new technologies that emerge gradually within a state, and policy shocks are assumed to be absorbed by year fixed effects. A more conservative specification is to replace state trends and year fixed effects with state-by-year fixed effects. This specification will effectively absorb the effects of any arbitrary shock, including technological booming and policy reform, that is specific to a state in any given year. The results in dark blue in Fig. 3 (model 4) indicate that the estimated relationship between acreage and climate normals is still very robust even after allowing state-level time effects to be fully non-parametric, although some estimates become less precisely estimated.

The literature has documented the salience effect of extreme weather events on agriculture (e.g., Kuwayama et al., 2018). One concern is that the estimated effects of climate normals are mechanically driven by responses to recent weather events, since climate normals are formed by averages of historical weather. I address this concern by estimating a specification with lagged weather variables included alongside climate normals. The lagged weather variables are specified in the same fashion as the climate normals so that spatial heterogeneity is permitted for estimating the effects of lagged weather.

The estimated coefficients of climate normals are plotted in light blue in Fig. 3 (model 5). There is no evidence that including lagged weather variables attenuates the estimated climate effects. As shown in column (5) in Appendix Table 2, lagged weather does play some role in affecting corn and soybean acreage. For example, a 1 °C higher in last growing season will induce about a 2% acreage increase in cool areas and about 11% acreage reduction in very hot areas. Slightly counter-intuitive, for very dry areas, receiving 10 cm more precipitation in last growing season will reduce about 11.7% planted acreage in the current year. This could be due to an expectation on the mean-reverting nature of year-to-year rainfall change.[12] In sum, these results suggest that, although recent weather shocks matter for acreage decision, they do not confound acreage response to long-run change in climate.

5.2. Sensitivity analysis with additional county-level controls

The baseline specification utilizes arguably exogenous temporal variation in climate normals to identify climate impacts on corn and soybean acreage. The baseline estimates intend to characterize the total effects of climate change, including effects that are transmitted through all possible channels. Although many socioeconomic and policy-relevant variables that affect acreage decision are time-varying at the county level, leaving them out would not invalidate the identification of climate impacts if climate affects acreage through these factors or these factors work independently with climate. However, if these factors are systematically correlated with local climate, or even influence local climate in some way, the estimated climate impacts are subject to the omitted variable bias. I therefore evaluate the sensitivity of my baseline results by adding county-level socioeconomic and policy relevant controls, including population, areas insured under the Federal crop program, areas enrolled in the Conservation Reserve Program (CRP), cash rents, and total cropland acres, to the baseline specification.

5.2.1. Population

An increasing population may reflect urban expansion, which changes land use, for instance, by contracting planted acres of certain crops. At the same time, population and urban growth could also correlate with the local climate. On one hand, cities may attract higher populations if their climate becomes more favorable. On the other hand, increased human activities may affect local climate. A typical example is the “heat-island” effect, which refers to the situation in which the built-up urban region becomes significantly warmer than the surroundings. This potential issue is tested by including county population into the regression. Gray marker and error bars in Fig. 4 (model 6) show the results after adding logarithmic population to the baseline specification. It is evident that adding population does not influence the estimates of climatic variables. As shown in Appendix Table 3, the coefficient of the population is negative. This negative association may partly reflect the phenomenon that urban expansion reduces crop acres.

5.2.2. Federal crop insurance program

The Federal crop insurance program has gone through considerable changes since the 1980s. It has been shown that the subsidized premium rates have induced acreage expansion that brings marginal land into production (Goodwin et al., 2004; Yu et al., 2017). To examine if the development of Federal crop insurance program confounds the estimation of climate impacts, I include county-level insured areas of corn and soybeans into the baseline regression. The climate estimates are presented in

[11] As shown in column (3) in Appendix Table 2, the coefficients on corn and soybean prices are 0.056 and −0.029, respectively. Because corn and soybean acres have been aggregated to form the dependent variable, the price coefficients are not directly interpretable. Since the per-acre yield ratio is about 1:3, I use a linear combination of the price coefficients with 3/4 and 1/4 as weights. It yields a point estimate of 0.04 with a 95% confidence interval of (0.02, 0.06), suggesting that corn and soybean acres are positively influenced by their lagged prices. This price estimate is qualitatively consistent with previous studies in the supply response literature.

[12] The precipitation coefficient for 60–70 cm group is also statistically significant, but the magnitude (0.0007) is much smaller in terms of the economic significance.

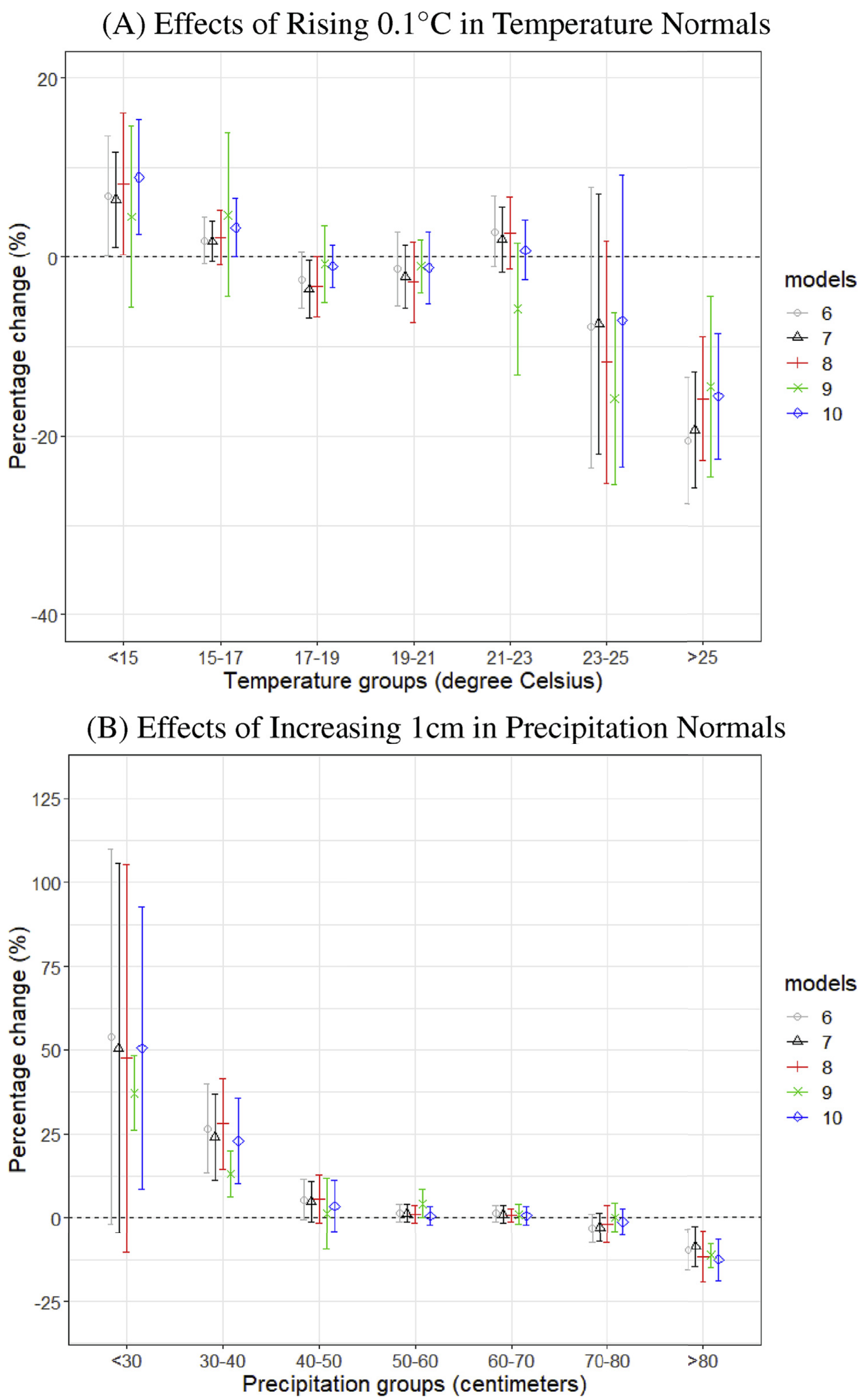

Fig. 4. Heterogeneous climate change impacts on corn and soybean acreage: Sensitivity analysis of adding county-level controls. *Notes:* Results are obtained from estimating equation (2) adding various controls: logarithmic population (model 6), insured areas (model 7), CRP area (model 8), cash rent (model 9), total cropland area (model 10). Markers represent point estimates and error bars represent 95% confidence intervals constructed based on state-clustered standard errors. See Appendix Table 2 for numerical results.

black in Fig. 4 (model 7). The results are very similar to the baseline estimates. As shown in Appendix Table 3, the insured areas are positively and significantly correlated with corn and soybean planted acreage, in line with previous findings.

5.2.3. CRP program

CRP program is another policy-relevant factor that affects acreage decisions. I include county-level cumulative CRP-enrolled areas to test the sensitivity of climate effects to CRP implementation. Because CRP was signed into law in 1985, the sample for this analysis is restricted to the period of 1986–2015. The estimated climate impacts are shown in red in Fig. 4 (model 8). The results are still highly similar to those in the baseline, confirming that CRP does not confound the identification of climate impacts on corn and soybean acreage.

5.2.4. Rental rates

Rental rates are important for determining acreage adjustments as the rates reflect the cost of acreage expansion. To evaluate how rental rates affect the estimation of climate impacts on acreage, I include cash rent (GDP deflated) as an additional control in the baseline regression. Due to data limitation, there are a few compromises in this exercise. NASS only started to provide county-level rental rates since the mandate in the 2008 Farm Bill.[13] In addition, state-level rental rates are available since 1994 from NASS. I therefore impute state-level rental rates to the county level for 1994–2007, and combine them with county-level rental rates during 2008–2014. The climate estimates are shown in green in Fig. 4 (model 9). The results are still similar to the baseline estimates, despite that lower temperature coefficients are less precisely estimated.

5.2.5. Total cropland areas

As discussed earlier, one margin of acreage expansion is to bring in land that was not used for agricultural production. The feasibility of this type of adjustment is partly constrained by the total amount of arable land. I therefore test if including total cropland areas at the county level influences the estimation results of climate impacts. The most reliable county-level data on total cropland acres are documented in the US Census of Agriculture. For this reason, I implement the regression analysis only using data in Census years. The estimates associated with climate normals are presented in blue in Fig. 4 (model 10). The estimates yield patterns very similar to those of the baseline estimates. As reported in model (10) in Appendix Table 3, the total cropland acreage is positively correlated with corn and soybean acreage. Taking the estimate at face value, it suggests a 1% increase in total acreage is associated with a 0.62% increase in corn and soybean acreage. Although this value should not be viewed as an accurate causal estimate, it is consistent with the conjecture that more arable land allows for more corn and soybean acreage. However, this effect does not confound the climate impacts on corn and soybean acreage.

5.3. Consistent evidence across alternative modeling choices

The empirical strategy of this paper is related to the “long-difference” approach in Burke and Emerick (2016) that measures potential adaptive behavior in crop yields using US county-level data. The idea of “long-differencing” is to take two snapshots of the economic outcome and climatic variables at two endpoints on an extended time horizon and examine the relationship with a cross-sectional regression after first-differencing all variables across the two periods.[14]

To compare the baseline results with the “long-difference” estimates, I apply the “long-difference” approach to measuring acreage response to climate change. I define

$$\Delta \log(\overline{A}_i^{corn} + \overline{A}_i^{soy}) = \log(\overline{A}_{i,2011-2015}^{corn} + \overline{A}_{i,2011-2015}^{soy}) - \log(\overline{A}_{i,1981-1985}^{corn} + \overline{A}_{i,1981-1985}^{soy}),$$

where $\overline{A}_{i,\tau_1-\tau_2}^{k}$ indicates a five-year average acreage for crop k in county i from year τ_1 to τ_2. For any 30-year average weather variable $\widetilde{Z}_{it}$, I define $\Delta\widetilde{Z}_i$ as $(\widetilde{Z}_{i,2015} - \widetilde{Z}_{i,1985})$. The “long-difference” version regression is therefore

$$\Delta \log(\overline{A}_i^{corn} + \overline{A}_i^{soy}) = \beta_j \Delta\widetilde{T}_{i,j} + \gamma_k \Delta\widetilde{P}_{i,k} + \delta_r + \varepsilon_i, \tag{3}$$

where the heterogeneous groups j and k are defined in the same way as in equation (2), and δ_r represents state fixed effects. Different from Burke and Emerick (2016), I use 30-year average weather instead of 5-year average weather when constructing the first-differenced climatic variables, in order to make the “long-difference” estimates directly comparable with the baseline estimates.

Estimated coefficients are plotted in Fig. 5 in blue, against the plots of baseline estimates in red. The two sets of estimates display consistent patterns. The largest difference occurs in the estimated coefficient of the highest temperature group, with a much larger estimate from the “long-difference” approach. Since the highest temperature group contains fewer counties, its corresponding estimate may be more sensitive to different modeling choices. Nevertheless, the general agreement between the two sets of estimates confirms that the baseline estimates do capture the long-run relationship between crop acres and climate.

[13] County-level annual records are available for 2008–2014. The report was shifted to every other year since 2014.

[14] In Burke and Emerick (2016), the outcome of interest is crop yields, and both yields and climatic variables are calculated by averaging 5 years around the endpoint years.

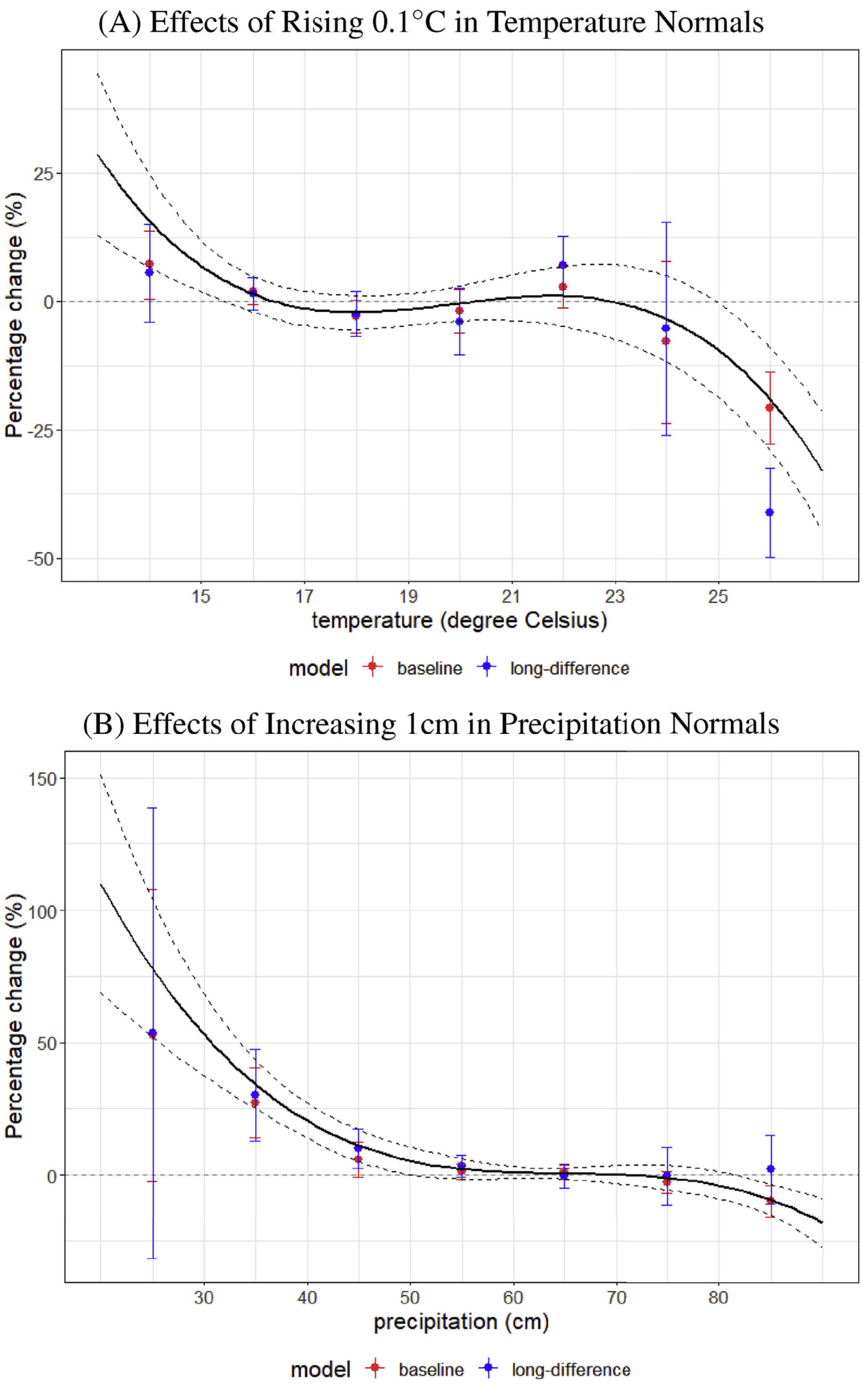

Fig. 5. Estimated climate effects on corn and soybean acreage: Comparing different modeling choices. *Notes:* Red dots and error bars are estimated coefficients and 95% confidence intervals obtained from the baseline estimation of equation (2). Blue dots and error bars are estimated coefficients and 95% confidence intervals obtained from the "long-difference" estimation of equation (3). The solid black lines are marginal effects plotted based on the estimates of equation (4), and the dashed lines govern the 95% confidence intervals, constructed by applying Delta's method to state-clustered standard errors. See Appendix Tables 4 and 5 for numerical results.

Regarding regional heterogeneity, Burke et al. (2015) and Hsiang (2016) argue that heterogeneous linear local responses should be reconciled with global nonlinear responses if the empirical models successfully characterize the underlying relationship. To lend greater support to the regional heterogeneity reflected in the baseline estimates, I further explore the response heterogeneity in terms of a global nonlinear relationship. I use the following regression model that characterizes the relationship between logarithmic acreage and climate normals as a smooth nonlinear function,

$$\log(A_{it}^{corn} + A_{it}^{soy}) = q(\widetilde{T}_{it}; \beta) + q(\widetilde{P}_{it}; \gamma) + \alpha_i + \delta_t + h_r(t) + \varepsilon_{it}. \tag{4}$$

In addition to notations defined in equation (2), $q(\cdot)$ is a fourth-degree polynomial function, with parameter vectors β and γ to be estimated. Under this modeling choice, the marginal effects of climate normals depend on the specific temperature and precipitation levels at which to be evaluated.

Fig. 5 presents the marginal effects of temperature and precipitation normals estimated from equation (4) in smooth black curves, overlaid with the baseline and "long-difference" estimates. Over the observed ranges of temperature and precipitation normals, the polynomial estimates yield marginal effect patterns very similar to the baseline and "long-difference" estimates, showing that heterogeneous local linear effects and global nonlinear effects are indeed reconciled. It is worth noting that the polynomials specification tends to predict large marginal effects around the minimum and maximum of the observed temperature or precipitation normals. This observation is a note of caution for extrapolating estimated effects beyond the observed levels of climate normals when relying on polynomial estimates.[15]

5.4. Robust results of different time lengths for forming climate normals

The choice of 30 years for constructing climate normals is guided by the scientific convention. This choice has been adopted in previous studies of climate change impacts (Mendelsohn et al., 1994; Schlenker et al., 2005, 2006; Moore and Lobell, 2014). Averaging over a long period of time effectively smooths out weather anomalies and successfully captures the first moment of local climate. If the period to be averaged over is too short, the variation in climate normals over time will contain more noise introduced by short-run weather fluctuations than signals that reflect the long-run change in climate. Short-run weather fluctuations may also affect planting decisions (e.g., Miao et al., 2016; Cohn et al., 2016), but this effect is different from the behavioral response to climate change.

Although scientists define climate normals using 30 years, the empirical results of the analysis should not change qualitatively if a smaller but not too small number is chosen. Some recent work on climate change impacts has employed statistical procedures like cross-validation to determine some tuning parameters (e.g, Burke and Emerick, 2016). However, this procedure is not appropriate for the purpose of this paper. This paper aims at identifying the causal relationship between climate change and crop acreage rather than finding the best predictor of planting decisions, especially given that many other economic factors may have also played a significant role in affecting crop acreage. In addition, statisticians have suggested the remaining issue of over-fitting when using the standard cross-validation approach (Shao, 1993, 1997; Arlot and Celisse, 2010; Cui et al., 2018).

To evaluate the sensitivity to different time lengths for forming climate normals, I implement baseline regression of equation (2) using climate normals formed over 30, 25, 20, and 15 years, respectively. Results are plotted in Fig. 6. Estimates based on different time lengths yield consistent patterns. However, both temperature and precipitation coefficients display a tendency of shrinking toward zero as the time length for climate normals becomes shorter. This is reasonable because the strength of the signal differs when different time lengths are used. Conceptually, a change in climate normals formed over a longer time more likely reflects a long-run change, and therefore has a higher likelihood of incentivizing behavioral responses.

5.5. Nonlinear response to changes in temperature normals

An important discovery in the recent literature on yield response is the nonlinear temperature effect. For corn and soybeans, it has been shown that, within a growing season, accumulation of moderate heat benefits crop growth but exposure to excessive heat damages crop yields, and the temperature threshold is around 29–30 °C (Schlenker and Roberts, 2009; Burke and Emerick, 2016; Miao et al., 2016). However, as discussed above, under climate change, acreage changes can be induced by relative changes in how climate change affects crop productivities. Especially for the crop substitution effect, an increase in heat accumulation would only encourage (or discourage) more corn and soybean acres if its benefits (or damages) to corn and soybeans outweigh its potential benefits (or damages) on other competing crops. It is therefore unclear whether the nonlinearity in yield response to contemporaneous temperature implies a similar nonlinear relationship between crop acreage and long-run temperature normals.

To empirically examine how corn and soybean acres respond to a change in the normals of within-season heat distribution, I revise equation (2) and use the following bin regression model to characterize the effects of temperature accumulation in different temperature ranges within a growing season.

$$\log\left(A_{it}^{corn} + A_{it}^{soy}\right) = \sum_j \beta_j \widetilde{T}bin_{it,j} + \gamma_k \widetilde{P}_{it,k} + \alpha_i + \delta_t + h_r(t) + \varepsilon_{it}, \tag{5}$$

[15] On addressing this issue, Auffhammer et al. (2017) impose a linear response when projecting beyond the observed range of the data, in the context of electricity demand.

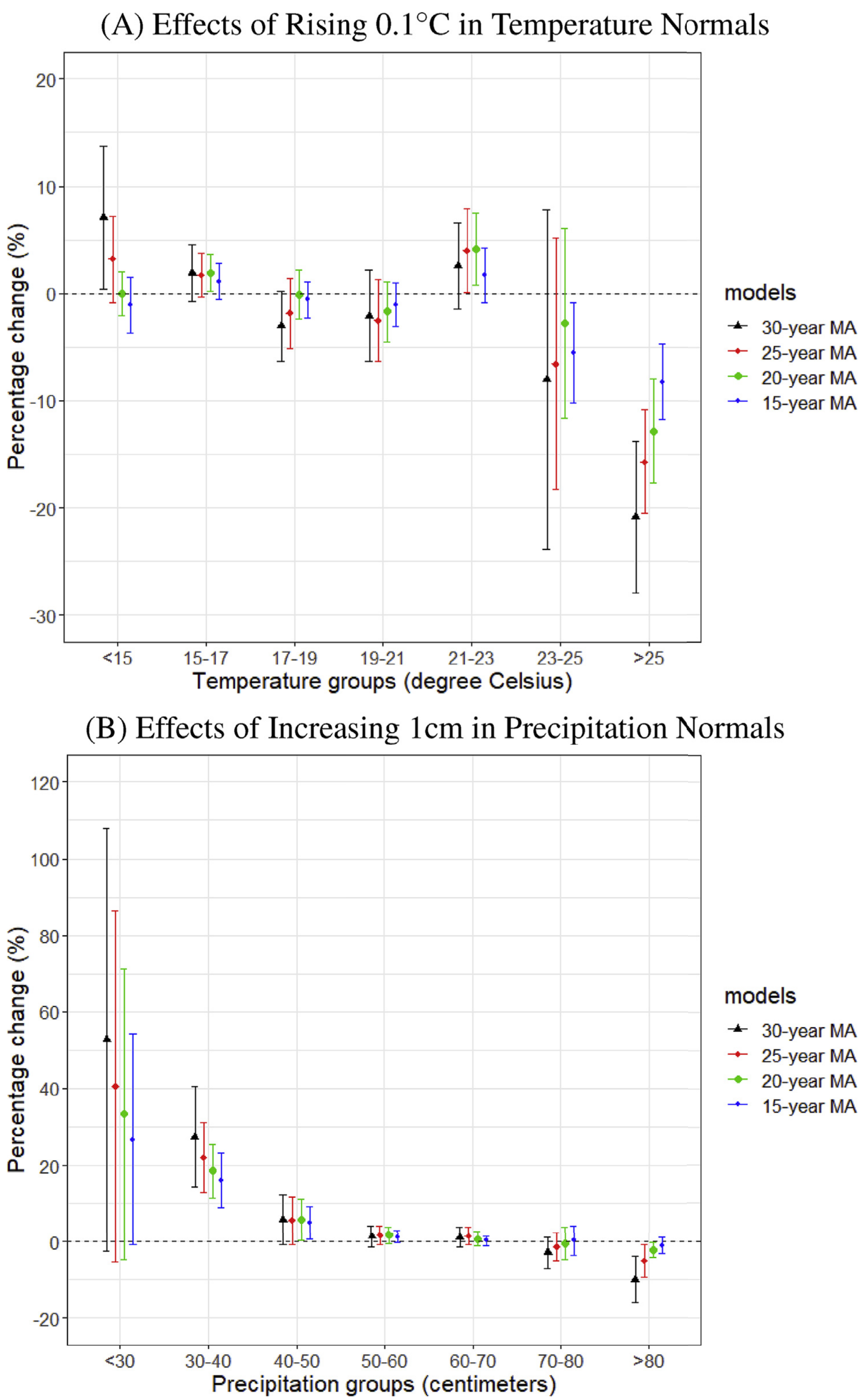

Fig. 6. Robust results of different time lengths for forming climate normals. *Notes:* Results are obtained from implementing equation (2) using various time lengths for constructing climate normals. Four time lengths are considered: 30 years, 25 years, 20 years, and 15 years. Each set of coefficients is presented in a unique color, as labeled in the legend. The markers represent point estimates and the error bars represent 95% confidence intervals based on state-clustered standard errors. See Appendix Table 6 for numerical results.

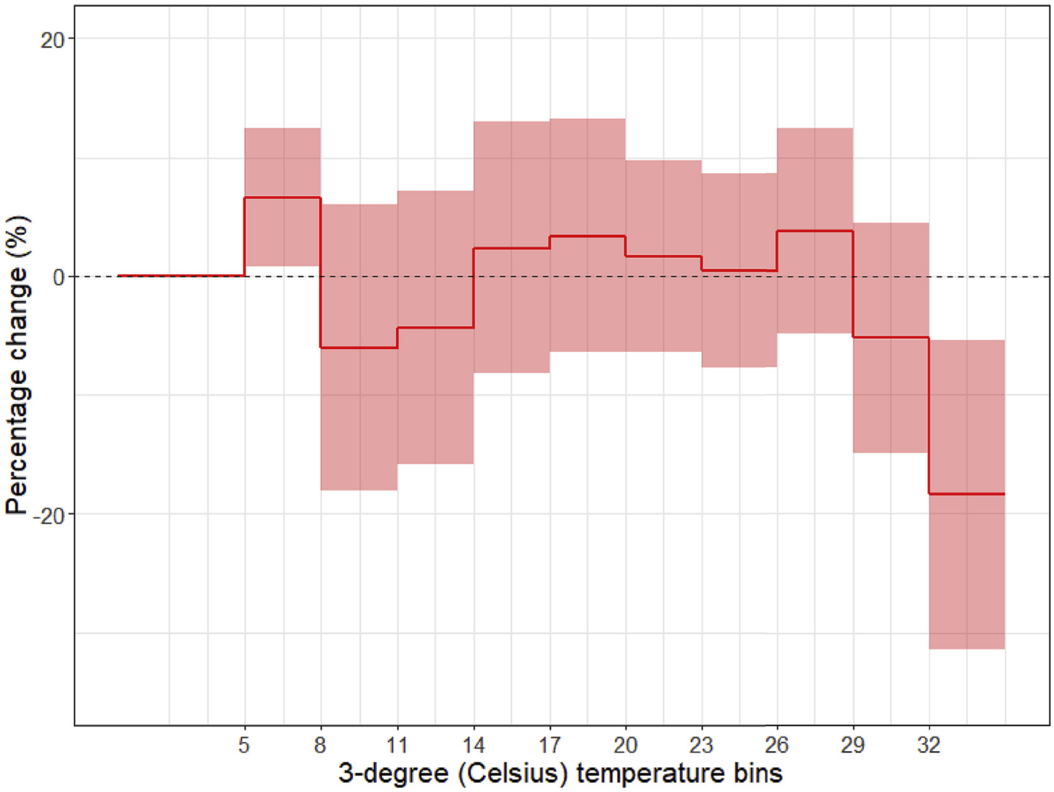

Fig. 7. Marginal effects of changing the normals of heat distribution. *Notes:* Estimates are obtained from the regression of equation (5). The dark line indicates estimated coefficients for different temperature bins, and the shallow band represents 95% confidence intervals constructed based on state-clustered standard errors. See Appendix Table 7 for numerical results.

where the group-specific average temperature normals in equation (2) are replaced by normals of the temperature bins, $\widetilde{Tbin}_j$, which account for the 30-year averages of the number of days with daily temperature falling into the jth temperature bin. The following temperature bins are considered: 5–8 °C, 8–11 °C, 11–14 °C, 14–17 °C, 17–20 °C, 20–23 °C, 23–26 °C, 26–29 °C, 29–32 °C, and above 32 °C. For example, the lowest bin variable $\widetilde{Tbin}_{it,1}$ is formed by averaging the number of days with daily temperature falling in the range of 5–8 °C over the 30 years preceding year t in county i.

The estimated coefficient β_j is interpreted as follows. If the 30-year average of the days with daily temperature within the jth bin increases by one, the associated change in acreage is β_j.[16] For example, as shown in Fig. 7, if the 30-year average of the days with daily temperature between 5 and 8 °C increases by one day, the associated change in corn and soybean acres is a statistically significant 6.6%. Warming at the low-temperature range implies that suitable weather condition for sowing corn and soybeans arrives earlier. Considering the relatively high profitability of corn and soybeans among the crop mix in cool areas, the feasibility of growing corn and soybeans allowed by a longer growing season under warming may incentivize growers to increase their planted acres of corn and soybeans. This result also aligns with the positive effect of temperature normals in the cool area found in the baseline result.

Conversely, if the 30-year average of the days with daily temperature higher than 32 °C increases by one day, corn and soybean acreage will be reduced by 18.4%. This finding is also consistent with the negative effects of temperature normals identified for hot regions in the baseline model. In these regions, an increase in excessive heat damages corn and soybeans much more than some other crops, causing corn and soybean acres to contract. The estimated coefficient for the 29–32 °C bin is negative but not statistically significant, reflecting that exposure to heat slightly above the critical threshold for yield does not necessarily lead to an acreage shift away from corn and soybeans. This may suggest the induced reduction in corn and soybean yields is not sufficiently large.

Major distinctions exist in the interpretation of these results in contrast to the qualitatively similar estimates of yield responses that appear in the literature. First, the estimated responses in Fig. 7 are responses to changes in 30-year moving averages instead of year-by-year fluctuations. These estimates characterize how the normals of within-season heat distribution based on observations over a long period, namely 30 years, affect the planting decision for corn and soybeans. Second, an impor-

[16] Because the bin with temperature below 5 °C is omitted from the model, it naturally serves as the reference. So the estimated β_j characterizes the marginal effect relative to the effect of exposing to temperature below 5 °C.

tant driving force of the induced acreage is the relative change in crop productivity. This also explains why warming effects are not significant over most temperature bins, as the relative effect of additional heat accumulation over these temperature ranges is not significantly larger on corn and soybeans than on other alternatives. Although these bin estimates are helpful in supporting the main finding, the baseline estimates are preferred as they are more intuitive and easier to interpret as elasticities.

6. Acreage elasticities and the magnitudes of climate impacts

Obtaining elasticities or semi-elasticities is essential for many empirical studies related to land use.[17] Therefore, I construct simple metrics of corn and soybean acreage elasticities with respect to climate based on the preferred estimates. Two metrics are calculated to measure how the planted acres of corn and soybean respond to a uniform change in temperature normals and precipitation normals, respectively.

$$\text{Temperature elasticity of acreage} = \frac{\sum_i \widehat{\beta}_j \times \overline{A}_{i,2011-15} \times \mathbf{1}(i \in \{\text{group } j\})}{\sum_i \overline{A}_{i,2011-15}}, \tag{6}$$

$$\text{Precipitation elasticity of acreage} = \frac{\sum_i \widehat{\gamma}_k \times \overline{A}_{i,2011-15} \times \mathbf{1}(i \in \{\text{group } k\})}{\sum_i \overline{A}_{i,2011-15}}. \tag{7}$$

$\widehat{\beta}_j$ and $\widehat{\gamma}_k$ refer to the preferred estimates obtained from equation (2). These group-specific temperature or precipitation coefficients are multiplied with the county-level base acres of corn and soybeans, $\overline{A}_{i,2011-15}$, formed by averaging county-level planted acres of corn and soybeans over 2011–2015 to represent the most recent status. The calculated acreage changes are then aggregated across all counties, and the semi-elasticities are obtained by dividing the aggregated acreage changes by the aggregated base acres. The results show that, evaluated at the 2011–2015 period, the semi-elasticities are −0.9% for a 0.1 °C increase in temperature normals and 4.0% for a 1 cm increase in precipitation normals, respectively.[18]

To contextualize the magnitude of these climate elasticities, I compare them with price elasticities estimated in the literature. A direct comparison is not feasible since my estimates are essentially semi-elasticities. To get around this issue, I gauge the magnitude of the estimated elasticities by referring to the temporal variability of climate normals and prices over the sample period. I first calculate the standard deviation of climate normals in each county, which reflects the extent of temporal variability of local climate. The mean of these county-level standard deviations is about 0.10 °C for temperature normals and 1.35 cm for precipitation normals, respectively. Combining these values with the estimated semi-elasticities implies that a one standard-deviation variation in temperature normals is associated with about −0.9% in acreage, and a one standard-deviation variation in precipitation normals is associated with about 5.4% in acreage.[19] It suggests that acreage is more responsive to precipitation normals than to temperature normals.

Utilizing the same strategy, I calculate the standard deviation of real received crop prices in each state, given that the received prices are only available at the state level. The mean of the standard deviation is 1.24 US dollars for corn and 2.49 US dollars for soybeans. Measured over the mean prices of corn and soybeans, a one standard deviation in price roughly equals a 30% price change for both crops.[20] A survey of the literature shows that the own-price acreage elasticities for corn and soybeans range from 0.05 to 0.95. Using 0.50 for a rough calculation, a one standard-deviation variation in crop price roughly translates into a 15% change in acreage, much higher than the effect of a one standard-deviation change in climate normals. It shows that acreage is less responsive to climate normals than to prices.

There are several key points to note regarding the interpretation of these climate elasticities. First, these elasticities reflect corn and soybean acreage responsiveness to long-run change in climate rather than short-run fluctuation in weather. One should use these elasticities for projections only when evaluating climate change impacts over long periods like a few decades. Although the occurrence of weather extremes may mechanically drive climate normals to vary in a short time frame, applications of the estimated elasticities are inappropriate for predictions in a short-run context. Moreover, these elasticities should be viewed as local estimates as they can be sensitive to the choice of the evaluation period. If the projected climate to be evaluated is far beyond the range of observed actual climate, extrapolating these elasticities is likely subject to serious external validity concerns.

To provide some more context on the overall impact of climate change on corn and soybean acreage, I apply a back-of-the-envelope calculation on the aggregate corn and soybean acreage change that is induced by climate change over the past 30 years. To obtain this quantitative measure, I first calculate the county-specific rate of change in corn and soybean acreage that

[17] Relying on estimating supply elasticities, an early strand of literature focuses on farm program evaluation (e.g., Morzuch et al., 1980; Chavas et al., 1983; Lee and Helmberger, 1985), and a more recent literature studies implications of the bio-fuel mandate (e.g., Roberts and Schlenker, 2013; Hendricks et al., 2014; Miao et al., 2016).

[18] This calculation is based on all climate coefficients. When only using significant coefficients, the corresponding temperature and precipitation semi-elasticities are 0.2% and 2.2%, respectively.

[19] These two numbers will become 0.2% and 3.0% if acreage elasticities are calculated using only significant estimates in the baseline regression.

[20] The mean real prices are 3.94 and 8.97 US dollars for corn and soybeans, respectively. Dividing the obtained standard deviations by these numbers yields 31.45% and 27.74%, respectively.

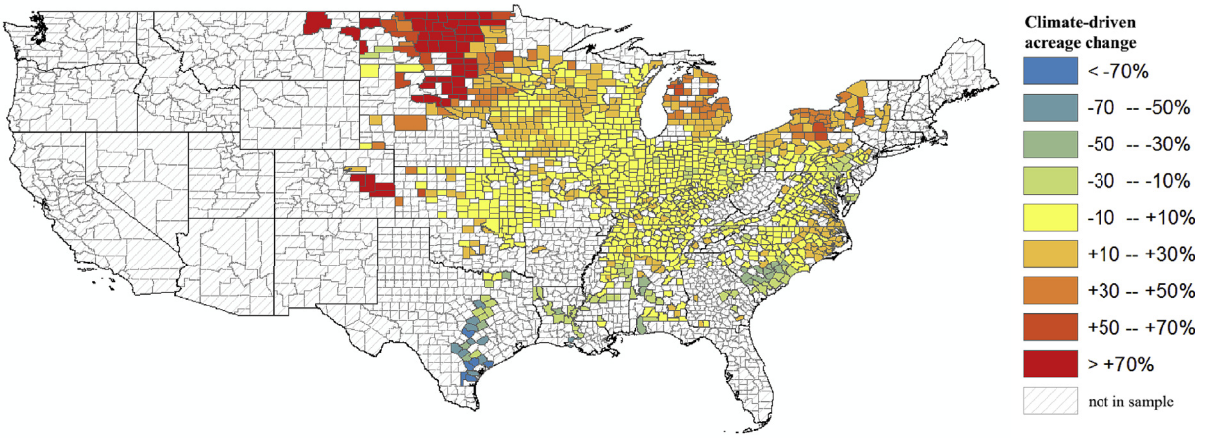

Fig. 8. County-specific corn and soybean acreage change induced by climate change: 1985–2015. *Notes:* The county-specific changing rate is calculated using equation (8).

is induced by climate change over the 1985–2015 time period, i.e.,

$$\Delta \log \widehat{A}_i = \widehat{\beta}_j(\widetilde{T}_{i2015,j} - \widetilde{T}_{i1985,j}) + \widehat{\gamma}_k(\widetilde{P}_{i2015,k} - \widetilde{P}_{i1985,k}), \tag{8}$$

where $\widetilde{T}_{it,j}$ and $\widetilde{P}_{it,k}$ are temperature and precipitation normals, as defined in equation (2).

Fig. 8 shows the distribution of county-specific acreage changes calculated from equation (8). Most of the corn and soybean expansion occurs in the northern area, especially around the Dakotas. Some mainstream newspapers have documented conjectures that rising temperature and increasing precipitation have induced more corn and soybean acres in this region, consistent with this empirical finding.[21]

To calculate the overall impact, the planted acres of corn and soybeans are averaged across 1981–1985 to form the base acreage for each county, $\overline{A}_{i,1981-85}$. The induced total acreage change is then calculated by aggregating county-specific percentage changes weighted by the base acreage, i.e., $\Delta\widehat{A}_{1985-2015} = \sum_i \Delta \log \widehat{A}_i \times \overline{A}_{i,1981-85}$. Since this calculation is based on the baseline estimates of the reduced-form relationship between acreage and climate normals, the calculated acreage change captures climate change impacts on corn and soybean acres through all potential channels.

Over this 30-year period, the climate-driven total acreage expansion of corn and soybeans within the sample equals to 6.8 million acres. It accounts for about 3.8% of the current US total acreage of corn and soybeans, and about 35% of the observed total expansion of 19.2 million acres over past 30 years.[22] I note that this number should be viewed as an upper bound since the calculation is based on all climate coefficients including those are statistically insignificant. If implementing this calculation with only the significant estimates, the climate-driven acreage expansion becomes 1.9 million acres, about 1.1% of the total corn and soybean acreage and 10% of the observed expansion over the past three decades.

7. Crop substitution induced by climate change

According to the US Census of Agriculture, since the late 1970s, the total cropland acreage has been decreasing while the share of corn and soybean acreage has been increasing, as shown in Appendix Fig. 2. This fact suggests that the effect of climate change on corn and soybean acreage is at least partly realized through substitution with other crops. To empirically examine the effects of climate change on crop substitution, I bring five additional US crops into consideration, including barley, spring wheat, winter wheat, sorghum, and cotton. These crops, plus corn and soybeans, account for about 75% of the total cropland acreage in the United States.[23]

I study how climate change affects corn and soybean planted acres relative to another major crop, rather than examining the acreage response of each alternative crop independently. The analysis aims to infer how climate change has altered the comparative advantage of corn and soybeans. It neither assumes away conversion between cropland and non-cropland, nor

[21] Examples include "US Corn Belt Expands to North" on June 13, 2013, in the *New York Times*, "Shifting Climate Has North Dakota Farmers Swapping Wheat for Corn" on August 13, 2014, on the *National Public Radio*, and others.

[22] The current US total acreage of corn and soybeans is about 180 million acres. The observed total expansion is calculated by differencing the aggregate planted acres of corn and soybeans over two periods: 1981–1985 and 2011–2015, i.e., $\sum_i \overline{A}_{i,2011-15} - \sum_i \overline{A}_{i,1981-1985}$.

[23] Hay is also an important field crop. Unlike other major field crops, hay can be harvested multiple times in a year. Accurate data on its planted acres are not available.

precludes acreage shifts among the alternative crops. Specifically, the regression equation is:

$$\frac{A_{it}^{corn} + A_{it}^{soy}}{A_{it}^{corn} + A_{it}^{soy} + A_{it}^{alt}} = \beta_j \widetilde{T}_{it,j} + \gamma_k \widetilde{P}_{it,k} + \alpha_i + \delta_t + h_r(t) + \varepsilon_{it}, \tag{9}$$

where A_{it}^{alt} is the planted acreage of a specific alternative crop, and other terms follow equation (2). The identification rests on the underlying assumption that a county's relative acres of corn and soybeans with respect to the alternative crop would have changed in a similar way, had the county experienced the same change in climate normals as in other counties, after controlling for state-level trends and nation-level shocks.

The dependent variable is a ratio, 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. Including corn and soybean acres into the denominator guarantees that the ratio is bounded between zero and one, and the estimated marginal effects can be interpreted as proportional changes. Each regression 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 where the alternative crop has been planted.[24]

Results are shown in Fig. 9. The coefficients and 95% confidence intervals estimated from equation (9) are plotted in black. Alongside these estimates, I plot estimates obtained by using a richer set of state-by-year fixed effects in blue, as a robustness check. Each panel presents estimated temperature or precipitation coefficients from the regression equation for a specific alternative crop. The coefficient is interpreted as the proportional acreage change of corn and soybeans relative to the alternative crop, induced by a marginal change in temperature or precipitation normals within a certain temperature or precipitation group. The crop geography implies that some alternative crops are not grown everywhere, resulting in missing coefficients of certain temperature and precipitation groups for some crops.[25]

Barley and spring wheat are grown primarily in the northern region. Rising temperature does not significantly affect corn and soybean acres relative to barley, but significantly increases acres of corn and soybean relative to spring wheat. In the temperature groups of 15–17 °C and 17–19 °C, a 0.1 °C increase in temperature normals will increase corn and soybean planted acres by about 3.0% relative to spring wheat.

More precipitation is shown to favor corn and soybean acres relative to both barley and spring wheat in dry areas with cumulative precipitation below 50 cm. A 1 cm increase in precipitation normals is associated with as high as a 3.6% proportional increase in corn and soybean acres relative to barley, and a 7.1% proportional increase relative to spring wheat. However, a 1 cm increase in precipitation normals will decrease corn and soybean acres relative to spring wheat by 2.4% in places where the initial precipitation normals have been higher than 50 cm.

Winter wheat spreads across the United States, partly overlapping with the Corn Belt. The results indicate that a 0.1 °C rising temperature decreases corn and soybean acres relative to winter wheat by about 0.9% in the 21–23 °C temperature group, and a 1 cm higher precipitation increases them by about 0.9% in the 60–70 cm precipitation groups. Effects in other temperature or precipitation groups are not statistically significant.

Most rain-fed sorghum and cotton is grown in the southern region. Higher temperature generally decreases corn and soybean acres relative to sorghum. The magnitude of the effects varies from zero to 5.4%. Changes in precipitation normals do not factor into the relative acres of corn and soybeans with respect to sorghum. There is no evidence that corn and soybean acres relative to cotton respond to changes in temperature normals. But a 1 cm increase in precipitation normals in the 70–80 cm precipitation group significantly increases corn and soybean acres relative to cotton by 2.7%.

The acreage dynamics estimated above tie closely to the bio-physical characteristics of these crops, since climatic factors influence planting decisions through their anticipated impacts on crop productivity, holding prices constant. It is worth emphasizing that the estimated effects are all in relative terms with respect to the alternative crop. If a climatic change has incurred an impact on the profitability of the alternative crop similar to that of corn and soybeans, no effect would have been detected on the relative acreage between them.

In cool areas, where spring wheat has been mostly grown, warming implies additional heat accumulation that could make planting corn and soybeans profitable. However, in warm areas, rising temperature will depress corn and soybean growth more than crops that are relatively more heat-resistant, like winter wheat and sorghum in the southern region. Cotton can also bear more heat than corn and soybeans, but the higher switching cost of cotton, compared to sorghum and winter wheat, reduces the likelihood of switching from corn and soybeans to cotton, as indicated by the statistically insignificant temperature estimates in the cotton estimation.

Changes in precipitation affect the profitability of crops differently as water requirement differs across crops. 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. In wet areas, more precipitation favors corn and soybean acres relative to winter wheat and cotton. But these effects are likely based on different reasons. The peak water-use stage for winter wheat only marginally overlaps with the growing season of corn and soybeans. Too much water during this period may impose higher yield risks for winter wheat than for corn and soybeans. For cotton, excessive rainfall may damage cotton bolls before harvesting, but this problem does not apply to corn and soybeans. These facts imply

[24] To avoid results driven by marginal counties, the regression is restricted to counties that have planted the alternative crops for at least 20 years, consistent with the rule in implementing equation (2).

[25] For example, the cotton regression is only implemented for southern counties, so that some lower temperature groups are nonexistent.

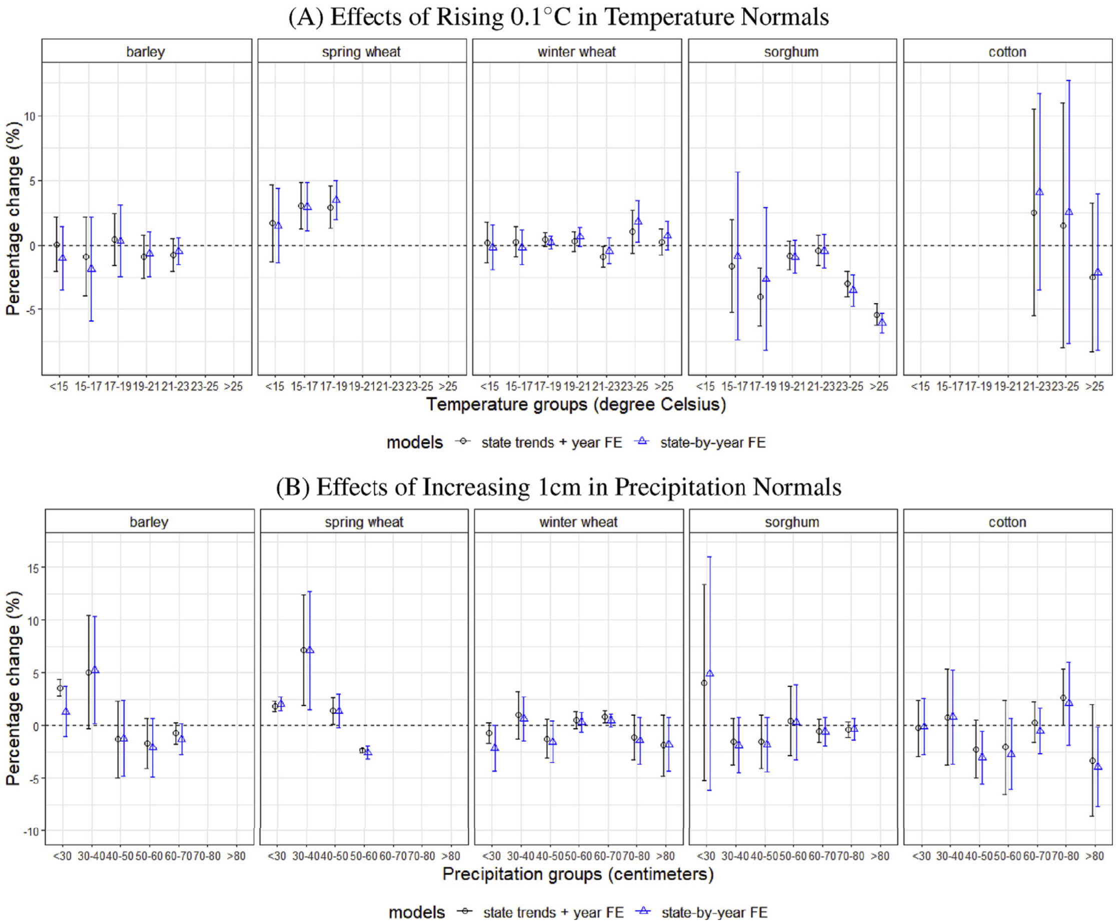

Fig. 9. Climate change impacts on the relative acres of corn and soybeans to other major crops. *Notes:* Results are obtained from implementing equation (9) for each alternative crop. Markers represent point estimates and error bars represent 95% confidence intervals constructed based on state-clustered standard errors. Panels in the first (second) row display estimates of temperature (precipitation) normals. In each row, each panel corresponds to the estimates regarding a specific alternative crop, as indicated by the top label. See Appendix Tables 8 and 9 for numerical results.

that corn and soybeans are more advantageous when precipitation increases in places that typically received adequate rainfall. The statistical insignificance of higher precipitation-group estimates likely results from a lack of variation in these groups, as only a few counties are included.

The crop substitution effects partly explain the corn and soybean acreage response to climate change. In cool areas, substituting for spring wheat may have contributed to some of the warming-induced corn and soybean expansion. In warm areas, the relative increase in sorghum likely factors into the induced reduction of corn and soybeans under a higher temperature. The precipitation-boosting effect in dry areas can be traced to the substitution from barley and spring wheat to more corn and soybeans. However, the induced substitution effects regarding the five studied crops do not provide much information on the negative corn and soybean acreage response to more precipitation in wet areas. This may reflect the phenomenon that winter wheat, sorghum, and cotton all experience contracted acres in a relatively similar magnitude to corn and soybeans when precipitation is increasing in the wettest region.

8. Heterogeneity in acreage response to climate change

8.1. Major and minor producing areas

Corn and soybean acreage response to climate change could be different for major and minor producing regions. Minor regions may have more land available for conversion into corn and soybeans when climate becomes more favorable to these crops. However, major regions could also be more responsive considering the infrastructure they already have for activities related to corn and soybean production. To examine the potential heterogeneity across major and minor producing regions, I conduct sub-sample regressions for two sets of counties using the baseline specification.

I divide the full sample into two sub-samples based on the average planted acres of corn and soybeans from 1981 to 2015. To preserve marginal counties in this analysis, I do not exclude counties planted corn and soybeans for less than 20 years from this analysis. I use 30 thousand acres as the sample division cutoff as it is the round number most close to the median. I consider the counties above this cutoff as major areas and the rest as minor areas.

Fig. 10 presents the results for the two sub-sample regressions. Because major areas do not contain counties with initial precipitation normals below 30 cm, the major area's coefficient corresponding to that precipitation group is not estimated. The results show that warming-induced acreage expansion in the cool region is mostly driven by major producing areas. A 0.1 °C increase in temperature normals will induce a 18.4% expansion in major areas in the coolest region, while the effect on minor areas in the same region is only about 3.4% and statistically insignificant. In the hottest region, the warming-induced acreage reduction is slightly smaller in major areas than in minor areas.[26]

These differentiated temperature effects suggest that major areas are more responsive to warming in the cool region, but slightly less responsive to warming in the hot region. Growers in the major areas tend to have more knowledge and experience in planting corn and soybeans, so that they may understand better the value of warming and therefore more willing to expand corn and soybean acres. The better infrastructure and industry service may also play a role in encouraging growers to plant more corn and soybeans. These advantages can also explain major areas' smaller response to warming in the hot region, as they are more equipped with coping ability to bear heat and therefore less incentivized to reduce acreage.

For precipitation effects, in the region with initial precipitation normals within 70–80 cm, more rainfall is shown to only decrease corn and soybean acres in minor areas. This may reflect the higher resilience to unfavorable climate in major areas as discussed above. The sharpest contrast between major and minor areas occurs in the region receiving the highest precipitation. For this most rainfall-abundant region, 1 cm increase in precipitation normals decrease corn and soybean acres by 9.6% in minor areas and 29.6% in major areas. However, this huge difference should be interpreted with caution as the variation for identifying the negative effect of 29.6% only comes from six counties scattered in four states.

The heterogeneous responses across major and minor producing areas provide some suggestive evidence on the different incentives in acreage adjustments to the changing climate. The difference in incentives may also reflect different adjustment costs faced by major and minor areas. In particular, the warming-induced acreage expansion in the cool region is very limited in minor producing areas. This finding suggests that specific policy arrangements may be needed to lower the costs and ease the obstacles for acreage expansion in these places as an effort to facilitate adaptation.

8.2. Dryland and irrigated areas

The paper focuses on non-irrigated counties since they constitute the majority of corn and soybean producing areas. According to various USDA reports, irrigated acreage roughly accounts for only 10% of the total corn and soybean acreage in the United States. However, for these irrigated areas, irrigation will change how crop yields respond to changes in temperature and precipitation (Cline, 1996; Mendelsohn and Dinar, 2003; Schlenker et al., 2005; Tack et al., 2012), which likely leads to climate change adaptation different from that in the dryland.

To infer the differentiated adaptation in irrigated areas, I draw on a subset of counties where detailed data on irrigated acreage are available. The USDA provides county-level irrigated harvested acres of corn and soybeans for a set of states.[27] Using these data, I empirically examine how irrigated acreage of corn and soybeans responds to climate change using the baseline specification. Since the irrigated acreage information is based on the harvested rather than the planted, I control for weather in the current growing season to isolate contemporaneous weather effects.

Fig. 11 plots the estimates for the irrigated alongside the baseline estimates for the dryland. Some estimates for the irrigated regression do not exist because the irrigated sample does not cover those areas.[28] The temperature coefficients for the irrigated are not substantially different from the dryland. However, the temperature effect in the coolest area becomes barely significant, which could be due to the smaller sample size for the irrigated. The other temperature coefficients are statistically insignificant, similar to those dryland estimates. The precipitation effects are very different in the irrigated, compared with the dryland. In dry areas, an increase in precipitation normals no longer increases corn and soybean acreage when irrigated. This finding suggests that irrigation has provided sufficient water for growing preferred crops in the dry area so that additional rainfall does not alter the relative advantage of growing corn and soybeans.

The limited response of irrigated acreage to climate change is in sharp contrast with the significant acreage response in dryland agriculture, especially regarding the precipitation effects. This finding also has important implications for policy discussions. For crop production, irrigation serves as a local adaptation to climate change along the intensive margin (i.e., yield) as it largely isolates the linkage between rainfall and crop growth. However, this local adaptation in turn refrains the grower from making adjustments on the extensive margin (e.g., adjusting crop acreage and location). This situation may increase agri-

[26] Warming in the region with initial temperature normals between 17 and 19 °C significantly reduces corn and soybean acres in minor areas. Since the identifying variation for this specific coefficient mostly comes from the region near West Virginia, Virginia, and North Carolina, this negative estimate likely reflects a higher relative return of warming in producing other cash crops (e.g., apples and tobacco).

[27] Details of the data are included in Appendix Section 1. Also see Appendix Table 11 for summary statistics.

[28] There is only one county with initial temperature normals above 25 °C, and only one county with initial precipitation within 70–80 cm. I categorize these two counties into the 23–25 °C and 60–70 cm groups, respectively.

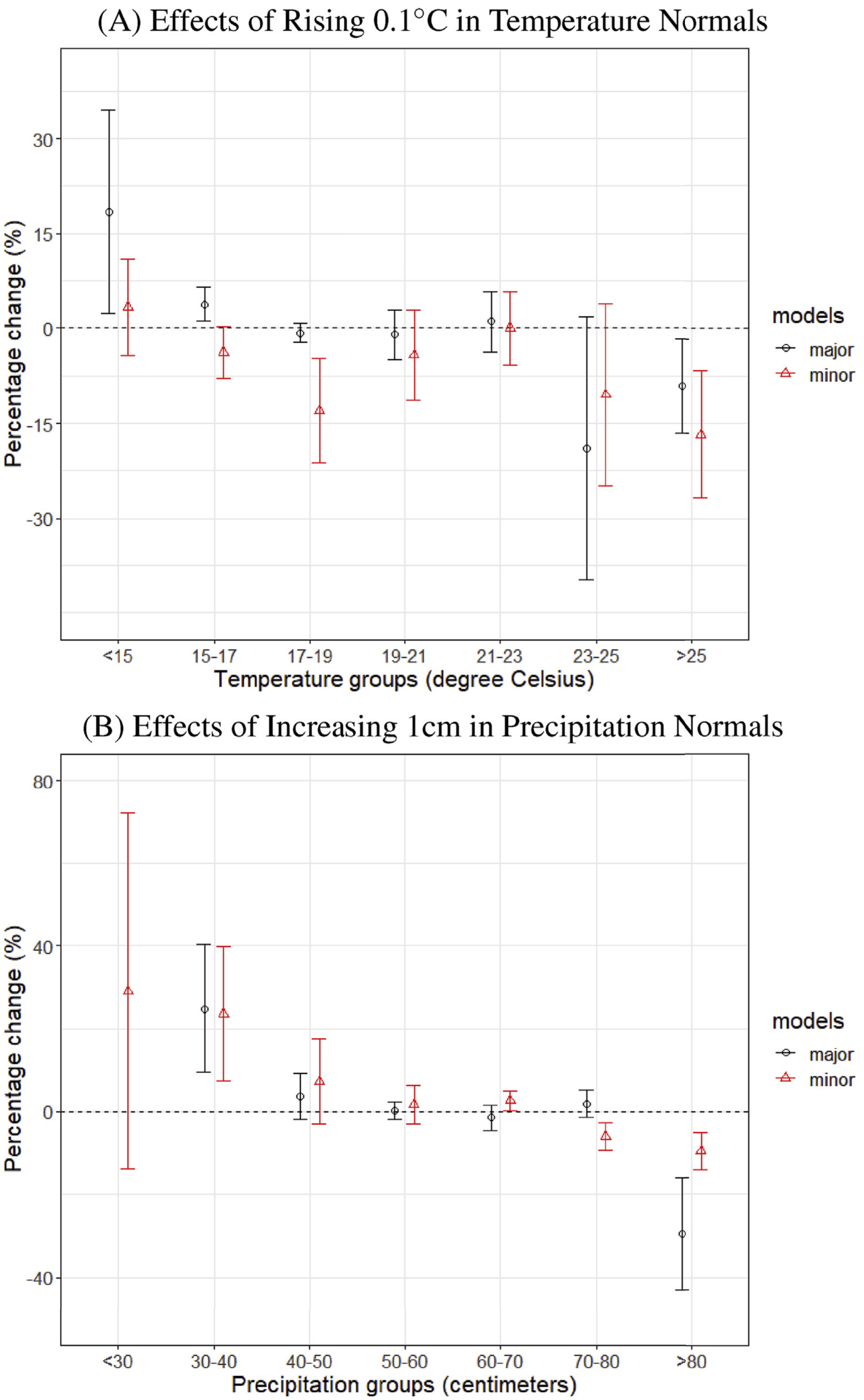

Fig. 10. Corn and soybean acreage response: Heterogeneity between major and minor producing areas. *Notes:* Results are obtained from estimating equation (2) on two subsamples including counties with average corn and soybean planted acres above and below 30,000 acres. The markers represent point estimates and the error bars represent 95% confidence intervals based on state-clustered standard errors. See Appendix Table 10 for numerical results.

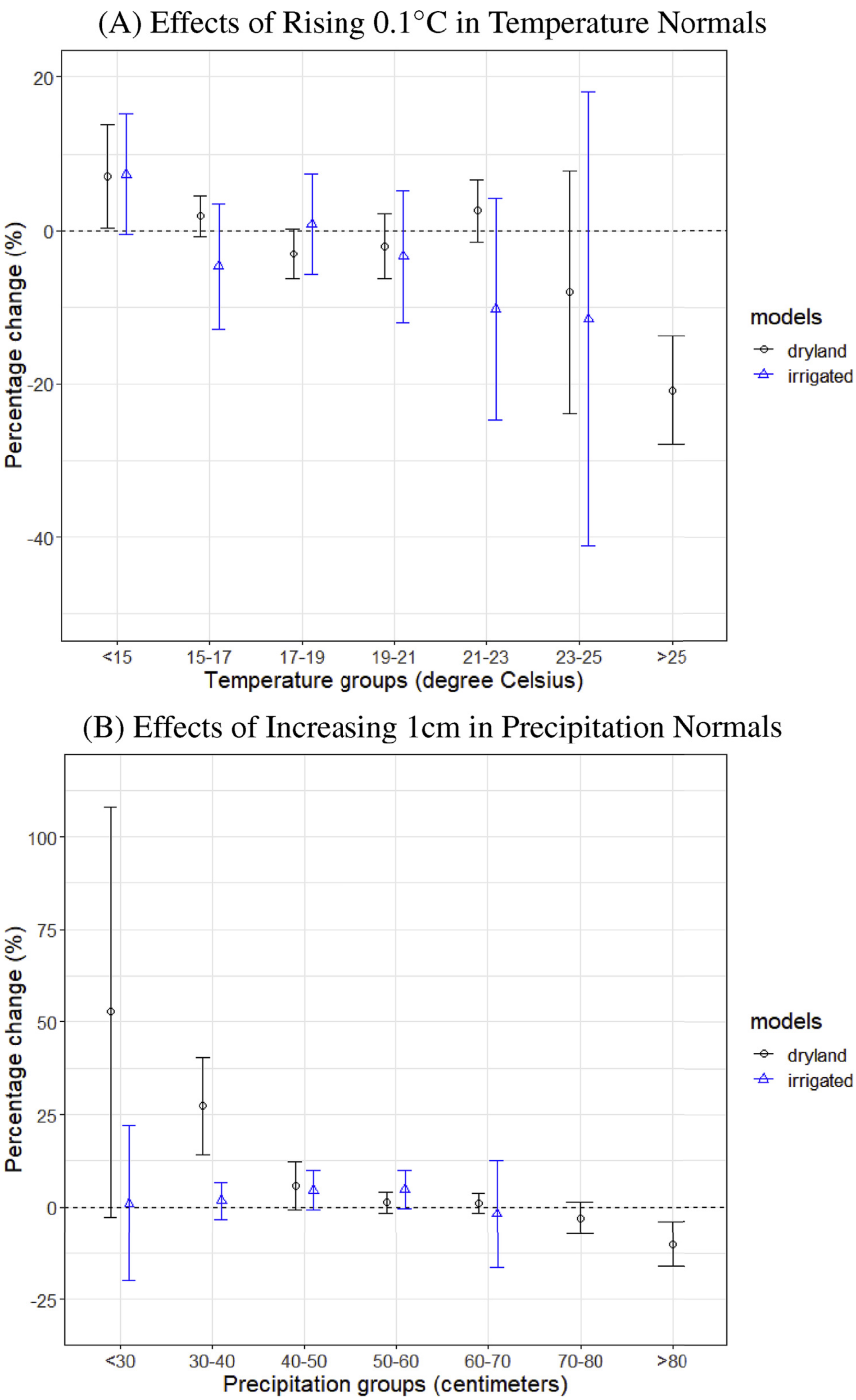

Fig. 11. Estimated climate effects on corn and soybean acreage: Comparing dryland with irrigated. *Notes:* The markers represent point estimates and the error bars represent 95% confidence intervals based on state-clustered standard errors. Dryland estimates replicate the baseline estimates. Irrigated estimates are obtained from implementing equation (2) on irrigated harvested acres with additional controls of current weather. See Appendix Table 12 for numerical results of the irrigated estimates.

culture's vulnerability in the long run. On one hand, climate change may exacerbate the dependence on irrigation, especially on groundwater resources. On the other hand, groundwater may not be sustainable for many aquifers in the United States as the recharge has not been meeting the extraction. The path dependence in water institutions as well as the heavy subsidies on groundwater can further amplify these issues.

9. Conclusion

The recent literature on climate change impacts on agriculture predominately focuses on measuring responses of crop yields, but the role of acreage adjustments has been largely overlooked. This paper examines how climate change, represented by temporal variation in decades-long weather averages, has affected planted acres of the two leading crops in the United States. The induced adjustments in planted acres are significant in rainfed agriculture. Rising temperature and precipitation positively affect corn and soybean acreage in cool and dry areas, but the effects are reversed in hot and wet areas. These effects on corn and soybean acreage are partly realized through acreage substitution with other major crops.

I construct semi-elasticities of corn and soybean acreage with respect to climate based on the reduced-form estimates. The obtained semi-elasticities suggest that acreage is more responsive to long-run change in precipitation than temperature, and the responsiveness of acreage to changing climate is smaller than to changing prices. However, the persistency in climate change still leads to substantial adaptation in corn and soybean production through acreage adjustments. Retrospectively, the estimates suggest that, over the past 30 years, about 10–35% of the observed total expansion in corn and soybean acreage can be explained by the realized climate change. The finding is also consistent with the historical observation on strong adaptability in crop planting in the United States (Olmstead and Rhode, 2011).

The acreage response of corn and soybeans is found to be heterogeneous across major and minor producing areas and across dryland and irrigated areas. These findings shed light on policy discussions on future climate change adaptation. Better infrastructure related to corn and soybean production may help reduce the cost of acreage expansion in response to climate change in certain areas. However, irrigation, as a local adaptation, may hinder adaptation through adjustments on crop acreage and crop location, potentially increasing vulnerability of agricultural production under future climate.

This study has some limitations. Rather than fully decomposing the environmental, technological, and socioeconomic drivers of the changing cropping patterns, the analysis focuses on the reduced-form relationship between climate change and crop acres. Understanding the relative importance of different drivers may require imposing more structure on the estimation. 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 relative acreage ratios. Future research should incorporate data that are more disaggregated. Additionally, this paper considers a limited number of field crops beyond corn and soybeans. Studying the acreage effects on other crops and grazing may provide further insights for understanding how climate affects the US agricultural landscape.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jeem.2020.102306.

References

Adams, Richard M., Rosenzweig, Cynthia, Peart, Robert M., Ritchie, Joe T., McCarl, Bruce A., Glyer, J David, Bruce Curry, R., Jones, James W., Boote, Kenneth J., Allen, L Hartwell, 1990. Global climate change and US agriculture. Nature 345 (6272), 219–224.
Arlot, Sylvain, Celisse, Alain, 2010. A survey of cross-validation procedures for model selection. Stat. Surv. 4, 40–79.
Askari, Hossein, Cummings, John Thomas, 1977. Estimating agricultural supply response with the Nerlove model: a survey. Int. Econ. Rev. 257–292.
Auffhammer, Maximilian, Baylis, Patrick, Hausman, Catherine H., 2017. Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States. In: Proceedings of the National Academy of Sciences 201613193.
Auffhammer, Maximilian, Hsiang, Solomon M., Schlenker, Wolfram, Adam, Sobel, 2013. Using weather data and climate model output in economic analyses of climate change. Rev. Environ. Econ. Pol. 7 (2), 181–198.
Barrows, Geoffrey, Sexton, Steven, Zilberman, David, 2014. Agricultural biotechnology: the promise and prospects of genetically modified crops. J. Econ. Perspect. 28 (1), 99–119.
Blanc, Elodie, Schlenker, Wolfram, 2017. The use of panel models in assessments of climate impacts on agriculture. Rev. Environ. Econ. Pol. 11 (2), 258–279.
Burke, Marshall, Emerick, Kyle, 2016. Adaptation to climate change: evidence from US agriculture. Am. Econ. J. Econ. Pol. 8 (3), 106–140.
Burke, Marshall, Hsiang, Solomon M., Miguel, Edward, 2015. Global non-linear effect of temperature on economic production. Nature 527 (7577), 235–239.
Carter, Colin, Cui, Xiaomeng, Ghanem, Dalia, Mérel, Pierre, 2018. Identifying the economic impacts of climate change on agriculture. Ann. Rev. Resour. Econ. 10, 361–380.
Chavas, Jean-Paul, Pope, Rulon D., Kao, Robert S., 1983. An analysis of the role of futures prices, cash prices and government programs in acreage response. J. Agric. Resource Econ. 27–33.
Chen, Shuai, Chen, Xiaoguang, Xu, Jintao, 2016. Impacts of climate change on agriculture: evidence from China. J. Environ. Econ. Manag. 76, 105–124.
Cline, William R., 1996. The impact of global warming of agriculture: comment. Am. Econ. Rev. 1309–1311.
Cohn, Avery S., VanWey, Leah K., Spera, Stephanie A., Mustard, John F., 2016. Cropping frequency and area response to climate variability can exceed yield response. Nat. Clim. Change 6 (6), 601–604.
Costinot, Arnaud, Donaldson, Dave, Smith, Cory, 2016. Evolving comparative advantage and the impact of climate change in agricultural markets: evidence from 1.7 million fields around the world. J. Polit. Econ. 124 (1), 205–248.
Cui, Xiaomeng, Ghanem, Dalia, Todd, Kuffner, 2018. On Model Selection Criteria for Climate Change Impact Studies. arXiv preprint arXiv:1808.07861.
Deschênes, Olivier, Greenstone, Michael, 2007. The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. Am. Econ. Rev. 354–385.

Gammans, Matthew, Mérel, Pierre, Ortiz-Bobea, Ariel, 2017. Negative impacts of climate change on cereal yields: statistical evidence from France. Environ. Res. Lett. 12 (5), 054007.
Goodwin, Barry K., Vandeveer, Monte L., Deal, John L., 2004. An empirical analysis of acreage effects of participation in the federal crop insurance program. Am. J. Agric. Econ. 86 (4), 1058–1077.
Gouel, Christophe, Laborde, David, 2018. The Crucial Role of International Trade in Adaptation to Climate Change. National Bureau of Economic Research Working Paper 25221.
Hendricks, Nathan P., Smith, Aaron, Sumner, Daniel A., 2014. Crop supply dynamics and the illusion of partial adjustment. Am. J. Agric. Econ. 96 (5), 1469–1491.
Hennessy, David A., 2006. On monoculture and the structure of crop rotations. Am. J. Agric. Econ. 88 (4), 900–914.
Hsiang, Solomon, 2016. Climate econometrics. Ann. Rev. Resour. Econ. 8, 43–75.
IPCC, 2014. Climate Change 2014: Synthesis Report. Intergovernmental panel on climate change. IPCC Secretariat Geneva.
Just, Richard E., Schmitz, Andrew, Zilberman, David, 1979. Technological change in agriculture. Science 206 (14), 1277–1280.
Kurukulasuriya, Pradeep, Mendelsohn, Robert, 2007. Crop Selection: Adapting to Climage Change in Africa. The World Bank 4307.
Kuwayama, Yusuke, Thompson, Alexandra, Bernknopf, Richard, Zaitchik, Benjamin, Vail, Peter, 2018. Estimating the impact of drought on agriculture using the US drought monitor. Am. J. Agric. Econ. 101 (1), 193–210.
Lee, David R., Helmberger, Peter G., 1985. Estimating supply response in the presence of farm programs. Am. J. Agric. Econ. 67 (2), 193–203.
Lee, Hyunok, Sumner, Daniel A., 2015. Economics of downscaled climate-induced changes in cropland, with projections to 2050: evidence from Yolo County California. Climatic Change 132 (4), 723–737.
Libecap, Gary D., 2011. "Institutional path dependence in climate adaptation: Coman's" Some unsettled problems of irrigation". Am. Econ. Rev. 101 (1), 64–80.
Melillo, Jerry M., Richmond, T.T., Yohe, G., 2014. Climate Change Impacts in the United States: Third National Climate Assessment. US Global Change Research Program.
Mendelsohn, Robert, Dinar, Ariel, 2003. Climate, water, and agriculture. Land Econ. 79 (3), 328–341.
Mendelsohn, Robert O., Massetti, Emanuele, 2017. The use of cross-sectional analysis to measure climate impacts on agriculture: theory and evidence. Rev. Environ. Econ. Pol. 11 (2), 280–298.
Mendelsohn, Robert, Nordhaus, William D., Shaw, Daigee, 1994. The Impact of Global Warming on Agriculture: A Ricardian Analysis, pp. 753–771 American Economic Review.
Miao, Ruiqing, Khanna, Madhu, Huang, Haixiao, 2016. Responsiveness of crop yield and acreage to prices and climate. Am. J. Agric. Econ. 98 (1), 191–211.
Moore, Frances C., Lobell, David B., 2014. Adaptation potential of European agriculture in response to climate change. Nat. Clim. Change 4 (7), 610.
Morzuch, Bernard, J., Weaver, R.D., Helmberger, P.G., 1980. Wheat acreage supply response under changing farm programs. Am. J. Agric. Econ. 62 (1), 29–37.
Nerlove, Marc, 1958. Distributed lags and estimation of long-run supply and demand elasticities: theoretical considerations. J. Farm Econ. 40 (2), 301–311.
Olmstead, Alan L., Rhode, Paul W., 2011. "Adapting North American wheat production to climatic challenges, 1839–2009. Proc. Natl. Acad. Sci. Unit. States Am. 108 (2), 480–485.
Roberts, Michael J., Schlenker, Wolfram, 2013. Identifying supply and demand elasticities of agricultural commodities: implications for the US ethanol mandate. Am. Econ. Rev. 103 (6), 2265–2295.
Schauberger, Bernhard, Archontoulis, Sotirios, Arneth, Almut, Balkovic, Juraj, Ciais, Philippe, Deryng, Delphine, Elliott, Joshua, Folberth, Christian, Khabarov, Nikolay, Müller, Christoph, et al., 2017. Consistent negative response of US crops to high temperatures in observations and crop models. Nat. Commun. 8, 13931.
Schlenker, Wolfram, Lobell, David B., 2010. Robust negative impacts of climate change on African agriculture. Environ. Res. Lett. 5 (1), 014010.
Schlenker, Wolfram, Roberts, Michael J., 2009. Nonlinear temperature effects indicate severe damages to US crop yields under climate change. In: Proceedings of the National Academy of Sciences, vol. 106, pp. 15594–15598 37.
Schlenker, Wolfram, Hanemann, W Michael, Fisher, Anthony C., 2005. Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. Am. Econ. Rev. 95 (1), 395–406.
Schlenker, Wolfram, Hanemann, W Michael, Fisher, Anthony C., 2006. The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions. Rev. Econ. Stat. 88 (1), 113–125.
Scott, Paul, 2013. Dynamic Discrete Choice Estimation of Agricultural Land Use. Toulouse School of Economics Working Paper 526.
Seo, S Niggol, Mendelsohn, Robert, 2008. An analysis of crop choice: adapting to climate change in South American farms. Ecol. Econ. 67 (1), 109–116.
Shao, Jun, 1993. Linear model selection by cross-validation. J. Am. Stat. Assoc. 88 (422), 486–494.
Shao, Jun, 1997. An asymptotic theory for linear model selection. Stat. Sin. 221–242.
Tack, Jesse, Harri, Ardian, Keith, Coble, 2012. More than mean effects: modeling the effect of climate on the higher order moments of crop yields. Am. J. Agric. Econ. 94 (5), 1037–1054.
Taraz, Vis, 2017. Adaptation to climate change: historical evidence from the Indian monsoon. Environ. Dev. Econ. 22 (5), 517–545.
USDA, 2016. National agricultural statistics service: quick stats. https://quickstats.nass.usda.gov/, (Accessed 10 August 2016).
USDA, 2017. USDA foreign agricultural serivce's global agricultural trade system: database. http://apps.fas.usda.gov/gats, (Accessed 8 November 2017).
Wang, Jinxia, Mendelsohn, Robert, Dinar, Ariel, Huang, Jikun, 2010. How Chinese farmers change crop choice to adapt to climate change. Clim. Change Econ. 1 (3), 167–185.
Weber, Elke U., Stern, Paul C., 2011. Public understanding of climate change in the United States. Am. Psychol. 66 (4), 315.
Welch, Jarrod R., Vincent, Jeffrey R., Auffhammer, Maximilian, Moya, Piedad F., Dobermann, Achim, Dawe, David, 2010. Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. In: Proceedings of the National Academy of Sciences, vol. 107, pp. 14562–14567 33.
Yu, Jisang, Smith, Aaron, Sumner, Daniel A., 2017. Effects of crop insurance premium subsidies on crop acreage. Am. J. Agric. Econ. 100 (1), 91–114.