How Large is the Potential Economic Benefit of Agricultural Adaptation to Climate Change?

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Although climate change may severely impact agriculture, farmers can mitigate it by adapting to their new climates. Using US data, we estimate the amount of potential loss in agricultural profits, due to climate change, that can be reduced by agricultural adaptation. We propose two panel frameworks that differ only in their fixed effects specifications, where this difference allows us to estimate the climate change impact on agricultural profits with or without adaptation taken into account. Comparing these estimates, we find that adaptation has the potential to offset about two-thirds of the end-of-this-century loss in agricultural profits potentially resulting from climate change. (JEL Q15, Q51, Q54)

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The fact that farmers can adapt to climate change by adjusting their agricultural practices to maximize profits makes it challenging for an econometrician to estimate the true negative impact that climate change might have on agriculture. If such adaptive responses were not considered, an econometric study could overestimate the true damage of climate change and its policy recommendation might be more aggressive than necessary. Since Mendelsohn, Nordhaus, and Shaw (1994), significant progress has been made on improving the methodology for estimating the impact of climate change while taking agricultural adaptation into account (Schlenker, Hanemann, and Fisher 2005, 2006, Kurukulasuriya and Mendelsohn 2008, Massetti and Mendelsohn 2011). However, despite these advances, little is known about how much agricultural adaptation can help to limit the damage of climate change on agriculture. Therefore, this paper aims to estimate the potential value of long-run adaptation, expressed by the mitigating effect that adaptation might have in reducing the potential loss of agricultural profits resulting from climate change.

From a policy perspective, having an estimate of this mitigating effect may enable us to appreciate how severe the implications of climate change truly are. Moreover, it may be useful for informing governments on the returns on assisting farmers adapt to climate change. Adaptation is not costless, and some adaptation measures may require large amounts of investments that farmers could not afford.[1] If financial markets are

[1] For example, warming may encourage a maize producing farmer to switch land use to citrus production, as it could be more profitable to produce citrus than maize in hot areas. However, this switching may involve large amount of investments including the years forgone while waiting for a sapling to mature into

unavailable for a farmer to borrow from, the costs of adaptation may hinder the farmer's ability to adapt and the continued use of sub-optimal farming methods may cause him to lose significant future profits. As such, estimates on the value of adaptation may help governments to weigh the costs and benefits of supporting adaptation activities.

Currently, the estimates of the value of agricultural adaptation to climate change are mainly available from micro-level, multinomial model studies that focus on the benefits of adaptation accruing to specific adaptation measures. However, when it comes to estimating the total benefits of adaptation – which is what we aim to do here – it is not feasible to estimate the benefits accruing to each possible adaptation measure and then aggregating these benefits up across all measures. For example, to adapt to climate change, farmers can adjust production inputs such as water, fertilizers, pesticide, and labor, adopt a heat tolerant variety of the same crop, shift growing season, switch land use between wheat, maize, soybean, rice, and dozens of other crops, change land use from crop production to grazing, orchards, forestry, etc. Farmers may also implement these measures in isolation or in combination. Thus, the value of adaptation associated with a specific method may be omitted or doubly counted if the total value of adaptation is computed by estimating and aggregating up the value of each adaptation method. Although micro-based studies on adaptation have provided important insights into the potential value of adaptation to climate change associated with various agricultural

a productive citrus tree (usually takes 5 years) and ongoing investments in specific pesticide sprayers and warehouse for citrus.

practices, little is known about the size of the overall benefits accruing to the full range of adaptation methods available.

How may we address this issue? In principle, the total benefits of long-run agricultural adaptation to climate change may be estimated by comparing two climate change impact estimates – one that takes all potential long-run adaptations into account and another that does not. For example, to estimate the value of adaptation to warming, as measured by the amount of agricultural profits that can be saved from doing so, we need to separately estimate how warming affects agricultural profits when adaptation occurs and when there is no adaptation. Then, we may compare these two impact estimates to uncover the value of adaptation. However, the main concern with this approach is that the econometric models that generate these impact estimates may differ quite significantly. Therefore, comparisons of these models would be like "comparing apples and oranges", and the difference between their climate change impact estimates may reflect not only the value of adaptation but also differences in their specifications. A similar concern has been articulated by Hanemann (2000), who argues that the value of adaptation cannot be measured by comparing the climate change impact estimate from the cross-sectional hedonic model of Mendelsohn, Nordhaus, and Shaw (1994), which incorporates the benefits accruing to the full range of adaptation measures, with the impact estimate from a production-function model such as that of Adams (1989), which omits the benefits of adaptation completely, as these models differ in specifications, assumptions, and the type of data employed.

The "apples and oranges" issue in estimating the value of long-run adaptation is challenging. In our view, this problem cannot be avoided completely as it would entail the impossible of using an identical model (to compare "apples with apples") to generate both climate change impact estimates where one accounts for long-run adaptation and another does not. Instead, the best we can do is to use two *nearly* identical models, such that the single difference between them will determine if their impact estimates take the effects of adaptation into account. Hence, building upon several key insights from the literature, we propose an approach that identifies the total value of long-run adaptation by comparing the impact estimates from two nearly identical panel models where the only difference between them is their fixed effects specification.

Our first panel model includes time fixed effects only. This seemingly trivial specification has a profound consequence, in that it will help us estimate the impact of climate change that incorporates the benefits of long-run adaptation. To understand why, note that if the size of the inter-annual weather fluctuation for a given year is nearly the same across regions (see Fisher et al., 2012),[2] the time fixed effect will enable us to flush most of these fluctuations out so that the remaining weather variation will mainly be driven by cross-sectional climate differences. The impact of climate change on agriculture identified by these cross-sectional climate differences, according to Mendelsohn, Nordhaus, and Shaw (1994), would then incorporate the benefits of adaptation. For example, by exploiting the cross-sectional variation in temperature to

[2] Fisher et al. (2012) show that state-by-year fixed effects tend to eliminate most of the inter-annual weather fluctuations in the US county-level data, which implies that the inter-annual weather fluctuation for a given year is nearly the same across a U.S. state. Section I in this paper also provides some empirical evidence to support this fact.

estimate the effect of warming on agricultural profits, we are in effect considering an experiment of changing a region's long-run temperature into that of another in order to study the impact of this temperature change on agriculture. However, if this cross-sectional temperature shift were true, we can also expect farmers in the former region to eventually behave more like farmers in the latter.[3] Hence, the impact of warming on agricultural profits identified by cross-sectional temperature variation will contain not only the direct effect of a temperature rise but also the effects of long-run adaptation by farmers.

Our second panel model is the same as the first except that it only includes county fixed effects (as county-level data is used here). The county fixed effect will eliminate all (long-run) cross-sectional inter-county climate differences, leaving the inter-annual weather fluctuation intact. However, the impact of climate change identified by inter-annual weather fluctuations will not incorporate the effects of long-run adaptation. For example, by exploiting inter-annual temperature fluctuations to generate temperature changes, which are then used for estimating the effect of warming on agricultural profits, the impact estimate will contain the direct effect of a temperature rise as before. However, because inter-annual temperature fluctuations are not permanent, farmers would at most respond *ex-post* by adjusting their farming practices in a limited way (Massetti and

[3] Our first panel model can be viewed as a modified hedonic model that improves upon the traditional hedonic model in the sense that hedonic estimates from single years' cross-sectional data could be unstable over time due to misspecifications (Deschênes and Greenstone 2007), and Massetti and Mendelsohn (2011) have shown that this problem could be addressed by estimating the hedonic model in a panel framework.

Mendelsohn 2011, Seo 2013, Moore and Lobell 2014).[4] Thus, although the impact of warming on agricultural profits identified by inter-annual temperature fluctuations will contain the direct effect of a temperature rise, this impact will not be mitigated by long-run adaptation as farmers are unlikely to make permanent adjustments in response to inter-annual weather fluctuations.

After obtaining the climate change impact estimates from these two panel models, we may uncover the total value of adaptation by examining the difference between these estimates.[5] We apply this approach to a panel data on US county-level agricultural production and climate data and consider various climate change projections. Our estimates show that without adaptation to climate change (under the RCP4.5 climate change scenario), 10.56 billion dollars (at 2012 constant values) of yearly agricultural profits, or 30% worth of current yearly profits, could be destroyed by climate change by

[4] It is important to note that there could be some *ex-post* adjustments by farmers in response to inter-annual weather fluctuations, such as change the using of labour, fertilizers, and pesticides. These responses reflect temporary but not permanent (i,e, long-run) measures to short run weather fluctuations. These short-run responses can be made with or without climate change, which is a long-run phenomenon. When we estimate the benefits of adaptation to long-run climate change, we prefer to focus on long-run responses to climate change but not short run responses to weather fluctuations.

[5] The idea of estimating the benefits of adaptation by comparing the climate change impact identified by long-run climate differences and that identified by short-run weather fluctuations is in line with the argument of Moore and Lobell (2014). However, they did not come up with a good method to separate long-run climate differences from short-run weather fluctuations. See Appendix E for a comparison of their model with the model of the current paper.

the end of this century. However, with adaptation, the loss in yearly agricultural profits by the end of this century is expected to be 3.18 billion dollars, or 9% worth of current yearly profits. Therefore, adaptation can help to offset about two-thirds of the potential loss in agricultural profits resulting from climate change. As a caveat, this estimated value of adaptation is likely to reflect a lower bound; the actual benefits of adaptation could be larger than what is reported here. The reason is that our first panel model only enables us to estimate the climate change impact that incorporates the benefits of *existing* but not future adaptation methods, which could be more effective in limiting the negative impact of climate change.[6]

Our paper contributes to the literature in the following ways. First, by attempting to estimate the total potential benefits of adaptation to climate change, our paper takes a macro-perspective on estimating the value of adaptation. Currently, research on the value of adaptation is mainly conducted at the micro-level that focuses on estimating the value associated with specific methods. For example, Kurukulasuriya and Mendelsohn (2008) have found that crop-switching can help Africa farmers reduce the damage of climate change by 98 USD per hectare per year under a Canadian Climate Centre (CCC) climate

[6] It is also possible that the benefits of adaptation can be overestimated due to irrigation. Irrigation water is depletable and unevenly distributed across regions. Therefore, irrigation may become unavailable as an adaptation method in the future in some regions. Hence, the benefit of adaptation could be overestimated if we assume that currently irrigated regions would continue to have access to the same level of irrigation in the future. To deal with this problem, as detailed in Appendix C, we follow the literature to use data only from US counties east of the 100 °meridian, where agricultural production depends mainly on precipitation but not irrigation (see, for example, Schlenker, Hanemann, and Fisher 2006).

scenario by the year 2100. Seo and Mendelsohn (2008) have found that African farmers can benefit from switching among different kinds of livestock when adapting to warming.[7] Di Falco and Veronesi (2013) have shown that adaptation by adopting water and soil conservation behaviors can also help to reduce the negative impact of climate change on crop profits.

Second, our paper is one of the few to consider the issue of estimating the total value of adaptation. In this regard, it is most closely related to Burke and Emerick (2016) who have estimated the total value of adaptation, and in particular, the adaptation to recent climate trends. To do so, they compare the climate change impact estimates from a model that identifies the impact through recent climate trends and another through inter-annual weather fluctuations, but have found that the difference between these estimates to be statistically *insignificant*. This result, which suggests that the value of adaptation to climate trends is small, could be attributed to the fact that farmers may have found it hard to recognize real changes in climate trends and therefore under-react to them.[8] Hence, if farmers respond weakly to climate trends, the mitigating effects of adaptation to climate trends may not fully reflect the value of adaptation to climate change. For this reason, we

[7] For example, they have found that the net revenue from each beef cattle will drop by 78.8 USD while that from each goat will increase by 2.4 USD by the year of 2060 under a CCC climate scenario. As such, their revenue can increase by switching from cattle to goat livestock.

[8] Farmers may not fully recognize and adapt to climate trends because these trends are often obscured by large inter-annual weather fluctuations. In the Appendix D, a Bayesian learning process shows that, ten years after a once-and-for-all mean temperature rise, only about 40 percent of the change is recognized by farmers (i.e. farmers on average underestimate the change in the temperature).

focus on adaptation to climate change as reflected by cross-sectional changes in the climate as opposed to adaptation to climate trends considered by Burke and Emerick (2016).

The large value of long-run adaptation suggests an important role that government can play in reducing the potential damage of climate change on agriculture. As illustrated by Kelly, Kolstad, and Mitchell (2005), there are tremendous adjustment costs associated with agricultural adaptation to climate change. In addition, farmers may simply not fully recognize the climate trend considering the finding of Burke and Emerick (2016) that farmers' adaptation to current climate trend is limited. Despite the large potential value of long-run adaptation, farmers who do not have enough resources to adapt to climate change or are simply unaware of climate change may not significantly benefit from adaption. Therefore, government policies that help farmers recognize and adapt to climate change could in turn help to reduce the damage of climate change on agriculture.

This paper proceeds as follows. Section I explains the methodology and the data source that we use. Section II presents the estimation results. Section III presents further results related to several robustness checks. Section IV concludes.

I. Methodology and Data

We propose a panel data approach to estimate the economic benefits that may accrue to agricultural adaptation in response to climate change. To illustrate how such benefits can be captured in our framework, consider a generic climatic variable (w_{it}) for county i in year t. This variable may represent temperature, precipitation, growing season degree-days, etc. which reflects various aspects of the climate. First, let us decompose w_{it} into three components:

$$w_{it} = T_i + d_t + \varepsilon_{it}$$

where T_i is the long-term average weather outcome (i.e., climate) of county i that varies across counties; d_t represents the inter-annual weather fluctuation in year t that is common across counties but varies across years; and ε_{it} is the county-specific weather shock.[9]

To estimate the potential value of long-run adaptation, we first rely on the observation by Fisher et al. (2012) that the size of the inter-annual weather fluctuation is generally the same across regions in a given year (also see Table B1 and Figure B1 in Appendix B for empirical evidence supporting this fact). Because the inter-annual weather fluctuation consists of two components – the common component d_t and the idiosyncratic component ε_{it} – Fisher et al. (2012) observation implies that the inter-annual weather fluctuation would be driven mostly by the common weather component (d_t) and that the size of the county-specific weather shock (ε_{it}) is very small.

Given that the county-specific weather shock is small, we may approximate w_{it} by

[9] Here, we assume the climate of county i (T_i) is constant for the period considered in this paper. However, relaxing this assumption would not affect the weather decomposition. Because the climate trend over time is usually common across counties, it can be captured in the second part d_t. In the following econometric estimations, we control for the climate trend by a continuous time trend.

(1) $$w_{it} \approx T_i + d_t$$

Without loss of generality, let w_{it} represent temperature. To estimate the impact of warming (i.e. a rise in w_{it}) on agricultural profits, Eq. (1) shows that we may estimate this impact by exploiting the variation in T_i or d_t to generate changes in w_{it}.

Our first panel model exploits the variation in T_i to estimate the impact of warming. To achieve this, it contains time fixed effects to shut down the variation in d_t. Importantly, as Mendelsohn, Nordhaus, and Shaw (1994) suggest, the estimated impact of warming identified by the variation in T_i would have incorporated the benefits of adaptation. To understand why, suppose county *j* has a higher average temperature (i.e. T_j) than county *i* (i.e. T_i). In this panel model, we estimate the impact of warming by asking what could happen to county *i*'s agricultural profits if its long-run temperature rises from T_i to T_j. However, if this long-run temperature rise were true, farmers in county *i* would also behave more like farmers in county *j* in the long run. Hence, the impact of warming identified by the cross-sectional inter-county temperature variation (i.e. the T_i component) will contain the mitigating effects of long-run adaptation when farmers adopt technologies used more prevalently in warmer climates (Mendelsohn, Nordhaus, and Shaw 1994).

To estimate the value of long-run adaptation, we need to disentangle the benefits of adaptation from the above warming impact estimate. To do so, we will compare this impact estimate with another that is "cleaned" of the benefits of adaptation. To obtain the latter impact estimate, which avoids the confounding influence of adaptation, we need a model that shuts down the variation in T_i. This model will then have to employ another source of variation in temperature to estimate the impact of warming.

Thus, unlike our first panel model, our second panel model includes county fixed effects to partial out T_i, and will identify the impact of warming by inter-annual temperature fluctuations (i.e. the d_t component). Given that inter-annual temperature fluctuations are transitory, farmers generally do not respond to these fluctuations in a permanent manner (Massetti and Mendelsohn 2011, Seo 2013). Hence, we do not expect the impact estimate from the second panel to contain the effects of long-run adaptation.

A. Econometric approach

To estimate the potential value of long-run adaptation, we will employ two panel models. The first panel model, where the coefficients on the climatic variables are estimated by exploiting the cross-sectional climate variation, is shown in Eq. (2):

$$y_{it} = \rho \sum_{j \in N} w_{ij} y_{jt} + \sum_{k \in K} c_{itk} \alpha_k + \sum_{g \in G} l_{itg} \beta_g + \gamma_{st} + u_{it} \qquad (2)$$

$$i = 1, \ldots, \mathrm{N};\ t = 1, \ldots, T$$

where y_{it} denotes agricultural profits per acre in county i and year t; N denotes the set of the n counties; c_{itk} is the kth climatic variable among the five considered in this paper, which include the temperature measures of growing season degree-days (GDD) and its quadratic term, the precipitation measures of growing season total precipitation (GTP) and its quadratic term, and square root of growing season harmful degree-days (GHDD), which is a measure of the extreme heat (see Appendix C for a discussion on how each climatic variable is calculated); K denotes the set of the five climatic variables; l_{itg} is the g^{th} land quality indicator that we use as a control (there is a maximum of 10 in total); G denotes the set of the 10 land quality indicators; γ_{st} is the state-by-year dummy that is used to filter out year-to-year weather and other fluctuations that are common across counties within each state, and also to capture all state-level determinants of agricultural profits whether or not they are observed or unobserved, time-varying or time-invariant; and u_{it} is an $i.i.d.$ distributed error term.

The second panel model, where coefficients on the climatic variables are estimated by exploiting inter-annual weather fluctuations, is shown in Eq. (3):

$$y_{it} = \rho \sum_{j \in N} w_{ij} y_{jt} + \sum_{k \in K} c_{itk} \alpha_k + \sum_{g \in G} l_{itg} \beta_g + \tau_i + \theta q_t + \varepsilon_{it} \qquad (3)$$

$$i = 1, \ldots, n; \; t = 1, \ldots, T$$

Notice that Eqs. (2) and (3) differ primarily in their fixed effects structures. Specifically, county fixed effects (τ_i) are included in Eq. (3) but not in Eq. (2). On the other hand, state-by-year fixed effects (γ_{st}) are included in Eq. (2) but not in Eq. (3). Besides fixed effects, Eq. (3) includes a time trend q_t to partial out any confounding trend effects, such as that of technological improvements, from the effect of inter-annual weather fluctuations.[10] The time trend also helps to partial out any adaptation to climate trends

[10] In Eq. (3), we are not seeking to control for the effect of inter-annual price shocks induced by output fluctuations because price shocks can be seen as a "natural insurance" for farmers against weather fluctuations. Eliminating price shocks will overestimate the impact of weather fluctuations.

that farmers may undertake, although Burke and Emerick (2016) have shown that the mitigating effects of adaptation to climate trends, if they exist, are small.

By including state-by-year fixed effects but not county fixed effects, the coefficients on the climatic variables in Eq. (2) will be estimated by exploiting the within-state cross-sectional inter-county variation in these variables. Therefore, as discussed, the predicted climate change impact based on Eq. (2) would incorporate the benefits of long-run adaptation. On the other hand, by including county fixed effects but not state-by-year fixed effects, the coefficients on the climatic variables in Eq. (3) will be estimated by exploiting the inter-annual fluctuations in these variables themselves. Because inter-annual fluctuations are transitory and farmers do not permanently adapt to them, the predicted climate change impact based on Eq. (3) would reflect the impact without long-run adaptation.

In both Eqs. (2) and (3), we include a spatial autoregression term (Anselin 1988, Elhorst 2010), where the dependent variable of county i is spatially related to that of all other counties. In climate change studies, there is evidence that agricultural profits across regions are spatially related (see, for example, Schlenker, Hanemann, and Fisher 2006).[11] We capture this spatial relationship by including $\sum_{j \in N} w_{ij} y_{jt}$ in Eq. (2), where w_{ij} is a spatial-weight defined as the inverse of the distance between counties i and j,

[11] For the US counties east of the 100 °meridian, which is our sample, we have tested for the presence of spatial dependence using the semiparametric method of Frees (2004) and find strong evidence to reject the null hypothesis of spatial independence.

calculated as the distance between the county centroids. By using w_{ij} as weights, the relationship between the dependent variables of counties i and j would be weaker the further apart these counties are. In Eqs. (2) and (3), whether or not spatial dependence is relevant for agricultural profits depends on the parameter ρ. In our study, we allow for ρ to be non-zero to let the data speak on whether spatial dependence in agricultural profits across counties exists in the conditional mean itself. If ρ is zero, Eqs. (2) and (3) becomes a standard fixed effects panel regression model.

In many panel studies that investigate the impact of climate change, the issue of spatial correlation is usually addressed by clustering the error term at a larger spatial resolution, or by adjusting the error term with a spatial-weighting matrix, so that the correlation between the unobservables of the cross-sectional units decays smoothly with distance (Deschênes and Greenstone 2007, Fisher et al. 2012). If the spatial correlation is caused by the spatial correlation between the omitted determinants of profits, and if these omitted determinants are themselves uncorrelated with the climatic variables, the standard (non-spatially autocorrelated) panel estimators will be consistent but inefficient.

However, if these omitted determinants are correlated with the climatic variables, the standard panel estimators of the climatic variable coefficients will be biased and inconsistent. In this case, the appropriate approach is to include spatial lags into the model instead of adjusting for spatial correlation by clustering the error term (Lee 2002, Lee and Yu 2010). Hence, to be on the safe side, we use spatial lags to account for the possibility of spatial dependence between counties. However, in one of our robustness checks reported in Table 4 below, we find that our main conclusion (that adaptation can help to offset at least two-thirds of the damage of climate change) is not sensitive to the omitting spatial autoregression term from our model (i.e. setting $\rho = 0$) and clustering the standard errors in place of it.

B .Estimating the value of long-run adaptation

After estimating Eqs. (2) and (3), we feed into these models the end-of-this-century climate projections generated by the climate models commonly considered in the literature (i.e. CCSM4, CESM1-BGC, CanESM2, and NorESM1-M).[12] In doing so, we may obtain the end-of-this-century impact of climate change on agricultural profits with and without adaptation, respectively. To estimate the benefits of long-run adaptation, we will look at the difference in the climate change impact predicted by these two models. It is worth pointing out, as in the hedonic approach, that the benefits of adaptation estimated in this manner would reflect only a lower bound. This is because we can only estimate the potential benefits of adaptation based on current production technologies and management methods, but not future and possibly more effective innovations that are unobserved.

C. A comparison with Deschênes and Greenstone (2007)

Readers might find the panel regression models expressed by Eqs. (2) and (3) to be reminiscent of the Deschênes and Greenstone (2007) model:

(4) $$y_{it} = \sum_{k=1}^{K} c_{itk}\alpha_k + \sum_{g=1}^{G} l_{itg}\beta_g + \tau_i + \gamma_{st} + \sigma_{it}$$

$$i = 1,\ldots,n;\;\; t = 1,\ldots,T$$

[12] See Section I.D for more details.

where for y_{it}, c_{itk} and l_{itg} are the same variables as that in Eqs. (2) and (3). If the spatial dependence coefficient ρ in Eqs. (2) and (3) is equal to zero, the only difference between Eqs. (2), (3), and (4) is in their fixed effects structure, where Eq. (2) only includes state-by-year fixed effects (γ_{st}), Eq. (3) only includes county fixed effects (τ_i), and Eq. (4) includes both county and state-by-year fixed effects.

While the difference between Eqs. (2), (3), and (4) appears to be minor, it has profound implications on the way the coefficients on the climatic variables are estimated. By including both county and state-by-year fixed effects as the Deschênes and Greenstone (2007) model (i.e. Eq. (4)) does, the cross-sectional inter-county climate differences and the common inter-annual fluctuations will be eliminated from the climatic variables. As such, the coefficients on the climatic variables in Eq. (4) can only be estimated by using the remaining the climatic variation – county-specific weather shocks.

As discussed, the size of county-specific weather shocks is usually very small (Fisher et al. 2012). Thus, caution should be exercised when using the estimated impact of these shocks on agricultural profits to infer what the impact of climate change is. For example, none of the counties in this study have an absolute county-specific temperature shock that is at least 1 ℃. Therefore, the estimated impact of these shocks on agricultural profits may not allow us to construct a reliable counterfactual impact of climate change that is associated with, say, a 1 ℃ rise in temperature. This is because a county-specific weather shock of that magnitude does not exist.[13]

By contrast, unlike Eq. (4), Eq. (2) only includes state-by-year fixed effects (γ_{st}), which eliminate the inter-annual common weather fluctuations. In this case, the coefficients in Eq. (2) will be estimated by exploiting the cross-sectional inter-county climate variation within states, and this variation is much larger than that of county-specific weather shocks (see Table B1 in Appendix B). By the same token, unlike Eq. (4), Eq. (3) only includes county fixed effects (τ_i), which eliminate all cross-sectional climate differences. Hence, the coefficients in Eq. (3) will be estimated by exploiting the inter-annual weather fluctuation generated by common weather shocks, and these fluctuations vary more substantially than county-specific weather shocks do (see Table B1 in Appendix B).

D. Hybrid panel models

Our estimation approach uses two panel models to generate two climate change impact estimates, where one model exploits the between county climatic variation and the other the within-county inter-annual variation. Another way is to use the hybrid approach, which estimates the between and within effects of a time and cross-sectionally varying variable (such as temperature) within a single panel model (see Appendix E for detailed

[13] According to the IPCC Fifth Assessment Report (2014), the lower bound of the best prediction of mean temperature increase is 1.0 ℃. However, as shown in Row A1 of Table B1, no temperature variation pertains to ε_{it} exceed 1.0 ℃.

discussion). While the hybrid approach seems more parsimonious than the two-panel approach, it has certain limitations. For example, unlike Eq. (3), the hybrid approach is not compatible with the use of county fixed effects, as they will eliminate the between county effects of the climatic variable contained in the hybrid model. For this reason, the hybrid approach is to be implemented with random effects, but this necessitates the assumption that the unobserved components are uncorrelated with the observables in the model. Therefore, instead of estimating the between and within county effects of the climatic variables using the hybrid approach, we estimate them by implementing two separate panel regressions instead, as this allows us to employ the appropriate fixed effects to take care of the unobserved components of the model.

E. Data

Our study makes use of a panel data on county-level agricultural production, climate and other socio-economic and geophysical data for 2155 US counties east of the 100 º meridian drawn from various sources. Below, we briefly summarize the variables that are used in this study. Detailed information on the data source, data processing, and summary statistics are presented in the Appendix C.

Agricultural profits and farmland value: we follow the literature to construct US county-level agricultural profits per acre from *Census of Agriculture* for the census years of 1982, 1987, 1992, 1997, 2002, 2007, and 2012. Agricultural profits are used as the dependent variable in both our panel models. We also derive farmland values from the *Census of Agriculture* and consider it as a dependent variable in our robustness checks.

*Historical climate data***:** the daily maximum temperature, minimum temperature and precipitation data from 1981 to 2012 are derived from Parameter-elevation Regressions on Independent Slopes Model (PRISM 2014). We follow the literature to construct the standard county-level measures of climatic variables: growing season degree-days (GDD), growing season harmful degree-days (GHDD) and growing season total precipitation (GTP) (Schlenker, Hanemann, and Fisher 2006, Deschênes and Greenstone 2007).

*Climate change predictions***:** we use the latest high resolution climate predictions from General Circulation Model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor, Stouffer, and Meehl 2012). We will mainly consider climate projections based on the medium scenario RCP4.5 from four of the most widely used CMIP5 models: CCSM4, CESM1-BGC, CanESM2, and NorESM1-M. Each model provides the daily maximum temperature, minimum temperature and precipitation from 2006 to 2100 under various climate scenarios (including RCP4.5). As a robustness check, we also use climate projections for the highest scenario RCP8.5 from these four CMIP5 models and estimate the value of adaptation based on them.

Control variables: we follow Mendelsohn, Nordhaus, and Shaw (1994) and others to use various county-level soil quality measures as controls. These data are obtained from the National Resource Inventory. The soil quality measures include soil salinity, sand content, clay content, K-Factor, flood risk, permeability, slope length, moisture in top soil, share of wetland and irrigated land. We also use county-level per capita income, population density, and centroid latitude as control variables in our robustness checks.

II. Empirical Results

We first estimate Eqs. (2) and (3) and focus on the effect that the five climatic variables have on agricultural profits. After which, we plug into the estimated versions of Eqs. (2) and (3), the climate change projections from the four climate models to obtain predictions for the end-of-this-century impact of climate change with and without the mitigating effects of adaptation. The benefits of adaptation can then be calculated as the difference between the two end-of-this-century impacts predicted by Eqs. (2) and (3). To simplify our discussion, we will refer to Eq. (2) as the *model with adaptation* and Eq. (3) as the *model without adaptation* interchangeably.[14]

A. Baseline model estimates

In Table 1, Columns 1a and 2a report the estimated coefficients on the climatic variables for Eqs. (2) and (3), respectively.[15] For both models, we find that the responses of agricultural profits to GDD and GTP are hump-shaped, and the effect of the square root of GHDD is negative. These estimates are in line with what the literature has documented (see, for example, Schlenker, Hanemann, and Fisher 2006) and offer some evidence that

[14] Eqs. (2) and (3) are estimated using the maximum likelihood estimation routine of (Belotti, Hughes, and Mortari 2014).

[15] Estimates reported in Columns 1b, 2b, 3a, and 3b are robustness checks that will be discussed in the following section. To facilitate the comparison with the results from the main regressions (1a and 1b), we put them together in a single table.

the *qualitative* relationship between these climatic variables and agricultural profits does not depend on whether adaptation is accounted for in the estimation problem.

Table 1. Regression results of the effects of climatic variables on agricultural profits and farmland values

Independent Variables	Profits: With adaptation		Profits: No adaptation		Farmland values: With adaptation	
	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)
GDD (℃) (per 100 unit)	7.80	7.34	12.3	12.3	255.6	277.8
	(2.35)	(2.37)	(1.10)	(1.10)	(21.3)	(21.5)
GDD square (per 10000 unit)	-0.17	-0.16	-0.29	-0.29	-5.37	-5.85
	(0.05)	(0.05)	(0.03)	(0.03)	(0.45)	(0.45)
GTP (inches)	2.06	2.10	0.38	0.36	19.9	24.9
	(0.69)	(0.69)	(0.61)	(0.61)	(10.8)	(10.8)
GTP square	-0.03	-0.04	-0.03	-0.03	-0.05	-0.08
	(0.01)	(0.01)	(0.01)	(0.01)	(0.22)	(0.22)
GHDD square root	-3.94	-4.14	-10.05	-10.11	-180.2	-179.1
	(1.46)	(1.47)	(0.95)	(0.95)	(30.4)	(30.2)
Control for spatial dependence	Yes	Yes	Yes	Yes	Yes	Yes
State-by-year fixed effects	Yes	Yes	No	No	Yes	Yes
State-fixed effects	Yes	Yes	No	No	Yes	Yes
County-fixed effects	No	No	Yes	Yes	No	No
Time trend	No	No	Yes	Yes	No	No
10 land quality indicators	Yes	No	Yes	No	Yes	No

Notes: This table shows the estimated coefficients of the climatic variables in Eqs. (2) and (3). Columns 1a and 1b report estimates from model (2) with agricultural profits as the dependent variable; column 2a and 2b report estimates from model (3) with agricultural profits as the dependent variable; columns 3a and 3b report estimates from a variation of model (2) that use the farmland value as the dependent variable. The only difference between the "a" and "b" versions of the model is that version "b" excludes the soil controls. The Huber-White heteroskedastic consistent standard errors are reported in parentheses.

However, *quantitatively*, there is a difference between the estimated coefficients of Eq. (2) (i.e. model with adaptation) and Eq. (3) (i.e. model without adaptation). For example, we find that the optimal GDD that maximizes agricultural profits is 2294 degree-days when adaptation is accounted for, as opposed to 2121 degree-days without adaptation. This suggests that with adaptation, agricultural production could become more heat tolerant on average. Similarly, the optimal GTP is larger in the model with adaptation, which means agricultural production can benefit more from precipitation if there is adaptation. The negative effect of GHDD is weaker with adaptation than without, which implies that adaptation can help reduce the damage of extreme heat on agricultural production.

B. Predicted end-of-this-century benefits of adaptation

Figure 1 presents two predicted end-of-this-century impacts of climate change on agricultural profits: one that takes adaptation into account (green circle) and another that does not (red circle). These impacts are calculated by plugging in the end-of-the-century climate projections under the RCP4.5 climate scenario – CCSM4, CESM1-BGC, CanESM2 and NorESM1-M – into the estimated model with adaptation (i.e. Eq. (2)) and without (i.e. Eq. (3)). Figure 1 also presents the results of some robustness checks which are shown by the green triangle, red triangle, and green square. We will discuss these robustness checks in the next section.

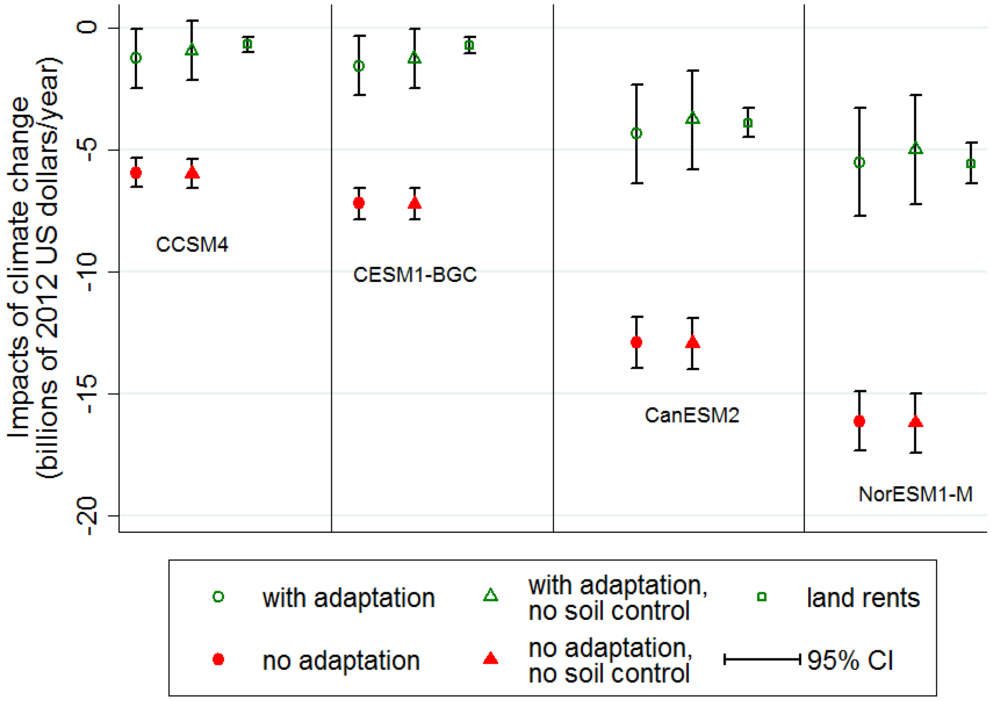

Figure 1. Predicted end-of-this-century impact of climate change on agricultural profits and farmland rents (Billions of 2012 US dollars per year)

Notes: This figure reports the impact of climate change projections from four climate models (CCSM4, CESM1-BGC, CanESM2, and NorESM1-M) under the scenario RCP4.5. See the climate projection for each climate model in Table C2. All entries are calculated for the 2155 rain-fed non-urban sample counties. Total impacts are calculated by summing impacts across all sample counties. The historical average total annual profits for these sample counties are $35.3 billion. See the text for further details.

From Figure 1, we find that the predicted impact of climate change on agricultural profits is negative whether or not adaptation is accounted for these impact estimates. However, the negative impact is less severe with adaptation (green circle) than without (red circle). Using the end-of-this-century climate projection from each of the CCSM4, CESM1-BGC, CanESM2 and NorESM1-M climate models, the end-of-this-century changes in agricultural profits predicted by the model with adaptation are -1.27, -1.57, -

4.63 and -5.52 billion per year at 2012 constant dollars, respectively.[16] These changes are much smaller than what the model without adaptation predicts, which are -5.96, -7.21, -12.92, and -16.14 billion dollars per year, respectively. In addition, the t-test shows that for each of the four climate scenarios, the difference between the predicted climate change impacts with or without adaptation is statistically significant at 1%.

Table 2. Predicted end-of-this-century impact of climate change on agricultural profits and the benefits of adaptation (%)

Climate projection model	CCSM4	CESM1-BGC	CanESM2	NorESM1-M	Average
[1] damage estimated by model with adaptation	-3.6% (3.4)	-4.4% (3.4)	-12.4% (5.7)	-15.6% (6.3)	-9.0% (9.8)
[2] damage estimated by model without adaptation	-16.9% (1.7)	-20.4% (1.8)	-36.6% (3.0)	-45.7% (3.5)	-29.9% (5.2)
[3] benefits of adaptation: 100*(Row 2 – Row1)/Row 2	78.7% (3.8)	78.2% (3.9)	66.3% (6.5)	65.8% (7.2)	72.2% (11.1)

Notes: This table reports the percentage of climate change impact on agricultural profits with adaptation (Row 1) and without (Row 2). We also calculated the percentage of damage that can be offset by adaptation. The climate changes are the end-of-this-century projections from four climate models (CCSM4, CESM1-BGC, CanESM2, and NorESM1-M) under the scenario RCP4.5. The historical average total annual profits for these sample counties are $35.3 billion, which are the denominator of the calculation of percentage. The Huber-White heteroskedastic consistent standard errors of the impacts are reported in parentheses. See the text for further details.

[16] Since the projected warming is increasing from CCSM4, CESM1-BGC, CanESM2 and NorESM1-M in ascending order (see Table C2), we can say that the predicted total impacts increase with the magnitudes of predicted warming.

Table 2 reports the percentage of current levels of agricultural profits that would be lost at the end of the century because of climate change as predicted by the model with adaptation (Row 1) and without (Row 2). These percentages are calculated by dividing the estimated damages with adaptation (shown by the green circle in Figure 1) and without adaptation (shown by the red circle in Figure 1) by the total yearly agricultural profits of the sample area (35.3 billion constant US dollars per year). We find that with adaptation, climate change is expected to reduce current agricultural profits by -3.6%, -4.4%, -12.4%, or -12.4% based on climate change projections by climate models CCSM4, CESM1-BGC, CanESM2 and NorESM1-M. However, without adaptation, the estimated damages are -16.9%, -20.4%, -36.6%, or -45.7%. Therefore, adaptation can help to offset 66.3% to 78.7% of the potential output loss due to climate change. The last column of Table 2 reports the average percentage of damage and the average value of adaptation based on averaging the damage percentages and adaptation values associated with the four climate models. On average, the damage to agricultural profits is 9% with adaptation and 30% without adaptation; thus, adaptation may help to reduce 72.4% of the overall damages from climate change.

Table 3. A summary of previous studies on the end-of-century impact of climate change on US agriculture

Source	Dependent variable	Climate change scenario	Model and fixed effect (FE)	Including long-run adaptation	Climate change impact (%)
[1] Mendelsohn, Nordhaus, and Shaw (1994), Column 4 of Table 5	Farmland value	A uniform 2.7 ℃ warming and an 8 percent increase in precipitation	Cross-sectional model	**Yes**: Impacts are identified by cross-sectional climate differences	**-4.4%** Take 1982 data as an example
[2] Schlenker, Hanemann,	Farmland value	A uniform 2.7 ℃	Cross-sectional	**Yes**: Impacts are	**-4.6%** Take 1982 data as an

and Fisher (2005), Column 2 of Table 3		warming and an 8 percent increase in precipitation	model	identified by cross-sectional climate differences	example. Gross farm income in 1982 was $164 billion
[3] Massetti and Mendelsohn (2011), Column 3 of Table 4	Farmland value	A uniform 2.7 ℃ warming and an 8 percent increase in precipitation	Hsiao model (similar to panel model with time FE)	**Yes**: Impacts are identified by cross-sectional climate differences	**1.5%** 95% confidence interval: (-16.2%, 20.5%)
[4] Schlenker and Roberts (2009), Section B of Figure 2.	Yield of soybean	Hadley III-B2	Panel model with county FE	**No**: County FE eliminate inter-county climate differences	**-37%** An approximate value derived from Figure 2 of Schlenker and Roberts (2009)
[5] Fisher et al. (2012), Column 3b of Table 1	Agricultural profits	Hadley III-B2	Panel model with county FE and Year FE	**No**: County FE eliminate inter-county climate differences	**-56%** Standard error: 16.58

Notes: 1) In this simple comparison, we have omitted many of the important insights of these articles; 2) The results of Fisher et al. (2012) in Column 1 is used by the authors to test the result of Deschênes and Greenstone (2007). We did not include the result of Deschênes and Greenstone (2007) in this table because their panel model includes both county FE and *state-by-year* FE and the remaining climatic variation in their model is too small to identify meaningful climatic coefficients; 3) Each of these papers provided predictions of climate change impact for several climate change scenarios. In this summary, we only choose the prediction using scenarios that are most similar to the scenario RCP4.5 which we mainly consider in this paper.

To compare the estimates of this paper with those from the literature, Table 3 summarizes five previous studies that look at the impact of climate change on US agriculture. The climate change impact estimates may differ across studies because different climate change scenarios and climate prediction models have been used to generate these estimates. Similar to what our paper has found, the studies that account for the effects of long-run adaptation have reported much smaller damages of climate change than studies that do not. For example, Rows 1 to 3 of Table 3 show that the cross-sectional and panel studies that identify the climate change impact through cross-sectional climate differences have predicted much smaller end-of-this-century climate change impact on agriculture. These estimates, which range from -4.6% to 1.5%, are roughly in line with our impact estimates with adaptation that are associated with the CCSM4 and CESM1-BGC climate projections (-3.6% and -4.4% respectively). On the other hand, Rows 4 and 5 of Table 3 show that the panel studies that employ county fixed effects, which eliminate the cross-sectional climate differences and along with it the effects of long-run adaptation, have predicted much larger damages of climate change ranging from -37% to -56%. These estimates are similar to our impact estimates without adaptation, which could be as large as -46%.

III. Sensitivity Analysis

This section provides some robustness checks to explore the issues of the potential influence of unobserved county heterogeneity, yearly storage and inventory adjustments on the estimates, among others.

A. Unobserved county heterogeneity

In Eq. (3) (model without adaptation), the presence of county fixed effects takes care of unobserved county heterogeneity. However, Eq. (2) (model with adaptation) only contains state-by-year fixed effects, but not county fixed effects. As such, although the inter-annual common fluctuations and the inter-state time-invariant differences are controlled by state-by-year fixed effects in Eq. (2), the within-state inter-county heterogeneity in this model is controlled by the ten land quality indicators, not by county fixed effects.

We argue that this should not be a major concern. Other than the land quality indicators, there is no evidence that there are other permanent factors of agricultural output, as important as land quality, that are correlated with climate itself. Besides, if there are unobserved permanent factors which are themselves outcomes of climate, Dell, Jones, and Olken (2014) argue that including these factors in the model will partially eliminate the explanatory power of climatic variables, even though climate is the true underlying determinant.

While there is no formal test to evaluate how important unobserved county heterogeneity is in influencing our estimates, we may still get a sense of this issue through informal means. To do so, we check for the sensitivity of the estimated coefficients in Eq. (2) by dropping the most important county-level determinants of agricultural profits – all the soil quality controls and report the new estimates in Column 1b of Table 1. As discussed, it has been argued that no other permanent characteristics are as important as land quality for agriculture (Burke et al. 1989). If the estimated coefficients of Eq. (2) are robust despite the exclusion of the soil quality controls, then the other county heterogeneity may not have large effects on our estimates as well. For the model with adaptation, we compare Column 1a (with the soil controls) with Column 1b (without the soil controls) of Table 1 and find that the estimated coefficients on the climatic variables are very similar whether or not the county-level soil characteristics are controlled for. Moreover, with respect to the coefficient on each climatic variable estimated with or without the soil quality controls, the *t*-test shows that the difference between them is not statistically significant. We also find that the estimated coefficients are robust to the exclusion of various subgroups of the soil quality controls (results are omitted to save space).

Besides the estimated coefficients, the estimated climate change impact is also robust to the exclusion of the soil quality controls. To observe this, we plug the end-of-this-century climate projections into the Eq. (2) that is estimated without these controls, and from which, we generate a new estimate of the climate change impact with adaptation. This impact is marked in Figure 1 by the green triangle, and is to be compared with the predicted impact marked by the green circle, which is obtained from estimating the baseline model with adaptation and with soil quality controls. As Figure 1 shows, the estimated climate change impact from the model with the soil quality controls (green circle) and without (green triangle) are very close to each other. We have also conducted a t-test and find this difference to be statistically insignificant.

As a remark, while the model without adaptation (i.e. Eq. (3)) contains the county fixed effect, which takes care of any time-invariant county heterogeneity, we carry out the same sensitivity check as done for the model with adaptation and find its estimates to be robust to omitting the soil quality controls as well (compare Columns 2a with 2b of Table 1).[17] Thereafter, we use these estimates (Columns 2b of Table 1) to compute the climate change impact without adaptation and without controlling for soil quality. From Figure 1, we can see that the estimated end-of-this-century impacts of climate change are

[17] This result is perhaps not surprising as the soil quality variables are highly persistent across time, and therefore, have very little within-county inter-annual variation.

very similar regardless of whether the soil quality controls are included (red circle) or excluded (red triangle) from this model (i.e. Eq. (3)).

B. The influence of yearly storage and inventory adjustments

When annual agricultural profits is used as the dependent variable, there is a potential concern that the model does not take into account of yearly storage and inventory adjustments (Fisher et al. 2012). The annual profits data from the Census of Agriculture measures the difference between reported sales and expenditures in the same year. However, in response to output and price changes caused by weather fluctuations, farmers may adjust their storage and inventory to maximize their total discounted profits. Consequently, some of the current year's output might be sold in the following year, or part of the current year's profits might come from the previous year's production.

Even though our panel models do not explicitly control for storage and inventory adjustments, this does not necessarily imply that our conclusion – that the potential value of adaptation is large – is incorrect.[18] There are two reasons for this. Firstly, for the model with adaptation (i.e. Eq. (2)), its climate change impact estimate may not be severely biased even if storage and inventory adjustments were not controlled for. This is because storage and inventory adjustments are driven by inter-annual weather fluctuations, which are absorbed by the model's state-by-year fixed effects.

[18] For the sample area in our study, data on storage and inventory is not available. Hence, we cannot control for storage and inventory adjustments.

Secondly, for the model without adaptation (i.e. Eq. (3)), not accounting for storage and inventory adjustments in the dependent variable may bias our results in a good way by potentially causing us to underestimate the damage of climate change and therefore the value of adaptation. The reason is that inventory adjustments serve as a kind of "self-insurance" by reducing the output risks resulting from weather fluctuations.[19] Hence, by not holding inventory "fixed", the estimated damage of climate change from the model without adaptation could be mitigated by potential benefits arising from unobserved inventory adjustments. Given that the true damage of climate change without adaptation could be underestimated if storage and inventory adjustments were not controlled for, the benefits of adaptation reported here could be underestimated and our estimated value of adaptation could be more conservative than is true.

With respect to the model with adaptation, we may use indirect evidence to show that its estimates are unlikely to be severely biased even if storage and inventory adjustments were not controlled for. The evidence is based on the following argument: if our estimates of Eq. (2) have large biases from omitting storage and inventory adjustments, the estimated effect of climate change on agricultural profits per acre (our baseline) would be very different from that on farmland rents that are calculated from farmland value, since the latter incorporates storage and inventory adjustments.

[19] This argument is similar to Fisher et al. (2012), who view weather fluctuation caused price variation as a "natural insurance" for agricultural production, and believe that accounting for price fluctuations will overestimate the effect of weather fluctuations on profits.

Estimating Eq. (2) using farmland values as a dependent variable in place of agricultural profits, we find that the effect directions and significant levels of the estimated coefficients on the climatic variables (Column 3a of Table 1) are similar to those in the baseline regression.[20] Using these estimates, we predict the end-of-this-century impact of climate change on farmland values based on the four climate model projections, and transform this predicted impact into the impact on farmland rents using an implicit discount rate of 2.90 percent following Schlenker, Hanemann, and Fisher (2005). This prediction is shown in Figure 1 by the green square.

For any given climate model, we find that the end-of-this-century impact of climate change on farmland rents is similar to that on agricultural profits (green circle in Figure 1). From our t-tests, we also find that the estimated damages on agricultural profits are not statistically significantly different from those on farmland rents. Hence, even if we consider agricultural profits as the dependent variable, which omits information about storage and inventory adjustments, there is no evidence that this would cause the climate change impact estimate to be severely biased. It is worth pointing out that we have not estimated the effects of the climatic variables on farmland values for the model without adaptation because the parameters in this model are estimated by exploiting inter-annual

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[20] We have not estimated the effects of the climatic variables on farmland values based on Eq. (3) because the parameters in this model are identified by inter-annual weather fluctuations, but farmland values fluctuate little year to year as they are the present discounted values of the land rent stream into the infinite future.

weather fluctuations, and the farmland value has very little inter-annual fluctuations as it is by definition the present discounted value of the land rent stream into the infinite future.

C. Further robustness checks

So far, our main result is that adaptation could help to offset at least two-thirds of the potential loss in agricultural profits resulting from climate change. Table 4 reports a series of other robustness checks to examine how sensitive this result is to various alternative specifications of Eqs. (2) and (3).

All the alternative specifications considered here include the same fixed effects and soil quality controls as the original models do. For each alternative specification of Eqs. (2) and (3), we first estimate the end-of-this-century impact of climate change based on the climate projections from each of the four climate models, and then average up these predicted impacts. Following which, we calculate the value of adaptation as the difference between the predicted average impacts calculated from the alternative Eqs. (2) and (3).

Table 4. Robustness checks for the estimated impacts of climate change and the benefits of adaptation (billions of 2012 constant dollars/year)

	(1) Impact on profits: With adaptation	(2) Impact on profits: No adaptation	Benefits of adaptation	
			Value	Percent
[1] Assume $\rho = 0$ in the regressions but address the spatial correlation by clustering the error term at the state level	-3.71	-14.53	10.83	78.23%
[2] Include additional controls for population density, per capita income, and altitude	-4.61	-12.85	8.24	65.88%
[3] Exclude irrigated counties east of the 100 º meridian from the sample	-3.80	-12.00	8.20	70.29%

[4] Calculate degree-day by the minimum and maximum daily temperatures	-3.73	-15.21	11.48	79.07%
[5] Use the highest climate change scenario (RCP8.5)	-9.53	-28.54	19.01	67.32%

Notes: The entries report predicted the impacts of climate change on agricultural profits and the estimated benefits of adaptation using the regression results from alternative versions of models (2) and (3) and the climate change predictions of the four climate models listed in Table C2 (i.e., CCSM4, CESM1-BGC, CanESM2, and NorESM1-M). Columns (1) and (2) show the estimated impacts based on alternative versions of Eqs. (2) and (3), respectively. In the last two columns, the benefits of adaptation were calculated as the difference between the estimates reported in columns (1) and (2), and "Percent" indicates the percentages of damages that could be offset by adaptation. All the values are simple averages of the estimations that were derived from the four climate models. The historical average total annual profits for these sample counties were $35.3 billion. See the text for further details.

The first robustness check examines if our results are sensitive to whether the spatial autoregression is included in Eqs. (2) and (3). In this robustness check, we assume that $\rho = 0$ in Eqs. (2) and (3) and account for any spatial correlation by clustering the error term at the state level. Row 1 of Table 4 reports the damages of climate change based on Eqs. (2) and (3) with the restriction that $\rho = 0$. Compared with the baseline estimates (see Table 2), we still arrive at the same conclusion that the estimated damages are much smaller when adaptation is taken into account, and that adaptation can offset at least two-thirds of the potential loss in agricultural profits resulting from climate change.

In the second robustness check, we examine how sensitive our results are when new control variables are included. If our results are robust to varying the set of controls, this can be taken as additional evidence that omitted variable bias, if it exists, is not a major concern. Row 2 of Table 4 provides the new estimates of Eqs. (2) and (3) that now include county-level population density, per capital income, and altitude as additional controls.[21] When these variables are controlled for, the estimated damage on agricultural profits with adaptation is only 4.1 percentage points higher than that obtained without these controls (i.e. the estimated damage with adaptation rises from 9.0% in the baseline case to 13.1% here). In addition, based on the new estimates, we find that adaptation could still help to offset about two-thirds of the damage from climate change. We also tried various specifications that include only one or two of these three variables and arrive at the same conclusion.

The third robustness check explores the consequence of excluding irrigated counties from our sample. Counties west of the 100 ^{o} meridian have already been excluded from this study to address the concern that unmeasurable irrigation differences across regions may give rise to biased estimates. However, even though most counties east of the 100 ^{o} meridian depend on rainfall for agriculture, some of these counties may still supplement rainfall with irrigation water. In this exercise, we exclude counties east of the 100 ^{o} meridian that employ irrigation.[22] As Row 3 of Table 4 shows, whether or not these

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[21] We do not include these controls in our main regressions because if these variables are not correlated with climate, omitting them will not cause a bias in the estimation; if they are correlated with climate, it is most likely that these variables are themselves outcomes of climate but not the cause. In this case, including these factors in the model will partially eliminate the explanatory power of climatic variables, even though climate is the true underlying determinant (Dell, Jones, and Olken 2014).

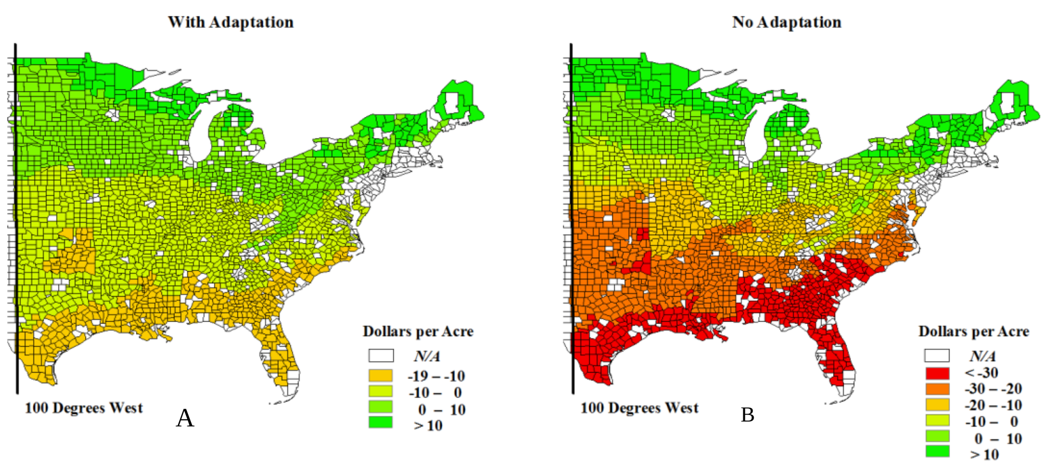
[22] We follow Schlenker, Hanemann, and Fisher (2005) to define the counties with more than 20 percent of irrigated farmland as the irrigated counties. We also tried to exclude counties with more than 5 percent or 10 percent of irrigated farmland and obtained reasonably similar results.

irrigated counties are excluded does not drive the main conclusion of this paper, suggesting that the influence of unmeasurable irrigation difference between counties in our sample, if any, is small.

The forth robustness check considers another way of calculating growing season degree-day. Following the literature, we have calculated degree-day from the daily mean temperature. This notion of degree-day was proposed by agronomists who examined the relationship between daily mean temperatures and the biomass yield of crops via field experiments (Ritchie and NeSmith 1991). Recently, it was suggested that degree-day calculated from daily minimum and maximum temperatures, instead of the usual daily mean temperatures, would more accurately predict crop yields (Schlenker and Roberts 2009, Tack, Barkley, and Nalley 2015). In this exercise, we follow the method of Schlenker and Roberts (2009) to calculate degree-day by minimum and maximum temperatures and investigate if the way in which degree-day is calculated matters for our results. As shown in Row 4 of Table 4, when degree-days are calculated by using minimum and maximum temperatures, the damage from climate change without adaptation (i.e. -15.21%) remains much larger than the damage with adaptation (i.e. -3.73%). We also find that adaptation can help to offset 79.1% of the damage of climate change, which is significantly larger than our baseline estimate of 72.2% (see Table 2).

The fifth and final robustness check re-estimates the impact of climate change under the highest climate change scenario, namely the RCP8.5 scenario. The RCP4.5 and RCP8.5 scenarios are the medium and upper bound climate change scenarios developed for the latest IPCC Fifth Assessment Report. So far, we have followed much of the literature by studying the impact of climate change under the RCP4.5 scenario. In this exercise, we will consider the climate change projections from the four climate models under the RCP8.5 scenario.[23] For the models with and without adaptation, we re-estimate the damages of climate change based on each of these climate projections.

The damage estimates under the RCP8.5 scenario with and without adaptation are reported in Row 5 of Table 4. Here, we find that both models with and without adaptation predict much higher damages, which is not surprising given that RCP8.5 is a more severe climate change scenario. However, just as before, the predicted damages with adaptation are much smaller than without, and comparing these predictions shows that adaptation can still help to offset about two-thirds (i.e. 67.3%) of the potential damage from climate change under the RCP8.5 scenario.



[23] For example, the predicted mean temperature rise from model CanESM2 under RCP8.5 is 6.3 ℃ by the end of this century, while the predicted mean temperature rise by the same model under RCP4.5 is only 2.3 ℃. When measured in growing season degree-days, the model CanESM2 predicted a 1,199 degree-days rise using RCP8.5 compared to a 583 degree-days rise using RCP4.5.

Figure 2. Geographic distribution of county-level effects of climate change by the end of this century under scenario CCSM4 RCP4.5

Notes: the left figure presents the effects that include adaptations and the right figure presents the effects without adaptations. The county-level effects are calculated by combining the estimated climate coefficients from models (2) and (3) with the predicted county-level climate changes. Here we take the predictions from climate model CCSM4 as an example; the geographic distributions of effects predicted from other climate models are quite similar. The sample includes 2155 rain-fed non-urban counties east of the 100 ^{o}meridian. All values are expressed in 2012 constant dollars.

Finally, Figure 2 maps the geographic distribution of the climate change impact on agricultural profits. Taking the climate projection from the CCSM4 climate model as an example, we calculate the county-level climate change impact with and without adaptations for each county in our study. From Panel B of Figure 2, we can see that warming will hurt the southern counties but benefit the northern counties most. However, as Panel A shows, if adaptations take place, the potential losses in the southern counties would be smaller while the potential gains in the northern counties would be larger. For example, based on climate change predictions take adaptations into account, we find that no counties would lose more than 20 dollars per acre per year (Panel A). However, without adaptations, 863 southern counties could lose more than 20 dollars per acre per year, and 321 counties among them could lose more than 30 dollars per acre per year (Panel B).

IV. Concluding Remarks

In this article, we attempt to estimate the value of agricultural adaptation as measured by how much adaptation can help in reducing the potential loss in agricultural profits due to climate change. Because there are numerous ways in which farmers can adapt to climate change, it is not feasible to estimate the total benefits of adaptation by estimating the benefits accruing to each adaptation method and aggregating these benefits up across all possible adaptation methods. It is also difficult to estimate the total benefits of adaptation by generating and comparing two climate change impact estimates, where the first takes adaptation into account and the second does not, as the difference between these estimates may reflect not only the value of adaptation but also differences in the models that generate these estimates. To address the latter issue, we propose the use of two panel models, which are the same in every aspect except for the specification of the fixed effects that these models used. By employing the appropriate fixed effect in each model, we argue that it would be possible for us to obtain two impact estimates such that one of them accounts for adaptations but the other does not.

We find that with adaptations, climate change (under the RCP4.5 scenario) could cause the end-of-this-century agricultural profits per year to be 9% less than the current agricultural profits per year, or 3.18 billion dollars less per year in profits at the end of this century than what we currently observe (at 2012 constant values). Without adaptations, the end-of-this-century agricultural profits per year could be reduced from current levels by as much as 30%, or 10.56 billion dollars, per year. Therefore, adaptations by farmers can help to offset about two-thirds of the potential loss in agricultural profits due to climate change, and this conclusion is robust in several robustness checks that consider the implications of model specification, omitted variable bias, the influence of inventory and storage, and alternative climate change scenarios.

We would like to highlight some limitations in our work. Firstly, the estimation of the value of adaptation in this paper is based on the assumption that farmers are able to take all the currently available adaptation methods in adapting to future climate change. This assumption is valid in the long run, such as one hundred years as used in the estimation of this paper. But in the short-run, farmers are unlikely to adopt all adaptation methods quickly because some adaptation methods require a large amount of investment. Therefore, even though this paper indicates large attainable value of adaptation in the long run, the short-run benefits from adaptation depends on the extent to which farmers are able to adopt the adaptation methods.

Secondly, this paper makes an implicit assumption that agricultural prices are constant. This assumption is reasonable if most of the negative effects of climate change in currently hot regions are offset by the positive effects of climate change in currently cold regions. Otherwise, agricultural prices will rise if there is less production resulting from climate change, and this price increase could mitigate the loss in agricultural profits even in the absence of adaptation. As such, the benefits of adaptation could be underestimated.

Thirdly, this study does not account for the beneficial fertilisation effects of higher CO_2 concentration. Evidence from agronomic experiments suggests that CO_2 concentration has the potential to partly offset the negative effect of global warming on agriculture, although the magnitude of this effect is still debated (Long et al. 2006). Finally, to avoid the potential bias from unpredictable availability of irrigation in the future, we have followed the literature and used only data from counties where rainfed agricultural production dominates. Hence, our results may only be valid to rainfed agriculture regions.

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For Online Publication Appendix

A. The remaining variation after different fixed effects are employed in a panel model

In Table A1, we demonstrate how a generic weather variable would be transformed by employing certain fixed effects in a climate change impact panel study. To simplify this discussion, we consider a balanced panel with two years and two counties. In Panel A of Table A1, we let w_{it} represent the weather realization of county i in year t, where $i, t \in (1,2)$. Each weather observation can be decomposed into three parts: the first part T_i represents the county i's climate (e.g. the long-term average temperature or precipitation), which has variations across counties; the second part d_t measures the inter-annual weather fluctuations that are common across counties in the same year but vary over time; the last part ε_{it} represents the county-specific weather shock. The within-county means and within-year means, which are used in the discussion below, are also reported in Panel A of Table A1.

Panel B of Table A1 shows that including time fixed effects into a panel study on climate change would transform the model by subtracting the yearly weather realizations of each county with the average weather outcome across counties in the same year. Hence, when time fixed effects are included, the common inter-annual weather fluctuation (d_t) will be filtered out and what remain in the weather variation are the county-specific climate (T_i) and the county-specific weather shock (ε_{it}). If the variation pertaining to the latter is small, the impact of the weather variable (when time fixed effects are included) would be identified mainly through cross-sectional climate differences (i.e. $T_1 - T_2$ or $T_2 - T_1$).

Table A1. The consequences of fixed effects on the climate change impact panel study

	Year 1	Year 2	Within-county mean
Panel A. No fixed effects			
County 1	$w_{11} = T_1 + d_1 + \varepsilon_{11}$	$w_{12} = T_1 + d_2 + \varepsilon_{12}$	$T_1 + \frac{d_1 + d_2}{2} + \frac{\varepsilon_{11} + \varepsilon_{12}}{2}$
County 2	$w_{21} = T_2 + d_1 + \varepsilon_{21}$	$w_{22} = T_2 + d_2 + \varepsilon_{22}$	$T_2 + \frac{d_1 + d_2}{2} + \frac{\varepsilon_{21} + \varepsilon_{22}}{2}$
Within-year mean	$d_1 + \frac{T_1 + T_2}{2} + \frac{\varepsilon_{11} + \varepsilon_{21}}{2}$	$d_2 + \frac{T_1 + T_2}{2} + \frac{\varepsilon_{12} + \varepsilon_{22}}{2}$	
Panel B. Time fixed effects: subtracting within-year mean from each observation			
County 1	$\frac{T_1 - T_2}{2} + \frac{\varepsilon_{11} - \varepsilon_{21}}{2}$	$\frac{T_1 - T_2}{2} + \frac{\varepsilon_{12} - \varepsilon_{22}}{2}$	
County 2	$\frac{T_2 - T_1}{2} + \frac{\varepsilon_{21} - \varepsilon_{11}}{2}$	$\frac{T_2 - T_1}{2} + \frac{\varepsilon_{22} - \varepsilon_{12}}{2}$	
Panel C. County fixed effects: subtracting within-county mean from each observation			
County 1	$\frac{d_1 - d_2}{2} + \frac{\varepsilon_{11} - \varepsilon_{12}}{2}$	$\frac{d_2 - d_1}{2} + \frac{\varepsilon_{12} - \varepsilon_{11}}{2}$	
County 2	$\frac{d_1 - d_2}{2} + \frac{\varepsilon_{21} - \varepsilon_{22}}{2}$	$\frac{d_2 - d_1}{2} + \frac{\varepsilon_{22} - \varepsilon_{21}}{2}$	
Panel D. Two way fixed effects: subtracting within-county and within-year mean, and plus sample mean			
County 1	$\frac{\varepsilon_{11} - \varepsilon_{12} - \varepsilon_{21} + \varepsilon_{22}}{4}$	$-\frac{\varepsilon_{11} - \varepsilon_{12} - \varepsilon_{21} + \varepsilon_{22}}{4}$	
County 2	$-\frac{\varepsilon_{11} - \varepsilon_{12} - \varepsilon_{21} + \varepsilon_{22}}{4}$	$\frac{\varepsilon_{11} - \varepsilon_{12} - \varepsilon_{21} + \varepsilon_{22}}{4}$	

Notes: w_{it} is the weather outcome of county i in year t, where $i, t \in (1,2)$; T_i represents the climate of county i, which is assumed to be constant over time but different across counties; d_t measures the inter-annual weather fluctuations that are common across counties in the same year but vary over time; ε_{it} is the county-specific weather shocks.

Panel C of Table A1 shows that including county fixed effects into a panel study on climate change would transform the model by subtracting the within-county mean from each county. In this case, what remain are the common inter-annual weather fluctuation (d_t) and the county-specific weather shock (ε_{it}). As before, if the variation pertaining to the latter (ε_{it}) is small, the impact of the weather variable would be identified mainly through inter-annual weather fluctuation (i.e. $d_1 - d_2$ or $d_2 - d_1$).

Finally, Panel D of Table A1 shows that including county fixed effects along with year fixed effects would eliminate both cross-sectional differences in the climate (T_i) and the common inter-annual weather fluctuation (d_t). Consequently, the climate change impact will be identified by the variation in the county-specific weather shock (ε_{it}).

B. The magnitude of county-specific weather shock

Our panel approach of estimating the value of adaptation relies on the assumption that $w_{it} = T_i + d_t + \varepsilon_{it}$ can be approximated by $w_{it} \approx T_i + d_t$. This approximation is reasonable if the county-specific weather shock (ε_{it}) is small. To get some evidence if this is true, let us consider a panel of county-level temperature and precipitation data during 1987-2012 for 2155 US counties.

Row A1 of Table B1 shows the temperature variation pertaining to the county-specific temperature shock (ε_{it}), which can be obtained by using county fixed effects and state-by-year fixed effects to eliminate the long-run county-specific temperature component (T_i)

and the common inter-annual temperature fluctuation (d_t) from temperature itself (see Panel D of Table A1 in Appendix A for illustration).[24] As Row A1 of Table B1 shows, the variation pertaining to the county-specific weather shock (ε_{it}) is small: there are no counties with an absolute value of ε_{it} that is larger than 1 ℃, while more than 95% of counties have an absolute value of ε_{it} that is smaller than 0.4 ℃.

Table B1. Climatic variations after using different fixed effects

Panel A. Percentage of counties with remaining temperature variation below/above (℃):				
	±0.4	±0.6	±0.8	±1.0
(A1). State-by-year fixed effects and county fixed effects	4.8	0.7	0.2	0.0
(A2). State-by-year fixed effects only	68.5	53.9	40.6	29.2
(A3). County fixed effects only	79.4	64.5	48.8	34.6
Panel B. Percentage of counties with remaining precipitation variation below/above (Inches):				
	±4	±6	±8	±10
(B1). State-by-year fixed effects and county fixed effects	10.3	2.4	0.6	0.2
(B2). State-by-year fixed effects only	20.4	8.0	3.6	1.4
(B3). County fixed effects only	32.5	14.2	5.1	1.5

Notes: All entries are the percentage of counties with a remaining temperature deviation from a zero-mean that is at least as large as the corresponding values reported in the column heading (i.e. ±4, ±6, ±8, and ±10). All entries are calculated from a balanced county-level panel data for census years from

[24] The state-by-year fixed effect is equal to imposing individual year-fixed effect for each state. Since the US covers large geographic areas, the state-by-year fixed effect is better than the year-fixed effect in accounting for inter-annual common fluctuations. In fact, using state-by-year fixed effects instead of year-fixed effects is a common practice in the empirical study.

1987 to 2012 for 2155 US sample counties. The temperature is measured by growing season average temperature (℃), and the precipitation is measured by growing season total precipitations (inches). See Appendix C for detailed data descriptions.

By contrast, there is evidence that the variation in the long-term temperature component (T_i) is much larger than the county-specific temperature shock (ε_{it}).For example, by using the state-by-year fixed effect, we may purge the common inter-annual fluctuation (d_t) from temperature itself. The residual temperature variation will then be driven mainly by the long-run component (T_i) and the county-specific shock (ε_{it}) (see Panel B of Table A1). As Row A2 of Table B1 shows, this residual component exceeds 0.8 ℃ for about 40% of counties and 1 ℃ for 29.2% of counties. Since we have evidence that the county-specific shock is small, this result suggests that there is significantly more variation in the long-run temperature component T_i than the county-specific shock itself.

Similarly, there is evidence that the inter-annual temperature fluctuation (d_t) has much greater variation than the county-specific temperature shock (ε_{it}). For example, by using county fixed effects, we may purge the long-term temperature component (T_i) and what remains will be the common inter-annual fluctuation (d_t) and the county-specific shock (ε_{it}) (see Panel C of Table A1). As Row A3 of Table A2 shows, this residual component exceeds 0.8 ℃ for nearly 50% of counties and 1 ℃ for nearly 35% of counties.

Therefore, there is evidence that the common inter-annual temperature fluctuation is large relative to the county-specific temperature shock.[25]

Besides temperature, Panel B of Table B1 shows that the county-specific precipitation variation is very small relative to the cross-sectional inter-county precipitation variation and inter-annual precipitation fluctuations. For other weather variables such as yearly mean temperature and growing season degree-day, we find the same is also true about their county-specific variations (results omitted here to save space). This suggests that the county-specific component in each of these climatic variables is small relative to their respective long-run cross-sectional components and common inter-annual fluctuations. As such, the approximation of $w_{it} = T_i + d_t + \varepsilon_{it}$ with $w_{it} \approx T_i + d_t$ appears to be reasonable for the climatic variables we consider in our panel approach.

In Figure B1, we provide some additional graphical evidence to show that the variation in the county-specific weather shock is very small. Take the US state of Louisiana as an example and consider temperature as the weather variable. Figure B1 shows the county-level long-run average yearly mean temperatures and the inter-annual temperature fluctuations for each of the 64 counties (parishes) within Louisiana. To get a sense of what the inter-annual temperature fluctuation for each county might be, we plot the county's deviation of its 1983 and 1998 mean temperatures from its long-term average temperature, where 1983 is representative of a "cold" year and 1998 a "hot" year. This deviation in the 1983 and 1998 annual temperatures contains the inter-annual

[25] In the case of the county-specific weather shock, the mean is zero.

temperature fluctuations that are common across counties and the county-specific temperature shock.

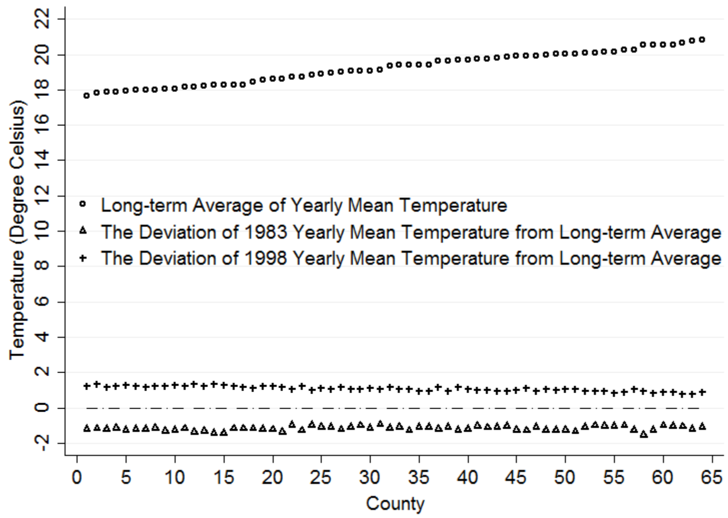

Figure B1. County-level long-term average of yearly mean temperature and inter-annual temperature fluctuations (i.e. deviations) for the US state of Louisiana

Notes: This figure depicts long-term (1981–2000) county-level average of yearly mean temperature and two sample years' (1983 and 1998) yearly mean temperature deviations from long-term county-level averages for all of the 64 counties (parishes) within the US state of Louisiana. The x-axis denotes counties sorted by yearly mean temperature.

If the county-specific temperature shock is equal to zero, the yearly temperature deviation will be equal to the size of the common inter-annual fluctuation and the temperature deviation (during 1983 and 1998) will be the same across counties. Therefore, any cross-county variation in the yearly temperature deviation must be caused by county-specific temperature shocks. Based on this argument, we can get a sense of how much variation the county-specific temperature shock has by comparing the differences in the temperature deviations across counties. As Figure B1 shows, the differences in the temperature deviations across counties are very small when compared to the size of the temperature deviations and the range of long-run temperatures across counties. For example, the difference in the temperature deviation between county 1 (Claiborne Parish) and county 64 (Plaquemines Parish) is 0.12 ℃ in 1983, but the difference in their long-term average temperatures is 3.18 ℃. Moreover, the average temperature deviation across counties for the same year is 1.19 ℃. This suggests that the variation in the county-specific weather shock is very small when compared with the inter-county climate variation and to the common inter-annual temperature fluctuation.

C. Data sources and summary statistics

This study makes use of a panel of county-level agricultural production, climate and other socio-economic and geophysical data for 2155 US counties east of the 100°meridian. This section provides data sources and summary statistics.

Agricultural production: we follow the literature to construct US county-level agricultural profits per acre from *Census of Agriculture* for the census years of 1982, 1987, 1992, 1997, 2002, 2007, and 2012. Agricultural profits are calculated as the difference between agricultural revenue and agricultural expenditure.[26] In this data source, agricultural revenue measures the before-taxes total market value of all agricultural products sold in a county during a particular year. These products include livestock,

[26] The agricultural profits data is constructed for the years after 1987 since expenditure data are only available after this time.

poultry, and other derivative products, as well as crops that include nursery and greenhouse crops and hay. Agricultural expenditure covers all variable costs for agricultural production, farm business related interest paid on debts, and maintenance costs.

As a robustness check, we consider farmland value per acre as another measure of agricultural productivity.[27] Farmland values estimate the value of land and buildings used in agricultural production. These county-level aggregate measures are divided by farmland area to obtain the county-level agricultural profits per acre and farmland value per acre, which are the dependent variables of the econometric study. The farmland area includes acres used in crops, grazing, and pasture.[28]

Climate: the daily maximum temperature, minimum temperature and precipitation data from 1981 to 2012 are derived from Parameter-elevation Regressions on Independent Slopes Model (PRISM 2014). PRISM Climate Group provides 4×4 kilometre gridded daily data after the year of 1981 for the entire US, which is regarded as one of the most reliable small scale climatic data sets. County-level climate measures are calculated as the simple averages of the climate cells over the agricultural land within each county. This study follows the literature to construct the standard county-level

[27] The hedonic approach usually considers farmland value per acre as the dependent variable. Therefore, we follow the same as a robustness check, although we do not focus on it in our paper as it has little time-variation for a panel study.

[28] See previous studies such as Deschênes and Greenstone (2007) for more detailed agricultural production data descriptions.

measures of climatic variables: growing season degree-days (GDD), growing season harmful degree-days (GHDD) and growing season total precipitation (GTP) (Schlenker, Hanemann, and Fisher 2006, Deschênes and Greenstone 2007).

GDD measures the cumulative exposure to heat between 8 ℃ and 32 ℃ during the growing season from April to September. In detail, a day with a mean temperature (say $\bar{z}$) below 8℃ contributes zero degree-days, between 8℃ and 32℃ contributes $\bar{z} - 8$ degree-days, above 32℃ contributes 24 degree-days. GDD is then calculated as the sum of the daily degree-days in the growing season.

GHDD is calculated as the sum of degree-days above a harmful threshold. We set the threshold of harmful temperature as 32℃. Thus, a day with a mean temperature (say $\bar{z}$) above 32℃ contributes $\bar{z} - 32$ harmful degree-days; otherwise, it contributes zero harmful degree-days (Ritchie and NeSmith 1991).[29] Finally, GTP is the total precipitation in inches during the growing season.

Climate predictions: we use the latest high resolution climate predictions from General Circulation Model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor, Stouffer, and Meehl 2012). The data of 42 climate projections from 21 CMIP5 GCMs and two Representative Concentration Pathways

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[29] The agronomy literature suggests a range of possible thresholds for harmful degree-days. The most frequently used one is 34 ℃ (Ritchie and NeSmith 1991). A more recent study that examined nonlinear temperature effects suggests that crop yields decrease sharply for *mean* temperatures higher than 29°–32 ℃ (Schlenker and Roberts 2009). Since the heat below 32 ℃ has been included in the calculation of GDD, we prefer to set the threshold of GHDD as 32 ℃.

(RCP) scenarios (RCP4.5 and RCP8.5)[30] are available from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset.[31] Each model provides daily maximum temperature, minimum temperature and precipitation under various scenarios for the periods from 2006 to 2100, and with a spatial resolution of 0.25 degrees × 0.25 degrees (about 25 km × 25 km). Each model also provides simulated historical daily data from 1950 to 2005 for the same spatial resolution. Since point estimates based on a single climate projection can be misleading (Burke et al. 2015), to estimate the impact of climate change here, we use the climate projection for the medium scenario RCP4.5 from four of the most widely used CMIP5 models: CCSM4, CESM1-BGC, CanESM2, and NorESM1-M.[32]

Control variables: we follow the literature to use a set of county-level soil quality variables as controls. These data are from the National Resource Inventory and have been widely used. The soil quality controls include measures of soil salinity, sand content, clay content, K-Factor, flood risk, permeability, slope length, moisture in top soil, share of

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[30] The RCPs include four climate change scenarios which were developed for the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), and the RCP4.5 and RCP8.5 represent the medium and highest scenarios, respectively.

[31] Data from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset is available from https://cds.nccs.nasa.gov/nex-gddp/.

[32] There are over twenty recognized climate change prediction models available, and large prediction discrepancies are observed across models. We do not have evidence that any particular model is more reliable than others (Solomon 2007). See http://cmip-pcmdi.llnl.gov/cmip5/availability.html for details of modelling centers.

wetland and irrigated land.[33] Since the land qualities are almost constant over time, the missing values in the soil quality controls are interpolated. We also use county-level per capita income and population density as control variables for robustness check.

Irrigation water is generally heavily subsidized, depletable, and unevenly distributed across regions. Therefore, irrigation may become unavailable as an adaptation method in the future in some regions. Hence, the benefit of adaptation could be overestimated if we assume that currently irrigated regions would continue to have access to the same level of irrigation in the future; including counties where agricultural production depends heavily on irrigation will bias the estimation of the value of adaptation upward. In order to avoid this potential bias,, we follow Schlenker, Hanemann, and Fisher (2006) in using only data from counties east of the 100 °meridian, which account for a large proportion (71.6%) of US agricultural profits. Importantly, in these counties, farming largely relies on rainfall, as opposed to farming in the arid West that depends mainly on irrigation. As such, we will address the issue of unmeasurable irrigation differences by focusing on counties east of the 100 °meridian.

We also exclude urban counties in this study as farming in these counties usually occurs on a very small scale. Urban counties are defined as counties having a population density of more than 400 people per square mile (Schlenker, Hanemann, and Fisher 2005). We exclude counties with missing values during the sample years to form a balanced panel. Hence, we are left with 2155 non-urban rain-fed sample counties across the seven

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[33] See Appendix A of Mendelsohn, Nordhaus, and Shaw (1994) for a detailed description of soil controls.

census years. All profits and land prices are translated into 2012 dollars using the GDP implicit price deflator.

Table C1. A summary of agricultural production data

	1982	1987	1992	1997	2002	2007	2012
County average of:							
Farmland prices ($1/acre)	2073	1387	1363	1614	1927	2566	3332
Agricultural profits ($1/acre)	--	66	66	83	42	83	99
Areas of land in farms (th. acres)	366	366	362	365	370	372	375
Agricultural expenses ($1/acre)	--	242	253	264	264	335	432

Notes: All entries are county-level averages over the 2155 rain-fed non-urban counties weighted by acres of farmland. Agricultural profits and expenses are not available prior to 1987. All dollars are in 2012 constant values.

Table C1 summarizes the agricultural production data. Large non-linear variations in farmland prices and agricultural profits are observed during 1982–2012, but no obvious correlations can be found between them. The farmland areas remain almost constant, while agricultural expenses show an increasing trend.

Table C2. Summary Statistics of Climate Normal and Climate Predictions

	Growing Season:			
	Average temperature (℃)	GDD (℃)	GHDD (℃)	GTP (Inches)
Climate Normal				
	20.23	2272	0.11	23.50
	(3.25)	(558)	(0.43)	(3.60)
Predicted climatic changes by the end of this century under scenario RCP4.5:				
CCSM4	1.95	379	0.38	1.90
	(0.61)	(55)	(0.66)	(2.17)
CESM1-BGC	2.04	384	0.49	2.63
	(0.99)	(65)	(1.55)	(2.97)
CanESM2	2.27	583	1.47	0.41
	(0.50)	(74)	(3.01)	(1.61)
NorESM1-M	2.79	547	3.13	1.35
	(0.80)	(89)	(4.92)	(1.80)

Notes: All entries are simple averages over the 2155 sample counties. See the text for how the climate normal and climate predictions are calculated. Standard deviations are reported in parentheses.

Table C2 reports the summary statistics of climate normal and climate projections (temperature and precipitation). County-level climate normal is calculated as a 20 year average of the climatic variable (i.e. average temperature, GDD, GHDD or GTP) from 1981 to 2000 for each county. The projected county-level climates based on various scenarios for each climate projection model (i.e. CCSM4, CESM1-BGC, CanESM2 or NorESM1-M) are calculated by the following steps: **Step 1**: Map the gridded climate predictions from each climate projection model into each state to provide state-level climate predictions,[34] **Step 2**: Calculate state-level climate change predictions as the difference between the predicted 2081–2100 average and the simulated historical average of 1981–2000 based on each model, **Step 3**: Add the predicted state-level climate changes from Step 2 to the county-level climate normal to form county-level climate predictions for the end of this century.[35]

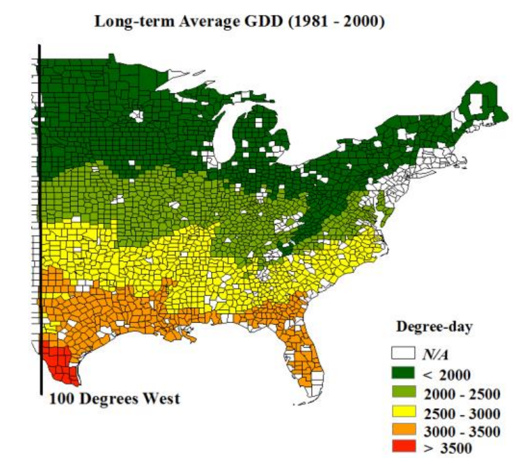
Compared with the climate normal, the predicted mean temperature rise based on these four climate models ranges from 1.95 ℃ to 2.79 ℃, which is within the range of the best prediction of mean temperature increase (i.e. 1.0 ℃ to 3.7 ℃) by the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (2014).

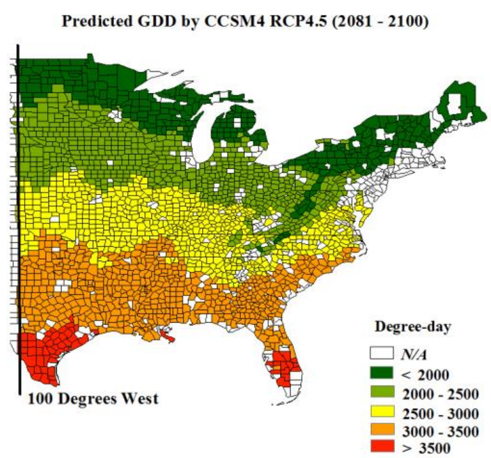
[34] The spatial resolution of climate predictions does not allow us to calculate the county-level predictions.

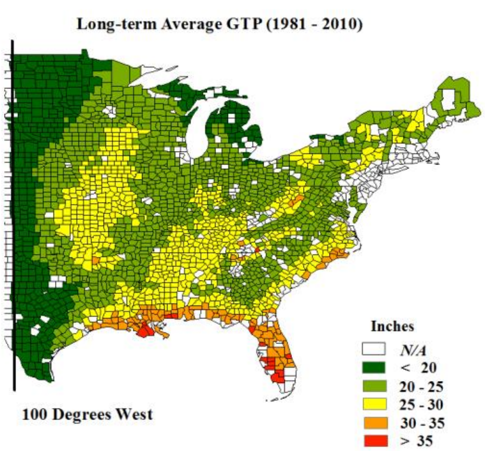
[35] The climate normal is usually defined as a 30 year average, but the daily fine scale data before 1981 is not available, and the simulated historical data after 2006 is not provided by CMIP5 models. Calculating climate normal as a 20 or 30 year average should have no significant effect on climate change impact predictions. The crucial thing is to make sure that the period during which the climate normal is calculated is the same as the base period that is used to formulate climate change predictions for each model, because the model output is not at the same spatial resolution as the observed data (Fisher et al. 2012).

Large changes in the GDD are predicted to range from 379 to 547. The GHDD normal, which is a simple average of GHDD over all sample counties, is very small (i.e. only 0.11). This comes from the fact that a large share of counties has a mean temperature of less than 32 ℃ and these counties contribute zero GHDD.

That being said, 30% of sample counties contribute positive GHDD and 70 hot counties have more than 1 GHDD (with large standard deviations). Because there are observed counties with extreme GHDD, we may credibly predict what might happen in the event of hot temperatures (i.e. when GHDD is large).







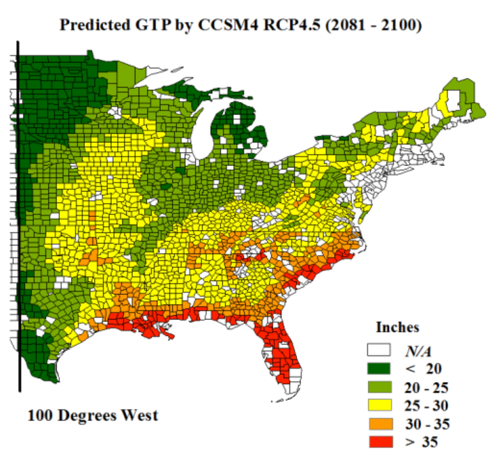


Figure C1. Geographic distributions of GDD and GTP for climate normal and scenario CCSM4 RCP4.5

Notes: The samples are 2155 rain-fed non-urban counties east of the 100 °meridian. This figure compared the geographic distribution of the climate prediction of the representative scenario CCSM4 RCP4.5 with the distribution of climate normal.

Lastly, Figure C1 compares the geographic distribution of the climatic variables of climate normal with the distribution of predictions from the representative model CCSM4 RCP4.5. The distributions of predictions from the other three models are quite similar. For the climate normal, the GDD is decreasing from southern counties to northern counties, and the GTP is decreasing from east counties to west counties. The predictions from CCSM4 RCP4.5 follow the same geographic pattern, but predict a hotter and wetter climate. We mapped distributions of the prediction from other climate models and find similar results.

D. A Bayesian learning simulation of the believed climate trend

This section argues that farmers may not fully recognize and adapt to the recent climate trends because large inter-annual weather fluctuations that accompany them may obscure farmers' recognition of these trends. As shown in Figure D1, even though there is a significantly increasing trend in the yearly mean temperature in the US from 1960 to 2010, the inter-annual temperature fluctuation is much larger than the warming trend.

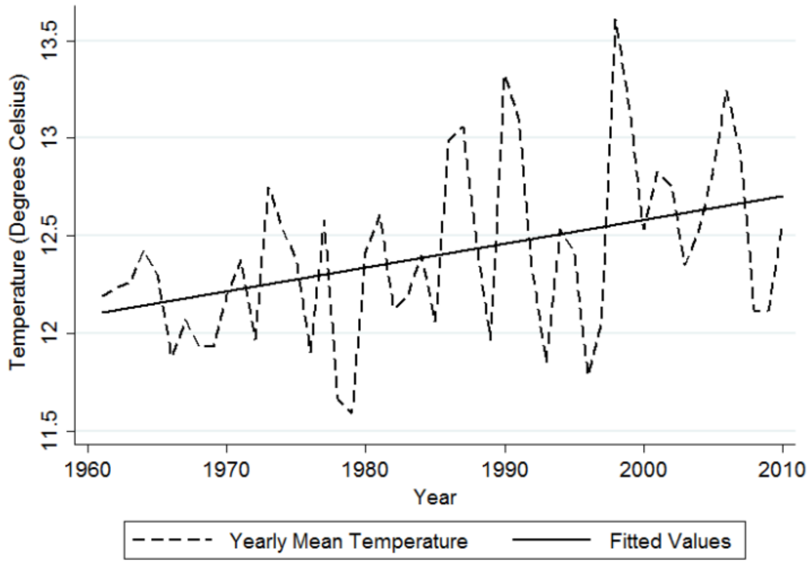


Figure D1. Yearly mean temperature fluctuations in the US, 1960–2010

Data source: Physical Sciences Division of National Oceanic and Atmospheric Administration (http://www.esrl.noaa.gov/psd/)

This section provides a simple learning model to show that even when there are obvious climate trends, farmers' may underestimate these trends. Let us suppose that farmers' belief of the "true" mean temperature follows a simple Bayesian learning process. Denote farmers' belief of mean temperature in period t as c_t and the precision of their belief as φ_t. In each period, they observe the realized temperature s_t and update their belief to c_{t+1} using a weighted combination of their prior belief and the realized temperature. For simplicity, let us assume that the variance (σ^2) of the realized temperature is unchanged when mean temperature increases and denote $\delta = 1/\sigma^2$. When the temperature increases suddenly by the amount Δc in the base year, the farmers' belief about mean temperature after T years will be given by:

$$c_T = \frac{\varphi_t c_t + T\delta s_t}{\varphi_t + T\delta}$$

with $\varphi_{t+1} = \varphi_t + \delta$ (DeGroot (1970). In expectation, the difference between the believed temperature change and the true temperature change is given by:

(5) $$D = \frac{\Delta c}{1 + T\delta / \varphi_0}$$

We combine Eq. (5) with the empirical data used in Figure D1 to simulate draws of farmers' beliefs. Assuming that the initial precision of their beliefs (φ_0) is the inverse of the variance of temperature during 1960-1970 (i.e. a period before large temperature variance), and that the temperature variance during 1970-2010 is σ^2. Then, we can simulate the evolution of farmers' beliefs after a once for all, say 5 ℃, mean temperature rise in the base year.

The result, which is shown in Figure D2, shows that after 10 years, only about 40 percent of the mean temperature rise is believed to be a true temperature increase rise, and after 50 years, only about 80 percent of the mean temperature rise is recognized as a permanent change. Given the believed climate change is much smaller than the actual change, farmers' adaptation to recent climate trends could be weak.

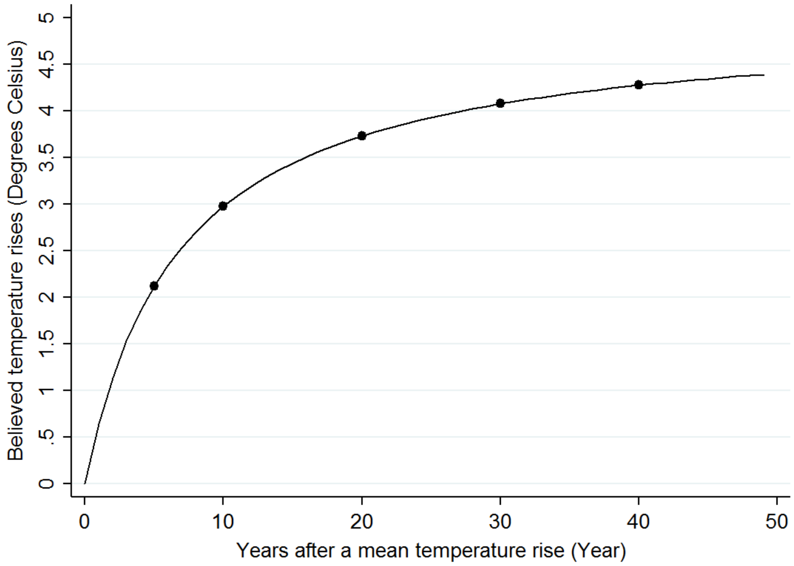


Figure D2. A simulation of farmers' believed "true" temperature rise after an assumed 5 °C temperature increase in the base year

E. A comment on hybrid panel models

To implement the hybrid approach (e.g., Bell and Jones 2015), we may estimate a model such as

$$y_{it}^{s} = \rho \sum_{j \in N} w_{ij} y_{jt}^{s} + \sum_{k \in K} \bar{c}_{ik}^{s} \alpha_{k}^{B} + \sum_{k \in K} (c_{itk}^{s} - \bar{c}_{ik}^{s}) \alpha_{k}^{W} + \sum_{g \in G} l_{itg}^{s} \beta_{g} + \mu_{i} + u_{it} \tag{6}$$

$$i = 1, \ldots, \mathrm{N}; \; t = 1, \ldots, T$$

where the superscript *s* is introduced here to denote the state which county *i* is in, c_{itk}^{s} and l_{itg}^{s} represent county *i*'s k^{th} climatic variable and the g^{th} control variable, respectively. In the hybrid model, we decompose c_{itk}^{s} into $\bar{c}_{ik}^{s}$, which is its time-average, and $(c_{itk}^{s} - \bar{c}_{ik}^{s})$, which is its deviation around its time-average. The coefficient α_{k}^{B} on $\bar{c}_{ik}^{s}$ captures the between effect of the k^{th} climatic variable, and the coefficient α_k^W on $(c_{itk}^s - \bar{c}_{ik}^s)$ captures its within county effect. In the hybrid approach, the between and within effects of a climatic variable can be estimated within a single model represented by Eq. (6).

However, to estimate Eq. (6), we have to assume that μ_i is a random effect. Once we impose distributional assumptions for μ_i and u_{it}, we may estimate Eq. (6) using Generalized Least Squares (GLS) regression. Note that μ_i cannot be a fixed effect: if we assume as such, the between effects of climatic variables (i.e. α_k^B) will not be identified. This is a key limitation of the hybrid approach that can be avoided by implementing the two-panel approach instead.

Interestingly, Moore and Lobell (2014) implement an approach that resembles the hybrid approach. For example, if we adapt Moore and Lobell's (2014) approach to our problem, we will estimate a regression that looks like

$$
\begin{aligned}
y_{it}^s = \rho \sum_{j\in N} w_{ij} y_{jt}^s + \sum_{k\in K} \bar{c}_{ik}^s \alpha_k^B + \sum_{k\in K} \left(\bar{c}_{ik}^s\right)^2 \tilde{\alpha}_k^B + \sum_{k\in K} (c_{itk}^s - \bar{c}_{ik}^s)^2 \alpha_k^W \\
+ \sum_{g\in G} l_{itg}^s \beta_g + \mu_s + \mu_s * (t + t^2) + u_{it} \qquad (7) \\
i = 1,..., \text{N}; \; t = 1,..., T
\end{aligned}
$$

where μ_s is the state fixed effects, and $\mu_s * (t + t^2)$ captures the potentially nonlinear state-specific time trend. Moore and Lobell (2014) include $\bar{c}_{ik}^s$ and its square, and $(c_{itk}^s - \bar{c}_{ik}^s)^2$, which utilize the between and within variations of the original climatic variable c_{itk}^s, respectively. However, unlike the hybrid approach, these variables are not derived as decompositions of c_{itk}^{s} . In fact, in the hybrid model, the variable $\left(\bar{c}_{ik}^{s}\right)^2$ will not appear and the square of the mean deviation $(c_{itk}^{s} - \bar{c}_{ik}^{s})^2$ will not be used in place of the mean deviation itself (see Eq. (6)). Intuitively, since $(c_{itk}^{s} - \bar{c}_{ik}^{s})^2$ transfer all negative mean deviations of yearly climatic variables (such as temperature) into positive deviations through the square, the coefficient on $(c_{itk}^{s} - \bar{c}_{ik}^{s})^2$ captures quite different effects compared with the coefficient on $(c_{itk}^{s} - \bar{c}_{ik}^{s})$ in the hybrid approach. As such, the Moore and Lobell (2014) approach is not a hybrid approach and therefore is not comparable to the two-panel approach implemented here.