THE UNIVERSITY of ADELAIDE

School of Economics

Working Papers

ISSN 2203-6024

The Economic Impacts of Global Warming on US Agriculture: the Role of Adaptation

Kaixing Huang

Working Paper No. 2016-03
February 2016

Copyright the author

CRICOS PROVIDER 00123M

adelaide.edu.au

seek LIGHT

The Economic Impacts of Global Warming on US Agriculture: the Role of Adaptation[#]

By KAIXING HUANG*

Studies of climate change impacts on agricultural profits using panel data typically do not take account of adaptations over time by farmers, and those that do tend to use the standard hedonic approach which is potentially biased. As an alternative, this paper develops a panel framework that includes farmer adaptation. When tested with United States data, this study finds that the negative impact of expected climate change on farm profits by 2100 is only one-third as large once likely adaptation by farmers is taken into account. (JEL Q15, Q51, Q54)

* School of Economics, The University of Adelaide, 10 Pulteney Street, Adelaide, SA, 5000 (Kaixing.huang@adelaide.edu.au)

[#] First version: October 2015. This version: February 2016.

Agriculture is expected to be the most vulnerable sector to climate change, since temperature and precipitation are direct inputs to agricultural production. Disentangling the effects of climate change on agricultural production is crucial for understanding food security problems and potential costs associated with greenhouse gas emissions (Hansen 1991, Lobell and Asner 2003). However, the economic literature has debated the sign and magnitude of the potential impacts, leading to opposing policy recommendations (see, for example, Adams 1989, Mendelsohn, Nordhaus, and Shaw 1994, Schlenker, Hanemann, and Fisher 2005, Deschênes and Greenstone 2007, Fisher et al. 2012).

The role of adaptation is central to the debate surrounding the impacts of climate change on agriculture. In an effort to avoid the potential downward bias of the production-function approach due to omitting adaptation, Mendelsohn, Nordhaus, and Shaw (1994) proposed a hedonic approach to identify climate change impact through cross-sectional climatic differences.[1] Specifically, the impacts are identified by examining how climate in different regions affects the value of farmland. Since agricultural agents have completely adapted to the climate of their particular regions, the full range of adaptations are included in this approach. The hedonic approach has become the standard in the economic literature.[2]

Even though the hedonic approach is appealing, many believe that the cross-sectional method is particularly vulnerable to misspecification. As an alternative, a panel method that identifies climate change impacts through random inter-annual weather fluctuations has been applied in a rapidly growing body of literature (see, for example, Deschênes and Greenstone 2007).[3] The major advantage of employing random weather fluctuations is avoiding misspecification, the drawback, however, is not including adaptations. Since farmers do not adapt to random year-to-year weather fluctuations, climatic coefficients identified by this approach do not contain the benefit of adaptation (Seo 2013). Hence, the merits of this panel method depend on how much adaptation will actually occur to offset the estimated impacts.

It seems that a hedonic study that carefully deals with potential misspecifications should provide a reliable estimate. However, previous studies have found that even in a well-controlled hedonic regression, the hedonic estimates are extremely sensitive to sample time and sample location (Deschênes and Greenstone 2007, 2012). By examining the frequently used US farmland value data, we find that there are significant measurement errors in farmland values and these errors are correlated with inter-annual weather fluctuations as well as cross-sectional climates. Since the hedonic model depends on farmland values as the dependent variable, the estimated climatic coefficients are potentially biased, and the sign and magnitude of the biases depend on the sample time and sample location. This fact provides another explanation of why hedonic estimates have been extremely sensitive to sample time and sample location.

After taking into consideration the inconsistences of findings from previous studies and the potential biases that result from omitting adaptations, misspecifications or measurement

[1] Before Mendelsohn, Nordhaus, and Shaw (1994), research mainly relied on the production-function approach (see, for example, Adams et al. 1990), which is still a widely used method.

[2] The method has been applied to examine the impacts of climate change on the agriculture of more than 30 countries (Massetti and Mendelsohn 2011).

[3] See Dell, Jones, and Olken (2014) for a survey.

errors in the widely used methodologies, this study develops a panel method to include adaptations and avoid these biases. Based on the basic idea of the hedonic approach, we have modified the previous panel method that relies on inter-annual weather fluctuations to develop a panel framework that identifies climate change impacts through cross-sectional climate differences. Since the effects are identified though cross-sectional climate differences, as in the hedonic approach, the full range of adaptations are included. On the other hand, the panel framework enables us to use agricultural profits data instead of farmland value data, and hence avoids the potential bias from the measurement errors of farmland values. Lastly, the panel framework with fixed-effects dramatically reduces the chance of misspecification.

This framework is combined with a panel of US county-level agricultural production and climate data and the output of various climate models to project the long-run impacts of climate change on US agricultural profits. The empirical results show that, when taking into account adaptations, the estimated overall damages are about 9 percent (or 3.18 billion US dollars in 2012 constant values) per year by the end of this century. In order to infer the benefit of adaptations, we also estimate impacts by the panel model that depends on random inter-annual weather fluctuations and which does not include adaptations. We find that if adaptations are omitted, the overall damages are as high as 30 percent (or 10.56 billion US dollars) per year. Therefore, adaptations will help to offset about two-thirds of the overall damages, and methods omitting adaptations can substantially overestimate the damages. These results are robust to numerous specification checks.

This paper proceeds as follows. Section I is the conceptual framework that illustrates how to include adaptations in a panel framework and how to explicitly estimate the potential benefit of adaptations. Section II contains the data sources and summary of statistics. Section III provides the details of our panel model and its differences from previous models. Empirical results are shown in section IV. The last section concludes this paper.

I. Conceptual Framework

A. Climate change, weather fluctuation and adaptation

Climate describes the long-run average of weather outcomes for a given region, while weather refers to a particular year's realization of climate distribution (Dell, Jones, and Olken 2014). Three sources of variation can be employed to identify climate change impacts: cross-sectional climate differences as used in the hedonic approach; inter-annual random weather fluctuations as adopted by panel studies such as Deschênes and Greenstone (2007); and long-term climate trends as employed by long-term panel studies such as Burke and Emerick (2015). The following definition of adaptation illustrates that only the studies that are based on cross-sectional climate differences incorporate the full range of adaptations.

Following the general understanding of the literature, this study defines adaptation of agriculture to climate change as production behavior adjustments by agricultural agents in order to moderate negative effects or exploit beneficial opportunities from the changed climate (Zilberman, Zhao, and Heiman 2012, Lobell 2014, Burke and Emerick 2015). Here we stress the difference between long-run adaptation to climate change and short-run responses to weather fluctuations: in adapting to long-run climate change, farmers can adjust land use and other *ex-ante* production behavior; but in responding to the random inter-annual weather variations, farmers only have limited *ex-post* adjustments due to time constraints or because large fixed investments are required (Massetti and Mendelsohn 2011, Seo 2013).

According to this perspective, impacts identified through cross-sectional climate differences should include the benefit of adaptations because, as assumed in the hedonic approach, farmers should have adapted to the climate of their regions. On the other hand, impacts identified through inter-annual weather fluctuations will not include adaptations since farmers have only limited *ex-post* adjustments in response to random weather outcomes, and this short-run response is not seen as adaptation to climate change.

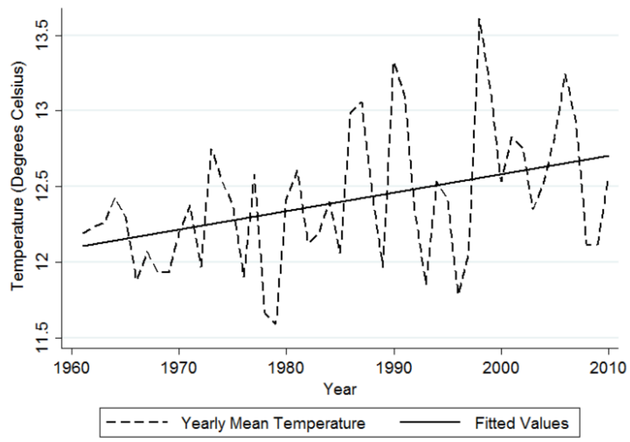

FIGURE 1. YEARLY MEAN TEMPERATURE FLUCTUATIONS IN THE US, 1960–2010

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

In addition, if the time trend of climate is large enough and has been perceived by farmers, impacts identified though the long-term climate trend should also include adaptations. However, the time trend is generally too small for the period during which production data is available. For example, as shown in Figure 1, the mean temperature in the US has only increased by about 0.6 ℃ during the past half century.[4] More importantly, farmers may not fully recognize and adapt to this climate trend because large inter-annual weather fluctuations accompanied with it may obscure farmers' recognition of the long-term trend (see the dotted line of Figure 1)[5]. Another problem is that it is hard to separate the effects of climate trends on agricultural outputs from the effects of various other concurrent trends such as technological improvements.

Therefore, the best way to incorporate adaptation is by employing cross-sectional climate differences, which are large enough and have been recognized and adapted to by agricultural agents. Accounting for adaptation by examining the effects of cross-sectional climate variation is the main argument of the hedonic approach. However, the hedonic approach is vulnerable to misspecifications and is potentially biased due to the correlation between measurement error of farmland values and climatic variables. In the following

[4] According to the IPCC Fifth Assessment Report (2014), the best prediction of mean temperature increase by the end of this century ranges from 1.0° to 3.7 °C. Hence, the impact prediction based on climate trend depends heavily on extrapolation. Considering the widely documented non-linear effects of temperature on agricultural productivity, an extrapolation is generally unreliable.

[5] In Appendix B, a Bayesian learning process shows that, ten years after a once for all mean temperature rise, only about 40 percent of the change is recognized by farmers.

section, an improved panel framework that incorporates adaptations and avoids the potential drawbacks of the hedonic approach is developed.

B. Incorporating adaptations in a panel framework

The basic idea of this panel framework is that time-fixed effects can be used to account for inter-annual weather fluctuations that are common across observations in the same year, and hence the remaining meteorological variation pertains only to cross-sectional climate differences and idiosyncratic local shocks. Since the local shocks are quite small, the impacts are identified mainly through cross-sectional climate differences and thus the full range of adaptations are included.

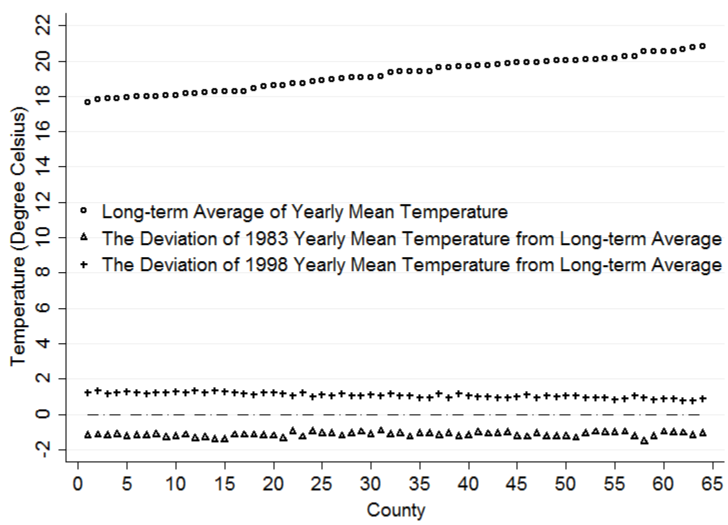

FIGURE 2. COUNTY-LEVEL LONG-TERM AVERAGE OF YEARLY MEAN TEMPERATURE AND DEVIATIONS OF GIVEN YEARS YEARLY MEAN TEMPERATURE FROM THE LONG-TERM AVERAGES FOR COUNTIES WITHIN THE US STATE OF LOUISIANA

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. See section II for the data source and descriptions.

Obviously, this idea depends crucially on the fact that the magnitudes of yearly weather deviations are almost equal across observations in the same year. We take the inter-annual temperature fluctuations for all of the 64 counties (parishes) within the US state of Louisiana as an example to visually show this fact. Figure 2 depicts county-level long-run average yearly mean temperatures and deviations from these averages of the representative "cold" year 1983 and "hot" year 1998. We find that despite the large inter-county long-term average temperature differences (ranged from 17.6 ℃ to 20.8 ℃), the inter-annual deviations from the averages are almost the same for all counties in a given year.

TABLE 1—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	$x_{11} = T_1 + \Delta_1 + \varepsilon_{11}$	$x_{12} = T_1 + \Delta_2 + \varepsilon_{12}$	$T_1 + \frac{\Delta_1 + \Delta_2}{2} + \frac{\varepsilon_{11} + \varepsilon_{12}}{2}$
County 2	$x_{21} = T_2 + \Delta_1 + \varepsilon_{21}$	$x_{22} = T_2 + \Delta_2 + \varepsilon_{22}$	$T_2 + \frac{\Delta_1 + \Delta_2}{2} + \frac{\varepsilon_{21} + \varepsilon_{22}}{2}$
Within year mean	$\Delta_1 + \frac{T_1 + T_2}{2} + \frac{\varepsilon_{11} + \varepsilon_{21}}{2}$	$\Delta_2 + \frac{T_1 + T_2}{2} + \frac{\varepsilon_{12} + \varepsilon_{22}}{2}$	
Panel B. Time-fixed effects: subtracting within year mean from each observations			
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 observations			
County 1	$\frac{\Delta_1 - \Delta_2}{2} + \frac{\varepsilon_{11} - \varepsilon_{12}}{2}$	$\frac{\Delta_2 - \Delta_1}{2} + \frac{\varepsilon_{12} - \varepsilon_{11}}{2}$	
County 2	$\frac{\Delta_1 - \Delta_2}{2} + \frac{\varepsilon_{21} - \varepsilon_{22}}{2}$	$\frac{\Delta_2 - \Delta_1}{2} + \frac{\varepsilon_{22} - \varepsilon_{21}}{2}$	
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: x_{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; Δ_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.

Table 1 shows the consequences of fixed effects in the climate change impact panel study. To simplify the analysis and without loss of generality, we take an example of a balanced panel with only two years and two counties. As shown in Panel A of Table 1, x_{it} represents 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 climate (i.e., long-term average of temperature and precipitation) of county i, which is assumed to be constant over time but different across counties; the second part Δ_t measures the inter-annual weather fluctuations that are common across counties in the same year but vary over time;[6] the last part ε_{it} is the county-specific weather shocks. The within county means and within year means are also reported.

[6] Here we assume no time trend in T_i. In fact, the climate trend is captured in the second part Δ_t, because the trend is usually common across counties.

The consequence of time-fixed effects is presented in Panel B of Table 1. The time-fixed effect is equivalent to subtracting the within year mean from each observation. Thus, the common inter-annual weather fluctuation Δ_t is filtered out; the remaining variation pertains only to the differences in climate T_i and the variances in county-specific weather shocks ε_{it}. If the variation pertaining to ε_{it} is very small, the impacts are mainly identified through the cross-sectional differences in climate T_i.

Table 2 depends on US county-level empirical data to show the actual size of the variation pertains to ε_{it}. It can be measured by county-specific inter-annual weather deviations from within county mean after state-by-year fixed effects (see Panel B of Table 1).[7] As shown in Panel A of Table 2, after state-by-year fixed effects, there are less than 5 percent of counties with inter-annual temperature deviation of more than 0.4 ℃, and no counties with the deviation more than 1 ℃. However, without fixed effects, there are 79.4 percent of counties with inter-annual temperature deviation of more than 0.4 ℃, and 34.6 percent of counties with the deviation more than 1 ℃. Panel B of Table 2 shows that the state-by-year fixed effects can also eliminate a large share of inter-annual variation in precipitation.

TABLE 2—REMAINING INTER-ANNUAL VARIATION IN WEATHER VARIABLES AFTER TIME-FIXED EFFECTS

Panel A. Percentage of counties with inter-annual temperature variance below/above (℃):				
	±0.4	±0.6	±0.8	±1.0
State-by-year fixed effects	4.8	0.7	0.2	0.0
No fixed effects	79.4	64.5	48.8	34.6
Panel B. Percentage of counties with inter-annual precipitation variance below/above (Inches):				
	±4	±6	±8	±10
State-by-year fixed effects	10.3	2.4	0.6	0.2
No fixed effects	32.5	14.2	5.1	1.5

Notes: The inter-annual variation refers to the deviation of each county's yearly weather outcome from its long-run average. All entries are the percentage of counties with inter-annual variation at least as large as the corresponding values reported in the column heading. All entries are calculated from a balanced panel of county-level data for census years from 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 section II for detailed data description.

Obviously, the variation pertaining to county-specific weather shocks ε_{it} is quite small, especially for temperature. Hence, in a panel model that regresses US county-level agricultural profits against climatic variables and other controls, if state-by-year fixed

[7] State-by-year fixed effect is equal to imposed 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.

effects are included, the climatic coefficients are mainly identified through the cross-sectional differences in climate T_i. According to the basic idea of the hedonic approach, the climatic coefficients identified through cross-sectional climate differences should include the benefits of adaptations. Combining these coefficients with climate change predictions, we can project the potential impacts of climate change on agricultural profits with a full range of adaptations. The details of the econometric model and its differences from previous methodologies are presented in Section III.

C. The benefits of adaptations

Understanding how much adaptation is likely to occur is central to any climate change impact study and is also of paramount importance from the policy perspective (Burke and Lobell 2010, Di Falco, Veronesi, and Yesuf 2011, Di Falco 2014). The importance of adaption is well recognized, with hedonic studies usually citing an illustrative relationship, as shown in Figure 3. The upper locus, shown as the heavier line, is the maximum profits from land use. Suppose the temperature increases from T_1 to T_2. If farmers adapt to this change by adjusting inputs and managements but do not switch from wheat to corn, profits with move from A to C along wheat's response curve. If land use substitutions are also allowed, the profits will end up at B. If no adaptations are made, the profits may end up at some point under the wheat response curve, such as at D. The difference between B and D measures the benefits of adaptation.

Empirically, numerous studies have estimated the benefits of particular adaptation measures. For example, Kurukulasuriya and Mendelsohn (2008) examined the benefits of crop switching as a method of adaptation. Seo and Mendelsohn (2008) provided evidence that farmers benefit from switching among different kinds of livestock when adapting to warming. Falco and Veronesi (2013) identified the adaptation benefits from a portfolio of strategies, which included changing crop varieties and adopting water and soil conservation behaviors.

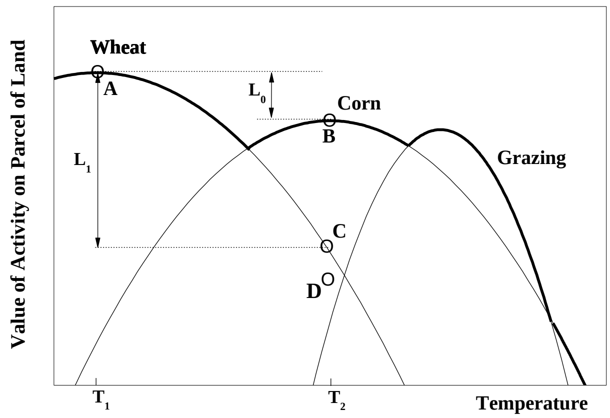

FIGURE 3. VALUE OF LAND AS A FUNCTION OF AVERAGE TEMPERATURE

Adapted from Mendelsohn, Nordhaus, and Shaw (1994) and Kelly, Kolstad, and Mitchell (2005)

Nevertheless, as argued by Mendelsohn, Nordhaus, and Shaw (1994), innumerable potential adaptation methods can be taken by farmers, so it is impossible to capture the benefits of a full range of adaptations by examining individual adaptation methods. Hence, an approach to identify the benefits of a full range of adaptations without examining individual adaptation methods would be valuable. Unfortunately, an effective approach for evaluating the benefits of a full range of adaptations has not yet been developed. Even though the hedonic approach implicitly includes the benefits of complete adaptations, it cannot be used to explicitly evaluate the benefits of adaptations.[8]

In the literature, the most convincing method of identifying the adaptation benefit is the panel approach that infers adaptation benefit by comparing damages estimated from inter-annual weather fluctuations and damages identified from long-term climate trends (Dell, Jones, and Olken 2012, Burke and Emerick 2015). However, as mentioned before, there are still some potential drawbacks to examining adaptation benefits through long-term climate trends: the historical climate trend is not large enough to predict future impacts; farmers may only partly recognize and adapt to the climate trend; and many other concurrent trends might obscure the true effects of climate change.

This study proposes an alternative approach to estimating the benefit of adaptations. Briefly, we approximate the benefit of adaptation by comparing the estimates from two

[8] The numerical difference between estimates of losses using the production function approach, which is limited in including adaptation, and the hedonic approach cannot be taken as a reliable measure of the economic effects of adaptation (Hanemann 2000).

versions of the panel model; the first model relies on cross-sectional climate differences and the second model depends on inter-annual weather fluctuations. The former model alone, using cross-sectional climate differences, includes the benefit of adaptations. Hence, the differences between the predicted impacts from these two models should reflect the value of adaptations.[9]

The panel framework that identifies impacts through cross-sectional climate differences has been introduced. We now introduce the panel framework that depends only on inter-annual weather fluctuations. The basic idea is shown in Panel C of Table 1: the county-fixed effects are used to eliminate inter-county differences in climate T_i, and then the remaining variation pertains only to the common inter-annual weather fluctuations, Δ_t and the county-specific weather shocks ε_{it}. Since the variation of the county-specific weather shocks is very small, the impacts are mainly identified through the common inter-annual weather fluctuations and hence do not include adaptation benefits. The details of this model and related concerns are presented in the econometric approach section.

II. Data

This study makes use of on 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.

A. Data sources

Agricultural production: we follow the literature to construct US county-level agricultural profits and farmland value 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.[10] In this data source, agricultural revenue measures the before-taxes total market value of all agricultural

---

[9] A similar approach is applied by Schlenker and Roberts (2009), in which they infer the benefits of adaptation by comparing the effects of time series for weather variation with the effects of cross-sectional climate differences. However, they do not make this comparison in a panel framework; instead, they compare the long-term averaged cross-sectional model with the nationwide averaged time series model. In addition, their crop-level study omits the potential adaptation benefits from land use adjustments.

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

products sold in a county in a year. These products include livestock, poultry, and their products; and crops, including 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. 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.[11]

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 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 below 8 ℃ contributes zero degree-days; between 8 ℃ and 32 ℃ contributes the difference between the mean and 8 ℃; above 32 ℃ contributes 24 degree-days. GDD is the sum of daily measures across the growing season. GHDD measures the sum of degree-days above a harmful threshold. We set the threshold of harmful temperature as 32 ℃: a day with a mean temperature above 32 ℃ contributes the difference between the mean and 32 ℃; otherwise it contributes zero harmful degree-days (Ritchie and NeSmith 1991).[12] Finally, GTP is the total precipitation in inches during the growing season.

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

[12] The agronomy literature suggests a range of possible thresholds for harmful degree-days. The most frequently used one is 34 °C (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 °C (Schlenker and Roberts 2009). Since the heat below 32 °C has been included in the calculation of GDD, we prefer to set the threshold of GHDD as 32 °C. In addition, some studies prefer to calculate harmful degree-days through daily maximum temperatures. However, most of the heat used to calculate GHDD in this approach has already been

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 (RCP) scenarios (RCP4.5 and RCP8.5)[13] are available from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset.[14] 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 depending on a single climate projection can be misleading (Burke et al. 2015), in the climate change impact estimation of this study, we use the output for the medium scenario RCP4.5 from four of the most widely used CMIP5 models: CCSM4, CESM1-BGC, CanESM2, and NorESM1-M.[15]

Control variables: we follow the literature to include a rich set of county-level soil controls in the econometric analysis. These data are from the National Resource Inventory and have been widely used in previous studies. 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 wetland and irrigated land.[16] Since the land qualities are almost constant over time, the missing values are replaced by data interpolation. We also compiled county-level per capita income and population density as control variables.

included in the measure of GDD, because a day with a maximum temperature higher than 34 °C is most likely with the mean temperature below 32 °C.

[13] 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.

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

[15] 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.

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

B. Summary statistics

Irrigation water is heavily subsidized in the US, and it is impossible to control for irrigation differences among counties. In order to avoid the potential bias caused by unmeasurable irrigation differences, we follow Schlenker, Hanemann, and Fisher (2006) in using only data from counties east of the 100 ° meridian, where agriculture mainly depends on rainfall; in the arid West, farming mainly depends on irrigation. According to the data set, counties east of the 100 ° meridian generate 71.6 percent of US agricultural profits. We also exclude urban counties to avoid potential biases caused by urbanization. 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. We are left with 2155 non-urban rain-fed sample counties for each of the seven census years. All profits and land prices are translated into 2012 dollars using the GDP implicit price deflator.

TABLE 3—INTER-ANNUAL VARIATION OF AGRICULTURAL PRODUCTION

	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 3 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 areas of farmland remain almost constant, while agricultural expenses show an increasing trend. One interesting question concerns the cause of the large non-linear variation of farmland values. Obviously, the constant total farmland areas and monotonously increasing production expenses cannot explain the non-linear land value variation. A possible explanation is provided in Appendix A.

TABLE 4—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 RCP45:				
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 4 reports statistics of climate normal and climate projections (temperature and precipitation). County-level climate normal is calculated as a 20 year average from 1981 to 2000 for each county. The predicted county-level climates for each model are calculated by the following steps: first, mapping the gridded climate predictions into each state to provide state-level climate predictions;[17] second, calculating state-level climate change predictions as the differences between the predicted 2081–2100 average and the simulated historical average of 1981–2000 for each model; and third, adding the predicted state-level climate changes to the county-level climate normal to form county-level climate predictions for the end of this century. [18]

Compared with the climate normal, the predicted mean temperature rise for these four climate models ranged from 1.95 ℃ to 2.79 ℃, which is within the range of the best prediction of mean temperature increase by the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment Report (2014), which predicted a 1.0 ℃ to 3.7 ℃ mean temperature rise. Large changes in the GDD are predicted, and the changes ranged from 379 to 547. The normal GHDD is only 0.11, because it is a simple average over all sample counties; a large share of counties have a mean temperature of less than 32 ℃ and hence contribute zero GHDD. However, 30 percent of sample counties contribute positive GHDD, and 70 hot counties have more than 1 GHDD (with large standard deviations), so there is no major concern about extrapolation when identifying the effects of extreme hot

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

[18] 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).

temperatures. The changes in GTP predicted by climate models are quite small relative to the predicted changes in GDD.

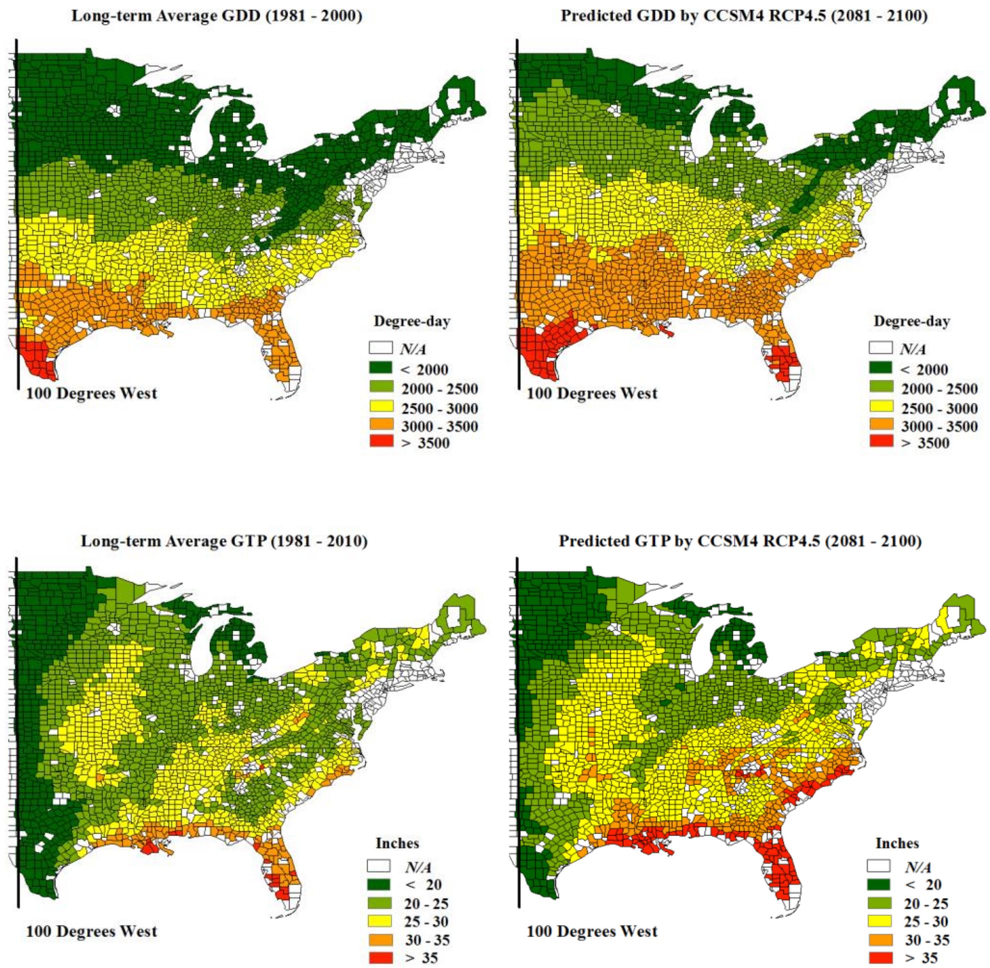

FIGURE 4. GEOGRAPHIC DISTRIBUTIONS OF GDD AND GTP FOR CLIMATE NORMAL AND SCENARIO CCSM4 RCP4.5

Notes: The samples are 2155 rain-fed non-urban counties east of the 100 ºmeridian. 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 4 compares the geographic distribution of the climatic variables of climate normal with the distribution of predictions from the representative model CCM4 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.

III. Econometric Approach

A. Models

The panel model identifying climate change impacts through cross-sectional climate differences is shown in equation (1), where y_{it} denotes agricultural profits per acre in county *i* and year *t*; c_{it} are climatic variables: including GDD, GTP, the quadratic term of GDD and GTP, and the square root of GHDD; l_{it} includes ten 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; ϵ_s are state dummies used to control for time-invariant differences among states, such as state-specific taxes, subsidies and crop diseases; w_{ij} is an inverse-distance spatial-weighting matrix, which is calculated from the coordinates and is used to capture the effect of potential spatial dependence that decays smoothly with distance; ρ, α , β are coefficients. Finally, μ_{it} are the identically and independently normally distributed (*iid*) error terms. If ρ is restrained to be zero, model (1) is a classical panel model with fixed effects. As shown in the conceptual framework, the coefficients of climatic variables are identified mainly by the within-state cross-sectional mean climate differences.[19]

(1)
$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{k=1}^{K} c_{itk}\alpha_k + \sum_{g=1}^{G} l_{itg}\beta_g + \gamma_{st} + \epsilon_s + \mu_{it}$$
$$i = 1, \dots, n\,; \quad t = 1, \dots, T$$

Model (1) is usually called the Spatial Autoregressive Model (SAR), which allows cross-sectional correlation of the dependent variable and models spatial dependence explicitly (Anselin 1988, Elhorst 2010). A growing body of literature recognized that panel data sets are likely to exhibit spatial dependence (De Hoyos and Sarafidis 2006). Agricultural profits are prone to spatial dependence because of unobserved profit determinants that are correlated with location and ultimately become part of the error term. We test the cross-sectional dependence of the panel model (1) that assumes $\rho = 0$ by the semi-parametric

[19] The within-state inter-county climate differences are large enough for climate change impact predictions. For example, there are 522 observations with more than 2 °C temperature deviations from their state means.

tests proposed by Frees (2004). The test strongly rejects the null hypothesis of spatial independence.

Previous panel studies of climate change impact address the spatial correlation problem by clustering the error term at a larger spatial resolution or adjusting the error term by a spatial-weighting matrix that allows the correlation to decay smoothly with distance (Deschênes and Greenstone 2007, Fisher et al. 2012). If the spatial correlation is caused by omitted profit determinants that are uncorrelated with climatic variables, the standard panel estimators are consistent but inefficient, and the estimated standard errors are biased. In this case, correcting for standard errors is a good choice. However, if the omitted determinants are correlated with climatic variables, the estimated climatic coefficients will be biased and inconsistent, thus simply adjusting spatial correlation of the error term is not enough (Lee 2002, Lee and Yu 2010).[20] Hence, this study prefers to model the spatial dependence explicitly by SAR.[21]

The model that identifies climate change impacts through inter-annual weather fluctuations is presented in equation (2). The settings for y_{it}, c_{it}, l_{it}, and w_{ij} are the same as in equation (1); the only difference is the inclusion of fixed effects. Model (2) includes the county-fixed effects τ_i, instead of state-by-year fixed effects, to eliminate inter-county climate differences. In addition, model (2) includes a time trend q_t to control for trend effects such as technological improvements and warming.[22] It is worth stressing that equation (2) does not include any kind of time-fixed effects, which tend to eliminate most of the year-to-year weather fluctuations.[23] Thus, the climatic coefficients of model (2) are estimated through the random year-to-year weather fluctuations, and do not include the benefit of adaptations. Finally, ε_{it} are the *iid* normally distributed error terms.

[20] In addition, the method of adjusting the standard error by clustering them within each state is not applicable in this study. Since the number of clusters (states) is very small compared to the overall sample size, we simply do not have sufficient ranks to perform the model test. Indeed, Fisher et al. (2012) report standard errors clustered by state in their panel study. However, as indicated in the log of their online data appendix, the *F* and *chi-square* model statistics were reported as missing whenever they ran a regression with a cluster-by-state command.

[21] Another choice is the spatial error model (SEM), but for such a large weight matrix (2155×2155) in a panel setting, we find that the maximum likelihood estimator of SEM usually does not converge.

[22] Controlling for trend effects in model (2) is necessary; model (2) is used to evaluate the climate change effects without adaptations, but farmers may partly adapt to the warming trends.

[23] We are not seeking to control for the effect of price shocks induced by output fluctuations in model (2), because the price shock can be seen as a "natural insurance" of farmers to weather fluctuations. Eliminating price shocks will overestimate the impact of weather fluctuations (Fisher et al. 2012).

(2) $$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{k=1}^{K} c_{itk} \alpha_k + \sum_{g=1}^{G} l_{itg} \beta_g + \tau_i + \theta q_t + \varepsilon_{it}$$

$$i = 1, \dots, n\,; \quad t = 1, \dots, T$$

Combining the estimated climatic coefficients from models (1) and (2) with climate change predictions, we can project the impacts with and without adaptations, respectively. The differences of the projection between these two models can be interpreted as the benefit of adaptations. It is worth pointing out that, as in the hedonic approach, the estimated adaptation benefit reflects only the lower bound of adaptation benefit; this approach only includes the potential benefit of adoption of production technology and management methods that already exist, but does not include the potential benefit of future innovations.

B. Comparing with the hedonic model

The classic hedonic model is presented in equation (3), in which V_i is farmland value of spatial area *i* (taking county as an example); $\bar{C}_i$ is a vector of the long-term average of climatic variables in county *i*; $\bar{L}_i$ includes land quality measures and other controls; β and γ are vectors of coefficients; and ω_i is the error term that may allow for spatial correlations or not. By examining how climate in different regions affects farmland prices, model (3) includes the benefit of adaptations in the estimated climatic coefficients. Following this idea, our panel model (1) includes state-by-year fixed effects to eliminate inter-annual weather fluctuations, and thus the climatic coefficients are also identified by the cross-sectional climate differences and adaptations are included.

(3) $$V_i = \alpha + \bar{C}_i' \beta + \bar{L}_i' \gamma + \omega_i$$

However, compared with model (3), panel model (1) is less vulnerable to the potential biases caused by misspecifications and measurement errors. Hedonic model (3) uses farmland value as the dependent variable.[24] However, farmland prices are sensitive to non-agricultural land demands that are correlated with climate (Chicoine 1981, Plantinga, Lubowski, and Stavins 2002). Without appropriate controls, the hedonic approach tends to mistakenly identify the effect of climate on other economic sectors as the effect on

[24] It is unwise to use yearly agricultural profits as the dependent variable in the cross-sectional hedonic study because profits are influenced by many inter-annual fluctuation factors which cannot be controlled in the hedonic model.

agriculture.[25] The panel framework of model (1) enables us to use agricultural profits as the dependent variable and hence avoids this bias. Another crucial problem of depending on farmland value is that, as shown in Appendix A, the measurement errors of farmland values are correlated with climatic variables, which results in a potential bias of the hedonic estimate.[26]

A potential concern of using annual agricultural profits as the dependent variable is the potential bias results from 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 during the same year. However, in response to output and price changes caused by weather fluctuation, farmers tend to adjust their storage and inventory in order to maximize total discounted profits. As a result, some of the outputs of this year might be sold in next year, or part of this year's profits might come from last year's production. Fortunately, this will not necessarily result in biased estimates in model (1) and (2). In model (1), these inter-annual adjustments are non-parametrically accounted for by the state-by-year fixed effects because, for counties within the same state, weather fluctuations and hence farmers' responses are generally the same in a given year. In model (2), which identifies impacts through inter-annual weather fluctuations, controlling for these adjustments is not necessary: these adjustments serve as a kind of "self-insurance" that helps to reduce risks resulting from weather fluctuations; eliminating these adjustments might overestimate the damages of weather fluctuations.[27]

C. Differences from previous panel models

Our panel models (1) and (2) are modified from the model as shown in equation (4), which was proposed by Deschênes and Greenstone (2007) and has been the standard panel model in the previous climate change impact studies (Dell, Jones, and Olken 2014). In

[25] For example, favored climates may result in better economic performances and hence higher demands for land, which may push up farmland values even though agricultural productivities are unchanged.

[26] Some previous hedonic studies also included location-fixed effects in the regressions to reduce potential biases from omitted variables.. However, including location-fixed effects in the cross-sectional regression has little effect on reducing potential biases from the measurement errors..

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

model (4), y_{it} is agricultural profits per acre in county *i* and year *t; C_{it}* is a vector of climatic variables; L_{it} is a vector of control variables; σ_{it} is the error term that may allow for spatial correlations or not. If it is assumed the spatial dependence coefficient $\rho = 0$, the only difference between models (1), (2), and (3) is in the use of fixed effects. Specifically, model (4) includes both county-fixed effects τ_i and state-by-year fixed effects γ_{st}; model (1) only includes state-by-year fixed effects γ_{st} and state-fixed effects ϵ_s; model (2) only includes county-fixed effects τ_i and a time trend q_t. However, this seemingly minor difference results in great discrepancy in the implication of the estimated climatic coefficients.

(4) $$y_{it} = C_{it}'\alpha + L_{it}'\beta + \tau_i + \gamma_{st} + \sigma_{it}$$

The consequence of the two-way fixed effects of model (4) is presented in Panel D of Table 1. The two-way fixed effects eliminate both the cross-sectional differences in climate T_i, and the inter-annual common weather fluctuations Δ_t. As a result, the impacts are identified through the county-specific inter-annual weather shocks ε_{it}. The strength of relying on the random county-specific weather shocks is in avoiding misspecification, the weaknesses, however, are in extrapolation and omitting adaptations. As presented in Table 2, less than five percent of the county-specific temperature shocks are higher than 0.4 ℃. However, Table 4 shows that climate models predicted more than 2 ℃ temperature rises by the end of this century, so the long-run impact predictions of model (4) depend heavily on extrapolation.[28] Considering the widely documented non-linear effects of warming on agricultural output, extrapolation is generally unreliable. More importantly, since farmers do not adapt to the random county-specific weather shocks, the benefit of adaptations are omitted.

Model (1) is developed to overcome the drawbacks of model (4), i.e., extrapolation and omitting adaptations. Only state-by-year and state-fixed effects are included in model (1) to account for inter-annual common weather fluctuations and inter-state climate differences, so the climatic coefficients are identified mainly through the large within-state inter-county climate differences pertaining to T_i and hence adaptations are incorporated. Model (2) is quite similar to model (4) in the sense that both depend on random inter-annual fluctuations.

[28] This fact was first demonstrated by Fisher et al. (2012).

The difference is that model (2) depends on the significant common fluctuation Δ_t, while model (4) depends on county-specific fluctuation ε_{it}, which is too small to avoid extrapolation. Hence, model (2) provides a way to predict the impacts that does not include adaptations.

It seems that our panel model (1) is still potentially vulnerable to omitted-variable bias. Even though the inter-annual common fluctuations and the inter-state time-invariant differences are well controlled by the fixed effects, we do not control for within-state inter-county differences apart from the ten land quality indicators.[29] In fact, in our panel model, omitted-variable bias should not be a major concern: omitting determinants of profit that do not correlate with climate will not result in biased estimates. If omitted variables are correlated with climate, it is most likely that these factors are themselves outcomes of climate but not the cause.[30] 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).[31] So we prefer not to include variables that are potentially influenced by climate, such as population density and income per capita. In addition, we test the potential magnitudes of omitting variable biases by dropping all land quality controls from the regression. Interestingly, this has only a negligible effect on the estimated impacts. Hence, a large bias resulting from unobservable inter-county land quality differences is unlikely.

IV. Empirical Results

This section combines the estimated climate coefficients from model (1) and (2) with various climate change projections to predict climate change impacts with and without

[29] In order to account for the inter-county unobservable differences, county-fixed effects are applied in model (4). The cost of applying county-fixed effects is eliminating all inter-county climate differences. As a result, no signals can be used to incorporate adaptations.

[30] In a few cases, climate can be both the cause and consequence of profit determinants. For example, climate is an important determinant of irrigation and tillage practice; at the same time, changes in irrigation and tillage have the potential to effect local climate (Lobell, Bala, and Duffy 2006). However, evidence from physical sciences suggests that the effect of local agricultural practice on climate is limited, so climate is mainly a cause of local agricultural practice.

[31] Nevertheless, this argument is not true for the model setting of hedonic studies. Farmland values are the dependent variable of the hedonic approach. It is influenced not only by agricultural profits but also by land demands from other economic sectors (Chicoine 1981, Plantinga, Lubowski, and Stavins 2002). If non-agricultural land demands are correlated with climatic variables, omitting controls for non-agricultural land demands will mistakenly identify the effect of climate on other economic sectors as the effect on the agricultural sector.

adaptations, respectively. The SAR Model (1) and (2) are estimated by the maximum likelihood method using the routing by Belotti, Hughes, and Mortari (2014). We also approximate the benefits of adaptation as the difference between predicted impacts of models (1) and (2).

Column 1a and 2a of Table 5 report the regression outputs from model (1) and (2) respectively. As usually found in previous studies, the responses of profits to GDD and GTP are hump-shaped, and the effect of the GHDD square root is negative for both models. More importantly, there are obvious differences in the estimated coefficients from these two models. According to the conceptual framework, the different climatic coefficients reflect the difference in incorporating adaptations. Specifically, the optimal GDD calculated from the coefficients is 2294 degree-days for model (1) and 2121 degree-days for model (2). It implies that with adaptations agricultural production is more heat-tolerant. The optimal GTP from model (1) is also higher than that from model (2), which means adaptation enables agriculture to benefit more from intensive precipitation. Also, the negative effect of GHDD in model (2) is much higher than that in model (1), implying that adaptations would help to reduce vulnerability to extreme heat.

TABLE 5—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)
100 GDD (℃)	7.80	7.34	12.3	12.3	255.6	277.8
	(2.35)	(2.37)	(1.10)	(1.10)	(21.3)	(21.5)
10000 GDD square	-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 show the estimated climatic coefficients from SAR panel models. Columns 1a and 1b report estimates from model (1) with agricultural profits as the dependent variable; column 2a and 2b report estimates from model (2) with agricultural profits as the dependent variable; columns 3a and 3b report estimates from a variation of model (1) that use the farmland value as the dependent variable. The only difference between models a and b is that model b excludes the soil controls. The Huber-White heteroskedastic consistent standard errors are reported in parentheses.

To test for omitted-variable bias in our panel approach, we drop all soil quality controls, which are the most important profit determinants, from the models. The results are reported in column 1b and 2b. As expected, there are no obvious effects on the predicted climate coefficients of model (2), because the inter-county soil differences are already accounted for by the county-fixed effects and the soil qualities are almost constant over time. Dropping all the soil controls has only quite small effects on the estimates from model (1). The *t*-tests that compare the coefficients of each climatic variable from models that include and exclude soil controls do not find statistically significant differences. The conclusion remains the same if we only exclude subgroups of soil controls from the models. This result supports our argument that in our panel model setting, omitted-variable bias is not a major concern.

Columns 3a and 3b of Table 5 show the estimates of a variation of model (1) in which the farmland value is used as the dependent variable.[32] Even though hedonic estimates that depend on a single year's farmland value data may be biased due to the correlation of the measurement error of farmland value with climatic variables, we are still able to estimate

[32] We have not estimated the effects of climatic variables on farmland values by model (2) because the estimation of model (2) is based on inter-annual weather fluctuations. The true farmland value is the present discounted value of the land rent stream into the infinite future, so it should not vary with random year-to-year weather fluctuations.

the effects of climatic variables on farmland values using panel model (1). This is because the measurement errors of farmland values from different years should be offsetting, and the mean farmland values are consistent with the true farmland values.[33] In addition, the coefficients in panel model (1) are identified through cross-sectional climate differences, so concern about the time-invariant property of farmland value is unnecessary. The influence of each climatic variable shows quite a similar pattern to the profits models, and the exclusion of soil controls still do not have statistically significant effects on the coefficients. These regression coefficients will be used to estimate the impact of climate change on farmland rents in the following.

The estimated overall impacts of climate change on agricultural profits are presented in columns 1a and 2a of Table 6. For estimates from the model that includes adaptations (column 1a), the overall impacts on agricultural profits are negative but generally quite small; the changes in agricultural profits are -1.27, -1.57, -4.63 and -5.52 billion dollars per year (or -3.6 percent -4.4 percent, -12.3 percent and -15.6 percent) by the end of this century for climate predictions from CCSM4, CESM1-BGC, CanESM2 and NorESM1-M, respectively. Since the projected warming is monotonically increasing from CCSM4 to NorESM1-M (see Table 4), we can say that the predicted total impacts increase with the magnitudes of predicted warming. On the other hand, the model that does not include adaptations (column 2a) predicts relatively large falls in agricultural profits, ranging from -5.96 to -16.14 billion dollars (or -16.8 percent to -45.7 percent) for different climate predictions. The average impacts of these four climate predictions, as reported in the last row of Table 6, are 9 percent with adaptations, and 30 percent without adaptations.[34] In addition, as reported in column 1b and 2b, omitting soil controls has only quite small effects on the estimated overall impacts. The *t*-tests that compare overall impacts from models that include and exclude soil controls do not find statistically significant differences.

[33] The time-fixed effects in panel model (1) make the estimation similar to running separate hedonic regressions for each year and then calculating the average effects over time. Hence, the biases resulting from the measurement errors of farmland values in different years should cancel each other out and result in an unbiased mean estimate.

[34] We prefer to use average value as the measure of overall falls in output because there is a large degree of uncertainty in existing projections of climate change; point estimates depending on a single climate projection can mislead (Burke et al. 2015).

TABLE 6—PREDICTED IMPACTS OF CLIMATE CHANGE ON U.S. AGRICULTURAL PROFITS AND FARMLAND RENTS BY THE END OF THIS CENTURY (BILLIONS OF 2012 CONSTANT DOLLARS/YEAR)

	Impact on profits: With adaptation		Impact on profits: No adaptation		Impact on land rents: With adaptation		Benefits of adaptation	
Climate model	(1a)	(1b)	(2a)	(2b)	(3a)	(3b)	Value	Percent
CCSM4	-1.27	-0.95	-5.96	-5.99	-0.69	-0.74	4.69	78.70%
	(1.21)	(1.22)	(0.59)	(0.59)	(0.31)	(0.31)		
CESM1-BGC	-1.57	-1.27	-7.21	-7.24	-0.73	-0.82	5.64	78.20%
	(1.21)	(1.21)	(0.64)	(0.64)	(0.34)	(0.34)		
CanESM2	-4.36	-3.78	-12.92	-12.97	-3.90	-4.04	8.56	66.30%
	(2.02)	(2.02)	(1.06)	(1.06)	(0.59)	(0.59)		
NorESM1-M	-5.52	-5.01	-16.14	-16.21	-5.57	-5.68	10.62	65.80%
	(2.23)	(2.22)	(1.22)	(1.22)	(0.82)	(0.82)		
Average	-3.18	-2.75	-10.56	-10.60	-2.72	-2.82	7.38	72.20%

Notes: This table reports the predicted overall climate change impacts of four most frequently used climate models under scenario RCP4.5. All entries are calculated for the 2155 rain-fed non-urban sample counties. Columns 1a and 1b report the impact on profits estimated from model (1) with agricultural profits as the dependent variable; columns 2a and 2b report the impact on profits estimated from model (2) with agricultural profits as the dependent variable; columns 3a and 3b report the impact on farmland rents estimated from a variation of model (1) that use the farmland value as the dependent variable. The only difference between model a and model b is that model b excludes the soil controls. The last two columns report the benefit of adaptation which is the difference between column 2a and 1a. 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. The Huber-White heteroskedastic consistent standard errors of the impacts are reported in parentheses. See the text for further details.

We calculate the benefit of adaptation as the difference between column 1a and column 2a, and report it in the last two columns of Table 6.[35] The benefit of adaptation ranges from 4.69 to 10.62 billion dollars per year, and this benefit increases with the level of predicted warming. We find that adaptations will help to offset 78.7 percent, 78.2 percent, 66.3 percent and 65.8 percent of potential output loss from the predicted climate change given by CCSM4, CESM1-BGC, CanESM2 and NorESM1-M, respectively. Adaptation is estimated to reduce 72.4 percent of the overall damages from climate change, on average. Hence, omitting adaptation from models will dramatically overestimate the impacts.

The impacts on farmland rents are reported in columns 3a and 3b of Table 6. We combined the estimates in columns 3a and 3b of Table 5 with climate predictions to predict the impact on farmland values and then transformed them to the impact on farmland rents using the implicit discount rate of 2.90 percent, as used by Schlenker, Hanemann, and Fisher (2005). Since the impacts in panel model (1) are identified through cross-sectional

[35] These are the lower bound of adaptation benefits; this approach only includes the potential benefits of adaptation through adopting production technology and management methods that already exist, and we do not take into account the benefits of potential future innovations.

climate differences, the benefits of adaptations are included in the estimated impacts on land rents. We find that, for given climate models, the impacts on farmland rents are quite similar to the impacts on annual agricultural profits that include adaptations (columns 1a and 1b of Table 6). The *t*-tests showed no statistically significant differences between the agricultural profits estimates and the land rents estimates. This result indirectly supports our argument that the yearly storage and inventory adjustments in agricultural production do not cause significant bias in the estimated impacts using agricultural profits data. Otherwise, the agricultural profits-based estimation would be significantly different from the farmland value-based estimation because farmland value is independent of yearly storage and inventory adjustments. In addition, we find that if the bias from the measurement errors of farmland values can be adjusted, the estimated impacts using farmland value data are statistically indifferent compared to the estimated impacts using agricultural profits data.[36]

TABLE 7—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) No adjustment for spatial correlation (assume $\rho = 0$)	-3.71	-14.53	10.83	78.23%
(2) Calculate degree-day by the minimum and maximum daily temperatures	-3.73	-15.21	11.48	79.07%
(3) Exclude irrigated counties east of the 100 ºmeridian from the sample	-3.80	-12.00	8.20	70.29%
(4) Include additional controls for population density, per capita income, and altitude	-4.61	-12.85	8.24	65.88%
(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 (1) and (2) and the climate change predictions of the four climate models listed in Table 4 (i.e., CCSM4, CESM1-BGC, CanESM2, and NorESM1-M). Columns (1) and (2) show the estimated impacts based on alternative versions of models (1) and (2), 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 adaptations. 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.

Table 7 explores further the robustness of the results to alternative specifications. All the specifications include the same fixed effects and soil quality controls as presented in models (1) and (2). For each specification, we first estimated the damages of the climate

[36] Notwithstanding, the benefits of adaptations still cannot be identified from models that use farmland value as the dependent variable. As shown in the conceptual framework, the benefits of adaptations are identified by comparing the panel models with and without adaptations. It is impossible to develop a panel model with farmland value as the dependent variable and to not include adaptations because farmland values should not vary with inter-annual weather fluctuations.

change predicted by each of the four climate models (i.e., CCSM4, CESM1-BGC, CanESM2, and NorESM1-M), and then calculated the simple average of the estimated impacts from these four models (see Table 7). The benefits of adaptations are calculated as the differences between the estimates in column (2) and column (1).

Row (1) shows the estimates from model (1) and model (2) that are not adjusted for spatial correlations (assuming the spatial correlation coefficient $\rho = 0$). Since agricultural profits are affected by unobservable factors that are potentially spatially correlated, adjusting for spatial correlations using the spatial autoregressive model should improve estimations. Nevertheless, as shown in row (1), the main conclusions of this paper can also be obtained from the models that are not adjusted for spatial correlations: the overall damages are mild if adaptations are included, and adaptations will help offset a large share of the impacts.

Row (2) considers another way of calculating degree-day. As in most previous studies, this study calculated degree-day from the daily mean temperature because the idea 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). Recent economic studies have suggested that degree-day calculated from daily minimum and maximum temperatures is a more accurate predictor of crop yields (Schlenker and Roberts 2009, Tack, Barkley, and Nalley 2015). We follow their method to calculate degree-day by minimum and maximum temperatures and to test its effects on the predictions of this study. As shown in row (2), even though the panel model that does not include adaptations (column 2) predicts greater damage, the panel model that includes adaptations (column 1) still predicts mild overall damage, and adaptations can therefore be expected to offset even more damage.

Row (3) explores the effect of excluding irrigated counties in our sample. Counties west of the 100 °meridian have already been excluded from this study to avoid potential bias caused by heavily subsidized irrigation (see the summary statistics section). Even though agricultural production depends on rainfall in most counties east of the 100 °meridian, some east counties still use irrigation water to supplement rainfall. In this alternative estimation, we also exclude irrigated counties east of the 100 °meridian from the sample.[37] The table shows that the main conclusions of this paper are stable to this change.

Row (4) provides estimates from models with additional control variables. As suggested by Dell, Jones, and Olken (2014), variables that have the potential to influence agricultural profits and also correlate with climatic variables are most likely themselves outcomes of climate but not the cause. Including these factors in the model will partially eliminate the explanatory power of climatic variables, even though climate is the true underlying determinant. Nevertheless, it is still interesting to check if including these kinds of controls would change the estimates significantly. Accordingly, in this alternative model setting, we include county-level population density, per capital income, and altitude as controls.[38] We find that, inclusion of these variables only results in a 4.1 percent higher damage estimation for the model that include adaptations (estimated damage rises from 9.0 percent to 13.1 percent), and the adaptations could still offset about two-thirds of the damages. We also tried models that include only one or two of these three variables and arrived at similar results.

Row (5) estimates the impacts of climate change under the highest climate change scenario, namely RCP8.5. As in most previous studies, only the medium climate change scenario is used in the main analysis because it provides the most likely outcome. RCP4.5 and RCP8.5 are the medium and highest climate change scenarios developed for the latest IPCC Fifth Assessment Report. In this study, we mainly use the climate change predictions from the four climate models (i.e., CCSM4, CESM1-BGC, CanESM2, and NorESM1-M) under scenario RCP4.5. These four models also provide climate change predictions under RCP8.5, but the predictions are much higher.[39] We therefore estimated the damages of climate change projected by each of the four models under RCP8.5 and report the average damages in row (5). As expected, both the panel models that include and does not include adaptations predict much higher damages. However, the predicted damages from the model

[37] 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.

[38] It is well known that socioeconomic variables such as population density and per capital income are influenced by climate and that the effect of altitude on agricultural profits is partly due to differences in climates.

[39] 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.

that includes adaptations are still much smaller than the predicted damages from the model that does not include adaptations and adaptations will still help offset about two-thirds of the damages (67.3 percent).

Overall, the estimates in Table 7 suggest that the main conclusions of this paper are quite robust to numerous specification checks. Specifically, under the medium climate change scenario RCP4.5, the predicted changes in climate will lead to mild damages if adaptations are included. In addition, potential adaptations will help to offset at least two-thirds of the damages predicted by the model that does not include adaptations, even under the highest climate change scenario RCP8.5.

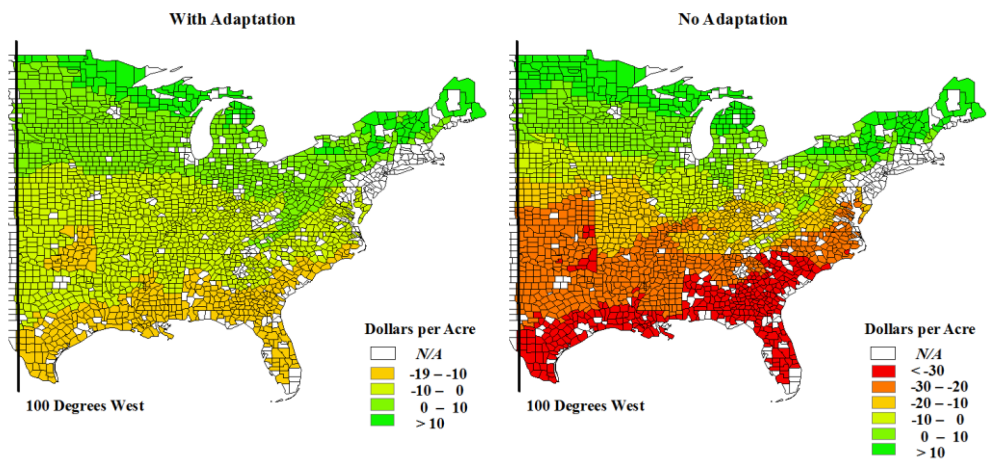

FIGURE 5. GEOGRAPHIC DISTRIBUTION OF COUNTY-LEVEL EFFECTS OF CLIMATE CHANGE BY THE END OF THIS CENTURY UNDER SCENARIO CCSM4 RCP4.5

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 model (1) and (2) 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 °meridian. All values are expressed in 2012 constant dollars.

Finally, Figure 5 maps the geographic distribution of climate change impacts on agricultural profits. Taking the prediction from climate model CCSM4 as an example, we calculate the county-level impacts with and without adaptations for each sample county. In general, the south counties will lose and the north counties will gain. But if taking into account the adaptations, more northern counties will benefit from warming and the loss of counties in the south is much smaller. Specifically, if predictions are made with adaptations no counties will lose more than 20 dollars per acre per year (left of Figure 5), while a large number of southern counties are predicted to lose more than 20 dollars or even 30 dollars per acre per year if the potential benefits from adaptation are omitted (right of Figure 5).

V. Concluding Remarks

This study has combined the traditional hedonic approach to modelling the effects of climate change on farmland values with the panel method proposed by Deschênes and Greenstone (2007), developing a panel framework that can be used to incorporate adaptations to climate change and to estimate their benefits. The panel framework depends on the key fact that inter-annual weather fluctuations are generally common across regions in the same year. This fact enables the development of two versions of the panel model with different fixed effects; the first model relies on cross-sectional climate differences while the second model depends on inter-annual weather fluctuations. The former model alone, using cross-sectional climate differences, includes the benefit of adaptations. Hence, the differences between the predicted impacts from these two models should reflect the value of adaptations.

Combining this framework with a panel of US agricultural profits and climate data, we find that when predictions that incorporate adaptations are made, the overall fall in agricultural profits will be about 9 percent or 3.18 billion US dollars per year by the end of this century. However, when assessments are made omitting adaptations, the estimated overall damages are about 30 percent or 10.56 billion US dollars per year. In other words, methods that incorporate adaptation will produce results which offset 72.4 percent of the overall fall in agricultural profits demonstrated by methods omitting adaptation. These conclusions are robust to various specification checks.

The most significant way in which this paper differs from hedonic studies such as that of Mendelsohn, Nordhaus, and Shaw (1994) is that the benefits of adaptation can be explicitly estimated in this paper. In addition, empirical evidence revealed that the hedonic approach, which depends on farmland value data, is potentially biased because the measurement errors of farmland values are correlated with climatic variables. A parallel analysis showed that, if the bias from the measurement errors of farmland values can be adjusted, the estimated impacts using farmland value data are statistically indifferent compared to the estimated impacts using agricultural profits data.

More adaptations are included in this study than in previous panel models that depend on inter-annual weather fluctuations, such as that proposed by Deschênes and Greenstone (2007). The panel model (1) of this paper depends on cross-sectional climate differences and hence includes a full range of farmers' adaptations to climate change. However, previous panel models that depend on inter-annual weather fluctuations only include the benefits of farmers' responses to yearly weather fluctuations. Even so, these short-term behavioral changes are generally not seen as adaptations to climate change because climate change is a long-term phenomenon. Another important difference is the climatic variations used in impact identification. The identification of panel models in the study of Deschênes and Greenstone (2007) depends on county-specific inter-annual weather shocks, which are generally too small to identify meaningful impacts (Fisher et al. 2012). However, the identification of models in this paper depends on within-state inter-county climate differences (the model with adaptations) or inter-annual common weather fluctuations (the model without adaptations), and these climatic variations are substantial enough to identify the impacts.

Even though 10 soil quality controls and various fixed effects have been included in the regressions, there are still potential omitted variables in our panel model (1). Previous panel models that tried to account for all potential omitted variables actually eliminated almost all climatic variations and resulted in misleading conclusions (Fisher et al. 2012). However, omitted variables are not necessarily result in biased estimates in our panel models: omitting determinants of profit that do not correlate with climate will not result in biased estimates. If omitted variables are correlated with climate, it is most likely that these factors are themselves outcomes of climate but not the cause (Dell, Jones, and Olken 2014). Including these factors in the model will partially eliminate the explanatory power of climatic variables, even though climate is the true underlying determinant. The robustness tests demonstrate that including more or less controls does not change the main conclusions of this paper.

There are several important caveats in explaining the empirical result. First, this study does not take into account the fertilisation effects of higher CO_2 concentration. In fact, evidence from agronomic experiments suggest that CO_2 concentration has the potential to offset in part the negative effect of global warming on agriculture, but the magnitude of this effect is still debated (Long et al. 2006). Second, in this partial equilibrium analysis, agricultural prices are assumed constant under climate change. This assumption is reliable if most of the negative effects in currently hot areas are offset by the positive effects in currently cold regions. Otherwise, agricultural prices will rise resulting in a smaller overall profit loss. Third, to avoid potential bias from irrigation, we follow the literature and use only data from US counties east of the 100 °meridian. Hence, the results of this paper apply to only the eastern US and not to the whole country. Finally, the potential benefits from technological advancements induced by climate change are not included in the adaptation benefit estimation; hence, this study only estimates the lower boundary of adaptation benefits.

References

Adams, Richard M. 1989. "Global climate change and agriculture: an economic perspective." *American Journal of Agricultural Economics* 71 (5):1272-1279.

Adams, Richard M, Cynthia Rosenzweig, Robert M Peart, Joe T Ritchie, Bruce A McCarl, J David Glyer, R Bruce Curry, James W Jones, Kenneth J Boote, and L Hartwell Allen. 1990. "Global climate change and US agriculture." *Nature* 345:219-224.

Anselin, L. 1988. *Spatial Econometrics: Methods and Models*. Vol. 4: Springer Science & Business Media.

Belotti, Federico, Gordon Hughes, and Andrea Piano Mortari. 2014. "XSMLE: Stata module for spatial panel data models estimation." *Statistical Software Components*.

Burke, Marshall, John Dykema, David B Lobell, Edward Miguel, and Shanker Satyanath. 2015. "Incorporating climate uncertainty into estimates of climate change impacts." *Review of Economics and Statistics* 97 (2):461-471.

Burke, Marshall, and Kyle Emerick. 2015. "Adaptation to Climate Change: Evidence from US Agriculture." *Working paper, University of California, Berkeley*.

Burke, Marshall, and David Lobell. 2010. "Food security and adaptation to climate change: What do we know?" In *Climate Change and Food Security*, 133-153. Springer.

Chicoine, David L. 1981. "Farmland values at the urban fringe: an analysis of sale prices." *Land Economics*:353-362.

De Hoyos, Rafael E, and Vasilis Sarafidis. 2006. "Testing for cross-sectional dependence in panel-data models." *Stata Journal* 6 (4):482.

DeGroot, Morris H. 2005. *Optimal statistical decisions*. Vol. 82: John Wiley & Sons.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2012. "Temperature Shocks and Economic Growth: Evidence from the Last Half Century." *American Economic Journal: Macroeconomics* 4 (3):66-95. doi: doi: 10.1257/mac.4.3.66.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Olken. 2014. "What Do We Learn from the Weather? The New Climate-Economy Literature." *Journal of Economic Literature* 52 (3):740-98.

Deschênes, Olivier, and Michael Greenstone. 2007. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather." *The American Economic Review*:354-385.

Deschênes, Olivier, and Michael Greenstone. 2012. "The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather: Reply." *The American Economic Review* 102 (7):3761-3773.

Di Falco, Salvatore. 2014. "Adaptation to climate change in Sub-Saharan agriculture: assessing the evidence and rethinking the drivers." *European Review of Agricultural Economics* 41 (3):405-430.

Di Falco, Salvatore, Marcella Veronesi, and Mahmud Yesuf. 2011. "Does adaptation to climate change provide food security? A micro-perspective from Ethiopia." *American Journal of Agricultural Economics* 93 (3):829-846.

Elhorst, J. Paul. 2010. "Spatial Panel Data Models." In *Handbook of Applied Spatial Analysis*, edited by Manfred M. Fischer and Arthur Getis, 377-407. Springer Berlin Heidelberg.

Falco, Salvatore Di, and Marcella Veronesi. 2013. "How Can African Agriculture Adapt to Climate Change? A Counterfactual Analysis from Ethiopia." *Land Economics* 89 (4).

Fisher, Anthony C, W Michael Hanemann, Michael J Roberts, and Wolfram Schlenker. 2012. "The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment." *The American Economic Review* 102 (7):3749-60.

Frees, Edward W. 2004. *Longitudinal and panel data: analysis and applications in the social sciences*: Cambridge University Press.

Hanemann, W Michael. 2000. "Adaptation and its measurement." *Climatic Change* 45 (3):571-581.

Hansen, LeRoy. 1991. "Farmer response to changes in climate: the case of corn production." *Journal of Agricultural Economics Research* 43 (4):18-25.

Kelly, David L, Charles D Kolstad, and Glenn T Mitchell. 2005. "Adjustment costs from environmental change." *Journal of Environmental Economics and Management* 50 (3):468-495.

Kurukulasuriya, Pradeep, and Robert Mendelsohn. 2008. "Crop switching as a strategy for adapting to climate change." *African Journal of Agricultural and Resource Economics* 2 (1):105-126.

Lee, Lung-Fei. 2002. "Consistency and efficiency of least squares estimation for mixed regressive, spatial autoregressive models." *Econometric theory* 18 (02):252-277.

Lee, Lung-fei, and Jihai Yu. 2010. "Estimation of spatial autoregressive panel data models with fixed effects." *Journal of Econometrics* 154 (2):165-185.

Lobell, David B. 2014. "Climate change adaptation in crop production: Beware of illusions." *Global Food Security* 3 (2):72-76.

Lobell, David B, and Gregory P Asner. 2003. "Climate and management contributions to recent trends in US agricultural yields." *Science* 299 (5609):1032-1032.

Lobell, DB, G Bala, and PB Duffy. 2006. "Biogeophysical impacts of cropland management changes on climate." *Geophysical Research Letters* 33 (6).

Long, Stephen P, Elizabeth A Ainsworth, Andrew DB Leakey, Josef Nösberger, and Donald R Ort. 2006. "Food for thought: lower-than-expected crop yield stimulation with rising CO2 concentrations." *Science* 312 (5782):1918-1921.

Massetti, Emanuele, and Robert Mendelsohn. 2011. "Estimating Ricardian models with panel data." *Climate Change Economics* 2 (04):301-319.

Mendelsohn, Robert, William D Nordhaus, and Daigee Shaw. 1994. "The impact of global warming on agriculture: a Ricardian analysis." *The American Economic Review*:753-771.

Parameter-elevation Regressions on Independent Slopes Model Climate Group. 2014. "PRISM Climate Data." Oregon State University Accessed 02 March 2014. http://www.prism.oregonstate.edu/recent/.

Plantinga, Andrew J, Ruben N Lubowski, and Robert N Stavins. 2002. "The effects of potential land development on agricultural land prices." *Journal of Urban Economics* 52 (3):561-581.

Ritchie, JT, and DS NeSmith. 1991. "Temperature and crop development." In *Modeling plant and soil systems. Agron. Monogr*, 5-29.

Schlenker, Wolfram, W Michael Hanemann, and Anthony C Fisher. 2005. "Will US agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach." *The American Economic Review* 95 (1):395-406.

Schlenker, Wolfram, W Michael Hanemann, and Anthony C Fisher. 2006. "The impact of global warming on US agriculture: an econometric analysis of optimal growing conditions." *Review of Economics and Statistics* 88 (1):113-125.

Schlenker, Wolfram, and Michael J Roberts. 2009. "Nonlinear temperature effects indicate severe damages to US crop yields under climate change." *Proceedings of the National Academy of Sciences* 106 (37):15594-15598.

Seo, S Niggol, and Robert Mendelsohn. 2008. "Measuring impacts and adaptations to climate change: a structural Ricardian model of African livestock management1." *Agricultural economics* 38 (2):151-165.

Seo, S. Niggol. 2013. "An essay on the impact of climate change on US agriculture: weather fluctuations, climatic shifts, and adaptation strategies." *Climatic Change* 121 (2):115-124. doi: 10.1007/s10584-013-0839-8.

Solomon, Susan. 2007. *Climate change 2007-the physical science basis: Working group I contribution to the fourth assessment report of the IPCC*. Vol. 4: Cambridge University Press.

Tack, Jesse, Andrew Barkley, and Lawton Lanier Nalley. 2015. "Effect of warming temperatures on US wheat yields." *Proceedings of the National Academy of Sciences*:201415181.

Taylor, Karl E, Ronald J Stouffer, and Gerald A Meehl. 2012. "An overview of CMIP5 and the experiment design." *Bulletin of the American Meteorological Society* 93 (4):485-498.

Zilberman, David, Jinhua Zhao, and Amir Heiman. 2012. "Adoption versus adaptation, with emphasis on climate change." *Annual Review of Resource Economics, Vol 4* 4 (1):27-53.

For Online Publication Appendix

A. A potential bias of the hedonic approach

The hedonic approach uses farmland values as the dependent variable. This section provides empirical evidences to show that the measurement error of farmland value is correlated with climatic variables. As a result, the estimated climatic coefficients of the hedonic approach are potentially biased.

Few parcels of farmlands are sold every year, so we generally do not observe the market farmland price. The farmland value data used in previous studies are mainly from farmers' estimates, which may be significantly in error. Since we do not observe the true farmland value, the formal test of the measurement error is unavailable. Fortunately, the measurement error can be indirectly tested by examining the correlation between reported inter-annual farmland value changes and random inter-annual weather fluctuations. The true farmland value is the present discounted value of the land rent stream into the infinite future. Hence, the inter-annual changes in farmland value should be independent of random year-to-year weather fluctuations.[40] If they are correlated, the correlation is most likely driven by the measurement error that is correlated with climatic variables.[41] In addition, the share of inter-annual land value variation explained by random weather fluctuations reflects the magnitude of the measurement error.

As shown in Table 3, there are large non-linear intertemporal changes in the reported US county-level farmland value. We test the correlation between these inter-annual farmland value variation and the random year-to-year weather fluctuations through model (5). In this model, $\mathrm{d_{it}}$ is the deviation of land values from the long-term average in county *i* and year *t*. $\mathrm{C_{it}}$ is a vector of climatic variables, including GDD, GTP and their square terms. $\mathrm{C_{i(t-1)}}$ is a vector of climatic variables lagged by one year. L_{it} is a vector of county-level controls, including ten soil quality indicators, population density and income per capita; τ_i is a

[40] If we control for the climate trend, the remaining inter-annual weather fluctuations in a given site can be seen as random. There are many potential causes of intertemporal land value variation, such as changes in long-run agricultural prices, climate trends and technological improvements, but none of these factors is potentially correlated with the random weather fluctuations.

[41] We provide a possible explanation for this correlation: even though farmers estimate their land values based on all available information, they may weigh recent shocks more heavily. For example, if random weather outcome in the present year caused significant damage, farmers may underestimate their land values, although this loss would be offset later by another random good season, while the real land values are unaffected.

county-fixed effect; q_t is a continuous time trend; ε_{it} is the error term that is identically and independently normally distributed. Finally, α, γ, β, θ are coefficients.

(5) $$d_{it} = C'_{it}\alpha + C'_{i(t-1)}\gamma + L'_{it}\beta + \tau_i + \theta q_t + \varepsilon_{it}$$

Because the time trend and county-fixed effects are included in model (5), the climatic coefficients capture the effects of random year-to-year weather fluctuations on inter-annual land value changes. The regression result shows that most of the climatic coefficients are significant at the 1 percent level, which means there are significant measurement errors in the farmland values, and these errors are highly correlated with inter-annual weather fluctuations. Since the marginal effect of weather fluctuation changes with the mean climate, it is reasonable to believe that the measurement error should also be correlated with the mean climate. This fact can be shown by the correlation between the magnitudes of the measurement error and cross-sectional climate normal.

We use the share of intertemporal land value variation explained by random weather fluctuations as a proxy for the measurement error, and plot this share for each state against the state-level GDD normal. To do this, we first run separate regressions of model (5) for each state and then calculate the state-level shares by comparing the residual variance of the complete model with the residual variance of the model that excludes climatic variables. As presented in Figure A1, on average, about 30 percent of inter-annual land value variation can be explained by random weather fluctuations. Further, it seems that the share explained in each state is correlated with the state-level GDD. Specifically, there is a U-shaped relationship between the variation explained and GDD when GDD is lower than 2100; and a slightly negative relationship when GDD is higher than 2100. This result indicates that the significant measurement errors are potentially correlated with cross-sectional climate.

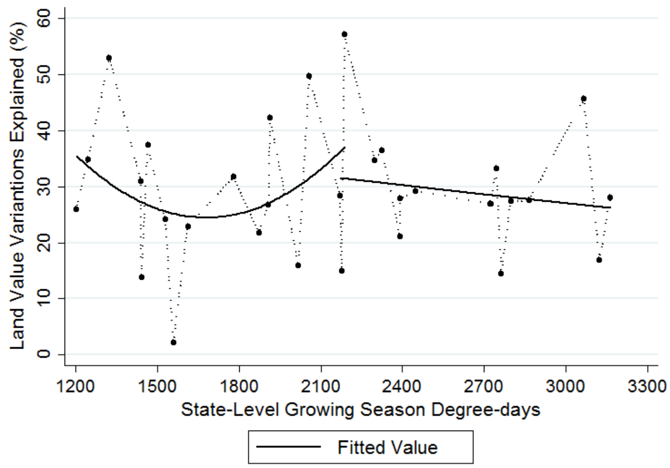

FIGURE A1. THE STATE-LEVEL SHARE OF INTER-ANNUAL VARIATION IN LAND VALUE EXPLAINED BY WEATHER FLUCTUATIONS AND ITS CORRELATION WITH STATE-LEVEL GDD NORMAL

Notes: The y-axis measures the state-specific shares of intertemporal land value variation explained by weather fluctuations in model (5). To calculate the state-level shares, we first run regression (5) for each state separately, and then calculate the share as 1 minus the ratio of the residual variance over the residual variance from model (5) when weather variables are excluded. The x-axis measures the state-level GDD normal, which is the simple average of county-level GDD normal across all counties within each state.

To explore this possibility further, we plot the county-specific standard deviation of farmland value over time against deciles of the cross-sectional distributions of GDD normal and GTP normal. As presented in Figure A2, there are obvious hump-shaped relationships between the standard deviations and the climate normal measures. This evidence further supports the argument that the magnitude of farmland value measurement error is correlated with the cross-sectional climate normal. When we regress the county-level standard deviations against the climate normal and controls for land quality and other inter-county differences, the hump-shaped relationships remain the same.

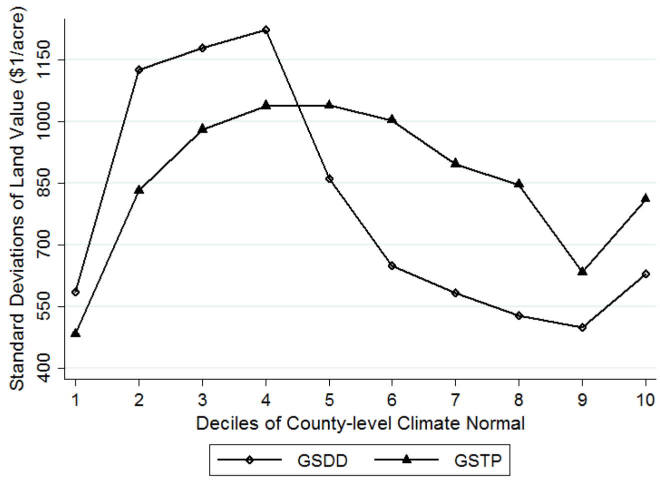

FIGURE A2. THE CORRELATION BETWEEN COUNTY-SPECIFIC STANDARD DEVIATIONS OF FARMLAND VALUE AND CLIMATE NORMAL

Notes: The y-axis measures the county-specific standard deviation of farmland values over time. The x-axis measures deciles of the distribution of growing season degree-day (GDD) normal and growing season total precipitation (GTP) normal across all simple counties, and the normal climate values are the long-term average during 1981–2000. The line "GDD" and "GTP" plot the relationship between standard deviations of land value and the midpoint of each decile of degree-day and precipitation, respectively. Points on each line are the coefficients of indicator variables for deciles from the regression with standard deviations of land values as the dependent valuable and with indicators of decide as the independent variables.

To sum up, this section provides indirect evidence that the measurement error of farmland value is potentially correlated with inter-annual weather fluctuations as well as cross-sectional climate differences. Consequently, the climatic coefficients identified by the hedonic approach are potentially biased, and the sign and magnitude of the bias depend on the sample year and sample location. These empirical results provide another possible explanation of why the hedonic approach is extremely sensitive to minor sample choices, as found in Deschênes and Greenstone (2007).

B. A Bayesian learning simulation of the believed climate trend

This section provides a simple learning model to show that, even when there are obvious climate trend in the inter-annual weather fluctuations, farmers' adaptations to the climate trend are very limited.

We follow Burke and Emerick (2015) to assume farmers' belief of "true" mean temperature follows a simple Bayesian learning process. Denote farmers' belief of mean temperature in period *t* as c_t and with precision φ_t. In each period, they observe the realization of temperature s_t and update their belief to c_{t+1} using a weighted combination of prior belief and the realized temperature. Denote $\delta = 1/\sigma^2$, here σ^2 is the variance of realized temperature, it is assumed to be unchanged when mean temperature increases. According to DeGroot (2005), for a sudden temperature increase, such as Δc, in the base year, the farmers' belief about mean temperature after *T* years is given by $C_T = (\varphi_t c_t + T\delta s_t)/(\varphi_t + T\delta)$, with $\varphi_{t+1} = \varphi_t + \delta$. In expectation, the difference between belied temperature change and true temperature change is given by equation (6):

(6) $$D = \frac{\Delta C}{1+T(\frac{\delta}{\phi_0})}$$

We combine equation (6) with the empirical data in Figure 1 to draw a simulation of farmers' belief. Assume the initial precision of belief, φ_0, as the inverse of the variance of temperature during 1960-1970, which is a period before large temperature variance. Assume the temperature variance during 1970-2010 as σ^2. Then we can simulate the evolution of farmers' belief after a once for all, for example 5 ℃, mean temperature increase in the base year. The result is shown in Figure A3. After 10 years, only about 40 percent of the mean temperature change is believed as true temperature rise and only about 80 percent of the change is believed after 50 years. Since the believed climate change is much small than the actual change, farmers' adaptation should be quite limited.

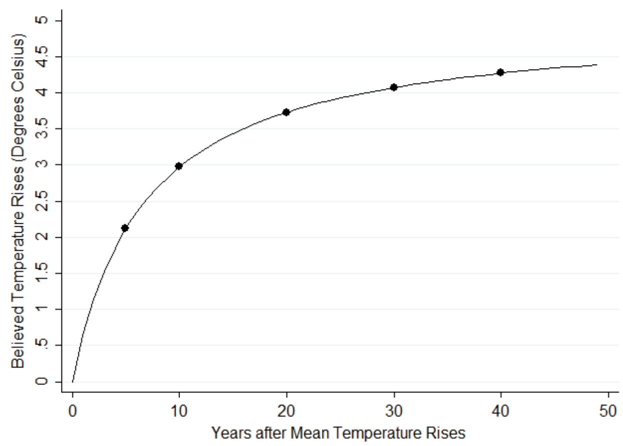

FIGURE A3. SIMULATION OF FARMERS' BELIEVED "TRUE" TEMPERATURE RISE AFTER AN ASSUMED 5 ℃ TEMPERATURE INCREASE IN THE BASE YEAR