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

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Working Paper No. 2015-20
October 2015

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The Economic Impacts of Global Warming on 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)

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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

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.
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 inconsistencies of findings from previous studies and the potential biases that result from omitting adaptations, misspecifications or measurement errors in the widely used methodologies, this study develops a new panel method to include adaptations and avoid these biases. Based on the basic idea of the

\(^2\) 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.
hedonic approach, we have modified the previous panel method that relies on inter-annual weather fluctuations to develop a new 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.

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.
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 °C during the past half century. 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). 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

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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.
between measurement error of farmland values and climatic variables. In the following 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](image)

**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**

*Note: 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 °C to 20.8 °C), 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

<table>
<thead>
<tr>
<th>Year 1</th>
<th>Year 2</th>
<th>Within county mean</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel A. No fixed effects</td>
<td></td>
<td></td>
</tr>
<tr>
<td>County 1</td>
<td>( x_{11} = T_{11} + \Delta_{11} + \epsilon_{11} )</td>
<td>( x_{12} = T_{12} + \Delta_{12} + \epsilon_{12} )</td>
</tr>
<tr>
<td>County 2</td>
<td>( x_{21} = T_{21} + \Delta_{21} + \epsilon_{21} )</td>
<td>( x_{22} = T_{22} + \Delta_{22} + \epsilon_{22} )</td>
</tr>
<tr>
<td>Within year mean</td>
<td>( \frac{\Delta_{11} + \Delta_{12}}{2} + \frac{\epsilon_{11} + \epsilon_{12}}{2} )</td>
<td>( \frac{\Delta_{21} + \Delta_{22}}{2} + \frac{\epsilon_{21} + \epsilon_{22}}{2} )</td>
</tr>
</tbody>
</table>

Panel B. Time-fixed effects: subtracting within year mean from each observations

| County 1 | \( \frac{T_{11} - T_{12}}{2} + \frac{\epsilon_{11} - \epsilon_{12}}{2} \) | \( \frac{T_{21} - T_{22}}{2} + \frac{\epsilon_{21} - \epsilon_{22}}{2} \) |
| County 2 | \( \frac{T_{21} - T_{11}}{2} + \frac{\epsilon_{21} - \epsilon_{11}}{2} \) | \( \frac{T_{22} - T_{12}}{2} + \frac{\epsilon_{22} - \epsilon_{12}}{2} \) |

Panel C. County-fixed effects: subtracting within county mean from each observations

| County 1 | \( \frac{\Delta_{11} - \Delta_{12}}{2} + \frac{\epsilon_{11} - \epsilon_{12}}{2} \) | \( \frac{\Delta_{21} - \Delta_{22}}{2} + \frac{\epsilon_{21} - \epsilon_{22}}{2} \) |
| County 2 | \( \frac{\Delta_{11} - \Delta_{12}}{2} + \frac{\epsilon_{11} - \epsilon_{12}}{2} \) | \( \frac{\Delta_{21} - \Delta_{22}}{2} + \frac{\epsilon_{21} - \epsilon_{22}}{2} \) |

Panel D. Two way fixed effects: subtracting within county and within year mean, and plus sample mean

| County 1 | \( \frac{\epsilon_{11} - \epsilon_{12} - \epsilon_{21} + \epsilon_{22}}{4} \) | \( \frac{-\epsilon_{11} - \epsilon_{12} + \epsilon_{21} + \epsilon_{22}}{4} \) |
| County 2 | \( \frac{-\epsilon_{11} - \epsilon_{12} - \epsilon_{21} + \epsilon_{22}}{4} \) | \( \frac{\epsilon_{11} - \epsilon_{12} - \epsilon_{21} + \epsilon_{22}}{4} \) |

Note: \( x_{it} \) 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; \( \Delta_{i} \) measures the inter-annual weather fluctuations that are common across counties in the same year but vary over time; \( \epsilon_{it} \) 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 \( \Delta_{i} \) measures the inter-annual weather fluctuations that are common across counties in the same year but
vary over time;\(^6\) the last part \(\varepsilon_{it}\) is the county-specific weather shocks. The within county means and within year means are also reported.

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 \(\Delta_t\) is filtered out; the remaining variation pertains only to the differences in climate \(T_i\) and the variances in county-specific weather shocks \(\varepsilon_{it}\). If the variation pertaining to \(\varepsilon_{it}\) 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 \(\varepsilon_{it}\). 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°C, and no counties with the deviation more than 1°C. However, without fixed effects, there are 79.4 percent of counties with inter-annual temperature deviation of more than 0.4°C, and 34.6 percent of counties with the deviation more than 1°C. 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

<table>
<thead>
<tr>
<th>Panel A. Percentage of counties with inter-annual temperature variance below/above (°C):</th>
<th>±0.4</th>
<th>±0.6</th>
<th>±0.8</th>
<th>±1.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>State-by-year fixed effects</td>
<td>4.8</td>
<td>0.7</td>
<td>0.2</td>
<td>0.0</td>
</tr>
<tr>
<td>No fixed effects</td>
<td>79.4</td>
<td>64.5</td>
<td>48.8</td>
<td>34.6</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B. Percentage of counties with inter-annual precipitation variance below/above (Inches):</th>
<th>±4</th>
<th>±6</th>
<th>±8</th>
<th>±10</th>
</tr>
</thead>
<tbody>
<tr>
<td>State-by-year fixed effects</td>
<td>10.3</td>
<td>2.4</td>
<td>0.6</td>
<td>0.2</td>
</tr>
<tr>
<td>No fixed effects</td>
<td>32.5</td>
<td>14.2</td>
<td>5.1</td>
<td>1.5</td>
</tr>
</tbody>
</table>

*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 (°C), and the precipitation is measured by growing season total precipitations (inches). See section II for detailed data description.

\(^6\) Here we assume no time trend in \(T_i\). In fact, the climate trend is captured in the second part \(\Delta_t\), because the trend is usually common across counties.

\(^7\) 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.
Obviously, the variation pertaining to county-specific weather shocks $\varepsilon_{it}$ 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 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). Unfortunately, the potential for adaptation is poorly understood and no effective way has been developed for evaluating adaptations. A major contribution to estimating adaptation has been made by the hedonic approach, which implicitly includes adaptation. However, the benefits of adaptations cannot be explicitly evaluated by this approach.⁸ There are also a large number of micro-level studies interested in examining the driving forces of adaptation decisions (See, for example, Kurukulasuriya and Mendelsohn 2008, Wang et al. 2010, Di Falco and Veronesi 2013). Most of these studies explain the responses to weather fluctuations as adaptation or infer adaptation benefits through examining the benefits of substitutions among a few crops. According to the definition of adaptation, these studies omitted all or part of the potential adaptation benefits from adjusting land use and *ex-ante* production behaviors.

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-

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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).
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 adaptation. Briefly, we approximate the benefit of adaptation by comparing the estimates from two 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, $\Delta_t$ and the county-specific weather shocks $\epsilon_{it}$. 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.

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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.
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 100º 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. In this data source, agricultural revenue measures the before-taxes total market value of agricultural products sold in a county in a year; it includes only the revenue produced from farmland. 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.

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

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

11 See previous studies such as Deschênes and Greenstone (2007) for more detailed agricultural production data descriptions.
(GHDD) and growing season total precipitation (GTP) (Schlenker, Hanemann, and Fisher 2006, Deschénes and Greenstone 2007).

GDD measures the cumulative exposure to heat between 8 °C and 32 °C during the growing season from April to September. In detail, a day with a mean temperature below 8 °C contributes zero degree-days; between 8 °C and 32 °C contributes the difference between the mean and 8 °C; above 32 °C 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 °C: a day with a mean temperature above 32 °C contributes the difference between the mean and 32 °C; otherwise it contributes zero harmful degree-days (Ritchie and NeSmith 1991). Finally, GTP is the total precipitation in inches during the growing season.

**Climate predictions:** we use the latest high resolution climate predictions from General Circulation Model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor, Stouffer, and Meehl 2012). The data of 42 climate projections from 21 CMIP5 GCMs and two Representative Concentration Pathways (RCP) scenarios (RCP4.5 and RCP8.5) are available from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset. 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), we also

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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 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, 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/.
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.\footnote{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.}

\textit{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.\footnote{See Appendix A of Mendelsohn, Nordhaus, and Shaw (1994) for a detailed description of soil controls.} 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.

\textit{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

<table>
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<tr>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Farmland prices ($/acre)</td>
<td>2073</td>
<td>1387</td>
<td>1363</td>
<td>1614</td>
<td>1927</td>
<td>2566</td>
<td>3332</td>
</tr>
<tr>
<td>Agricultural profits ($/acre)</td>
<td>--</td>
<td>66</td>
<td>66</td>
<td>83</td>
<td>42</td>
<td>83</td>
<td>99</td>
</tr>
<tr>
<td>Areas of land in farms (th. acres)</td>
<td>366</td>
<td>366</td>
<td>362</td>
<td>365</td>
<td>370</td>
<td>372</td>
<td>375</td>
</tr>
<tr>
<td>Agricultural expenses ($/acre)</td>
<td>--</td>
<td>242</td>
<td>253</td>
<td>264</td>
<td>264</td>
<td>335</td>
<td>432</td>
</tr>
</tbody>
</table>

Note: 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

<table>
<thead>
<tr>
<th></th>
<th>Average temperature (°C)</th>
<th>GDD (°C)</th>
<th>GHDD (°C)</th>
<th>GTP (Inches)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Climate Normal</td>
<td>20.23</td>
<td>2272</td>
<td>0.11</td>
<td>23.50</td>
</tr>
<tr>
<td>(3.25)</td>
<td>(558)</td>
<td>(0.43)</td>
<td>(3.60)</td>
<td></td>
</tr>
<tr>
<td>Predicted climatic changes by the end of this century under scenario RCP45:</td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>CCSM4</td>
<td>1.95</td>
<td>0.38</td>
<td>1.90</td>
<td></td>
</tr>
<tr>
<td>(0.61)</td>
<td>(0.38)</td>
<td>(2.17)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CESM1-BGC</td>
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<td>2.63</td>
<td></td>
</tr>
<tr>
<td>(0.99)</td>
<td>(0.66)</td>
<td>(2.97)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>CanESM2</td>
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<td>1.47</td>
<td>0.41</td>
<td></td>
</tr>
<tr>
<td>(0.50)</td>
<td>(1.55)</td>
<td>(1.61)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NorESM1-M</td>
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<td></td>
</tr>
<tr>
<td>(0.80)</td>
<td>(3.01)</td>
<td>(1.80)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: 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; second, calculating state-level climate

17 The spatial resolution of climate predictions does not allow us to calculate the county-level predictions.
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 °C to 2.79 °C, 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 °C to 3.7 °C 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 °C 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 temperatures. The changes in GTP predicted by climate models are quite small relative to the predicted changes in GDD.

Lastly, Figure 3 compares the geographic distribution of the climatic variables of climate normal with the distribution of predictions from the representative model CCSM4 RCP4.5; the distributions of predictions from the other three models are quite similar. For the climate normal, the GDD is decreasing from southern counties to northern counties, and the GTP is decreasing from east counties to west counties. The predictions from CCSM4 RCP4.5 follow the same geographic pattern, but predict a hotter and wetter climate. We mapped distributions of the prediction from other climate models and find similar results.

\(^{18}\) 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).
FIGURE 3. GEOGRAPHIC DISTRIBUTIONS OF GDD AND GTP FOR CLIMATE NORMAL AND SCENARIO CCSM4 RCP4.5

Note: The samples are 2155 rain-fed non-urban counties east of the 100° meridian. This figure compared the geographic distribution of the climate prediction of the representative scenario CCSM4 RCP4.5 with the distribution of climate normal.
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; \( \gamma_{st} \) 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; \( \epsilon_s \) 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; \( \rho, \alpha, \beta \) are coefficients. Finally, \( \mu_{it} \) are the identically and independently normally distributed (iids) error terms. If \( \rho \) 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

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

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 \( \rho = 0 \)

---

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.
by the semi-parametric 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). Hence, this study prefers to model the spatial dependence explicitly by SAR.\textsuperscript{20}

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 $\tau_i$, 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.\textsuperscript{21} 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.\textsuperscript{22} 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, $\varepsilon_{it}$ are the iid normally distributed error terms.

$\begin{align*}
y_{it} &= \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{k=1}^{K} c_{itk} \alpha_k + \sum_{g=1}^{G} l_{itg} \beta_g + \tau_i + \theta q_t + \varepsilon_{it} \\
i &= 1, \ldots, n; \quad t = 1, \ldots, T
\end{align*}$

\textsuperscript{20} Another choice is the spatial error model (SEM), but for such a large weight matrix ($2155 \times 2155$) in a panel setting, we find that the maximum likelihood estimator of SEM usually does not converge.

\textsuperscript{21} 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.

\textsuperscript{22} 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).
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; \( \beta \) and \( \gamma \) are vectors of coefficients; and \( \omega_i \) 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.

\[
V_i = \alpha + \bar{C}_i' \beta + \bar{L}_i' \gamma + \omega_i
\]

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.\(^\text{23}\) 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 agriculture.\(^\text{24}\) The panel framework of model (1) enables us to use agricultural profits as

---

\(^\text{23}\) 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.

\(^\text{24}\) 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.
the dependent variable and hence avoids this bias. Another 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.

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.\(^{25}\)

### 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 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; \(\sigma_{it}\) 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.

\(^{25}\) 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.
Specifically, model (4) includes both county-fixed effects $\tau_i$ and state-by-year fixed effects $\gamma_{st}$; model (1) only includes state-by-year fixed effects $\gamma_{st}$ and state-fixed effects $\epsilon_s$; model (2) only includes county-fixed effects $\tau_i$ and a time trend $q_t$. However, this seemingly minor difference results in great discrepancy in the implication of the estimated climatic coefficients.

$$y_{it} = C_i \alpha + L_t \beta + \tau_i + \gamma_{st} + \sigma_{it}$$

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 $\Delta_t$. As a result, the impacts are identified through the county-specific inter-annual weather shocks $\epsilon_{it}$. 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 °C. However, Table 4 shows that climate models predicted more than 2 °C temperature rises by the end of this century, so the long-run impact predictions of model (4) depend heavily on extrapolation.\(^\text{26}\) 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. The difference is that model (2) depends on the significant common fluctuation $\Delta_t$, while model (4) depends on county-specific fluctuation $\epsilon_{it}$, which is too small to avoid extrapolation. Hence, model (2) provides a way to predict the impacts that does not include adaptations.

\(^{26}\) This fact was first demonstrated by Fisher et al. (2012).
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.\textsuperscript{27} 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.\textsuperscript{28} 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).\textsuperscript{29} 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.

\textbf{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 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).

\textsuperscript{27} 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.

\textsuperscript{28} 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 affect 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.

\textsuperscript{29} 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.
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>
<thead>
<tr>
<th>Independent Variables</th>
<th>Adaptation (1a)</th>
<th>Adaptation (1b)</th>
<th>No adaptation (2a)</th>
<th>No adaptation (2b)</th>
</tr>
</thead>
<tbody>
<tr>
<td>100 GDD (º C)</td>
<td>7.80</td>
<td>7.34</td>
<td>12.3</td>
<td>12.3</td>
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<td>(1.10)</td>
</tr>
<tr>
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<td>-0.29</td>
<td>-0.29</td>
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<td>(0.05)</td>
<td>(0.05)</td>
<td>(0.03)</td>
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<td>GTP (inches)</td>
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<td>0.36</td>
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<td></td>
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<td>(0.69)</td>
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<td>(0.61)</td>
</tr>
<tr>
<td>GTP square</td>
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<td>-0.04</td>
<td>-0.03</td>
<td>-0.03</td>
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<td>(0.01)</td>
<td>(0.01)</td>
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<td>-4.14</td>
<td>-10.05</td>
<td>-10.11</td>
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<td></td>
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<td>(1.47)</td>
<td>(0.95)</td>
<td>(0.95)</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
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<td>Yes</td>
<td>No</td>
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</tr>
<tr>
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<td>Yes</td>
<td>No</td>
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<tr>
<td>County-fixed effects</td>
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<td>Yes</td>
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<td>10 land quality indicators</td>
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</tbody>
</table>

Note: This table reports the estimated climatic coefficients from SAR panel models. Columns 1a and 1b report estimates from model (1); column 2a and 2b report estimates from model (2). 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 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.

The estimated overall climate change impacts are presented in column 1a and 2a of Table 6. For estimates from the model that includes adaptations (column 1a), the overall impacts are negative but generally quite small; the changes in output 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 output, 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 are $9$ percent with adaptations, and $30$ percent without adaptations. In addition, as reported in column 1b and 2b, omitting soil controls has only quite small effects on the estimated overall impacts.

<table>
<thead>
<tr>
<th>Climate model</th>
<th>Adaptation (1a)</th>
<th>Adaptation (1b)</th>
<th>No adaptation (2a)</th>
<th>No adaptation (2b)</th>
<th>Benefit of adaptation</th>
</tr>
</thead>
<tbody>
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<td>-5.96</td>
<td>-5.99</td>
<td>4.69</td>
</tr>
<tr>
<td></td>
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<td>(1.22)</td>
<td>(0.59)</td>
<td>(0.59)</td>
<td></td>
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<tr>
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<td>-1.27</td>
<td>-7.21</td>
<td>-7.24</td>
<td>5.64</td>
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<td>(1.21)</td>
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<td>(2.02)</td>
<td>(1.06)</td>
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</tr>
<tr>
<td>NorESM1-M</td>
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<td>-5.01</td>
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</tr>
<tr>
<td></td>
<td>(2.23)</td>
<td>(2.22)</td>
<td>(1.22)</td>
<td>(1.22)</td>
<td></td>
</tr>
</tbody>
</table>

*Note: 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 used in this study. Columns 1a and 1b report the impact estimated from model (1); columns 2a and 2b report the impact estimated from model (2). The only difference between model a and model b is that model b excludes the soil controls. The last column reports 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.*

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30 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).
We calculate the benefit of adaptation as the difference between column 1a and column 2a, and report it in the last column of Table 6. 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.

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Finally, Figure 4 maps the geographic distribution of climate change impacts. 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 4), 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 4).

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 Deschenes and Greenstone (2007), developing a new 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 temperature fluctuations are generally common across regions in the same year. The empirical results show that when predictions are made incorporating adaptations, the overall fall in output is 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 about 72.4 percent of the overall fall in agricultural profits demonstrated by methods omitting adaptation.

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. 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


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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.\(^{32}\) If they are correlated, the correlation is most likely driven by the measurement error that is correlated with climatic variables.\(^{33}\) In addition, the share of inter-annual land value variation explained by random weather fluctuations reflects the magnitude of the measurement error.

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\(^{32}\) 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.

\(^{33}\) 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.
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, $d_{it}$ is the deviation of land values from the long-term average in county $i$ and year $t$. $C_{it}$ is a vector of climatic variables, including GDD, GTP and their square terms. $C_{i(t-1)}$ 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; $\tau_i$ is a county-fixed effect; $q_t$ is a continuous time trend; $\epsilon_{it}$ is the error term that is identically and independently normally distributed. Finally, $\alpha$, $\gamma$, $\beta$, $\theta$ are coefficients.

$$d_{it} = C_{it}'\alpha + C_{i(t-1)}'\gamma + L_{it}'\beta + \tau_i + \theta q_t + \epsilon_{it}$$  

(5)

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.

Note: 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.
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 $\varphi_t$. 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 $\sigma^2$ 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 $\Delta c$, in the base year, the farmers’ belief about mean temperature after $T$ years is given by $C_T = \left( \varphi_t c_t + T\delta s_t \right) / (\varphi_t + T\delta)$, with $\varphi_{t+1} = \varphi_t + \delta$. In expectation, the difference between belied temperature change and true temperature change is given by equation (6):

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

We combine equation (6) with the empirical data in Figure 1 to draw a simulation of farmers’ belief. Assume the initial precision of belief, $\varphi_0$, 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 $\sigma^2$. Then we can simulate the evolution of farmers’ belief after a once for all, for example 5 °C, 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 °C temperature increase in the base year.