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RESEARCH ARTICLE

The potential benefits of agricultural adaptation to warming in China in the long run

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Abstract

Understanding the extent to which agriculture can adapt to climate change and the determinants of farmers' adaptive capacity are of paramount importance from a policy perspective. Based on household survey data from a large sample in rural China, the present article adopts a panel approach to estimate the potential benefits of long-run adaptation and to identify the determinants of farmers' adaptive capacity. The empirical results suggest that, for various model settings and climate change scenarios, long-run adaptations should mitigate one-third to one-half of the damages of warming on crop profits by the end of this century. These findings support the basic argument of the hedonic approach that omitting long-run adaptations will dramatically overestimate the potential damage of climate change. The paper also finds that household-level capital intensity and farmland size have significant effects on farmers' adaptive capacities.

Keywords: Climate change; adaptation capacity; agriculture and China

JEL Classification: Q15; Q51; Q54

1. Introduction

Estimating the potential impacts of climate change on agriculture is crucial for understanding food security issues and for assessing the potential costs of greenhouse gas emissions (Lobell and Asner, 2003). However, any estimate of the impact of climate change is potentially biased if adaptation measures by farmers are not included (Lobell *et al.*, 2008). Thus, investigating the extent to which effective adaptation measures are likely to be implemented is central to the study of the potential impact of climate change on agriculture. An even more interesting issue from a policy perspective is identifying and understanding the determinants of farmers' adaptive capacity, as that knowledge can support the design of effective adaptation policies.

The adaptation of agriculture to climate change is usually defined in terms of production behavior adjustments by agricultural agents in order to moderate any negative effects or to exploit beneficial opportunities from the changed climate. Many previous studies have stressed the difference between long-term adaptations to climate change, and short-term responses to weather fluctuations: in adapting to long-term climate change, farmers can adjust land use and other *ex ante* production behaviors, but in responding to random inter-annual weather variations, farmers can only make limited *ex post* adjustments due to time constraints or the need for large fixed investments (Seo, 2013). Examining farmers' responses to inter-annual weather fluctuations or extreme weather events may shed important light on possible adaptations to changes in climate variation (see for example Huang *et al.*, 2015). However, in the present study, we focus only on adaptations to changes in the long-term climate trend; thus, for simplicity, the term 'adaptation' in this paper refers only to such long-term adaptation to the climate trend.

Empirically, a major contribution to the field of adaptation study involved the hedonic approach proposed by Mendelsohn *et al.* (1994), which implicitly included adaptations in its climate change impact estimation. The hedonic approach identifies climate change impacts through cross-sectional climatic differences. Since it is assumed that agricultural agents will have completely adapted to the climate of their particular regions, by examining how the local climate in different regions affects the value of farmland, this approach includes a full range of adaptations. Nevertheless, this approach cannot explicitly evaluate the benefits of adaptation (Hanemann, 2000).

On the other hand, numerous farm-level studies have explicitly 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, and Falco and Veronesi (2013) identified the adaptation benefits from adopting water and soil conservation behaviors. Even though existing farm-level adaptation studies have dramatically improved our understanding of adaptation, as argued by Mendelsohn *et al.* (1994), in reality, there are innumerable potential adaptation measures that farmers could apply in response to climate change, and it is impossible to capture the benefits of the full range of long-run adaptations by examining only individual adaptation measures.

Therefore, an approach to identifying the benefits of long-run adaptations without examining individual adaptation measures would be valuable. The value of long-run adaptations refers to the total benefits from all potential adaptation measures that could be taken by farmers given the current technological level and relative commodity prices.[1] The present study attempts to identify the value of long-run adaptations as a whole using a panel approach. In this approach, the value of long-run adaptations is approximated by comparing the estimated damage from cross-sectional climate differences and the identified damage from inter-annual weather fluctuations.

Two types of panel models were developed, based on the key fact that inter-annual weather fluctuations are generally common across regions in the same year[2]: one depending on cross-sectional climate differences and the other on inter-annual weather

[1] As with the hedonic approach and all other partial equilibrium studies, it is impossible to include the potential value of adaptations from future technological advancements and relative price changes. Hence, the potential value of future adaptations related to the development of new technologies and changes in relative prices are not included.

[2] This is especially true within a not too large geographic region, such as a province of China. In the following, we provide empirical evidence to support this point.

fluctuations. Only the former model, that is, the model using cross-sectional climate differences, includes the benefit of long-run adaptations. Thus, we hypothesized that the differences between the predicted impacts from these two models should reflect the value of adaptations that can be taken *only* in the long-run.[3] For simplicity, we refer to the benefits of adaptations that can be taken *only* in the long-run as 'the value of long-run adaptations'. By combining this panel framework with a panel of large-scale household-level survey data from rural China, the present study explicitly approximates the potential value of long-run adaptations for agricultural production in China.

Another at least equally important issue is identifying the determinants of farmers' adaptive capacity. Many studies are concerned with empirically assessing financial, informational, and institutional constraints on adaptation capacity (see, e.g., Kelly and Adger, 2000; O'Brien *et al.*, 2004). Some other studies take an experimental or empirical approach to inferring the determinants of adaptive capacity under climate change by examining farmers' responses to extreme weather conditions or natural disasters (see, e.g., Grothmann and Patt, 2005; Huang *et al.*, 2015). These studies shed important light on the determinants of adaptive capacity and generally imply that farmers with better infrastructure, higher crop diversification, more financial and technical support, and better information are better at adaptation.

Previous studies lack an explicit estimate of the overall value of long-run adaptations. Therefore, they generally evaluate the determinants of a specific adaptation behavior but not the determinants of overall adaptive capacity. Our study's panel approach allows us to explicitly identify the potential value of long-run adaptations as a whole, so it is possible to examine the factors influencing overall adaptive capacity. In our data set, complete farm and household characteristics are included. By combining these farm and household characteristics with the value of long-run adaptations, we were able to examine the influence of these characteristics on adaptation value and gain additional understanding of the determinants of farmers' adaptive capacity.

Three characteristics distinguish this paper from previous studies. First, this paper investigates the benefits of long-run adaptations of agriculture on climate change in China, while most previous studies examined the damage from climate change (see, e.g., Wang *et al.*, 2009; Chen *et al.*, 2016). Second, in this study, the value of a full range of long-run adaptations can be explicitly estimated, whereas the hedonic studies only implicitly include the potential benefits of a range of long-run adaptations, and other studies only explicitly examine the benefits of one or a few specific adaptation measures. Third, this paper provides empirical evidence on the determinants of the value of long-run adaptations in China.

The following sections describe the study's data sources and summary statistics, conceptual framework and econometric models, and empirical results.

2. Data sources and summary statistics

The data for agricultural production and household characteristics were collected from a large-scale household-level survey conducted in rural China in late 2012 and early 2013.

[3] As detailed in section 3, the adaptation methods that can be taken in the short run, such as shifting sowing time and using more pesticides, are most likely still available when dealing with the long-run climate change. Hence, the first model includes benefits from adaptation methods that can be taken only in the long run as well as methods that can be taken also in the short run, while the second model only includes the benefits from adaptation methods that can be taken in the short run. Therefore, their difference is the benefits of adaptation methods that can be taken *only* in the long run.

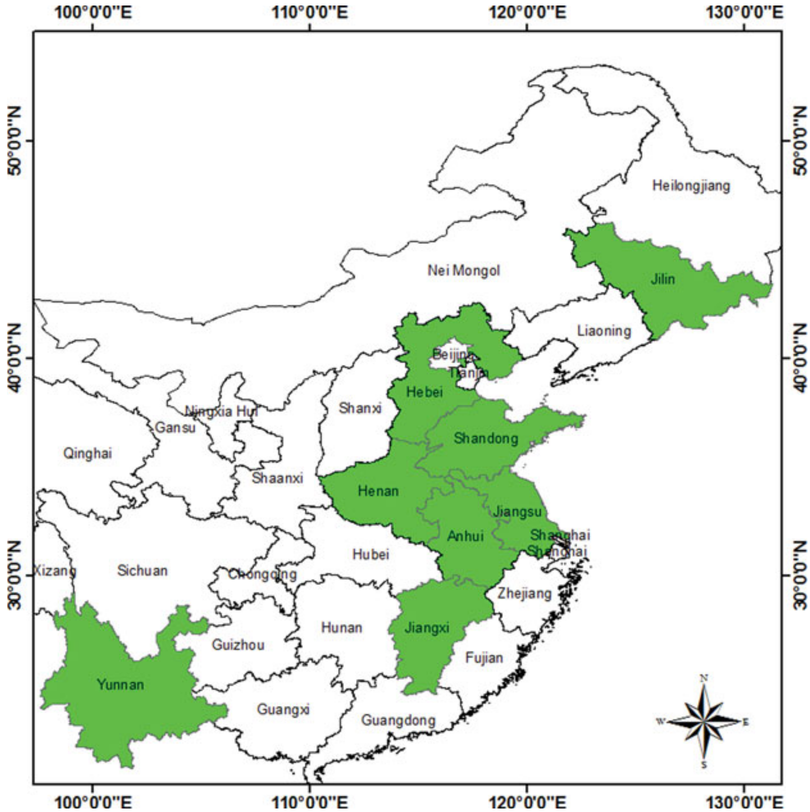

Figure 1. Sample provinces of the survey in China.

Funding was available for the field survey in eight of the 34 provinces and regions of China (see figure 1). The survey was dependent on funding from several separate projects supporting research in specific provinces or regions, so it was conducted only in those provinces supported by these projects. Specifically, the survey in the provinces of Hebei, Henan, Anhui, Shandong, and Jiangsu was mainly supported by funding from the Ministry of Science and Technology in China, the survey in the provinces of Jiangxi and Yunnan was mainly supported by funding from the Australian Centre for International Agricultural Research, and the survey in Jilin province was mainly supported by the National Natural Sciences Foundation in China.

Even though which provinces were included in the survey depended on funding availability, the eight sample provinces approximately represent the various agricultural systems in China. Specifically, the Jilin province represents the monoculture agricultural system in cold areas of China; Hebei, Henan, Anhui, Shandong, and Jiangsu represent the rotation agricultural system in China's temperate climate zone; the Jiangxi province represents rice production in southern China; and the Yunnan province represents agricultural production in the plateau climate zone. In addition, these eight sample provinces are important in Chinese agriculture. For example, they produced about 47 per cent of the total agricultural output in China each year; the other 53 per cent is produced by the remaining 26 provinces and regions in China.

Thirty-one sample counties were selected from the eight sample provinces. We selected three sample counties from each of seven sample provinces, but we selected 10 sample counties from Jiangxi because extra funding was available for this province. Within each sample province we divided all the counties into three groups (10 groups for Jiangxi) based on the condition of the agricultural production infrastructure and randomly selected one county from each group.

We selected the townships and villages before interviewing the actual households. Within each of the 31 selected counties, we divided all the townships into three groups based on the condition of the agricultural production infrastructure and randomly selected one township from each group. We used the same approach to select three villages from each township. Finally, we randomly selected 10 households for face-to-face interviews in each sampled village. We identified a total of 2,790 households in the eight provinces. After dropping the households with missing data for agricultural output, input, or household characteristics, the final sample used in the analysis comprised 2,733 households.

The farmlands in the survey are mainly used for crops and orchards.[4] The crop production and orchard data were collected separately. For land used for crop production, only the two larger plots were investigated if the household managed more than two plots. This sample selection rule helped to reduce measurement error because, in our data set, each household managed 7.6 plots on average and some plots were quite small. Collecting data from small plots might incur large measurement errors because, according to our experience, it is harder for farmers to precisely recall unit land inputs and outputs for a small plot. There is no major concern about the representativeness of the sample plots selected because, on average, the larger two plots took up 86.3 per cent of the cropland area managed by each farmer. For orchards, the data were collected for all orchards managed because each household usually managed only one or two orchards.

Household-level agricultural profits per hectare were collected for two years from 2010 to 2012.[5] According to the survey, farmers usually plant multiple crops in sequence in a plot within a year. The main growing season is usually used for staple crops, such as rice, wheat, and maize, while other seasons are used for minor crops, such as oilseed rape, beans, and vegetables. The profits per hectare were constructed as revenue minus cost. The revenues were the market value of all the products harvested in a year, and the costs were the total production expenditure in a year. The costs included only expenses for seed, fertilizers, pesticides, labor, and machinery.[6] Finally, the profits per hectare were translated into US dollars (USD) using China's rural Consumer Price Indices (CPI) and

[4]Forestry and animal husbandry were excluded from this survey because, in our sample provinces, mainly local governments, not households, manage the forests. In addition, the household-level animal husbandry in the sample is mainly free ranging and usually does not take up farmland. Orchards comprise fruits, vegetables, and nut-producing trees.

[5]This is because another purpose of this survey was to investigate the effects of natural disasters (drought and flood) on agricultural production. For each county, the year with the highest loss and the year with the lowest loss due to natural disasters were selected out of the three years from 2010 to 2012. Thus, the two sample years may differ between some counties, and consequently we can form only an unbalanced panel from this data set. To avoid the potential bias introduced by this sample selection rule, we include the percentage of profit loss due to natural disasters as a control variable in the following econometric regressions.

[6]Since the family members of each household provide most of the labor input, the labor costs are measured as the total labor inputs (in work days) for each hectare of farmland times the daily wage. The daily wage is the average daily wage for agricultural labor in each village.

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Table 1. Definition of variables

Variables	Definition
Dependent variable	
Crop profits	Profits from crop production only (2010 constant USD/ha)
Crop and orchard profits	Average profits from cropland and orchards weighted by land area (2010 constant USD/ha)
Climate variables	
Degree-day	Yearly degree-day (degrees)
Degree-day^2	Square of yearly degree-day
Harmful degree-day	Yearly harmful degree-day (degrees)
Precipitation	Yearly total precipitation (mm)
Precipitation^2	Square of yearly total precipitation
Farm and household characteristics	
Capital intensity	Production capital per hectare (1000 USD/ha)
Land size	Land area managed by a household (ha)
Labor intensity	Labor input per hectare (days/ha)[a]
Education	Education of head of household (years)
Age	Age of head of household (years)
Other control variables	
Market access	Distance to the nearest market of production inputs (km)
Soil quality	County-level land quality measured by loam in the soil (%)[b]
Road density	County-level density of paved road and railway (km/km^2)[c]
Agricultural price index	National-level agricultural price index[d]

[a]The labor intensity is measured by the total working days per hectare per year. Since there are usually multiple growing seasons within a year, the labor inputs are the sum across growing seasons within a year.
[b]Loam is a standard indicator of soil quality. Loam is considered ideal for agricultural uses because it retains nutrients and water, while still allowing excess water to drain away. The data come from Resources and Environment Data Centre of Chinese Academy of Sciences (http://www.resdc.cn/).
[c]The road density is calculated by the authors from a shapefile of 1:100,000 scale road information map for the year 2008 in China. Road density is measured as the kilometers of paved road and railway within a county divided by the total area of the county.
[d]The agricultural price index measures the prices received by farmers for agricultural goods and services. The data is derived from National Bureau of Statistics of China (http://www.stats.gov.cn).

the exchange rate between RMB and USD as of 2010. In the following econometric analyses, we mainly used crop profits per hectare as the dependent variable. As a robustness check, we also provide analyses using the weighted average of profits per hectare from cropland and orchards as the dependent variable.

Detailed farm and household characteristics with the potential to affect agricultural profits and adaptive capacity were also collected in the survey. As defined in table 1, these characteristics include the capital intensity, labor intensity, and farmland size of the household; education level and age of the head of household; and market access. County-level agricultural land quality and road density were also included as control variables. County-level land quality was measured as the percentage of loam in the soil,

Table 2. Summary statistics of variables

Variables	Mean	Standard deviation	Minimum value	Maximum value
Crop profits (USD/ha)	2186	1465	−2048	22156
Crop and orchard profits (USD/ha)	2259	1638	−2048	34922
Degree-day (degrees/year)	3471	998	1941	5688
Harmful degree-day (degrees/year)	2.7	5.2	0	23.5
Precipitation (mm/year)	1184	706	302	2866
Capital intensity (1000 USD/ha)	59.1	77.3	1.0	898.4
Land size (ha)	0.46	0.91	0.007	21.3
Labor intensity (days/ha)	0.5	0.8	0.0	19.0
Education (years)	6.8	3.0	0.0	16.0
Age (years)	52.8	10.3	18.0	88.0
Market access (km)	2.2	3.1	0.0	25.0
Loam (%)	30.9	4.9	21.8	40.0
Road density (km/km^2)	0.5	0.3	0.2	1.1

Note: The definitions of the variables are provided in Table 1.

while county-level road density was measured as the number of kilometers of paved road and railway within a county divided by the total area of the county. The summary statistics of the data are provided in table 2.

The county-level daily mean temperature and precipitation data were derived from the China Meteorological Data Sharing Service System (http://cdc.nmic.cn). This data set provides real data for each of the 677 meteorological stations throughout China and offers the most detailed and reliable climate data set in China. At least one meteorological station is sited in 22 of the 31 sample counties. For those counties with more than one meteorological station, county-level climate data was derived from the weather station that was the closest to the county centroid of each county. For the nine sample counties in which meteorological stations were not available, we instead used climate data from the nearest meteorological station.[7]

Daily mean temperature and precipitation were used to construct values for county-level yearly degree-days (DD), yearly harmful degree-days (HDD), and yearly total precipitation (TP).[8] DD measures cumulative exposure to temperatures of between 8 and 32°C during the year. For example, a day with a mean temperature below 8°C

[7]The alternative meteorological stations used were within a distance of 20km from the nearest border of the sample county.

[8]Some previous studies focusing on only one or several crops using growing season heat and precipitation measures. In the present study, since the agricultural profits relate to all crops planted in the plots during the whole year and not to only a specific crop, and since crops have quite different growing seasons, we preferred to use the yearly measures instead of the growing season measures. According to the survey, multiple planting in sequent seasons is a common practice in middle and low latitudes of China, and in some provinces plants are usually growing in every season of the year. For example, farmers in Yunnan province usually plant potatoes in the same plots after harvesting rice each September, while farmers in Jiangxi province plant oilseed rape from January to April before the temperature is high enough for other crops. Hence, it is impossible to find a discrete 'growing season' in the present study.

Table 3. Predicted changes in yearly climatic variables

Climate change scenario	Variable	Mean	Standard deviation	Minimum value	Maximum value
RCP4.5	Mean temperature	2.7	0.3	2.4	3.3
	Degree-day	684.0	127.2	500.2	941.0
	Total precipitation (mm)	98.2	76.2	12.1	240.5
RCP8.5	Mean temperature	5.2	0.5	4.6	6.2
	Degree-day	1400.7	211.4	1056.4	1668.0
	Total precipitation (mm)	109.7	66.5	21.9	215.5

Note: The predicted changes in climatic variables are calculated as the differences between the 30-year historical average (1976–2005) and the 30-year prediction average (2071–2100).

contributes zero DDs, between 8 and 32°C contributes the difference between the mean and 8°C, and above 32°C contributes 24 DDs. DD is the sum of daily measures across the calendar year. HDD captures the possible damage of extreme heat that exceeds this threshold. We follow previous studies such as Guiteras (2009) to calculate HDD by assigning each day with mean temperature above 34°C the difference between that day's mean temperature and 34°C, and then sum up the daily measures across the calendar year to get the yearly HDD. TP is the total precipitation in mm during the calendar year. For the robustness test in the econometric analysis, we also calculated the growing season degree-day and growing season total precipitation. We followed the literature in defining growing season to be from March to October.

Finally, to predict climate change impacts, we collected the latest climate change projections that were developed for the Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC). The climate projections from 21 modeling centers and two Representative Concentration Pathway (RCP) scenarios, namely RCP4.5 and RCP8.5, which represent the medium and highest scenarios, respectively, were downloaded from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) data set (https://cds.nccs.nasa.gov/nex-gddp). Each model provides daily minimum temperature, maximum temperature, and precipitation under each scenario for the period from 2006 to 2100, 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.

The climate change predictions were calculated as the difference between the 1976–2005 average and the 2071–2100 average. Specifically, we first mapped the gridded climate predictions into each sample province to formulate province-level climate predictions for each year, then calculated the 30-year historical simulation average (1976–2005) and the 30-year prediction average (2071–2100) for each province.[9] Since point estimates depending on a single climate projection can be misleading (Burke *et al.*, 2015),[10] we used the average prediction of the CMIP5 models in the following impact estimation. Table 3 reports the projected climate changes of scenarios RCP4.5

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

[10]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 the others (Solomon, 2007). For details of the modeling centers, see 'CMIP5

and RCP8.5. The projected yearly mean temperature rise is 2.7 and 5.2°C for RCP4.5 and RCP8.5, respectively. Despite the dramatic difference in the change of yearly degree-day predicted by these two scenarios, their predicted precipitation changes are quite similar.

3. Conceptual framework and econometric approach

Two sources of meteorological variation are usually employed to identify the impact of climate change: cross-sectional climate differences used in the hedonic approach, such as in Mendelsohn *et al.* (1994), and inter-annual random weather fluctuations adopted by panel studies, such as in Deschênes and Greenstone (2007).[11] Econometric methods based on these two sources of meteorological variation differ in their ability to incorporate long-run adaptations. Specifically, climate change impacts identified through cross-sectional climate variations should include the benefit of long-run adaptations because, as assumed in the hedonic approach, farmers should have adapted to the climate of their regions (Mendelsohn *et al.*, 1994). On the other hand, impacts identified through inter-annual weather fluctuations do not include the benefits of long-run adaptations since farmers will have made only limited *ex post* adjustments in response to random weather outcomes (Seo, 2013).

Even though the hedonic approach provides a potentially ideal way to implicitly incorporate long-run adaptations into climate change impact studies, this approach cannot be used to estimate explicitly the value of adaptations (Hanemann, 2000). Therefore, the merits of the hedonic approach depend crucially on the magnitude of the value of long-run adaptation: if the value of long-run adaptions is negligible, using the method depending on inter-annual weather fluctuations will not result in a significant bias due to omitting adaptations. In addition, explicitly estimating the value of long-run adaptations is necessary for identifying the determinants of overall adaptive capacity. Hence, an econometric approach that can be used to estimate the value of long-run adaptations is valuable.

Based on the key fact that inter-annual weather fluctuations are generally common across regions in the same year, Huang (2015) combined the basic idea of the hedonic approach with panel data and developed a panel framework that could be used to estimate explicitly the value of long-run adaptations. The basic idea of this panel framework is shown as equation (1):

$$w_{it} = T_i + d_t + \varepsilon_{it} \tag{1}$$

in which w_{it} is the weather outcome of county i in year t; T_i is the climate (i.e., long-term average weather outcome) of county i, which is assumed to be constant over time but differs across counties; d_t measures the inter-annual weather fluctuations that are common across counties in the same year but vary over time; and ε_{it} represents county-specific weather shocks.[12] In a panel model with time fixed effects, the inter-annual weather fluctuations that are common across observations (d_t) can be filtered out, and

Coupled Model Intercomparison Project', *Program for Climate Model Diagnosis and Intercomparison* (http://cmip-pcmdi.llnl.gov/cmip5/availability.html).

[11] 'Climate' describes the long-term average of weather outcomes for a given region, while 'weather' refers to a particular year's realization of climate distribution (Dell *et al.*, 2014).

[12] Here, we assume the climate of a county T_i is constant for not too long a time (such as three years). However, relaxing this assumption does not affect the weather decomposition as shown in equation (1). Because the climate trend over time is usually common across counties (as shown in table 4), it can be captured in the second part d_t.

Table 4. The magnitudes of inter-county climate (T_i) variation, inter-annual weather fluctuations (d_t), and local weather shocks (ε_{it})

Panel A. Percentage of counties with temperature variance below/above (°C):				
	±0.1	±0.2	±0.3	±0.4
(A1) Inter-county mean temperature variation	96.7	93.5	90.3	74.2
(A2) Inter-annual temperature fluctuations	83.3	70.9	55.8	36.8
(A3) County-specific temperature shocks	22.5	4.3	2.1	0.0
Panel B. Percentage of counties with precipitation variance below/above (mm):				
	±100	±200	±300	±400
(B1) Inter-county total precipitation variation	96.7	93.5	83.9	64.5
(B2) Inter-annual precipitation fluctuations	61.2	35.7	25.6	18.2
(B3) County-specific precipitation shocks	18.3	5.4	4.3	2.1

Note: Temperature is measured by the yearly mean temperature (°C), while precipitation is measured by the yearly total precipitation (mm). The 'inter-county mean temperature variation' and the 'inter-county total precipitation variation' represent the climate (T_i) differences, which are calculated as the deviation of the county mean from the sample mean. The 'inter-annual temperature fluctuations' and the 'inter-annual precipitation fluctuations' represent the weather fluctuations (d_t), which are calculated as the deviation from the county mean. The 'county-specific temperature shocks' and the 'county-specific precipitation shocks' measure the variation in local shocks (ε_{it}), which are calculated as the remaining variation after the county mean and the year mean are subtracted from each observation. All entries are calculated for the sample counties and sample years (2010–2012). See the text for further details.

thus the remaining meteorological variation pertains only to cross-sectional climate differences (T_i) and idiosyncratic local shocks (ε_{it}). Since the local shocks are quite small (as shown in table 4), the impacts are mainly identified through cross-sectional climate differences, and therefore the long-run adaptations are included. On the other hand, the county fixed effect can be used to eliminate inter-county differences in climate T_i, which is constant over time, with the remaining variation pertaining only to common inter-annual weather fluctuations (d_t) and county-specific weather shocks (ε_{it}). Since the variation in county-specific weather shocks is very small, the impacts are mainly identified through the common inter-annual weather fluctuations and thus do not include adaptation benefits.

Therefore, the difference of the impact identified from two panel models, one with time fixed effects and the other with county fixed effects, can be interpreted as the benefits of long-run adaptation. To show this, assume that A is the full set of adaptation methods that can be taken in the long run, and B is the full set of adaptation methods that can be taken in the short run. Considering that the adaptation methods that can be taken in the short run, such as shifting sowing time and using more pesticides, are most likely still available when dealing with the long-run climate change, we have $B \subset A$. We define the set of adaptation methods that can be taken *only* in the long run as C, so that $C = A - B$. The panel model with time fixed effects identifies the impact mainly through the cross-sectional climate differences (T_i) and hence includes the benefits of A. The panel model with county fixed effects identifies the impact mainly though the year-to-year weather fluctuations (d_t) and hence only includes the benefits of B. Therefore, their difference reflects the benefits of C, which are the full set of adaptation methods that can be taken *only* in the long run. As defined before, we refer to the benefits of C as the benefits of long-run adaptation.

Table 4 shows the actual size of the variation pertaining to ε_{it}, T_i, and d_t. Row (A1) shows that 74.2 per cent of the sample counties had deviations in their yearly mean temperature (T_i) from the sample mean that were larger than 0.4°C, while row (A3) shows that no counties had county-specific temperature shocks (ε_{it}) higher than 0.4°C. The same result applied to precipitation, with 64.5 per cent of the counties having more than 400 mm of deviation from the yearly total precipitation (T_i) from the sample mean and only 2.1 per cent of counties having local precipitation shocks (ε_{it}) of more than 400 mm (see rows (B1) and (B3)). Similarly, comparing rows (A3) and (B3) with rows (A2) and (B2), we find that the county-specific weather shocks are also negligible relative to the inter-annual weather fluctuations. These results support our argument that climate change impacts can be identified mainly through inter-county mean climate differences in a panel model with time fixed effects and through common inter-annual weather fluctuations in a panel model with county fixed effects.

However, since these climatic variables were calculated only for a three-year panel, it is likely that the small county-specific temperature and precipitation shocks, as shown in table 4, are the result of too short a panel period. To test this possibility, we calculated the values for the same variables as shown in table 4 using 30 years of weather data for the sample counties and found quite similar results. Since the magnitudes of inter-annual weather fluctuations were quite similar across regions, it is reasonable to find small county-specific weather shocks after removing the inter-county climate differences and the common inter-annual weather fluctuations. Similar results have been found in previous studies using US data (Fisher *et al*., 2012).

The panel model used to identify climate change impact through cross-sectional climate differences is shown in equation (2), in which y_{ijt} denotes the crop profits per hectare of household i in county j and year t; C_{it} is a vector of county-level climate variables, including yearly DD, yearly HDD, yearly total precipitation, and their quadratic terms; L_{ijt} is a vector of the farm and household characteristics as shown in table 1, including capital intensity, land size, labor intensity, head of household education and age, disaster loss, and market access; K_{jt} is a vector of the soil quality, transportation conditions, and agricultural price index as defined in the last three rows of table 1; α, β, and γ are coefficients; and ρ_{pt} represents the province-by-year dummy. The dummy was used to filter out year-to-year weather and other fluctuations that were common across counties within each province.[13] Thus, the coefficients of the climate variables in this model were identified mainly through the inter-county mean climate differences, and the benefits of adaptations could then be included. Finally, in the estimation, the error term μ_{it} is clustered at the province level in order to address the potential bias from the spatial correlation of the error term (Deschênes and Greenstone, 2007; Fisher *et al*., 2012).

$$y_{ijt} = C'_{jt}\alpha + L'_{ijt}\beta + K'_{jt}\gamma + \rho_{pt} + \mu_{ijt} \tag{2}$$

The model used to identify climate change impacts through inter-annual weather fluctuations is presented in equation (3). The settings for y_{ijt}, C_{jt}, L_{ijt}, and K_{jt} are the same as for equation (2). The only difference is in the use of fixed effects. Model (3) includes the county fixed effects τ_j to eliminate inter-county climate differences and does not use any

[13]The province-by-year fixed effect equates to imposing an individual-year fixed effect for each province. Since China covers a large geographic area, the province-by-year fixed effect is better than the individual-year fixed effect in accounting for inter-annual common fluctuations.

type of time fixed effects, as these tend to eliminate most of the year-to-year weather fluctuations.[14] Thus, the climatic coefficients are mainly identified through the year-to-year weather fluctuations and do not include the benefits of adaptations. Finally, the error term υ_{ijt} is clustered at the province level.

$$y_{ijt} = C'_{jt}\alpha + L'_{ijt}\beta + K'_{jt}\gamma + \tau_j + \upsilon_{ijt} \tag{3}$$

By combining the estimates of the climate variables from models (2) and (3) with the climate change predictions, we were able to project the impacts with and without adaptations, respectively. The differences in the projected impacts between these two models can be interpreted as the benefits of long-run adaptation.

The most significant advantage of this approach is evaluating the value of long-run adaptations as a whole, thus freeing the analyst from the burden of estimating the value of each of the innumerable adaptive responses by farmers. This advantage is derived directly from the basic idea of the hedonic approach: obtaining information about adaptations to future climate change by examining the current production differences across climate regions.[15] Large cross-sectional climate differences are observed, and farmers should have adapted to the long-run climate of their regions.

A large body of studies has shown that climate has tremendous effects on agricultural production across regions, and most of the cross-sectional differences in agricultural production practices resulting from climatic differences can be explained as the result of farmers' long-run adaptation to the climate of their regions. Specifically, the distribution of crop types and crop varieties across regions are mainly the result of farmers' adaptive choices based on their long-run climate observations. Regional gradients of temperature result in the distribution of different crops and varieties from north to south (Cramer and Solomon, 1993; Ramankutty *et al.*, 2002), while for regions with sufficiently warm temperatures, cultivation is strongly determined by the distribution of precipitation.

Even though crop choice is critically dependent on climate, humans have adopted various other adaptive behaviors to overcome natural limitations to some extent. In response to the observed climate, farmers in different climate regions choose the optimal farm-management practices for their regions. For example, the sowing time in the temperate zones of northern China is much later than it is in the tropics of southern China so that crops have sufficiently warm temperatures during germination (Chen *et al.*, 2005); moreover, busting is usually chosen in southeast China where precipitation is abundant during the growing season, while conservation tillage measures are taken by farmers in northwest China where precipitation is quite limited (Zhang *et al.*, 2011). In modern agricultural production, additional adaptive measures are available that depend on intensive investments, such as the adoption of greenhouse and ground water irrigation

[14] In equation (3) we are not seeking to control for the effect of price shocks induced by output fluctuations because the price shock can be seen as farmers' 'natural insurance' for weather fluctuations. Eliminating price shocks would thus overestimate the impact of weather fluctuations (Fisher *et al.*, 2012).

[15] Another way of forecasting adaptations to future climate change is by examining farmers' responses to historical climate change. Unfortunately, the historical climate changes were too small for the period during which agricultural production data is available. For example, the Inter-government Panel on Climate Change report of 1995 indicated that mean surface air temperature increased by about 0.3∼0.6°C in the prior 100 years, while the best prediction of mean temperature increase by the end of this century is about 2.5°C (see scenario RCP4.5 of table 3). Hence, the available historical time-series data may not offer much information about farmers' potential adaptations to future climate change.

systems to address insufficiency in growing season temperature and precipitation (Jin and Young, 2001; Thomas, 2008).

Even though climate differences and farmers' adaptive behaviors can explain many cross-sectional production differences, many other non-climatic factors also have significant effects. For example, differences in land quality and transportation also have significant effects on variations in agricultural profits. Nevertheless, cross-sectional climate differences can still be a useful instrumental variable for identifying the benefits of adaptation to future climate change. As suggested by Dell *et al.* (2014), non-climatic variables with the potential to influence agricultural profits and also correlate with climatic variables are themselves most likely the result of climate but not the cause of it. Omitting these variables will not necessarily result in biased estimates of the coefficients of climatic variables. Moreover, in our econometric analyses, we did our best to control for non-climatic determinants of agricultural profits, including capital intensity, land size, labor intensity, head of household education and age, market access, land quality, transportation, and price level.

4. Empirical results

The regression results are shown in table 5. Columns (1a) and (1b) present the regression results from model (2) and model (3) respectively, using crop profits as the dependent variable, while columns (2a) and (2b) represent the regression results from model (2) and model (3) respectively, using the average profits of crops and orchards as the dependent variable.

For all of the four regressions, the estimated coefficients of the yearly degree-day are statistically significant and show the inverted U-shaped relationship that is usually found in climate change impact studies and indicates agricultural profits increasing with degree-day up to a turning point, after which they decline. The coefficients of yearly harmful degree-day are all negative, reflecting the negative effect of extreme heat on agricultural production. It is not surprising to find that the coefficient of harmful degree-day is statistically insignificant in columns (1a) and (2a) because the province-by-year fixed effects applied tend to account for the extreme heat, which is likely part of the inter-annual weather fluctuations but not the climate normal in the sample areas.

The coefficients of precipitation are all statistically insignificant, presumably because the control variables, especially the fixed effects, account for a significant share of the effects of precipitation. Previous studies have generally found that precipitation is not a good measure of water supply for crops grown, especially for irrigated agriculture (Schlenker *et al.*, 2005). In the data, the agricultural production of 78.0 per cent of households depends on irrigation.[16] Hence, the estimated effects of the predicted changes in precipitation are unreliable. Therefore, in the following calculation of the impacts of climate change and the benefits of adaptations, we mainly focus on the effects of warming.

Most of the control variables in these four regressions have statistically significant effects on profits per hectare. Specifically, profits per hectare increase with increasing capital intensity until a turning point, after which the effect becomes negative, but

[16]Even though irrigation is an important factor that affects agricultural profits, it has not been included as a control variable in the models because, at the same time, it is an important adaptation to climate change. Including it will bias the climatic coefficients of the model that intend to capture the benefits of adaptation. See Row (6) of table 6 for a robustness check in which irrigation has been included as a control variable.

Table 5. Regression results of the effects of climatic variables and household characteristics on agricultural profits

Independent variables	Crop profits (1a)	Crop profits (1b)	Crop and orchard profits (2a)	Crop and orchard profits (2b)
Climate variables				
Degree-day (100 degrees/year)	324.12** (110.74)	1,029.52*** (252.82)	292.30*** (101.91)	861.74*** (292.62)
Degree-day^2	−5.15** (1.83)	−13.61*** (3.86)	−4.72** (1.73)	−11.23** (4.46)
Harmful degree-day (degrees/year)	−58.52 (264.63)	−530.36*** (184.81)	−121.88 (307.37)	−580.82*** (213.90)
Precipitation (100 mm/year)	−0.15 (0.69)	−0.32 (0.30)	−0.10 (0.67)	−0.54 (0.35)
Precipitation^2	1.86 (2.94)	2.51* (1.34)	1.84 (2.83)	3.35** (1.55)
Farm and household characteristics				
Capital intensity (1000 USD/ha)	6.41 (10.60)	21.23** (9.44)	11.56 (11.98)	24.81** (10.93)
Capital intensity^2	−0.00 (0.00)	−0.00** (0.00)	−0.00 (0.00)	−0.00* (0.00)
Land size (ha)	407.30** (143.05)	340.35*** (51.62)	479.34** (168.90)	443.97*** (59.75)
Land size^2	−23.86* (11.90)	−20.35*** (4.07)	−26.76* (13.75)	−25.43*** (4.71)
Labor intensity (days/ha)	0.79 (1.03)	0.57 (0.64)	0.21 (1.02)	0.03 (0.74)
Labor intensity^2	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Education (year)	21.00** (6.93)	19.32*** (6.37)	27.24*** (7.39)	24.91*** (7.37)
Age (year)	2.29 (1.94)	−0.21 (1.98)	0.52 (2.07)	−2.71 (2.29)
Other controls				
Market access	−55.41*** (11.93)	−32.13*** (7.15)	−53.05*** (10.00)	−31.22*** (8.27)
Soil quality control	38.07 (27.63)	–	43.64 (28.09)	–
Road density control	281.54 (350.49)	–	425.98 (373.57)	–
Agricultural price index	–	−216.7 (137.1)	–	−306.3* (158.7)

Continued.

Table 5. *Continued.*

Independent variables	Crop profits (1a)	Crop profits (1b)	Crop and orchard profits (2a)	Crop and orchard profits (2b)
Province-by-year fixed effects	Yes	No	Yes	No
County fixed effects	No	Yes	No	Yes
Observations	5,466	5,466	5,466	5,466
R-squared	0.133	0.182	0.104	0.147

Note: The definitions of the variables are given in table 1. Stand errors clustered at the province-level are reported in parentheses. Coefficients of soil quality control and road density control are omitted in columns (1b) and (2b) because these county-level variables are mainly time invariant and have been accounted for by the county fixed effects. Significance levels are $^{***}P < 0.01$, $^{**}P < 0.05$, $^{*}P < 0.1$.

the negative effect is negligible (the coefficient of the square term is approximate to zero). The effect of land size on profits also shows an inverted U-shaped relationship. In addition, profits per hectare rise significantly with the education level of the head of household and the volume of irrigation water used, and decline significantly with losses due to natural disasters and the distance to market. All these significant effects are quite intuitive.

However, quantitatively, there is a difference between the estimated coefficients of models with and without long-run adaptations. For example, using the regression coefficients we calculate that the marginal effect at 4000 degree-day, which is approximately the average degree-day under scenario RCP4.5, is −0.87 for the model without adaptation and −0.59 for the model with adaptation. This suggests that with adaptation, the damage of warming on agricultural profits could be smaller on average. Similarly, according to the coefficient of harmful degree-day, the negative effect of extreme heat is weaker with adaptation than without, which implies that adaptation can help reduce the damage of extreme heat on agricultural production.

We combined the estimated coefficients of degree-day, degree-day square, and harmful degree-day of models (2) and (3) with the climate change scenarios to predict the impacts of warming with and without long-run adaptations, respectively. Row (1) of table 6 reports the predicted yearly impact of warming on crop profits per hectare by the end of this century for two scenarios. The model that did not include long-run adaptations predicted much more damage (column (2)) than the model that included long-run adaptations (column (1)) for both scenarios. The t-test as reported in column (3) found statistically significant differences between the estimated impacts with and without long-run adaptations.

Specifically, under the most likely climate change scenario RCP4.5, the predicted changes in crop profits per hectare will be −193.8 USD and −412.1 USD with and without long-run adaptations, respectively. These damages correspond to 8.9 per cent and 18.9 per cent of the current mean annual profits per hectare in the sample area (see table 2). Column (4) reports the percentage of damages that will be offset by long-run adaptations. Long-run adaptations will help to mitigate 52.9 per cent and 51.4 per cent of the damages predicted by the model that did not include long-run adaptations for scenarios RCP4.5 and RCP8.5, respectively. In addition, relatively large standard deviations from the estimated damages were found, implying that there are significant regional differences in the impacts of warming.

Table 6. Impacts of warming on crop profits by the end of this century and the benefits of long-run adaptation (2010 constant USD per hectare per year)

Model setting	Scenario	Impacts: (1) With adaptation	Impacts: (2) No adaptation	(3) *T*-value of the *t*-test between columns (1) and (2)	(4) Percentage of damages offset by adaptation (%)
(1) Impacts of warming on crop profits	RCP4.5	−193.8 (114.9)	−412.1 (388.7)	28.1***	52.9
	RCP8.5	−1038.7 (274.9)	−2138.8 (1167.8)	47.9***	51.4
Robustness tests					
(2) Including the effects of changes in precipitation	RCP4.5	−187.3 (131.8)	−323.7 (449.5)	15.2***	42.1
	RCP8.5	−988.2 (352.5)	−2031.3 (995.1)	51.6***	51.3
(3) Excluding household characteristics and soil controls in the regressions	RCP4.5	−244.8 (131.8)	−409.7 (389.5)	20.9***	40.2
	RCP8.5	−1307.3 (386.7)	−2125.9 (1165.8)	34.8***	38.5
(4) Using the profits from both crops and orchards as the dependent variable	RCP4.5	−179.1 (111.5)	−342.0 (388.0)	21.0***	47.6
	RCP8.5	−992.8 (223.9)	−1911.1 (969.8)	48.2***	48.0
(5) Using growing season climatic variables	RCP4.5	−330.7 (198.9)	−610.9 (464.6)	28.9***	45.8
	RCP8.5	−1687.3 (532.8)	−2678.7 (1778.0)	27.9***	37.0
(6) Control for irrigation	RCP4.5	−254.6 (142.8)	−621.2 (471.8)	38.8***	59.0
	RCP8.5	−1281.0 (431.8)	−2724.4 (1806.4)	40.6***	52.9

Note: Standard deviations are reported in parentheses.
Significance levels are $^{***}P < 0.01$. See the text for further details.

The estimates of the impact of warming and the value of long-run adaptations are generally consistent with the literature. Previous hedonic studies, which include long-run adaptations, usually predict relatively small impacts of warming as in this paper. For example, under comparable climate change scenarios,[17] Wang *et al.* (2009) predict the

[17] By the comparable climate change scenario we mean scenarios predict about 2.7°C increase in mean temperature as predicted by the scenario RCP4.5 used in this paper. These scenarios include the HadCM3-A2 emissions scenario by 2050s (2.6°C), the HadCM3-B2 emissions scenario by 2050s (2.4°C), and the conventional CO_2 doubling scenario (5F or 2.8°C). In addition, the impact of a 2.7°C increase in mean temperature can also be approximately extrapolated from studies that report the temperature elasticity of agricultural output.

yearly loss of net revenue for rainfed farms in China would be 256.5 USD per hectare (or 11.7 per cent), Wang *et al.* (2014) find the net crop revenue will decline by 12.9 percent in North China, and Zhou and Turvey (2014) predict the change of the output of rice, wheat, and maize in China ranges from +8.0 per cent to −10.6 per cent depending on the crop types and varieties. On the other hand, studies depending on simulation models, which generally exclude long-run adaptations, predict larger impacts of warming. For example, under comparable climate change scenarios, Xiong *et al.* (2009) predict a 18 per cent decrease in total grain output in China, Matthews *et al.* (1997) predict the rice yield in the major rice-growing regions of Asia will drop by 21 per cent, and Tao and Zhang (2011) find decreases in the yields of irrigated maize range from 4.3 per cent to 32.1 per cent depending on the possibility of growing season shifting. Although previous studies do not predict the value of long-run adaptations in China, the differences between the impacts estimated from the hedonic studies and the simulation studies suggest that long-run adaptations can help to offset a significant share of the damage of warming.[18]

Rows (2) to (5) of table 6 provide robustness tests. The main analysis as shown in row (1) only includes the effects of warming. In row (2), the effects of changes in precipitation are also included in the estimation. We find that including precipitation in the estimation does not significantly change the estimated impacts and adaptations. Both models estimated slightly smaller damages for each scenario, and adaptations are still expected to offset about half of the damages.

A potential concern of panel model (2), which depends on inter-county climate differences, is omitted-variable bias. Even though the inter-annual common fluctuations and the inter-province time-invariant differences are well controlled by the province-by-year fixed effects, we did not control for within-province inter-county differences apart from the controls listed in table 1. To test for potential omitted-variable bias, we dropped all household-level controls and the soil-quality control from the regression. As shown in row (3), the estimated benefits of long-run adaptation drop from 52.9 per cent to 40.2 per cent for scenario RCP4.5 and from 51.4 per cent to 38.5 per cent for scenario RCP8.5. The results are similar if we only exclude control subgroups. Since omitting all these crucial determinants of crop profits only reduces the adaptation benefits by about 12 per cent, the remaining omitted variables might not cause a large bias.

The main analysis only includes profits from annual crops. Because the responses of perennial plants to climate change might be different from those of annual crops, including the profits from orchards for which production is mainly dependent on perennial plants, the analysis might lead to a different adaption estimate. Row (4) of table 6 shows this possibility. The impacts are estimated from regressions that used the weighted average of profits from crops and orchards as the dependent variable. For the model with long-run adaptations, the estimated impacts are quite similar to the impacts on crop profits. However, the model without long-run adaptations predicted significantly smaller damage than that reported in row (1), presumably because perennial orchards are more resistant than annual crops to inter-annual weather fluctuations. As reported in the last column, long-run adaptations will still help to reduce a significant share of the damages (i.e., 47.6 per cent under scenario RCP4.5 and 48.0 per cent under scenario RCP8.5).

[18]There are two formal predictions of the adaptation value for the US agriculture that generate comparable results with this paper. Huang (2015) predicts long-run adaptations will help to offset two-thirds of the potential damage of climate change on US agriculture, and Burke and Emerick (2016) find that, although with large uncertainty, long-run adaptations appear to have mitigated less than half of the large negative short-run impacts of extreme heat on agricultural productivity.

Since adjusting the growing season may be an important way of adapting to climate change, in the main analysis, we use yearly climatic variables instead of growing season climatic variables to allow for the adjustment of growing seasons in the long run. Intuitively, using growing season climatic variables in the estimation will underestimate the benefits of adaptation. In row (5), we provide the estimates using growing season climatic variables with a fixed growing season from March to October. As expected, the estimated benefits of adaptation drop to 45.8 per cent for scenario RCP4.5 and to 37.0 per cent for RCP8.5. The main conclusion remains that omitting long-run adaptations will dramatically overestimate the damages.

Irrigation has not been included as a control variable in the main analysis because it is an important adaptation to climate change. In places with higher temperature and lower precipitation, it is possible for farmers to use more irrigation water to reduce the negative effects of these unfavorable climate conditions. Therefore, if we control for irrigation in the model that depends on cross-section climate differences, the adaptation of irrigation will not be captured in the coefficients of climatic variables. On the other hand, since irrigation, which is an important determinant of agriculture profits, is not always available, excluding irrigation from the model may result in omitted variable bias. As a robustness check, row (6) of table 6 presents the estimation results from models that control for irrigation. We find that, comparing with row (1), including irrigation does not significantly change the estimated value of adaptation.

It is also interesting to check if the estimation results are sensitive to the study sample. To do so, we drop data from one province each time and re-do the estimation to generate 8 group of estimates. As presented in column (1) of table 7, the estimated damage from the model using cross-section climate variations is quite robust to this check. Specifically, the estimated loss of profit ranges from 197.4 to 199.8 under the scenario RCP4.5 and from 963.0 to 1062.2 under RCP8.5. This result suggests that omitted inter-province differences do not significantly affect the conclusion of this paper. In addition, as presented in the last column of table 7, although with noticeable variations, long-run adaptation will still help to offset at least one third of the damage of warming.

Finally, we investigated the effects of farm and household characteristics on the benefits of adaptation. We first calculated the impacts of warming predicted by RCP4.5 on crop profits for each household using the estimates from column (1a) and (1b) of table 5, respectively. Second, we calculated the household-level adaptation value as the difference in the impact estimated from these two models. Third, we performed a regression analysis of the household-level values of adaptation against the farm and household characteristics listed in table 1 and controlled for the mean temperature differences among counties. The significant regression coefficients are reported in equation (4):[19]

$$\begin{aligned}\text{Adaptation\_value} = {} & 20.7^{***} \times \text{Capital\_intensity} - 114^{***} \times \text{Land\_scale} \\ & + 10.5^{***} \times \text{Land\_scale}^2 - 20.4^{***} \times \text{Age} \\ & - 5.8^{***} \times \text{Degree-day} + 0.001^{***} \times \text{Degree-day}^2\end{aligned} \tag{4}$$

We found that the cross-sectional adaptation value first decreased and then increased with the degree-day. In other words, very cold and very hot areas have higher adaptation

[19]We also tried the regressions using adaptation values calculated from other warming scenarios and found almost no differences in the significance levels and effect directions of each variable.

Table 7. Testing the potential omitted variables bias by excluding samples for each province and reestimating the value of adaptation (2010 constant USD per hectare per year)

		Impacts			
Model setting	Scenario	(1) With adaptation	(2) No adaptation	(3) *T*-value of the *t*-test between columns (1) and (2)	(4) Percentage of damages offset by adaptation (%)
(1) Excluding sample from Anhui	RCP4.5	−199.0 (114.1)	−336.5 (386.1)	15.9***	40.8
	RCP8.5	−1062.2 (285.0)	−1802.1 (932.3)	35.4***	41.0
(2) Excluding sample from Shandong	RCP4.5	−197.5 (113.7)	−289.7 (430.5)	9.6***	31.8
	RCP8.5	−1100.1 (254.3)	−1699.1 (822.2)	32.5***	35.2
(3) Excluding sample from Hebei	RCP4.5	−198.2 (113.0)	−493.3 (409.7)	32.4***	59.8
	RCP8.5	−963.0 (331.0)	−2187.9 (1471.7)	37.9***	55.9
(4) Excluding sample from Henan	RCP4.5	−199.8 (113.2)	−562.4 (414.5)	39.4***	64.4
	RCP8.5	−970.7 (329.8)	−2341.1 (1615.9)	38.8***	58.5
(5) Excluding sample from Jiangsu	RCP4.5	−199.4 (113.9)	−403.9 (389.1)	23.5***	50.6
	RCP8.5	−1013.3 (308.7)	−1943.0 (1156.5)	36.3***	47.8
(6) Excluding sample from Jiangxi	RCP4.5	−197.7 (112.6)	−439.7 (352.2)	30.5***	55.0
	RCP8.5	−979.8 (323.1)	−1862.8 (1296.2)	30.9***	47.4
(7) Excluding sample from Yunnan	RCP4.5	−200.1 (112.7)	−459.3 (357.1)	32.3***	56.4
	RCP8.5	−969.1 (329.8)	−1889.6 (1334.7)	31.2***	48.7
(8) Excluding sample from Jilin	RCP4.5	−197.4 (114.3)	−490.9 (372.5)	35.2***	59.7
	RCP8.5	−963.0 (337.5)	−2029.4 (1434.8)	33.8***	52.5

Note: Standard deviations are reported in parentheses.
Significance levels are $^{***}P < 0.01$. See the text for further details.

values than temperate areas. This result is intuitive, because farmers in cold areas have more potential to adopt adaptation measures to exploit the beneficial opportunities of warming, while farmers in hot areas are more likely to take adaptation measures to moderate the negative effects of warming.

More importantly, both capital intensity and farmland size have statistically significant effects on the adaptation value. The coefficient of capital intensity suggests that 10 per cent increases in capital intensity from its current mean will raise the yearly benefits of adaptation by 124 USD per hectare. Hence, a government policy targeted at enhancing farmers' adaptive capacity can work by encouraging investment in the physical capital of agricultural production. On the other hand, the value of adaptation decreases with farmland size at first and then increases after the turning point, which is 5.4 hectares per household. If we increase the farmland managed by the average household by 1 hectare from its current mean, the yearly benefits of adaptation will drop by 104 USD per hectare. However, once the farmland size exceeds 5.4 hectares per household, further increases in farmland size will enhance adaptation benefits. A possible explanation is that, for small household farms in China, increasing farmland size means less labor can be input per hectare of land in response to warming. But once the land size is large enough, modern agricultural production methods such as mechanized agriculture production are available to reduce labor force constraints. Finally, an increase in the average farmer's age by one year will reduce the benefits of adaptation by 20.4 USD per hectare. This could reflect the fact that old farmers have less adaptation ability than young farmers.

5. Concluding remarks

This paper provides empirical support for the basic argument of the hedonic approach that omitting long-run adaptations will dramatically overestimate the damage of climate change. Depending on large-scale household-level survey data from rural China, the empirical results show that long-run adaptations are able to offset one third to one half of the damages of warming using various model settings and climate change scenarios. Hence, omitting long-run adaptations will dramatically overestimate the damages of warming. This study also finds that capital intensities and farmland size have significant effects on farmers' adaptive capacities.

There are several important caveats to the empirical results. First, the potential benefits from future technological advancements induced by climate change are not included in the estimation. Hence, this study estimates only the lower boundary of adaptation benefits. Second, forestry and animal husbandry were excluded from the survey. If it is possible for farmers to adapt to warming by switching land use among crops, animal husbandry, and forestry, this study would tend to underestimate the benefits of long-run adaptation. Third, in this partial equilibrium analysis, agricultural prices are assumed to be constant during climate change. This assumption is reliable if the positive effects in currently cold regions offset most of the negative effects in currently hot areas. Otherwise, agricultural prices will rise and the benefits of adaptation will be even greater. Finally, although the model suggests that long-run adaptations have the potential to significantly reduce the damage of warming, in the short-run, farmers will still be adapting to climate change and losses will be greater than what have been predicted by the model with long-run adaptations.

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