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Essays on the Economic Impacts of Climate Change on Agriculture and Adaptation

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For a thesis that contains publications

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Abstract

The thesis studies the potential economic impacts of climate change on agricultural production and estimates to what extent adaptations can help to offset the potential damages of climate change on agricultural profits. The thesis consists of three journal-style articles. Chapter 1 is the introduction.

Chapter 2 is the article "Why do econometric studies disagree on the effect of warming on agricultural output? A meta-analysis". This article conducts a meta-analysis based on 130 primary econometric studies to better understand the conflict among the existing estimates of warming on agriculture. We find that differences in the latitude of the study sample, the temperature measure that was used, the econometric approach that was applied, and publication biases can explain why the primary studies disagree. We also find that this disagreement can be reduced if the primary studies use a yearly temperature measure and adopt the hedonic modelling approach, as in doing so, they will tend to produce estimates with a similar but previously supported view that warming will lead to positive effects on agriculture in the high latitudes and negative effects in the low latitudes.

Chapter 3 is an article "How large is the potential economic benefit of agricultural adaptation to climate change? Evidence from the United States". Based on the meta-analysis of Chapter 2, this article argues that 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 chapter 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.

Chapter 4 is the third article “The potential benefits of agricultural adaptation to warming in China in the long run”. Based on a panel of household survey data from a large sample in rural China, the article adopts the panel approach proposed in Chapter 3 to estimate the potential benefits of adaptation and to identify the determinants of farmers’ adaptation capability. 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 chapter also finds that household-level capital intensity and farmland size have significant effects on farmers’ adaptive capacities.

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Chapter 1 : Introduction

There is a global concern that climate change could cause severe shortages in the world's food supply (Conway and Toenniessen 1999, Lobell and Asner 2003). To address this threat, policy makers would benefit from robust empirical evidence on the effect that climate change has on agricultural production. Understanding how much adaptation is likely to occur is central to any study of the impact of climate change on agriculture and is also of paramount importance from a policy perspective (Di Falco, Veronesi, and Yesuf 2011, Di Falco 2014). The role of adaptation is central to the debate surrounding the impacts of climate change on agriculture. Even more interesting from a policy perspective are the determinants of adaptation capability, because identifying the determinants of farmers' adaptation capabilities can support the design of effective adaptation policies. The main purposes of this thesis are to estimate the potential economic impacts of climate change on agriculture, to assess the extent to which adaptations will help to offset the damages, and to identify the determinants of farmers' adaptation capabilities.

1.1. The economics impacts of climate change on agriculture

There is a concern across the world that climate change may lead to severe shortages in the world's food supply (Conway and Toenniessen 1999, Lobell and Asner 2003, Brown and Funk 2008). To address this threat, it is important for policymakers to be informed by robust empirical evidence on the effect that global warming has on agriculture. However, in the applied econometrics literature, there is much contention on what this effect might be or if it even exists (see, for example, Mendelsohn, Nordhaus, & Shaw, 1994; G. C. Nelson et al., 2014; Schlenker & Roberts, 2009). Identifying the potential sources of this dispute can enable us to better understand how disagreements among studies on the effects of climate change may arise and to construct a more complete picture of the true effect of climate change. It is also a useful exercise for guiding future models of the relationship between climate change and agriculture.

Existing research on the effect of climate change on agricultural output is based on either a simulation or an econometric approach (Deschênes and Greenstone 2007, Robertson et al. 2013). The simulation approach simulates the effect of climatic variables on crop yield using what are known as process-based crop growth models (see, for example, Adams et al. 1990). The econometric approach, on the other hand, estimates the response of crop yield to climate change by conducting a regression analysis on the relationship between historical climate and crop production (see, for example, Deschênes and Greenstone 2007). In the simulation based literature, there is much consistency in the predicted effect of global warming, in that global warming will lead to positive yield changes in high latitudes while causing damages in low latitudes (Rosenzweig and Parry (1994)). However, in the econometric based literature, there is much disagreement on how warming would affect agriculture, even in places with similar latitudes.

For example, in the 130 econometric based studies we surveyed, 31.4% of them reported a positive and statistically significant effect of warming on crop yield for low latitude regions and 25.6% reported a statistically insignificant effect. Only 43% of these studies reported a negative and statistically significant effect, which is what simulation based studies had predicted for the low latitudes. In the econometric based literature, the estimates on the effect of warming were often mixed. On a topic as important as climate change, such mixed messages may cause confusion to policy makers seeking to get their response to climate change right.

Chapter 2 of the thesis identifies potential sources of the inconsistency among econometric based studies on how global warming affects agricultural output. To do so, we conduct a meta-analysis based on 130 primary studies, where we construct a meta-regression model that uses their econometric estimates (of the effect of warming on agriculture) as a meta-dependent variable and regressing it on several control variables, with each capturing a feature associated with these studies (e.g. the geographical location on which they are based, the type of crops studied, and the specification of the econometric model).

The meta-regression shows that 64.8% of the inconsistency among the 130 primary studies can be explained by the differences in model specification, biological characteristics of crops, study region and publication bias. We also find that for primary studies that have two fixed characteristics – the use of yearly temperature and the hedonic approach – their estimates will have less dispersion and will tend to concur with the prediction from the simulation-based literature that warming will lead to positive effects on agriculture in high latitude regions but damages in low latitude regions.

1.2. The extent to which adaptations help to offset climate change impacts

Understanding how much adaptation is likely to occur is central to any study of the impact of climate change on agriculture and is also of paramount importance from the policy perspective (Di Falco, Veronesi, and Yesuf 2011, Di Falco 2014). 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 caused by omitting adaptation, Mendelsohn, Nordhaus, and Shaw (1994) proposed a hedonic approach to identifying climate change impacts that includes adaptations. To address the potential bias due to misspecifications of the cross-sectional hedonic approach, Deschênes and Greenstone (2007) proposed a panel approach to identifying climate change impacts through random inter-annual weather fluctuations. However, because farmers can have only limited adaptations to the random year-to-year weather fluctuations, the merits of this panel approach depend on how much adaptation will actually occur in response to long-run climate change (Seo 2013).

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 (Zilberman, Zhao, and Heiman 2012, Lobell 2014, Burke and Emerick 2015). The idea of the potential value of adaptation is usually shown by an illustrative relationship as in Figure 1.1:

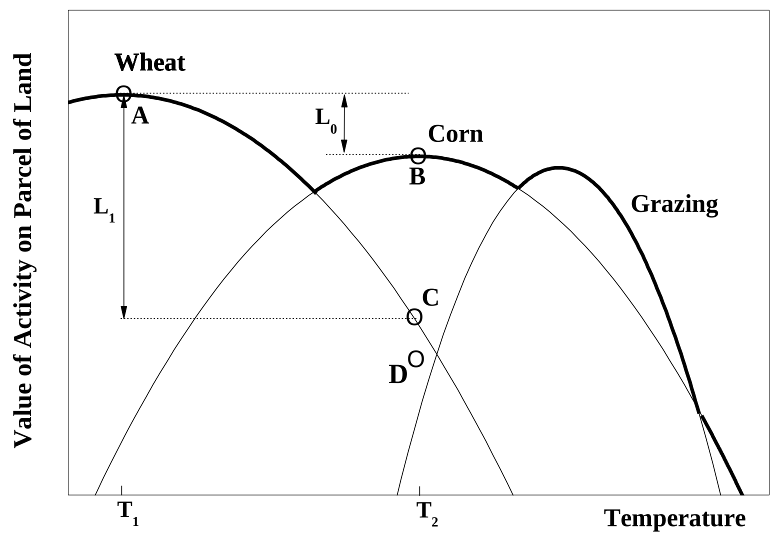

Figure 1-1: Value of land as a function of average temperature

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

The upper locus, shown as the heavier line, is the maximum profits from land use. Suppose the temperature increases from T_1 to T_2. If farmers adapt to this change by adjusting inputs and managements but do not switch from wheat to corn, profits with move from A to C along wheat's response curve. If land use substitutions are also allowed, the profits will end up at B. If no adaptations are made, the profits may end up at some point under the wheat response curve, such as at D. The difference between B and D is the value of adaptation. Here, the value of adaptation includes potential benefits from a full range of adaptations that could be taken by farmers, such as adjusting inputs and managements, and switching to new varieties, crops, and other land uses.

Empirically, 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; Falco and Veronesi (2013) identified the adaptation benefit from a portfolio of strategies, which included changing crop varieties and adopting water and soil conservation behaviors; Huang, Wang, and Wang (2015) investigated how rice farmers benefits from adjusting their farm-management practices in adapting to extreme weather events. The existing farm-level adaptation studies in the literature have dramatically improved our understanding of adaptation.

In reality, as argued by Mendelsohn, Nordhaus, and Shaw (1994), there are innumerable potential adaptation measures that farmers could apply in response to climate change. It is nearly impossible to capture the benefits of the full range of adaptations (as shown in Figure 1-1) by examining only individual adaptation measures. Hence, an approach to identify the benefits of a full range of adaptations to climate change without examining individual adaptation methods would be valuable.

Unfortunately, an effective approach for evaluating the benefits of a full range of adaptations has not yet been developed. Even though the hedonic approach such as that used by Mendelsohn, Nordhaus, and Shaw (1994) implicitly includes the benefits of complete adaptations by examining climate change impact through cross-sectional climatic differences, it cannot be used explicitly evaluated the benefits of adaptation (Hanemann 2000). In the literature, the most related method of identifying the adaptation benefit is the panel approach, which infers adaptation benefit by comparing damages estimated from inter-annual weather fluctuations and damages identified from long-term climate trends (Dell, Jones, and Olken 2012, Burke and Emerick 2015). However, as shown in the conceptual framework of this chapter, there are some potential drawbacks to examining adaptation benefits through long-term climate trends: the historical climate trend is not large enough to predict future impacts and hence adaptations; farmers may only partly recognize and adapt to the climate trend; and many other concurrent trends might obscure the true effects of climate change and adaptation.

Chapter 3 of this thesis proposes an alternative approach to estimating the potential value of a full range of adaptations. This approach depends on the basic idea that impacts identified through cross-sectional climate differences should include the benefit of a full range 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 the adaptations to long-run climate change because farmers have only limited ex-post adjustments in response to random year-to-year weather fluctuations, and this short-run response is not seen as adaptation to climate change. Two types of panel model were developed to estimate the potential impacts of climate change, one depended on cross-sectional climate differences, and the other on inter-annual weather fluctuations. Only the former model, namely that using cross-sectional climate differences, included the benefit of adaptations. Hence, the differences between the predicted impacts from these two models should reflect the value of a full range of adaptations.

This approach is combined with a panel of US county-level agricultural production and climate data and the output of various climate models to project the potential value of agricultural adaptation to climate change in the US. The empirical results show that, when taking into account adaptations, the estimated overall damages are about 9% (or USD 3.18 billion in 2012 constant values) per year by the end of this century. If adaptations are omitted, the overall damages are as high as 30% (or USD 10.56 billion) per year. Therefore, adaptations will help to offset about two-thirds of the overall damages, and analysis methods omitting adaptations can substantially overestimate the damages. These results are robust to numerous specification checks.

1.3. The determinants of farmers' adaptation capability

An even more interesting issue from the policy perspective is to understand the determinants of adaptation capability, as identifying the determinants of farmers' adaptation capability can support the design of effective adaptation policies. Empirically, a major contribution to the field of adaptation capability study involved the hedonic approach proposed by Mendelsohn, Nordhaus, and Shaw (1994), which implicitly includes adaptations in its climate change impact estimation.

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, whereas Seo and Mendelsohn (2008) provided evidence that farmers benefit from switching among different kinds of livestock when adapting to warming, and Di Falco and Veronesi (2013) identified the adaptation benefits from a portfolio of strategies that included changing crop varieties and adopting water and soil conservation behaviors. Even though the existing farm-level adaptation studies in the literature have dramatically improved our understanding of adaptation, as argued by Mendelsohn, Nordhaus, and Shaw (1994), in reality, innumerable potential adaptation measures could be applied by farmers in response to climate change, and it is impossible to capture the benefits of the full range of adaptations by examining only individual adaptation measures. In addition, most of the farm-level studies explain the responses to weather fluctuations as adaptations, so interpretation of these studies might have precluded some of the potential benefits of long-term adaptation from adjusting ex ante production behaviors (Seo 2013).

However, the study of the determinants of farmers' adaptation capability is incomplete. A great many studies within the adaptation literature are concerned with empirically assessing financial, informational, and institutional constraints on adaptation capacity (Kelly and Adger 2000, O'Brien, Sygna, and Haugen 2004, Parson et al. 2003). Some other studies take an experimental or empirical approach to infer the determinants of adaptation capability under climate change by examining farmers' responses to extreme weather conditions or natural disasters (See, for example, Golnaraghi and Kaul 1995, Podesta et al. 2002, Grothmann and Patt 2005, Huang, Wang, and Wang 2015). In these studies, the value of an adaptation is identified by comparing agricultural outputs from farms that take a certain adaptation measure with the outputs from those that do not take that adaptation measure. These studies shed important light on the determinants of adaptation capability and generally imply that farmers with better infrastructure, higher crop diversification, more financial and technical support, and better information are better at adaptation. However, since they lack an explicit estimate of the value of a full range of adaptations, previous studies do not examine the determinants of the overall adaptation capability.

Chapter 4 of this thesis provides more empirical evidence on the determinants of farmers' adaptation capability. Using the panel approach introduced in Chapter 3, we can explicitly identify the potential value of a full range of adaptations, so it is possible to examine the influencing factors of an overall adaptation capability. In our data set, complete farm and household characteristics are included, such as the capital and labor intensity of agricultural production and the farmers' ages and education levels. By combining these farm and household characteristics with the value of a full range of adaptations, we were able to examine the influence of these characteristics on adaptation value and were able to gain an additional understanding of the determinants of farmers' adaptation capability.

Statement of Authorship for Chapter 2

Statement of Authorship

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Principal Author

Name of Principal Author (Candidate)	Kaixing Huang
Contribution to the Paper	Performed analysis on all samples, interpreted data, wrote manuscript and acted as corresponding author.
Overall percentage (%)	85%
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.
Signature	Date 5/5/2016

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);

ii. permission is granted for the candidate in include the publication in the thesis; and

iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

Name of Co-Author	Nicholas Sim
Contribution to the Paper	Helped in data interpretation and manuscript evaluation and improvement.
Signature	Date 5/5/2016

Name of Co-Author	
Contribution to the Paper	
Signature	Date

Please cut and paste additional co-author panels here as required.

Chapter 2 : Why Do Econometric Studies Disagree on the Effect of Warming on Agricultural Output? A Meta-Analysis

Abstract

Having robust estimates of how global warming affects agriculture is important to policymakers, but the existing econometric-based studies have been at odds on what this effect might be. This chapter conducts a meta-analysis based on 130 primary econometric-based studies to better understand the conflict among the existing estimates of the effect of warming on agriculture. We find that differences in the latitude of the study sample, the temperature measure that was used, the econometric approach that was applied, and publication biases can explain why the primary studies disagree. We also find that this disagreement can be reduced if the primary studies use a yearly temperature measure and adopt the hedonic modelling approach, as in doing so, they will tend to produce estimates with a similar but previously supported view that warming will lead to positive effects on agriculture in the high latitudes and negative effects in the low latitudes. (JEL Q15, Q51, Q54)

Key words: Climate change impact, Agriculture, Meta-analysis, Inconsistency

2.1. Introduction

There is a concern across the world that climate change may lead to severe shortages in the world's food supply (Conway and Toenniessen 1999, Lobell and Asner 2003, Brown and Funk 2008). To address this threat, it is important for policymakers to be informed by robust empirical evidence on the effect that global warming has on agriculture. However, in the applied econometrics literature, there is much contention on what this effect might be or if it even exists (see, for example, Mendelsohn, Nordhaus, and Shaw 1994, Nelson et al. 2014, Schlenker and Roberts 2009).

In this chapter, we conduct a meta-analysis on 130 econometric-based studies to try to understand the fundamental causes of the disagreements on the effect of warming on agriculture. Among the 130 studies sampled here, 36.2% of them reported negative and statistically significant marginal effects of warming, 33.2% reported positive and statistically significant marginal effects, and the remaining 30.6% found this effect to be statistically insignificant.[1] As such, there is no consensus on the effect of warming on agriculture, which might explain why the effect of global warming remains a greatly debated issue. To examine the fundamental sources of this lack of consensus, we conduct a meta-analysis to help us understand why the econometric-based literature on climate change may disagree, and in particular, if the conclusions from such studies are dependent on the study design.

[1] See the data and statistical analysis section for more details. In the summary we include both published and unpublished primary studies. If summarize across only published studies, the shares are 31.7%, 41.4%, and 27% for studies report negative and significant, positive and significant, and insignificant marginal effects, respectively.

The existing literature on the effect of global warming on agriculture are based either on a simulation or an econometric approach (Robertson et al. 2013).[2] Although there are meta-analyses on the simulation-based studies (See, for example, Rosenzweig and Parry 1994, Challinor et al. 2014), our study is the first to conduct a meta-analysis on the econometric-based studies. Here, the main challenge we encounter is finding a so-called "effect-size", which in this context is a variable that says something about the effect of warming that is comparable across the econometric-based studies. Having a common effect-size is crucial for enabling us to conduct a meta-analysis to examine how the effect of warming is influenced by various features in the econometric studies.[3]

To proceed, we obtain the common effect-size as the *Z-values* of the marginal effect of warming on agriculture from the 130 econometric-based primary studies considered in our meta-analysis. We then construct a meta-regression model that uses these *Z-values* as the meta-dependent variable, which we regress on several independent variables capturing various aspects of the primary studies (e.g. the geographical location, the type of crops studied, and the specification of the econometric model). We find that a large share of the disagreement among the primary studies can be explained by the differences in the latitude which the study is based

[2] The simulation approach simulates the effect of climatic variables on crop yield using what are known as process-based crop growth models, while the econometric approach estimates the response of crop yield to climate change by conducting a regression analysis.

[3] Since meta-analysis requires a common effect-size that is comparable among studies and this common effect-size is not exists between the simulation study and the econometric study, it is impossible to include both econometric and simulation studies in a single meta-analysis.

upon, the temperature measure used (yearly versus growing season temperature), the econometric approach taken (hedonic versus non-hedonic models), and publication biases.

With the knowledge of how disagreements among these studies may arise, we then investigate to what extent the dispersion in the primary estimates can be reduced if the characteristics of the primary studies are fixed along certain dimensions. We find that for primary studies that have two fixed characteristics – the use of yearly temperature and the hedonic approach – their estimates will have less dispersion and will tend to concur with the prediction from the simulation-based literature that warming will lead to positive effects on agriculture in high latitude regions but damages in low latitude regions.[4]

For the remainder of the chapter, Section 2.2 introduces the meta-analysis approach that is used in this chapter, Section 2.3 discusses the data and variables, Section 2.4 presents the meta-regression results, and Section 2.5 concludes.

2.2. The meta-regression model

Meta-analysis is a method that uses the results from a pool of existing empirical studies that seek to answer a common question on a given topic. It enjoys widespread use in economics since the 1990s, such as in the area of environmental and resource economics (Nelson and Kennedy 2009), international trade (Disdier and Head 2008), fiscal policy (Gechert 2015), and foreign direct investments (Iršová and Havránek 2013), where the conclusions in the empirical literature vary substantially. Meta-regression analysis is the most frequently used meta-analysis

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[4] It is worth to stress that this sub-group exercise is only used to illustrate the importance of these factors in determining the observed inconsistency among primary studies, and we do not suggest that studies with these characteristics are more reliable than other studies.

technique in economics. One of the main purposes of meta-regression is to identify features in the research design that are responsible for the variation among reported empirical estimates on the same topic (Stanley and Jarrell 1989, Smith and Huang 1995, Klomp and De Haan 2010).

In a meta-regression analysis, the dependent variable is sometimes known as the "effect size," which is a quantifiable result of the primary studies covered in the meta-analysis. The effect-size can be the regression coefficient, marginal effect, elasticity, *T-value*, *Z-value*, significance level of a coefficient, or other measures that are comparable across studies (Nelson and Kennedy 2009). The chosen effect-size for the meta-regression must be measuring the same thing as it will be used to construct the meta-dependent variable (Stanley and Jarrell 1989).

In this study, the chosen effect-size (called meta-dependent variable hereinafter) is the *Z-value* of the estimated marginal effect of warming on agricultural output or profits from the primary study.[5] There are two advantages in using the *Z-value* over the estimated marginal effect itself. Firstly, the *Z-value*, unlike the marginal effect, has been normalized by the standard error, which reduces heteroscedasticity (Card and Krueger 1995, Becker and Wu 2007). Secondly, the *Z-value* is truly comparable across studies, unlike the marginal effect and regression coefficient which are usually incomparable as they depend on how the regressor of interest is defined (e.g. different units).[6]

[5] We focus on the marginal effect of temperature for two reasons. First, warming is the most important characteristic of climate change (IPCC, 2007). Second, the estimated marginal effects of precipitation is less reliable because precipitation is not a good measure of water supply for crops grown, especially for the irrigated agriculture (Schlenker, Hanemann, and Fisher 2005)

[6] More detailed definition of the meta-dependent variable is provided in the next section.

The independent variables capture the various characteristics of the primary studies (e.g. the geographical location where they are based on, the type of crops studied, and the specification of the econometric model). Let Z_i be the *Z-value* of the marginal effect of warming from primary study i. Our meta-regression model is

$$Z_i = \frac{\alpha_0}{se_i} + \sum_{k=1}^{K} \frac{\alpha_k X_{ik}}{se_i} + \frac{\mu_i}{se_i} \qquad \left(i = 1, 2, \ldots L\right) \tag{2.1}$$

where se_i is the standard error of the marginal effect from study i, X_{ik} is a *K*-vector of characteristics of the primary studies; α_0 is a constant term of the regression; α_k is the meta-regression coefficient on the k^{th} independent variable, and this captures the influence that the k^{th} study characteristic has on the heterogeneity across primary studies (Bel, Fageda, and Warner 2010); μ_i captures the remaining variation in Z_i beyond the study characteristics under consideration. As a clarifying remark, climate change impact studies are usually conducted with large samples**.** As such, the standardized marginal effect of warming can be approximated reasonably well by the standard normal distribution. For this reason, we refer to this standardized marginal effect as the *Z-value* instead of the *T-value*.

2.3. Data and the statistical analysis

To perform a good meta-analysis, it is important to cover the literature as widely and as comprehensively as possible (Cavlovic et al. 2000). We carried out a broad and inclusive search of the rapidly growing econometric-based literature that examines the effect of climate change on agricultural output. We searched the related published and unpublished studies from a variety of sources. For published papers, we looked up the Web of Science, Google Scholar, Academic OneFile, Academic Search Premier, JSTOR, and Scopus, as well as the websites of major publishers of academic journals, including Springer, Elsevier, Emerald, Blackwell, and Wiley. For unpublished papers (e.g. working papers, government reports, and dissertations), we searched Google Scholar, SSRN, websites of renowned research institutes, and the websites of major government agencies. In all, our search took about nine months (July 2014 - March 2015) and covered more than 1000 papers, of which we selected 130 papers based on the following criteria.

First, the papers must contain some econometric analysis; studies that were purely simulation based were excluded.[7] Second, they must focus on the effects of warming on the yield or profits of four major crops (maize, soybean, wheat and rice), on farmland values, or on agricultural profits. Third, the papers must provide enough information for us to obtain the marginal effect of warming evaluated at the mean temperature; studies that reported solely the effects of extreme temperatures, such as the effects of minimum and maximum temperature, were excluded. The temperature can be measured by yearly average temperature, yearly degree-day, growing season average temperature, or growing season degree-day. Finally, the papers must contain enough information for us to obtain or construct the *Z-value* pertaining to the marginal effect of warming on agriculture.

Even though several selection criteria were applied, the marginal effects of warming from the chosen primary studies are still not perfectly comparable for several reasons. Firstly, the dependent variable in the primary studies may be defined differently. For example, it could be the yield or profits of one, several or all crops, the agricultural profits, or the farmland value. Secondly, different measures of temperature (as an indicator of warming) may be adopted by different primary studies. For example, some studies adopted yearly or growing season average

[7] See footnote 3 for why we exclude simulation studies.

temperature as their temperature measure, others adopted yearly or growing season degree-day. Thirdly, the way these primary studies are conducted may vary across countries, especially in the use of different units for the dependent variable or the independent variables.

To make a reasonable comparison among the papers chosen for our meta-analysis, we will focus on the *Z-value* of the marginal effect of warming evaluated at the mean temperature. This *Z-value* tells us if an increase in temperature around its mean has a statistically significant and positive or a statistically significant and negative effect on agricultural output, or if this effect is statistically insignificant. Because it is a standardized statistic, it conveys information about the effect of warming on agriculture in a consistent way across the primary studies, unlike the regression coefficient on temperature which is generally not comparable. However, from a hypothesis testing perspective, the magnitude of the *Z-value* is meaningful only when compared with the threshold *Z-value* that stands for a particular significance level. Hence, we classify the *Z-value* as positive and significant if it is above 1.68, negative and significant if it is below -1.68, and insignificant otherwise.[8] As such, our study will focus on the direction of the marginal effect of warming and the significance level of this marginal effect evaluated at the mean temperature.[9]

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[8] The critical Z-value of ±1.68 corresponds to a 10% significance level in the large sample climate change impact studies. We also tried to use the critical values that correspond to 5% or 1% significance levels, and the major conclusions of this study keep the same.

[9] We do not compare the estimated future impacts of warming across different studies. This is because different climate change scenarios are usually used, which make the estimated future impacts generally incomparable.

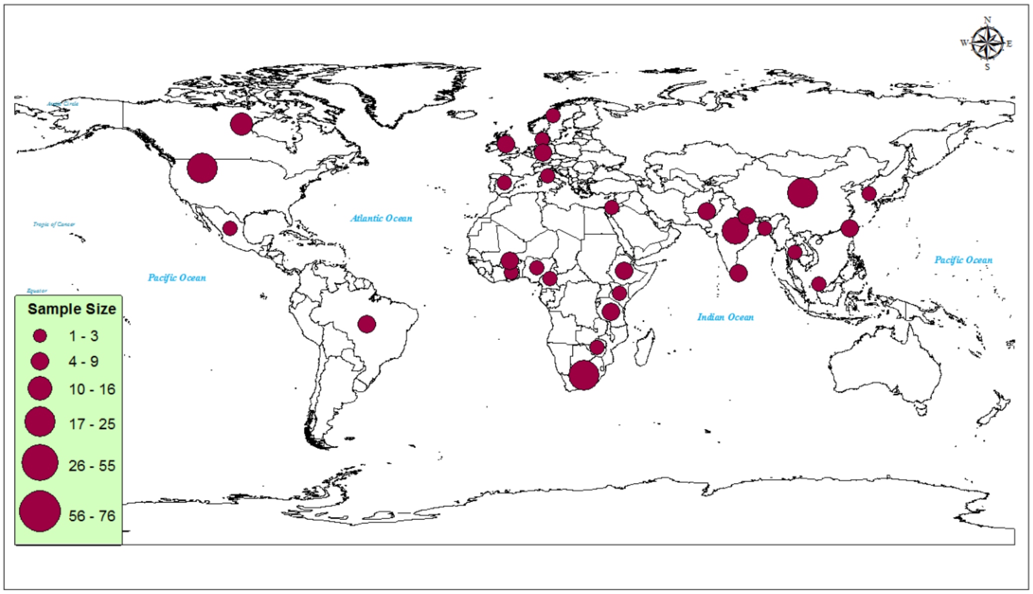

Figure 2-1: Geographic distribution of the observations

From the 130 papers, we constructed a dataset with 341 observations, which is the total number of estimates of the effect of warming on agriculture contained in these papers. If there are multiple estimates involving the same crop, profit, or farmland value in a primary study, we pick only one estimate for each of these from the primary study to avoid the problem of non-independence among observations on the effect-size.[10] The observations exceed the number of paper collected because each paper often reports estimates associated with several different crops. Figure 2-1 presents the geographic distribution of the observations, which are drawn from 36 countries and 103 locations. 27% of our sample is associated with studies on Africa, 22% on

[10] Estimates within one primary study may not be independent of each other. Including correlated effect-size estimates will result in biased standard error estimates in the meta-regression (Nelson and Kennedy 2009). Therefore, if there are multiple estimates involving the same crop, we will only choose one.

the United States, 21% on China, 7% on India, 6% on the European Union, and 17% for the rest of the world.

Table 2-1: Definition of the independent variables

Independent variables	**Definition**
Regional differences	
(1) *Latitude*	Mean latitude of the study area (Degree) §
Model specification	
(2) *Measures of output*	Agricultural output is measured by profits or quantity (1 = Profits , 0 = Quantity)
(3) *Temperature measures*	Using a yearly temperature measure or a growing season temperature measure (1 = Yearly, 0 = Growing season) †
(4) *Control for irrigation*	Did the primary study control for irrigation (1 =Yes, 0 = No)
Publication bias	
(5) *Research time*	Year of study (Year)
(6) *Publication status*	Published (in journal or book) or not (1 = Yes, 0 = No)
Including adaptation	
(7) *Adaptation*	Depending on the hedonic approach or not (1 = Yes, 0 = No)
Biological differences	
(8) C*rop types*	Maize, soybean, wheat, rice, agricultural profits, or farmland value (0 = farmland values, farmland rents or agricultural profits, 1 = Maize, 2 = Soybean, 3 = Wheat, 4 = Rice)#

§: We do not make a distinction between the latitude of Southern and Northern Hemisphere. For example, 23.43° N is treated the same as 23.43° S.

†: The yearly temperature measure includes yearly mean temperature and yearly degree-day; the growing season temperature measure contains growing season mean temperature and growing season degree-day.

#: Maize, soybean, wheat and rice are the most frequently studied crops. There are also lots of econometric studies examined the effect of warming on farmland rents, farmland values, and agricultural profits, which reflect the effect of warming on the combination of various crops and other farmland uses.

From each of these 341 observations, we gathered 8 study characteristics that we believe have the potential to explain the disagreement among the primary studies. These characteristics will be quantified and used as independent variables. Table 2-1 provides the definitions of the study characteristics, which are grouped into five categories: regional differences, model specification, publication bias, adaptation, and biological differences. The summary statistics of independent variables are presented in Table 2-2.

Table 2-2: Summary statistics of the independent variables

Panel A: Continuous variables	Mean	Standard Deviation	Min	Max
Latitude (Degrees)	30.07	14.80	0.005	64.32
Research time (Year)	2010	4	1992	2015

Panel B: Discrete variables	Variable = 1	Variable = 0
Measure of output (1 = Profits, 0 = Quantity)	145	196
Temperature measures (1 = Yearly, 0 = Growing season)	232	109
Adaptation (1=Hedonic approach, 0=others)	148	193
Control for irrigation (1 = Yes, 0 = No)	41	300
Publication status (1 = Published, 0 = Unpublished)	235	106
Maize (1 = Yes, 0 = No)	70	271
Soybean (1 = Yes, 0 = No)	23	318
Wheat (1 = Yes, 0 = No)	42	299
Rice (1 = Yes, 0 = No)	53	287
Land values, land rents or agricultural profits *(1 = Yes, 0 = No)*	152	189
Number of observations	341	

Note: the definition of independent variables can be found in Table 2-1.

The latitude is an important factor for how warming may influence agricultural production. To show this, we distribute the 341 observations evenly into five groups according to the latitudes associated with these observations. The *low* latitude group is defined as the first 20%

of observations nearest to the equator (either from the Southern or Northern Hemisphere). The *low-middle* latitude group is defined as the next 20% of observations nearest to the equator, and so on.

Figure 2-2 summarizes the meta-dependent variable corresponding to each of these five latitudes groups, and show that the latitude of the region where a study is based on may explain a significant share of the disagreement of the effects of warming among the primary studies. This is because the marginal effects of warming on agricultural output may vary depending on crop type, which in turn depends on regional gradients of temperature (Cramer and Solomon 1993, Ramankutty et al. 2002). From the existing meta-analyses of the simulation-based literature, we are now aware that warming mainly has negative effects on agricultural production in low latitudes and positive effects in high latitudes (Rosenzweig and Parry 1994, Challinor et al. 2014). However, as shown in Figure 2-2, even the econometric estimates of the effect of warming (i.e. the *Z-value* of the marginal effect) from studies in the same latitude region can be highly mixed.

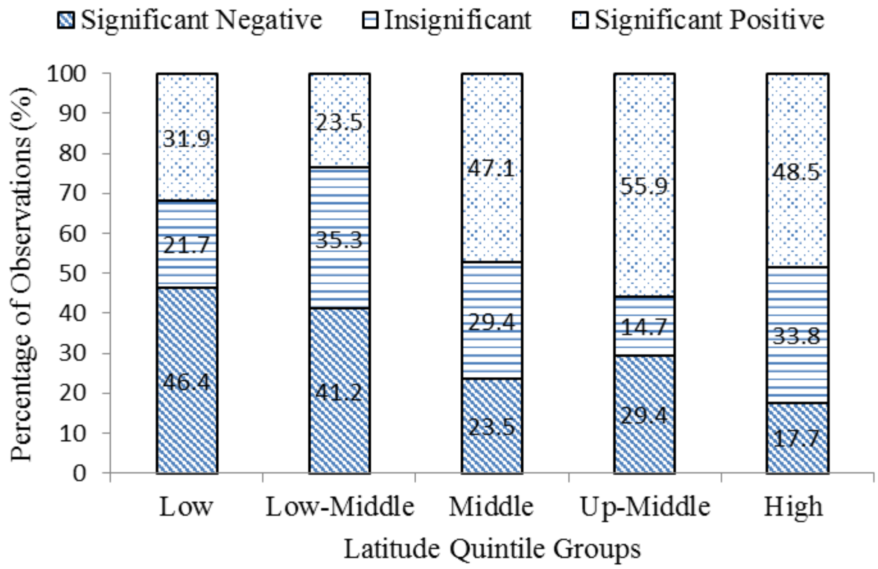

Figure 2-2: Distribution of the meta-dependent variable within each latitude quintile group

Note: This figure shows the percentage of observations reporting (i) positive and significant effects of warming, (ii) insignificant effects, (iii) negative and significant effects (all at the 10% significance level) for each of the five sample latitude quintile groups. The *Low* quintile group contains the first 20% of observations nearest to the equator, the *Low-Middle* quintile group contains the next 20% of observations nearest to the equator, and so on.

For example, among studies corresponding to the low latitude regions, as indicated by the *Low* group in Figure 2-2, 31.9% of the estimates show that warming has a positive and statistically significant marginal effect (at the 10% level), 21.7% of the estimates are statistically insignificant, and 46.4% of the marginal effects are negative and statistically significant. Such disparity can also be found among studies within each of the other four latitude groups. That being said, from Figure 2-2, there appears to be a relationship between the extent of the disagreement among the primary studies and the latitude in which the studies are based on. For example, the share of studies that reported positive and significant marginal effects increases with latitude. At the same time, the share of studies that reported negative and significant effects decreases with latitude.

Differences in the temperature measure could be an important reason for why the primary studies disagree on the effects of warming. In the econometric-based literature, temperature is usually measured either as yearly temperature (includes yearly mean temperature and yearly degree-day) or as growing season temperature (includes growing season mean temperature and growing season degree-day). However, this distinction is not trivial. Figure 2-3 shows that the differences in how temperature is measured can result in substantial disagreement about the effects of warming. For example, the share of studies that reported statistically significant and positive effects are much larger for studies using a yearly temperature measure than studies using a growing season temperature measure (Panel C in Figure 2-3).

The sensitivity of the effects of warming to the way in which temperature is measured could be due to the fact that different measures of temperature (i.e. yearly or growing season) capture different things. For example, the temperature affects crops mainly through the growing season during which crops are on the field. Therefore, the growing season temperature is a more relevant measure of temperature to study its effect on crops. However, the downside of using it is the difficulty in identifying the growing season because in certain areas, crops are grown throughout the year. While the yearly temperature is not as tightly linked to the growing season, it has the advantage of capturing such adaptations by farmers when farmers switch growing seasons in response to warming (Kurukulasuriya and Mendelsohn 2008).

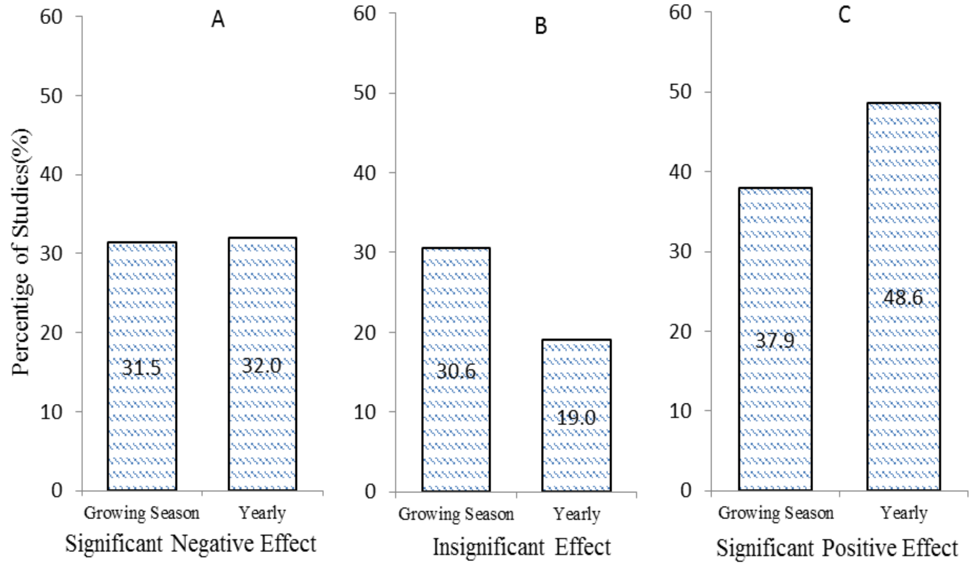

Figure 2-3: Temperature measures and the estimated effects of warming

Note: The yearly temperature measure includes yearly mean temperature and yearly degree-day; the growing season temperature measure contains growing season mean temperature and growing season degree-day.

Another possible source of disagreement is publication bias. Generally, there is evidence of publication bias in applied econometric research, as results that conform to prevailing views are more likely to be published (Rosenthal 1979). To capture the notion of publication bias, we consider the publication status (published or unpublished) and publication year of the primary studies as independent variables.

In the context of the global warming literature, Figure 2-4 shows that studies that reported negative effects of warming were more likely to be published than studies that reported positive effects. Our reading of the literature is that in the early stage of the climate change impact study, the publications tend to be related to research that reported dramatic negative effects of warming, which affirmed the view that warming was damaging to agriculture. However, the recent years have seen an increasing number of publications that reported mild negative effects or even positive effects of warming. That being said, Figure 2-4 demonstrates that studies showing favorable effects of warming are still more unlikely to be published than those showing either no effects or unfavorable effects of warming.

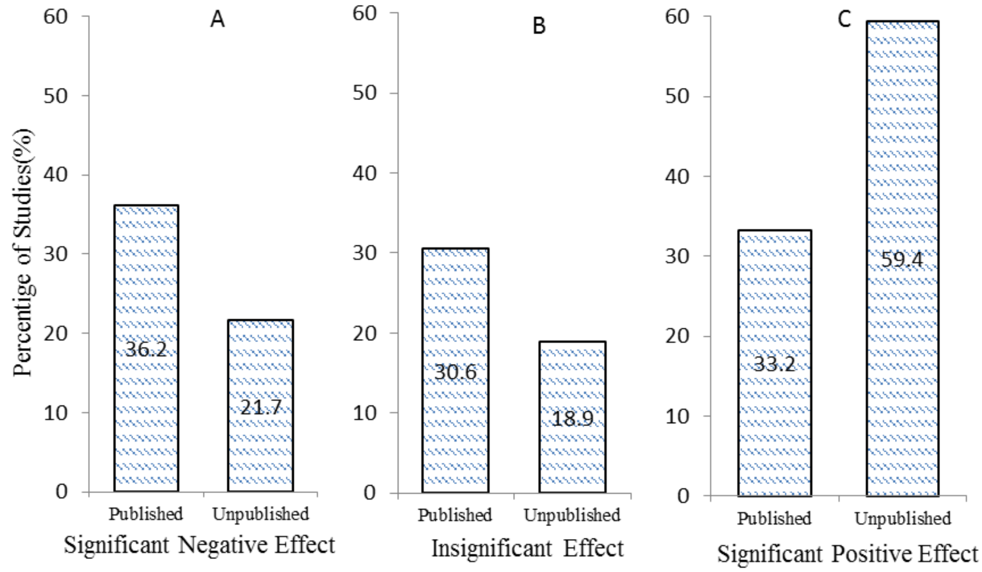

Figure 2-4: Publication status and the estimated effects of warming

Long-run adaptations can help farmers to exploit future benefits of climate change on agriculture or mitigate its future negative impact (Lobell et al. 2008). Here, the primary studies differ on whether long-run adaptations are accommodated in the design of their econometric analysis. In the literature, the hedonic approach developed by Mendelsohn, Nordhaus, and Shaw (1994) is the most common approach for capturing adaptations when estimating the impact of climate change. In this approach, the possibility of long-run adaptations is reflected by the cross-sectional differences in climate and agricultural output. The intuition is that over the long run, it is reasonable to assume that agricultural agents would have completely adapted to the climate of their particular regions. Therefore, the persistent regional difference in agricultural output would contain information about long-run adaptations by agricultural agents to their local climate.

Besides the hedonic approach, which looks mainly at the between-region effects of temperature on agricultural output, there are econometric models of climate change that exploit mainly the within-region effects of weather, whose variation comes from inter-annual weather fluctuations (Deschênes and Greenstone 2007). Impacts of warming identified through inter-annual weather fluctuations do not include the benefits of long-run adaptations as farmers typically make very limited *ex post* adjustments to random weather outcomes (Seo 2013). Consequently, compared with studies based on the hedonic approach, studies based on inter-annual weather fluctuations tend to understate the benefits of warming as they do not account for long-run adaptations. From Figure 2-5, we find some evidence to support this conjecture, as among studies that reported significant and positive effects of warming, the proportion of hedonic-based studies exceeds the proportion of the other types of studies by 14.1 percentage points. This implies that studies based on the hedonic approach (which takes into account of long-run adaptations) tend to have a more positive view about warming.

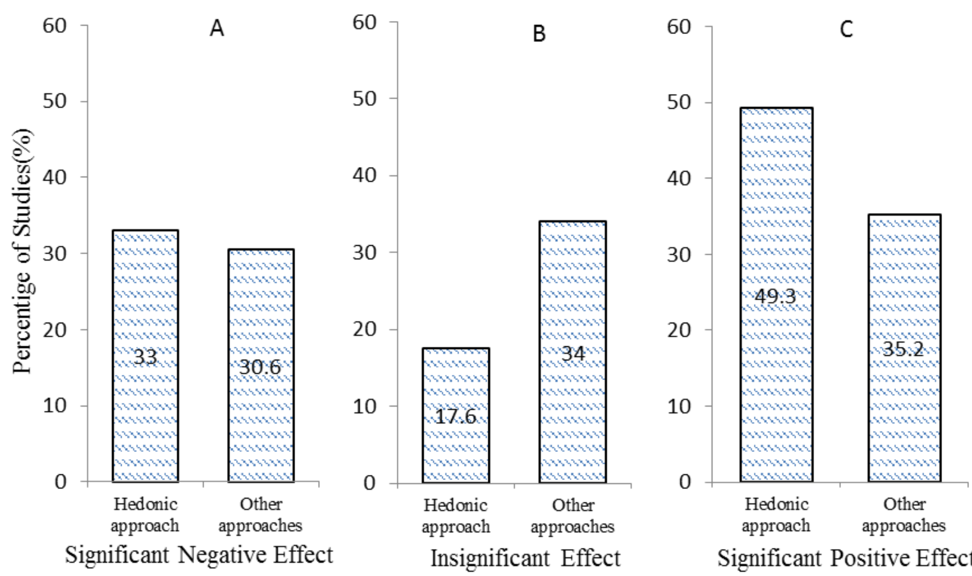

Figure 2-5: Incorporating adaptations and the estimated effects of warming

Note: Studies using the hedonic approach incorporate more long-run adaptations than studies using other approaches (Mendelsohn et al. 2004).

Finally, the biological difference among crops may explain why the primary studies disagree. In the climate change literature, there are four widely studied crops: maize, soybean, wheat, and rice. However, as shown in Figure 2-6, the estimated effect of warming on crops is dependent on the type of crops. For example, 78.3% of the primary studies on soybean reported positive effects while this is true for only 22.2% of the primary studies on rice. In other words, a positive effect of warming is more likely to be observed if the crop in question is soybean. However, the opposite is true if a study focuses on rice.

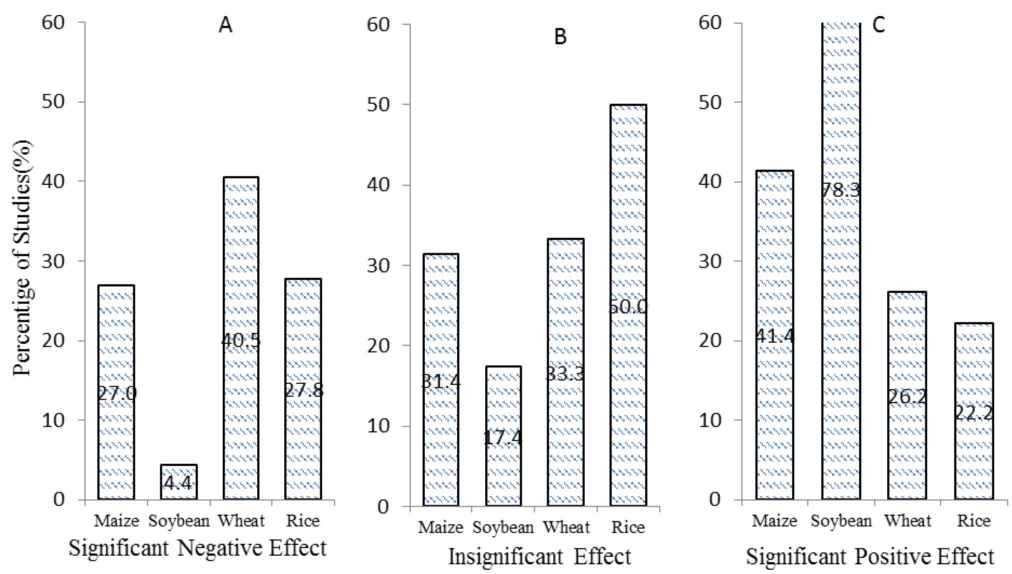

Figure 2-6: Biological differences and the estimated effects of warming

2.4. Meta-regression results

In this section, we report the meta-regression results that demonstrate to what extent the disagreement among the primary studies on the effect of warming on agriculture can be explained by the study characteristics that we have discussed. The meta-dependent variable of interest is *Z-value* pertaining to the marginal effect of warming evaluated at the mean temperature that are either reported by the primary studies or constructed by us from the information available in these studies. The definitions of the independent variables, each of which pertain to a specific study characteristic, can be found in Table 2-1.

Table 2-3 reports our regression results based on the estimation of eq. (2.1). Column (1) reports the baseline result that is obtained from estimating eq. (2.1) with the full sample. In Columns (2)-(4), we omit studies from various regions as a sensitivity check, where Column (2) excludes China, Column (3) excludes Africa, and Column (4) excludes the United States. These three regions are the most extensively studied regions among the primary studies in our sample.

Across Columns (1)-(4), the influence of the independent variables on the *Z-value* is quite consistent in terms of the direction of influence, magnitude, and statistical significance. This implies that our meta-regression results are not overly dependent on the regional composition of the primary studies used in this meta-analysis. The independent variables explain a significant proportion of the variation in the primary estimates (as expressed by the *Z-values*). For the full sample regression in Column (1), the adjusted R^2 of 56.28% indicates that the independent variables account for 56.28% of the variation in the primary estimates. For the sub-sample regressions across Columns (2)-(4), the adjusted R^2 ranges from 46% to 60.34%.

Table 2-3: The influence of primary study characteristics on the inconsistency of the estimated effects of warming

Independent variable	(1) Full Model	(2) Exclude China	(3) Exclude Africa	(4) Exclude the United States
Regional differences				
Latitude (Degree)	0.03***	0.03***	0.02***	0.02***
	(0.00)	(0.00)	(0.01)	(0.00)
Model specification				
Measures of output (1 = Profits , 0 = Quantity)	0.29*	0.25	0.60**	0.24
	(0.15)	(0.16)	(0.28)	(0.18)
Temperature measures (1 = Yearly, 0 = Growing season)	0.38***	0.39***	0.34***	0.47***
	(0.10)	(0.11)	(0.12)	(0.13)
Control for irrigation (1 = Yes, 0 = No)	-0.15	-0.13	-0.22	-0.13
	(0.16)	(0.19)	(0.18)	(0.26)
Publication bias				
Research time (Year)	0.03**	0.03**	0.03**	0.02
	(0.01)	(0.01)	(0.01)	(0.02)
Publication status (1 = Yes, 0 = No)	-0.80***	-0.91***	-0.75***	-0.63***
	(0.10)	(0.12)	(0.12)	(0.13)
Including adaptation				
Adaptation (1=Hedonic approach, 0=others)	0.46***	0.60***	0.74***	0.47***
	(0.15)	(0.17)	(0.22)	(0.17)
Biological differences				
Maize (1 = Yes, 0 = No)	0.58***	0.61***	0.50**	0.60***
	(0.15)	(0.19)	(0.23)	(0.20)
Soybean (1 = Yes, 0 = No)	0.97***	1.03***	0.86***	1.11***
	(0.19)	(0.23)	(0.26)	(0.25)
Rice (1 = Yes, 0 = No)	0.72***	0.90***	0.56**	0.66***
	(0.18)	(0.26)	(0.24)	(0.23)
Wheat (1 = Yes, 0 = No)	0.17	0.49**	0.03	0.14
	(0.17)	(0.21)	(0.24)	(0.21)
Constant	-59.10**	-59.80**	-71.26**	-39.11
	(25.89)	(28.53)	(29.26)	(34.90)
Observations	341	270	251	265
Adjusted R^2	56.28%	60.34%	50.26%	46.00%

Notes: The Huber-White heteroskedastic-consistent standard errors are reported in parentheses. Significance levels are *** p<0.01, ** p<0.05, * p<0.1. The definition of moderator variable is in Table 2-1.

From Table 2-3, we can gather some insights into why the estimated marginal effects of warming may vary across studies. The first major source of the disagreement among these studies comes from differences in where the primary studies are based on. For example, across the four regressions presented in Table 2-3, the coefficients on *latitude* are all positive and statistically significant, which imply that studies based on higher latitude regions are more likely to report positive effects of warming than studies based on lower latitude regions. This result is quite intuitive considering that the temperature in the low latitudes is much higher than that in the high latitudes and that the productivity response of crops to temperature is first increasing and then decreasing with temperature (Mendelsohn, Nordhaus, and Shaw 1994, Schlenker and Roberts 2009).

The second major source of the disagreement comes from differences in model specifications. For example, the positive and statistically significant coefficient on *temperature measure* (which is a dummy variable) in the meta-regression implies that primary studies using yearly temperature measures are more likely to report positive effects of warming than studies using growing season temperature measures. As discussed, the yearly temperature rather than the growing season temperature would be a more appropriate measure of temperature in view of adaptations, as farmers could switch to a growing season that differs from the one assumed in the growing season temperature measure (Kurukulasuriya and Mendelsohn 2008).

The third major source of the disagreement comes from publication bias. The coefficient on *publication status* in the meta-regression is negative and statistically significant, which implies that research that reported negative effects of warming were more likely to be published in books or journals. The positive coefficient on *research time* also suggests that studies belonging to a more recent vintage reported positive effects more frequently than earlier studies did. If these recent studies (which reported positive effects) were carried out with improved methodologies, the finding that they are less likely to be published than studies reporting negative effects suggests that publication bias is likely to be present. This bias is further supported when we run a meta-regression using only the sample of studies after 2010, which controls for vintage, and find that the coefficient for *publication status* is still negative and statistically significant.[11]

The forth major source of the disagreement comes from whether or not adaptation is captured in the paper's econometric design. In reality, farmers are likely to take adaptation measures to moderate any negative effect of climate change or to even exploit any beneficial opportunity that arise from warming. As such, econometric analyses that omit the adaptation by farmers could overestimate the damages or underestimate the benefits of warming. This argument is supported by the positive and statistically significant coefficient on *adaptation*, which suggests that the primary studies that take adaptation into account (i.e. through the hedonic modelling approach) tend to report *Z-values* that are either less negative or more positive than the *Z-values* from studies that do not.

Finally, the primary studies may disagree on what the effect of warming might be if they focus on different crops, which may respond to warming differently. As shown under the "Biological Differences" category, the statistically significant coefficients on the dummies for *maize*, *soybean*, and *rice* but not *wheat* imply that the response to warming may vary across crops.

For our sensitivity analysis, we examine if our full sample baseline meta-regression result (see Column (1) of Table 2-3) could be attributed to specific subsamples. In Column (1a) of Table 2-4, we restrict our sample to the set of primary estimates that considered the response of agricultural production as a whole, which is measured by agricultural profits or farmland values. By contrast, in Column (1b), we consider the subsample of primary estimates that focused only

[11] The result is available upon request.

on the response from the four major crops but not from agricultural production as a whole. In Columns (2a) and (2b), we consider the subsample of primary estimates that measure agricultural outputs based on quantities (Column 2a) or on profits and farmland values (Column 2b). In Columns (3a) and (3b), we consider the subsample of published primary studies (Column 3a) or unpublished primary studies (Column 3b). In Columns (4a) and (4b), we consider the subsample that uses the hedonic approach (Column 4a) or other non-hedonic approaches (Columns 4b).

Across the eight meta-regressions in Table 2-4 (Columns 1a-4b), we find very similar conclusions about what the key drivers of the disagreement among the primary studies are. Just as in Table 2-3, we find that all the coefficients on *latitude* and *temperature measures* across Columns (1a)-(4b) in Table 2-4 are positive and statistically significant. The coefficients on *publication status* are positive and statistically significant for most of the subsample meta-regressions; the only exception is with the subsample of studies employing the hedonic approach (Column 4a), where *publication status* is statistically insignificant. In our view, one possible explanation for why hedonic-based studies are not influenced by publication bias is because they have a good argument for the positive effects of warming (i.e., adaptations will help to offset the negative effects).

Table 2-4: The influence of primary study characteristics on the inconsistency of the estimated effects of warming (sub-group regressions)

Independent variable	(1a) All agricultural products	(1b) Four major crops	(2a) Quantity of output	(2b) Profits and farmland values
Regional differences				
Latitude (Degree)	0.01*	0.03***	0.01*	0.03***
	(0.01)	(0.00)	(0.00)	(0.00)
Model specification				
Measures of output (1 = Profits , 0 = Quantity)	0.47	0.40*	-	-
	(0.33)	(0.23)		
Temperature measures (1 = Yearly, 0 = Growing season)	0.89***	0.29**	0.43***	0.29**
	(0.22)	(0.12)	(0.15)	(0.12)
Control for irrigation (1 = Yes, 0 = No)	-0.41	-0.11	-0.12	-0.17
	(0.26)	(0.22)	(0.24)	(0.18)
Publication bias				
Research time (Year)	0.01	0.03*	0.09***	0.02
	(0.04)	(0.02)	(0.03)	(0.02)
Publication status (1 = Yes, 0 = No)	-1.09***	-0.74***	-0.75***	-0.81***
	(0.29)	(0.12)	(0.18)	(0.12)
Including adaptation				
Adaptation (1=Hedonic approach, 0=others)	0.53**	0.70***	1.00***	0.26
	(0.21)	(0.25)	(0.14)	(0.24)
Biological differences				
Maize (1 = Yes, 0 = No)	-	-0.35**	0.26**	0.51**
		(0.15)	(0.13)	(0.23)
Soybean (1 = Yes, 0 = No)	-	-0.21	0.19	0.68***
		(0.19)	(0.84)	(0.23)
Rice (1 = Yes, 0 = No)	-	-0.83***	-0.71*	0.10
		(0.17)	(0.37)	(0.23)
Wheat (1 = Yes, 0 = No)	-	-	0.29	0.85***
			(0.58)	(0.26)
Constant	-25.41	-58.71*	-190.32***	-36.81
	(74.91)	(31.71)	(57.39)	(31.96)
Observations	152	189	145	196
Adjusted R^2	61.04%	47.60%	88.66%	49.51%

Notes: The Huber-White heteroskedastic-consistent standard errors are reported in parentheses. Significance levels are *** p<0.01, ** p<0.05, * p<0.1. The definition of moderator variable is in Table 2-1.

Table 2-4 (continue): The influence of primary study characteristics on the inconsistency of the estimated effects of warming (sub-group regressions)

Independent variable	(3a) Published	(3b) Unpublished	(4a) Hedonic approach	(4b) Other approaches
Regional differences				
Latitude (Degree)	0.02***	0.04***	0.02***	0.03***
	(0.01)	(0.01)	(0.01)	(0.00)
Model specification				
Measures of output	0.23	0.67**	0.52	0.51***
(1 = Profits , 0 = Quantity)	(0.19)	(0.31)	(0.34)	(0.19)
Temperature measures (1 = Yearly, 0 = Growing season)	0.49***	0.40***	0.96***	0.31***
	(0.14)	(0.14)	(0.28)	(0.11)
Control for irrigation	0.03	-0.47**	-0.00	-0.41**
(1 = Yes, 0 = No)	(0.26)	(0.18)	(0.41)	(0.18)
Publication bias				
Research time	0.03**	0.03	-0.01	0.05***
(Year)	(0.02)	(0.03)	(0.04)	(0.02)
Publication status	-	-	-0.79	-0.81***
(1 = Yes, 0 = No)			(0.56)	(0.11)
Including adaptation				
Adaptation	0.63***	0.02	-	-
(1=Hedonic approach, 0=others)	(0.21)	(0.27)		
Biological differences				
Maize	0.54**	0.26	0.57	0.36**
(1 = Yes, 0 = No)	(0.21)	(0.30)	(0.49)	(0.18)
Soybean	1.27***	0.38	0.47	0.68***
(1 = Yes, 0 = No)	(0.30)	(0.32)	(0.79)	(0.22)
Rice	0.93***	-0.61	1.24	0.47**
(1 = Yes, 0 = No)	(0.23)	(0.51)	(0.90)	(0.21)
Wheat	0.55**	-0.66**	-0.09	-0.13
(1 = Yes, 0 = No)	(0.22)	(0.33)	(0.46)	(0.21)
Constant	-64.77**	-55.22	28.93	-101.20***
	(30.85)	(55.02)	(80.18)	(31.72)
Observations	235	106	148	193
Adjusted R^2	41.80%	64.19%	60.02%	57.27%

Notes: The Huber-White heteroskedastic-consistent standard errors are reported in parentheses. Significance levels are *** p<0.01, ** p<0.05, * p<0.1. The definition of moderator variable is in Table 2-1.

Besides *publication status*, the coefficients on *adaptation* are generally positive and statistically significant, except in Columns (2b) and (3b) where the estimates are statistically insignificant. With respect to the statistical insignificance of *adaptation* in Column (2b), the intuition is that studies based on farmland values rely mainly on the hedonic approach.[12] Given that the hedonic approach already takes into account of adaptation, it may not be surprising that the coefficient on *adaptation* is statistically insignificant in this instance. With respect to Column (3b), which looks at the subsample of unpublished papers, the statistical insignificance of *adaptation* suggests that the disagreement among the unpublished studies is not attributed to whether or not adaptation is captured.

The various meta-regressions suggest that a large share of the disagreement among the primary studies can be explained by differences in the latitudes which the studies are based on, the measure of temperature (a yearly temperature versus a growing season temperature), the modelling approach (hedonic versus other approaches), and publication bias. Therefore, as an exercise, we investigate to what extent the dispersion in the primary estimates can be reduced if the characteristics of the primary studies are fixed according to latitudes, temperature measure and the modelling approach. Because of the large permutation of these characteristics, we fix the temperature measure to yearly temperature, the modelling approach to the hedonic approach, but allow the latitudes to vary. The motivation of choosing the yearly temperature measure rather than the growing season temperature measure is to accommodate potential adaptations of switching growing season in response to warming (Kurukulasuriya and Mendelsohn 2008). In

[12] Most of the hedonic studies use farmland values or agricultural profits as the dependent variable, but there are also some hedonic studies using the profits of a specific major crop as the dependent variable.

addition, the hedonic approach is better than other econometric approaches in incorporating adaptations as discussed (Seo 2013).

For variations in latitudes, we again sort the studies into five latitude quintile groups: low latitudes, low middle latitudes, middle latitudes, upper-middle latitudes, and high latitudes. Compared with Figure 2-2 where the study characteristics are not fixed, Figure 2-7 shows that the primary estimates from studies within the same latitudes will have less dispersion if they all employ the yearly temperature measure and the hedonic approach. Interestingly, if we condition our studies on having these two characteristics, we will observe the conclusion that global warming mainly has positive effects on agriculture in the high latitudes and negative effects in the low latitudes. This is the same conclusion made by several meta-analyses on the simulation-based studies on climate change (Rosenzweig and Parry 1994, Challinor et al. 2014). As a caveat, what this exercise shows is that primary studies that use measures of yearly temperature and the hedonic approach will tend to agree with each other, conditioning on the latitudes that they are based on. This exercise does not suggest that studies with these two characteristics are more reliable than those without them.

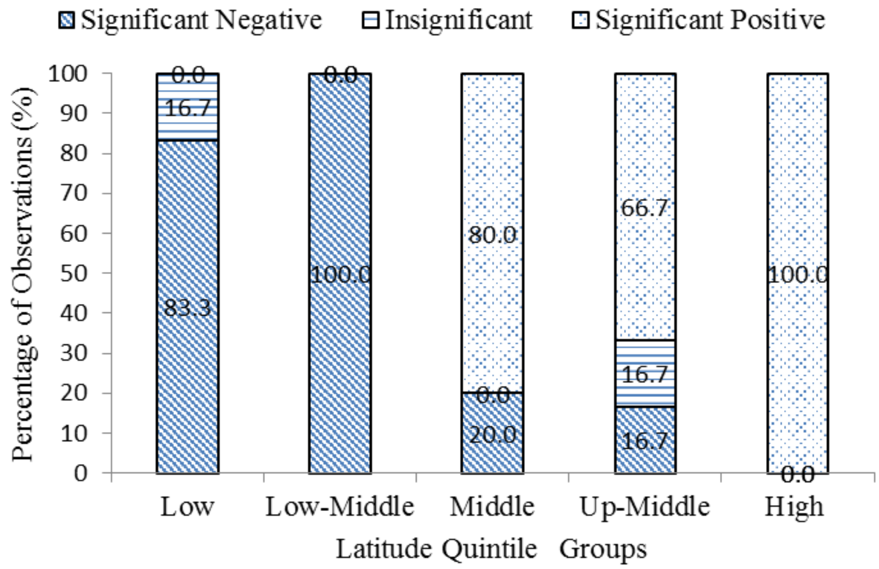

Figure 2-7: Distributions of the effects of warming within each latitude quintile group for hedonic studies that use yearly temperature measures

Note: This figure shows the percentage of observations reporting (i) positive and significant effects of warming, (ii) insignificant effects, (iii) negative and significant effects (all at the 10% significance level) for each of the five sample latitude quintile groups. The *Low* quintile group contains the first 20% of observations nearest to the equator, the *Low-Middle* quintile group contains the next 20% of observations nearest to the equator, and so on.

2.5. Conclusion

Having a good understanding of the relationship between global warming and agricultural production can help policy makers to better anticipate issues concerning food security. However, although there is a growing econometric based literature on this topic, there is also much disagreement on what the effect of warming is, in particular, whether it is positive or negative, or if there is an effect at all.

Employing a meta-analysis, this article identifies some potential sources of disagreement among 130 primary studies. Our meta-regression results suggest that differences in the latitude of the study sample, the temperature measure that was used, the econometric approach that was implemented, and publication bias can explain why the primary estimates differ. We also find that if the primary studies use the yearly temperature measure and adopt the hedonic modelling approach, their estimates will have less dispersion and will tend to concur with the prediction from the simulation-based literature that warming will lead to positive effects on agriculture in the high latitudes but damages in the low latitudes.

2.6. Appendix: primary studies included in the meta-analysis

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Chapter 3 : How Large is the Potential Economic Benefit of Agricultural Adaptation to Climate Change? Evidence from the United States

Abstract

Understanding how much adaptation is likely to occur is central to any study of the impact of climate change on agriculture and is also of paramount importance from the policy perspective. However, an effective approach for evaluating the benefits of potential adaptations has not been developed. This chapter develops a panel framework to estimate the potential value of adaptation. When tested with data from the United States, this study finds that the negative impact of expected climate change on farm profits by the year 2100 is only one-third as large once the possibility of adaptation by farmers is taken into account in the climate change impact estimate. (JEL Q15, Q51, Q54)

Key words: Climate change impact, agriculture, adaptation

3.1. Introduction

The fact that farmers can adapt to climate change by making adjustments to their agricultural practices makes it extremely hard for an econometrician to estimate the true impact that climate change might have on agriculture. By missing out on such adaptive responses an econometric study may substantially overstate the true damage of climate change and policy recommendations based on it may be more aggressive than necessary. Since Mendelsohn et al. (1994), significant progress has been made on the methodology of estimating the impact of climate change that accounts for adaptation (Schlenker, Hanemann, and Fisher 2005, 2006, Kurukulasuriya and Mendelsohn 2008, Massetti and Mendelsohn 2011), but yet, not much is known if adaptation has a large or small mitigating influence on the damage of climate change.

Having a good estimate of what the potential value of adaptation is would be useful from a policy perspective, especially for informing governments about the benefits of adaptation before they intervene in helping farmers to adapt. Adaptation is not often costly, and some measures may require large amounts of investments that farmers could not afford. For example, warming may encourage a maize producing farmer to switch land use to citrus production, as it is more profitable to produce citrus than maize in hot areas. However, this switching may involve large amount of investments including fixed investments such as the years forgone while waiting for a sapling to mature into a productive citrus tree (usually takes 5 years) and ongoing investments in specific pesticide sprayers and warehouse for citrus. If financial markets are not available for a farmer to borrow from, these investment costs may hinder the farmer's ability to adapt. As such, having estimates on the value of adaptation would be useful, as governments may be willing to support the farmers in dealing with the cost of adaptation if they know that the benefits of adaptation are large. Even if the cost of adaptation is low, which is the case if farmers adopt the witching growth season of crops, such estimates on the value of adaptation can also help governments to decide on whether to pursue a policy of influencing farmers' perception about climate change, as adaptation will not take place unless farmers' recognize that a change in the weather pattern actually reflects a change in the climate, which is a difficult thing for them to do.

Currently, the estimates of agricultural adaptation to climate change in the literature comes mainly from micro-level, multinomial model studies that focus on the benefits of adaptation accruing to specific adaptation measures. For example, Kurukulasuriya and Mendelsohn (2008) have found that crop-switching can help Africa farmers reduce the damage by 98 USD per hectare per year under a Canadian Climate Centre (CCC) climate scenario by the year of 2100. Seo and Mendelsohn (2008) have found that Africa farmers can benefit from switching among different kinds of livestock when adapting to warming; for example, they have found that the net revenue from each beef cattle will drop by 78.8 USD while that from each goat will increase by 2.4 USD by the year of 2060 under a CCC climate scenario. Falco and Veronesi (2013) have shown that adaptation by adopting water and soil conservation behaviors can also help to reduce damages of climate change on crop profits.

However, because numerous adaptation measures can potentially be applied by farmers, it is not feasible to estimate the total benefits of adaptation by first estimating the benefits accruing to each possible adaptation measure, and then aggregating these benefits up across all measures. For example, as an adaptive response, farmers can shift growing season, adjust production inputs such as water, fertilizers, pesticide, and labor, adopt a heat tolerant variety of the same crop, switch land use between wheat, maize, soybean, rice, and dozens of other crops, change land use from crop production to grazing, orchards, forestry, and many other uses. More importantly, farmers can implement these measures in isolation or in combination, and as such, the value of adaptation associated with a particular method may be omitted or double counted.

Hence, even though the micro-level adaptation studies have dramatically improved our understanding about the potential value of adaptation in agricultural practices to climate change, little is known about the size of the overall benefits accruing to the full range of adaptation methods that farmers can adopt when confronted with climate change.

Building upon a number of insights from the literature, we propose a simple approach to estimate the total benefit of agricultural adaptation to climate change. In principle, this can be achieved by obtaining two climate change impact estimates – one that takes adaptation into account and another that reflects the impact of climate change in the absence of any adaptive behavior – and then compare the difference between these estimates. However, the problem in doing so is that the econometric models that generate these estimates may differ quite significantly in model specification and the data type (e.g. cross-sectional versus panel data) that is used. As such, because comparing these econometric models is like "comparing apples and oranges", the difference between their climate change impact estimates may reflect not only the value of adaptation but also differences between features about the models themselves. A similar concern has also been articulated by Hanemann (2000), who argues that the value of adaptation cannot be measured by comparing the climate change impact estimate from the cross-sectional hedonic model of Mendelsohn, Nordhaus, and Shaw (1994), which incorporates the benefits accruing to the full range of adaptation measures, with the impact estimate from the production-function model of Adams (1989), which omits the benefits of adaptation completely, as these models differ in specification, model assumptions, and the type of data that they are based upon.

This "apples and oranges" issue in estimating the value of adaptation is a challenging problem. It is our view that this problem cannot be eliminated completely, as this would entail using an identical model (so as to compare "apples with apples") to generate a climate change impact estimate that takes the benefits of adaptation into account and another that does not, which is an infeasible thing to do. Instead, the best we can do is to use two nearly identical models, differing only in one aspect that determines whether or not the estimated climate change impact would have taken adaptation into account.

In this chapter, we propose an approach that identifies the value of adaptation by comparing the impact estimates from two panel models, where these models are the same except for the specification of the fixed effects that these models used. Specifically, our first panel model is constructed to include the time fixed effect only, so that the impact of climate change estimated from this model will include the benefits of adaptation. As Fisher et al. (2012) have observed, the magnitudes of inter-annual weather fluctuations for a given year are almost the same across regions. Therefore, by including the time fixed effect into this model, we will be able to purge most of the inter-annual weather fluctuations, leaving the cross-sectional climate differences as the remaining weather variation to be used for estimating the climate change impact. Furthermore, based on the insights from the hedonic approach of Mendelsohn, Nordhaus, and Shaw (1994), the impact of climate change identified through cross-sectional climate differences (which captures long-run climate differences) would include the benefits of adaptation as it is reasonable to assume that in the long run, farmers should have fully adapted to the climate of their regions. The underlying reason is that if a region's climate becomes similar to another region's due to climate change, we would expect farmers in the former to eventually to adopt farming methods as now practiced by farmers in the latter.

Our second model is the same as the first except that it includes only the county fixed effect (as we use county-level climate data), as opposed to the first model that includes only the time fixed effect. In doing so, our second model enables us to estimate what the impact of climate change might be in the absence of adaptation. Intuitively, the county fixed effect will eliminate all (long-run) cross-sectional inter-county climate differences, so that what remains in the weather variation will come from the inter-annual weather fluctuations. The impact of climate change identified through inter-annual weather fluctuations will reflect the impact in the absence of adaptation, since farmers can only implement limited *ex-post* adjustments in response to random year-to-year weather fluctuations, and such short-run responses are not viewed as long-run adaptation to climate change by the literature (Massetti and Mendelsohn 2011, Seo 2013, Moore and Lobell 2014).[13]

With the climate change impact estimates obtained from these two panel models, we may uncover the value of adaptation by taking the difference between the impact estimate from the first panel model (which incorporates adaptation) and that from the second panel model (which does not). We combine this approach with a panel of US county-level agricultural production and climate data and various climate change projections. Our results show that when taking into account of adaptation, climate change (under the *RCP4.5* climate change scenario) could cause the end-of-this-century agricultural profits per year to be 9% less than the current agricultural profits per year, or 3.18 billion dollars less per year in profits at the end of the century than what we currently observe (at 2012 constant values). If there are no adaptations, climate change could cause the end-of-this-century agricultural profits per year to be lower by 30%, or 10.56 billion dollars less per year, instead. Therefore, adaptation by farmers can help to offset about two-

[13] We admit that there are also some *ex-post* adjustments can be taken by farmers in response to inter-annual weather fluctuations, such as change the using of labour, fertilizers, and pesticides. Some household-level studies explain these short-run responses as adaptation. However, it worth to notice that these short-run responses can be made with or without climate change, which is a long-run phenomenon. Therefore, when we estimate the benefits of adaptation to long-run climate change, we prefer to exclude the benefits of the response to inter-annual weather fluctuation.

thirds of the potential overall damage from climate change when adaptation is absent. This conclusion is robust across a number of robustness checks that consider the implications of model specification, omitted variable bias, the influence of inventory and storage, and alternative climate change scenarios on the impact estimates.

It is worth pointing out that the benefits of adaptation estimated in this chapter are likely to be a lower bound and the actual benefits of adaptation could be larger than what we have estimated. Our first panel model identifies climate change impact through cross-sectional climate differences. This enables us to estimate the impact of climate change that incorporates the benefits of all *existing* adaptation methods, but not *future* adaptation methods that are possibly more effective in mitigating the effects of climate change. Therefore, our estimates of the value of adaptation are likely to reflect a lower bound, which suggests that adaptation could potentially help to reduce more than two-thirds of the damage caused by climate change in the absence of adaptation.

Our study makes the following contributions. Firstly, it proposes a new approach to estimate the value of adaptation by the amount of the damage by climate change that adaptation can help to mitigate. Hence, it complements the literature that focuses on adaptation and most notably, Burke and Emerick (2016), who have looked at estimating the economic benefit of adaptation to recent climate trends by comparing the estimated damages from a model that identifies the impact of climate change through recent climate trends and another model that does so through inter-annual weather fluctuations. Burke and Emerick (2016) have found that the difference in the climate change impact estimates from these two models is statistically insignificant. This can be reconciled by the fact that farmers usually have difficulty in recognizing the real changes in climate trends and thus adapt to them.[14] Given that farmers may not fully adapt to climate trends, the Burke and Emerick (2016) approach of estimating the value of adaptation based on the adaptation to climate trends may not be able to capture the value of long-run adaptation completely, which is what we hope to study in this chapter.

Our study related to the body of micro-level studies that attempt to estimate the value of adopting certain methods of adapting to climate change. In this literature, the focus is mainly on estimating the potential benefit that specific adaptation methods have (See, for example, Kurukulasuriya and Mendelsohn 2008, Seo and Mendelsohn 2008, Wang et al. 2010, Di Falco, Veronesi, and Yesuf 2011, Falco and Veronesi 2013), but not the potential benefit of accruing to adaptation which is the focus of this chapter. These studies are important for providing us with detailed knowledge about the benefits of specific adaptation methods and our study complements them by taking a more macro perspective on the issue of adaptation.

Our study also related to the literature that is interested in estimating the impact of climate change that accounts for adaptation (see, for example, Mendelsohn, Nordhaus, and Shaw 1994, Schlenker, Hanemann, and Fisher 2005, 2006, Kurukulasuriya and Mendelsohn 2008, Massetti and Mendelsohn 2011). The conclusion of this chapter that the impact of climate change on agricultural profits would be mild if adaptations are taken into account is consistent with previous studies that include adaptations. The differences is that the main focus of this chapter

[14] Farmers may not fully recognize and adapt to trends in the climate because climate trends are accompanied by large inter-annual weather fluctuations which obscure farmers' recognition of the trends. In the Appendix C, a Bayesian learning process shows that, ten years after a once-and-for-all mean temperature rise, only about 40 percent of the change is recognized by farmers (i.e. farmers on average under-estimate the change in the temperature).

is to identify the benefits of adaptation instead of estimating the damages of climate change on agricultural profits.

This chapter proceeds as follows. Section 3.2 explains the methodology and the data source that we use. Section 3.3 presents the estimation results. Section 3.4 presents further results related to several robustness checks. Section 3.5 concludes. Section 3.6 is the appendix of this chapter.

3.2. Methodology and Data

We propose a panel data approach to estimate the economic benefits that may accrue to agricultural adaptation in response to climate change. To illustrate how such benefits can be captured in our framework, let us focus on the weather outcome (w_{it}) of county i in year t. First, notice that w_{it} can be decomposed into three components:

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

where T_i is the climate (i.e., long-term average weather outcome) of county i that varies across counties; d_t represents the inter-annual weather fluctuation in year t that is common across counties but varies across years; and ε_{it} is the county-specific weather shock.[15]

This panel framework depends on a key fact emphasized by Fisher et al. (2012) that the size of the inter-annual weather fluctuation is generally the same across regions in a given year.

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

Because the inter-annual weather fluctuation consists of two components - the common component d_t and the idiosyncratic component ε_{it} - the observation of Fisher et al. (2012) implies that the inter-annual weather fluctuation would be driven mostly by the common weather component (d_t), which in turn suggests that the county-specific weather shock (ε_{it}) would be very small. Consequently, the decomposition of w_{it} can be approximated by

$$w_{it} \approx T_i + d_t \tag{3.1}$$

Recall that to estimate the value of adaptation, we need a climate change impact estimate that takes adaptation into account and another that does not. However, because these estimates come from two different models, the difference between them may reflect not only the value of adaptation itself, but also the fact that the models are different. To deal with the latter the best we can, we need two nearly identical models in which the only difference between them is the difference that will determine whether or not the climate change impact estimate would incorporate the benefits of adaptation. In our approach, we employ two nearly identical panel data models where the only difference between them lies in the component of the weather variation w_{it} in Eq. (3.1) (i.e. T_i or d_t) that each model uses when estimating the climate change impact, Since these components can be extracted from w_{it} by using the appropriate fixed effect, the two panel models will be identical in every aspect except for the type of fixed effects that they used.

Specifically, our first panel model contains the time fixed effect. This eliminates the inter-annual weather fluctuation caused by d_t, so that what is left after purging d_t from the weather outcome variable would be the long-run climate (T_i). Hence, in estimating the impact of climate change using the variation in T_i, which is generated by the cross-sectional inter-county climate differences, the impact estimate will capture the effect of adaptation to climate change in the long run. Intuitively, if climate change causes county *i*'s climate to become what we observe for county *j* now, we would expect farmers in county *i* to eventually adopt the farming practices adopted by farmers presently in county *j*. Therefore, as farmers are fully adapted to the climate of their regions, the impact of climate change on agriculture identified through cross-sectional regional differences in the climate would be capturing the mitigating effect from adaptation as well (Mendelsohn, Nordhaus, and Shaw 1994).

The second panel model contains the county fixed effect, which eliminates the long-run climate component (T_i). The remaining variation in the weather outcome that is used for identifying the impact of climate change would then be drawn from the inter-annual weather fluctuation (d_t). However, as discussed, farmers can only make limited *ex-post* adjustments in response to random year-to-year weather fluctuations and this short-run response is not a true reflection of adaptation to climate change (Massetti and Mendelsohn 2011, Seo 2013). As such, in a panel model with county fixed effects, which identifies the impact of climate change through inter-annual weather fluctuations, its estimated impact will reflect the impact of climate change in the absence of any long-run adaptive response.

Therefore, to estimate the potential value of adaptation to climate change, we may compare the climate change impact estimate of the first "time fixed effect" panel model, which incorporates the effects of adaptation, with that of the second "county fixed effect" panel model, which does not. These two models are the same in every aspect except that they use a different component in the weather outcome to identify the impact of climate change.

Before moving on to the discussion on the econometric models and dataset, we provide some empirical evidence to show that the county-specific weather shock (ε_{it}) is extremely small, especially relative to the cross-sectional climate variation and inter-annual weather fluctuations that are used by the first and second panel models for the climate change impact estimate. To do so, let us take a panel of county-level temperature and precipitation data during 1987-2012 for 2155 US counties as an example.

Table 3-1: Climatic variations after using different fixed effects

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

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

Row A1 of Table 3-1 shows the temperature variation that pertains to the county-specific weather shock (ε_{it}), which is the temperature variation after using state-by-year fixed effects to eliminate the inter-annual common weather fluctuations (d_t) and using county fixed to eliminate the inter-county climate differences (T_i).[16] This variation can be derived by first

[16] 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

subtracting state-by-year mean and then subtracting the remaining county mean from each observation (see Panel D of Table 3-5 in the Appendix A for an illustration). As Row (A1) of Table 3-1 shows, the variation pertaining to ε_{it} is extremely small: there are no counties with an absolute value of ε_{it} that is larger than 1°C, while only 4.8% of counties have an absolute value of ε_{it} that is larger than 0.4°C.

By contrast, there is a much wider range in the temperature component pertaining to T_i, which is obtained as the residual temperature after the state-by-year fixed effect has partialled out the common fluctuation (d_t) from temperature itself. As shown in Row (A2) of Table 3-1, the variation pertains to T_i (see Panel B of Table 3-5 in the Appendix A), which is the long run temperature of county *i*, exceeds 1°C for 29.2% of counties and 0.4°C for 68.5% of counties. Similarly, the variation pertaining to the within-county inter-annual temperature fluctuation d_t (see Panel C of Table 3-5 in the Appendix A), which can be obtained after purging out T_i from temperature using the county fixed effect, also has a much wider range of values relative to what is seen for the county-specific weather shock (ε_{it}). As shown in Row (A3) of Table 3-1, 34.6% of counties have an absolute value of inter-annual fluctuation that exceeds 1°C of its county mean, whereas none of the counties have a county-specific weather shock with that size.[17]

We also test the variation of precipitation after using different fixed effects and present the result in Panel B of Table 3-1. Similar results are found for precipitations: the variation pertains

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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.

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

to ε_{it} is quite small, while the variations pertaining to T_i and d_t are much larger. Furthermore, similar results are found when we replace the growing season average temperature by other temperature measures such as yearly mean temperature and growing season Degree-day (not reported here). All these tests support the fact that the county-specific component in each of these climatic variables is extremely small relative to the long-run cross-sectional component and the common inter-annual fluctuation associated with these variables.

A. Econometric approach

The first panel model, where the coefficients on the climatic variables are estimated by exploiting the cross-sectional climate variation, is shown in Eq. (3.2):

$$y_{it} = \rho \sum\nolimits_{j=1}^{n} w_{ij} y_{jt} + \sum\nolimits_{k=1}^{K} c_{itk}\alpha_k + \sum\nolimits_{g=1}^{G} l_{itg}\beta_g + \gamma_{st} + u_{it} \qquad (3.2)$$
$$i = 1,...,n;\ \ t = 1,...,T$$

where y_{it} denotes agricultural profits per acre in county i and year t; c_{it} consists of five climatic variables that include the temperature measures of growing season degree-days (GDD) and its quadratic term, the precipitation measures of growing season total precipitation (GTP) and its quadratic term, and square root of growing season harmful degree-days (GHDD), which is a measure of the extreme heat. All these climatic variables are calculated according to the commonly used method in the literature (see, for example, Schlenker, Hanemann, and Fisher 2006, Deschênes and Greenstone 2007). Detailed calculations for each variable are presented in the Appendix B.

The vector of control variable l_{it} includes ten land quality indicators; γ_{st} is the state-by-year dummy that is used to filter out year-to-year weather and other fluctuations that are common across counties within each state, and also captures all state-level determinants of agricultural profits whether or not they are observed or unobserved, time-varying or time-invariant; and u_{it} is an $i.i.d.$ distributed error term.

We model Eq. (3.2) with a spatial autoregressive structure (Anselin 1988, Elhorst 2010), where the dependent variable of county i is spatially related to that of all other counties. This spatial relationship is captured by $\sum_{j=1}^{n} w_{ij} y_{jt}$ in Eq. (3.2), where w_{ij} is a spatial-weight defined as the inverse of the distance between counties i and j, where this distance is calculated based on the coordinates of their respective centroids. By using w_{ij} as weights, the relationship between the dependent variables of counties i and j would be weaker the further apart these counties are. In Eq. (3.2), whether or not spatial dependence is relevant for determining a county's agricultural profits depends on the parameter ρ. In our study, we allow for ρ to be non-zero to let the data speak on whether spatial dependence in agricultural profits across counties exists. If ρ is zero, Eq. (3.2) becomes a standard panel regression with state-by-year fixed effects.

In the panel data literature, there has been increasing emphasis on the importance of modelling spatial dependence in the conditional mean (De Hoyos and Sarafidis 2006). In the context of climate change, there is evidence that the cross-sectional units in question are spatially related (see, for example, Schlenker, Hanemann, and Fisher 2006). For the US counties east of the 100º meridian, which is our sample, we have tested for the presence of spatial dependence using the semiparametric method of Frees (2004) and find strong evidence to reject the null hypothesis of spatial independence. Therefore, for our baseline study, we will control for spatial correlation in the regression model

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

However, if these omitted determinants responsible for the spatial dependence between counties are correlated with the climatic variables, the standard panel estimators of the climatic variable coefficients will be biased and inconsistent. In which case, the appropriate response is to include spatial lags into the model instead of adjusting for spatial correlation in the error term as has been done in this literature (Lee 2002, Lee and Yu 2010). For our study, to capture the cross-sectional dependence between counties, we model the spatial autoregressive structure in the econometric framework directly rather than accounting for spatial dependence by clustering the standard errors only. Nevertheless, in one of our robustness check (see Table 3-4 below), we find that our results are not sensitive to the omitting spatial autoregression from our model (i.e. setting $\rho = 0$) and in place of it. In particular, we find that the estimated benefit of adaptation is similar whether or not we control for spatial lags in the model or omit spatial lags but cluster the standard errors.

The second panel model, where coefficients on the climatic variables are estimated by exploiting inter-annual weather fluctuations, is shown in Eq. (3.3):

$$y_{it} = \rho \sum_{j=1}^{n} w_{ij} y_{jt} + \sum_{k=1}^{K} c_{itk} \alpha_k + \sum_{g=1}^{G} l_{itg} \beta_g + \tau_i + \theta q_t + \varepsilon_{it} \qquad (3.3)$$

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

where the descriptions for y_{it}, c_{itk}, l_{itg}, and w_{ij} in Eq. (3.2) apply here. The only difference between Eqs. (3.2) and (3.3) is in their fixed effects structure. Specifically, Eq. (3.3) includes the county fixed effect (τ_i) but not Eq. (3.2). Conversely, Eq. (3.2) includes the state-by-year fixed effect (γ_{st}) but not Eq. (3.3). In addition, Eq. (3.3) includes a time trend q_t to partial out any confounding trend effects such as technological improvements from the effect of inter-annual weather fluctuation.[18]

Eq. (3.2) includes the state-by-year fixed effect but not the county fixed effect so that its coefficients on the climatic variables will be estimated by exploiting the within-state inter-county climate differences. Therefore, the predicted climate change impact that we obtain from estimating Eq. (3.2) would have captured the benefit of adaptation. On the other hand, Eq. (3.3) includes the county fixed effect but not the state-by-year fixed effect so that its coefficients on the climatic variables will be estimated by exploiting the random year-to-year weather fluctuations. Therefore, the predicted climate change impact that we obtain by estimating Eq. (3.3) would not have taken adaptation into account.

B. Long-run benefits of adaptation

After estimating Eqs. (3.2) and (3.3), we feed into them the end-of-this-century climate projections generated by the climate models commonly considered in the literature (i.e. CCSM4,

[18] We are not seeking to control for the effect of price shocks induced by output fluctuations in Eq. (3.3), 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.

CESM1-BGC, CanESM2, and NorESM1-M)[19] to obtain the end-of-this-century impact on agricultural profits with and without adaptations respectively. The difference in the projected climate change impact from these two models would reflect the benefit of adaptation. It is worth pointing out that, as in the hedonic approach, the benefit of adaptations estimated in this manner is only a lower bound. This is because the projected impact containing the effects of adaptation can only capture the potential benefit of adaptation based on current production technologies and management methods, not future and possibly more effective innovations which is unobserved.

C. Comparison with Deschênes and Greenstone (2007)

Readers who are familiar with the literature might find the panel regression models in Eqs. (3.2) and (3.3) to be similar to the Deschênes and Greenstone (2007):

$$y_{it} = \sum_{k=1}^{K} c_{itk}\alpha_k + \sum_{g=1}^{G} l_{itg}\beta_g + \tau_i + \gamma_{st} + \sigma_{it} \qquad (3.4)$$

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

where the descriptions for y_{it}, c_{itk} and l_{itg} are the same as in Eqs. (3.2) and (3.3). If the spatial dependence coefficient ρ in Eq. (3.2) is equal to zero, the only difference between Eqs. (3.2), (3.3), and (3.4) is in their fixed effects structure. In particular, Eq. (3.2) only includes the state-by-year fixed effect (γ_{st}), and Eq. (3.3) only includes the county fixed effect (τ_i), but Eq. (3.4) includes both county and state-by-year fixed effects.

While the difference between Eqs. (3.2), (3.3), and (3.4) appears to be minor, it has significant implications on how the coefficients on the climatic variables are estimated. As

[19] See Section 3.2 for more details.

discussed, by including both the time fixed effect (i.e., state-by-year fixed effect here) and the location fixed effect (i.e., county fixed effect here), the cross-sectional climate difference and inter-annual common weather fluctuations will be eliminated from the climatic variable. Therefore, the coefficients on the climatic variables of Eq. (3.4) will be estimated using the climatic variation associated with the county-specific weather shock. However, as the county-specific weather shock is very small, the impact of climate change obtained by estimating Eq. (3.4) may not offer an accurate picture of the true extent of the impact of climate change (Fisher et al. 2012).[20]

By contrast, Eq. (3.2) only includes the state-by-year fixed effect (γ_{st}), which eliminates the inter-annual common weather fluctuations. In this case, the coefficients in Eq. (3.2) will be identified through within-state inter-county climate differences, which have substantial variation (see Row A2 of Table 3-1). In addition, unlike Eq. (4), Eq. (3.3) only includes the county fixed effect (τ_i) to eliminate the cross-sectional climate difference. Therefore the coefficients of Eq. (3.3) will be identified mainly through inter-annual common weather fluctuations generated by common weather shocks, which again have substantial variation (see Row A3 of Table 3-1).

D. Data

This study makes use of a panel data on county-level agricultural production, climate and other socio-economic and geophysical data for 2155 US counties east of the 100° meridian drawn

[20] According to the IPCC Fifth Assessment Report (2014), the lower bound of the best prediction of mean temperature increase is 1.0 ºC. However, as shown in Row A1 of Table 1, no temperature variation pertains to ε_{it} exceed 1.0ºC.

from various sources. Below, we will provide a brief summary of the variables used in this study. Detailed information on the data source, data processing, and summary statistics are presented in the Appendix B.

Agricultural profits and farmland value: we follow the literature to construct US county-level agricultural profits per acre from *Census of Agriculture* for the census years of 1982, 1987, 1992, 1997, 2002, 2007, and 2012. Agricultural profits are used as the dependent variable of the panel models expressed by Eqs. (3.2) and (3.3). As a robustness check, we also derive farmland value data from *Census of Agriculture* and used it as the dependent variable in Eq. (3.2).

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

Climate change predictions: we use the latest high resolution climate predictions from General Circulation Model (*GCM*) runs conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Taylor, Stouffer, and Meehl 2012). We mainly use the climate projection for the medium scenario RCP4.5 from four of the most widely used CMIP5 models: *CCSM4*, *CESM1-BGC*, *CanESM2*, and *NorESM1-M*. Each model provides daily maximum temperature, minimum temperature and precipitation under various scenarios for the periods from 2006 to 2100. As a robustness check, we also use climate projection for the highest scenario RCP8.5 from these four CMIP5 models. The climate projection data is used to calculate the state-level changes in climatic variables (see Appendix B for the details of the calculation).

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

3.3. Empirical Results

In this section, we will first estimate Eqs. (3.2) and (3.3), and in particular, focus on the effect that the five climatic variables might have on agricultural profits. We then plug into the estimated versions of Eqs. (3.2) and (3.3), the projections of climate change from the four climate models to obtain predictions for the end-of-this-century impact of climate change with and without adaptations. The benefits of adaptation can then be calculated as the difference in the end-of-this-century impacts predicted by Eqs. (3.2) and (3.3). To simplify our discussion, we will refer to Eq. (3.2) as the *adaptation model* and Eq. (3.3) as the *non-adaptation model* interchangeably.[21]

[21] Eqs. (3.2) and (3.3) are estimated using the maximum likelihood estimation routine of (Belotti, Hughes, and Mortari 2014).

A. Baseline model estimates

The estimated coefficients of the climatic variables in Eq. (3.2) and (3.3) are reported in Columns 1a and 1b of Table 3-2, respectively.[22] For both models, we find that the responses of agricultural profits to *GDD* and *GTP* are hump-shaped. In addition, the effect of the square root of *GHDD* is negative. These estimates concur with what the literature has presented (Schlenker, Hanemann, and Fisher 2006) and offer some evidence that the qualitative relationship between agricultural profits and the climatic variables does not depend on whether adaptation is accounted for.

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

Table 3-2 : Regression results of the effects of climatic variables on agricultural profits and farmland values

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

Notes: This table shows the estimated coefficients of the climatic variables in Eq. (3.2) and (2). Columns 1a and 1b report estimates from model (1) with agricultural profits as the dependent variable; column 2a and 2b report estimates from model (3)with agricultural profits as the dependent variable; columns 3a and 3b report estimates from a variation of model (1) that use the farmland value as the dependent variable. The only difference between the "a" and "b" versions of the model is that version "b" excludes the soil controls. The Huber-White heteroskedastic consistent standard errors are reported in parentheses.

However, quantitatively, there is a significant difference in the estimated coefficients across Eqs. (3.2) and (3.3), which is due to the fact that Eq. (3.2) accounts for adaptations but not Eq. (3.3). For example, from the estimates of the coefficients in Eqs. (3.2) and (3.3), the optimal

GDD that maximizes agricultural profits is found to be 2294 degree-days for the adaptation model (i.e. Eq. (3.2)) but 2121 degree-days for the non-adaptation model (i.e. Eq. (3.2)). This suggests that with adaptation, agricultural production would become more heat tolerant on average. Similarly, the optimal *GTP* associated with the adaptation model is higher than that associated with the non-adaptation model, and the negative effect of *GHDD* is weaker in the adaptation model than that in non-adaptation model.

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

Figure 3-1 presents the predicted end-of-this-century impact of climate change on agricultural profits with adaptation (green hollow-circle) and without (red circle). The impact is calculated by plugging into the estimated adaptation panel model (Column 1a of Table 3-2) and non-adaptation panel model (Column 2a of Table 3-2), the climate projections for the end of the century made by four climate models - *CCSM4*, *CESM1-BGC*, *CanESM2* and *NorESM1-M* – under the *RCP4.5* climate scenario. Figure 3-1 also presents some robustness checks as shown by the green triangle, red triangle, and green square. We will discuss these robustness checks in the next section.

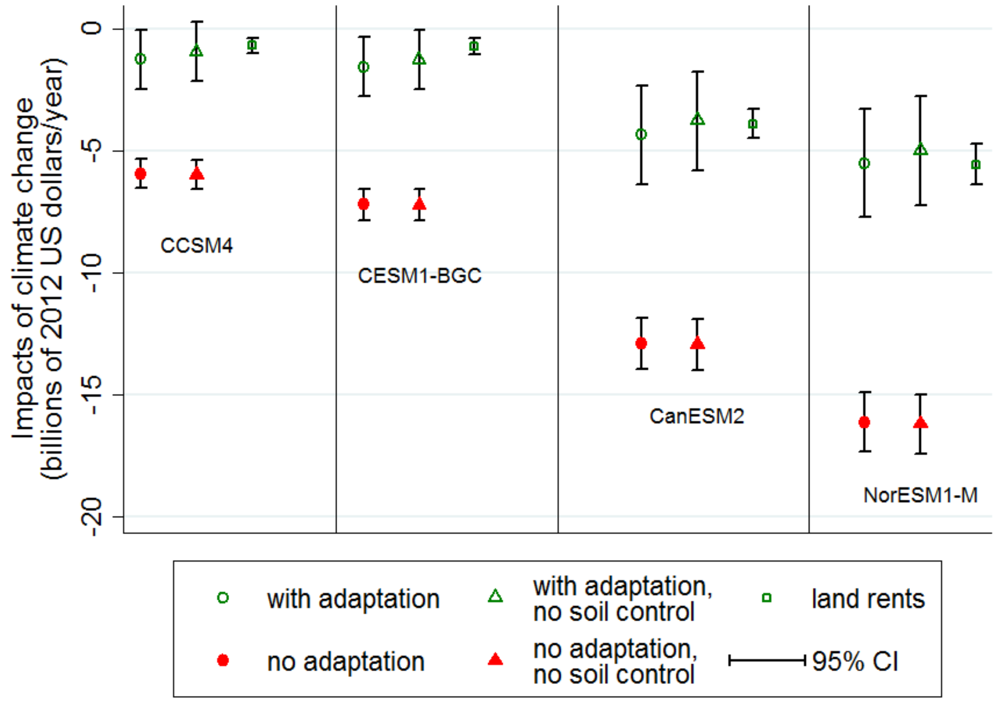

Figure 3-1: Predicted end-of-this-century impact of climate change on agricultural profits and farmland rents

Notes: This figure reports the impact of climate change projections from four climate models (CCSM4, CESM1-BGC, CanESM2, and NorESM1-M) under the scenario RCP4.5. See the climate projection for each climate model in Table 3-5. All entries are calculated for the 2155 rain-fed non-urban sample counties. Total impacts are calculated by summing impacts across all sample counties. The historical average total annual profits for these sample counties are $35.3 billion. See the text for further details.

From Figure 3-1, we find that the predicted impact of climate change on agricultural profits is negative regardless of whether adaptation is taken into account. However, the negative impact is less severe when it is calculated from the adaptation model (green hollow-circle) than when it is calculated from the non-adaptation model (red circle). Using the end-of-this-century climate projections from the *CCSM4*, *CESM1-BGC*, *CanESM2* and *NorESM1-M* climate models, the end-of-this-century changes in agricultural profits predicted by the adaptation model are -1.27,

-1.57, -4.63 and -5.52 billion per year at 2012 constant dollars respectively.[23] These changes are much smaller than what the non-adaptation model predicts, which are -5.96, -7.21, -12.92, and -16.14 billion dollars per year, respectively. In addition, the t-test shows that the difference in the predicted climate change impact with or without adaptation with respect to each of the four climate models (i.e. *CCSM4*, *CESM1-BGC*, *CanESM2* and *NorESM1-M*) is statistically significant at the 1% level.

Table 3-3: Predicted end-of-this-century impact of climate change on agricultural profits and the benefits of adaptation

Climate projection model	*CCSM4*	CESM1-BGC	CanESM2	NorESM1-M	Average
(1) damage estimated by the adaptation model	-3.6%	-4.4%	-12.4%	-15.6%	-9.0%
(2) damage estimated by the non-adaptation model	-16.9%	-20.4%	-36.6%	-45.7%	-29.9%
(3) benefits of adaptation [100*(Row (2) – Row(1))/Row(2)]	78.7%	78.2%	66.3%	65.8%	72.2%

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

[23] Since the projected warming is increasing from *CCSM4*, *CESM1-BGC*, *CanESM2* and *NorESM1-M* in ascending order (see Table 3-7), we can say that the predicted total impacts increase with the magnitudes of predicted warming.

In Table 3-3, we compare the impact of climate change estimated with and without taking adaptation into account. Using the climate projection from each of the four climate models, Table 3-3 first provides the percentage of damage caused by climate changed that is predicted by the model with adaptation (Row (1)) and without adaptation (Row (2)). These percentages are calculated by dividing the estimated damages with adaptation (as shown by the green hollow-circle in Figure 3-1) and without adaptation (as shown by the red circle in Figure 3-1) by the total yearly agricultural profits of the sample area (35.3 billion constant US dollars per year). To calculate the benefit of adaptation to climate change, Row (3) of Table 3-3 reports the proportion of the damage estimated by the model without adaptation that would be offset if adaptation had taken place.

We find that, if adaptations are taken into account, the damage on agricultural profits that climate change may cause is estimated to be -3.6%, -4.4%, -12.4%, or -12.4% based on climate change projections by climate models *CCSM4*, *CESM1-BGC*, *CanESM2* and *NorESM1-M*. However, by not taking adaptations into account, the corresponding damages are estimated to be -16.9%, -20.4%, -36.6%, or -45.7%. Therefore, adaptations can help to offset 78.7%, 78.2%, 66.3% or 65.8% of the potential output loss from the change in the climate projected by the *CCSM4*, *CESM1-BGC*, *CanESM2* and *NorESM1-M* climate models, respectively. The last column of Table 3-3 reports the average percentage of damage from climate change and the value of adaptation based on estimates associated with the four climate models. On average, the damage on agricultural profits is 9% with adaptations and 30% without adaptations, so that adaptation can help to reduce 72.4% of the overall damages from climate change. Hence, omitting adaptation from the econometric models will dramatically overestimate the negative impact of climate change.

3.4. Robustness Checks

This section provides some robustness checks to explore the issues of omitted variable bias, the potential influence of yearly storage and inventory adjustments on the estimation, among others.

A. Omitted variable bias

One concern with using Eq. (3.2) is that unobserved inter-county heterogeneity may cause our estimate of Eq. (3.2) to be biased. In particular, Eq. (3.2) takes care of the confounding effects of common inter-annual fluctuations and the time-invariant differences among states through the state-by-year fixed effects, but because it does not contain the county fixed effects, the unobserved inter-county heterogeneity within each state remains in the model.[24] If this unobserved heterogeneity is correlated with agricultural productivity and the climatic variables in Eq. (3.2), the estimated impact of climate change based on Eq. (3.2) could be biased.

To get a sense of how critical this issue might be, we check for the sensitivity of Eq. (3.2)'s estimates by dropping the most important profit determinants from our model – all the soil quality controls – and reporting the new estimates in Column 1b of Table 3-2. Intuitively, the county-level soil characteristics are highly persistent across time and thus look like fixed effects themselves. If the exclusion of the soil quality controls, though highly important for agricultural profits and correlated with climate (Burke et al. 1989), does not result in significant changes to our estimates of Eq. (3.2), it may be reasonable to infer that the unobserved permanent county factors would not have large confounding effects as well.

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[24] In order to account for the inter-county unobservable differences, county-fixed effects are applied in model (3). 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.

Comparing Columns 1a with 1b of Table 3-2, we find that the estimated coefficients on the climatic variables for the adaptation model are very similar whether or not the county-level soil characteristics are controlled for. In particular, the *t*-test shows that the difference between the coefficients on each climatic variable estimated with or without the soil quality controls is not statistically significant. The robustness of the estimated coefficients is also observed when we only exclude various subgroups of the soil quality controls.

The estimated impact of climate change is also robust to the exclusion or inclusion of the soil quality controls, and as such, it may be reasonable to infer that the estimated climate change impact is not significantly confounded unobserved county heterogeneity. To observe this, we plug into the estimated adaptation model without soil controls (see Column 1b of Table 3-2), the end-of-this-century climate projections to estimate the climate change impact. This predicted impact is also reported in Figure 3-1 as marked by the green hollow-triangle. As shown in Figure 3-1, the impacts estimated from the adaptation model without the soil quality controls (green hollow-triangle) and the adaptation model with the soil quality controls (green hollow-circle) are very close to each other. We conducted a t-test to statistically evaluate if there is a difference between them but find that this difference is not statistically significant.

As a side remark, while the non-adaptation model (Eq. (3.3)) contains county fixed effects, which take care of any unobserved time-invariant inter-county heterogeneity, we carried out the same sensitivity check as we do for the adaptation model and find its estimates to be robust to omitting the soil quality controls as well (compare Columns 2a with 2b of Table 3-2).[25] We use the estimates reported in Columns 2b of Table 3-2 to estimate the climate change impacts

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

without adaptation and report the results in Figure 3-1 (red triangle). We find that the estimated end-of-this-century impacts are virtually the same between the non-adaptation model that control for soil quality (red circle of Figure 3-1) and the non-adaptation model that does not control for soil quality (red triangle of Figure 3-1).

Based on these results, it appears unlikely that unobserved inter-county heterogeneity would have large enough confounding effects to invalidate our main conclusions on the potential benefits of long-run adaptations.

B. The influence of yearly storage and inventory adjustments

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

Not explicitly controlling for storage and inventory adjustments does not necessarily undermine our conclusion that the potential value of adaptation is large.[26] There are two reasons for this. First, for the non-adaptation model (i.e. Eq. (3.3)), not accounting for storage and

[26] Actually, for the sample area, the data for storage and inventory adjustments is not available, so we cannot control for these adjustments.

inventory adjustments potentially biases our results in a favorable way in that our estimate of the damage from Eq. (3.3) is likely to be a conservative one. The intuition is that inventory adjustments serve as a kind of "self-insurance" by reducing the output risks resulting from weather fluctuations.[27] Hence, by not holding inventory "fixed" which is what Eq. (3.3) does, the impact of climate change estimated from the non-adaptation model will be mitigated by any benefit that inventory adjustments may yield. Given that the estimated damages based on the non-adaptation model are expected to be less severe than what is true in reality if storage and inventory adjustments are not controlled for, the benefits of adaptation that we report in our baseline results are likely to be understated.

Second, for the adaptation model, the estimates may not necessary contain large biases even if it does not explicitly control for storage and inventory adjustments. Intuitively, the adaptation model accounts for these inter-annual adjustments non-parametrically through its state-by-year fixed effect. This is because within each state, much of the inter-annual weather fluctuations, which are the cause of inter-annual storage and inventory adjustments, come from common weather shocks (see Section 3.2 for the empirical evidence). If farmers within each state adjust their storage and inventory in a similar way, this adjustment (though unobserved) would be partially taken care of by the state-year fixed effect that is contained in the model.

Finally, we draw indirect evidence to show that the bias for adaptation model from not accounting for storage and inventory adjustments is unlikely to be large. The evidence is based on the following argument: if omitting storage and inventory adjustments causes our estimates

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

in Eq. (3.2) to have large biases, then the estimated effect of climate change on agricultural profits per acre (our baseline) would be very different from that on farmland rents that calculated from farmland value, as farmland value is not subject to the bias of storage and inventory adjustments.

Hence, we estimate Eq. (3.2) using farmland value as a dependent variable in place of agricultural profits. The estimated coefficients on the climatic variables in Eq. (3.2) that uses farmland value as the dependent variable are reported in Column 3a of Table 3-2.[28] Using these estimates, we predict the end-of-this-century impact of climate change on farmland values based on the four climate model projections, and transform this predicted impact into the impact on farmland rents following Schlenker, Hanemann, and Fisher (2005).[29] The results of this exercise are reported in Figure 3-1 as marked by the green hollow-square.

For any given climate model, we find that the end-of-this-century impact of climate change on farmland rents (green hollow-square in Figure 3-1) is similar to that on agricultural profits (green hollow-circle in Figure 3-1). From our t-tests, we find that the estimated damages on agricultural profits are also not statistically significantly different from that on farmland rents. This result supports the argument that even if we consider agricultural profits as the dependent variable, which omits information about storage and inventory adjustments, this would not cause the estimates of climate change impact from the adaptation model to suffer from large biases. It

[28] We have not estimated the effects of climatic variables on farmland values based on Eq. (3.3) because the parameters in this model are identified through inter-annual weather fluctuations and farmland value, which is the present discounted value of the land rent stream into the infinite future, has very little fluctuations year-on-year.

[29] The conversion is based on an implicit discount rate of 2.90 percent.

is worth pointing out that we have not estimated the effects of climatic variables on farmland values based on Eq. (3.3) because the parameters in this model are identified through inter-annual weather fluctuations but farmland value should have very little inter-annual fluctuations it is by definition the present discounted value of the land rent stream into the infinite future.

C. Further robustness checks

Table 3-4 reports a series of other robustness checks on how sensitive our results are to various alternative specifications of Eqs. (3.2) and (3.3), where the results to look out for are: *a*) climate change will lead to mild damages if adaptations are included, and *b*) potential adaptations will help to offset at least two-thirds of the damages that would take place without adaptations.

All the alternative specifications considered here include the same fixed effects and soil quality controls as in Eqs. (3.2) and (3.3). For each alternative specification of Eqs. (3.2) and (3.3), we first estimate the end-of-this-century impact of climate change based on the climate projections from each of the four climate models, and then average up the predicted impacts associated with these four models. Following which, we calculate the value of adaptation as the difference between the predicted average impacts calculated from the alternative adaptation and non-adaptation models.

Table 3-4: Robustness checks for the estimated impacts of climate change and the benefits of adaptation (billions of 2012 constant dollars/year)

	(1) Impact on profits: With adaptation	(2) Impact on profits: No adaptation	Benefits of adaptation	
			Value	Percent
(1) Assume $\rho = 0$ in the regressions but address the spatial correlation by clustering the error term at the state level	-3.71	-14.53	10.83	78.23%
(2) Include additional controls for population density, per capita income, and altitude	-4.61	-12.85	8.24	65.88%
(3) Exclude irrigated counties east of the 100º meridian from the sample	-3.80	-12.00	8.20	70.29%
(4) Calculate degree-day by the minimum and maximum daily temperatures	-3.73	-15.21	11.48	79.07%
(5) Use the highest climate change scenario (RCP8.5)	-9.53	-28.54	19.01	67.32%

Notes: The entries report predicted the impacts of climate change on agricultural profits and the estimated benefits of adaptation using the regression results from alternative versions of models (1) and (2) and the climate change predictions of the four climate models listed in Table 3-7 (i.e., CCSM4, CESM1-BGC, CanESM2, and NorESM1-M). Columns (1) and (2) show the estimated impacts based on alternative versions of models (1) and (2), respectively. In the last two columns, the benefits of adaptation were calculated as the difference between the estimates reported in columns (1) and (2), and "Percent" indicates the percentages of damages that could be offset by adaptations. All the values are simple averages of the estimations that were derived from the four climate models. The historical average total annual profits for these sample counties were $35.3 billion. See the text for further details.

The first robustness check examines if our results are sensitive to whether or not spatial correlation is explicitly modelled in Eqs. (3.2) and (3.3). In this robustness check, we assume $\rho = 0$ in Eqs. (3.2) and (3.3) and account for any spatial correlation by clustering the error term at the state level. Row (1) of Table 3-4 reports the damages of climate change estimated from Eqs. (3.2) and (3.3) with the restriction that $\rho = 0$. Compared with the baseline estimates (see Table 3-3), we still arrive at the same conclusion that the estimated damages are much smaller when adaptation is taken into account, and that adaptation can offset at least two-thirds of the potential damage that climate change can cause in the absence of any adaptive response.

In the second robustness check, we examine how sensitive our results are when new control variables are included. If our results are robust to varying the set of controls, this can be taken as additional evidence that omitted variable bias, if it exists, is unlikely to be strong enough as to invalidate our conclusion. Row (2) of Table 3-4 provides the new estimates of Eqs. (3.2) and (3.3) that now include county-level population density, per capital income, and altitude as additional controls.[30] We find that when these variables are controlled for, the estimated damage on agricultural profits from the adaptation model is only 4.1 percentage points higher than what was found without these controls (i.e. the estimated damage rises from 9.0% in the baseline case to 13.1% here). In addition, based on the new estimates, we find that adaptation could still help to offset about two-thirds of the damage from climate change. We also tried models that include only one or two of these three variables and obtain similar results.

The third robustness check explores the consequence of excluding irrigated counties in our sample. Counties west of the 100º meridian have already been excluded from this study to address the concern that unmeasurable irrigation differences across regions may give rise to biased estimates. However, even though the agricultural production of most counties east of the 100º meridian depends on rainfall, some these counties still use irrigation water as a supplement.

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

In this exercise, we exclude counties east of the 100º meridian that use irrigation.[31] As Row (3) of Table 3-4 shows, whether or not these irrigated counties are excluded does not drive the main results of this chapter. As such, our results are robust to any unmeasurable irrigation difference for counties east of the 100º meridian.

The forth robustness check considers another way of calculating degree-day. Following much of the literature, we have calculated degree-day from the daily mean temperature as the idea of degree-day was proposed by agronomists who examined the relationship between daily mean temperatures and the biomass yield of crops via field experiments (Ritchie and NeSmith 1991). Recently, there have been suggestions that degree-day calculated from daily minimum and maximum temperatures would be a more accurate predictor of crop yields (Schlenker and Roberts 2009, Tack, Barkley, and Nalley 2015). In this exercise, we follow the method of (Schlenker and Roberts 2009) to calculate degree-day by minimum and maximum temperatures and investigate if how degree-day is calculated matters for the results of this study. As shown in Row (4), when degree-days are calculated by minimum and maximum temperatures, the damage from climate change predicted by the non-adaptation model (-15.21%) (see Column (2)) remains much larger than the damage predicted by the adaptation model (-3.73%) (see Column (1)), and the benefit of adaptations in this case (where adaptation can help to offset 79.1% of the damage without adaptation) is significantly larger than our baseline estimate (72.2%) (see Table 3-3).

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

The fifth and final robustness check re-estimates the impact of climate change under the highest climate change scenario, namely the RCP8.5 scenario. The RCP4.5 and RCP8.5 scenarios are the medium and upper bound climate change scenarios developed for the latest IPCC Fifth Assessment Report. So far, we have followed much of the literature in examining the impact of climate change under the RCP4.5 scenario. In this exercise, we will consider the climate change projections from the four climate models under the RCP8.5 scenario,[32] and for the adaptation and non-adaptation models, re-estimate the damages of climate change based on each of these climate projections.

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

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

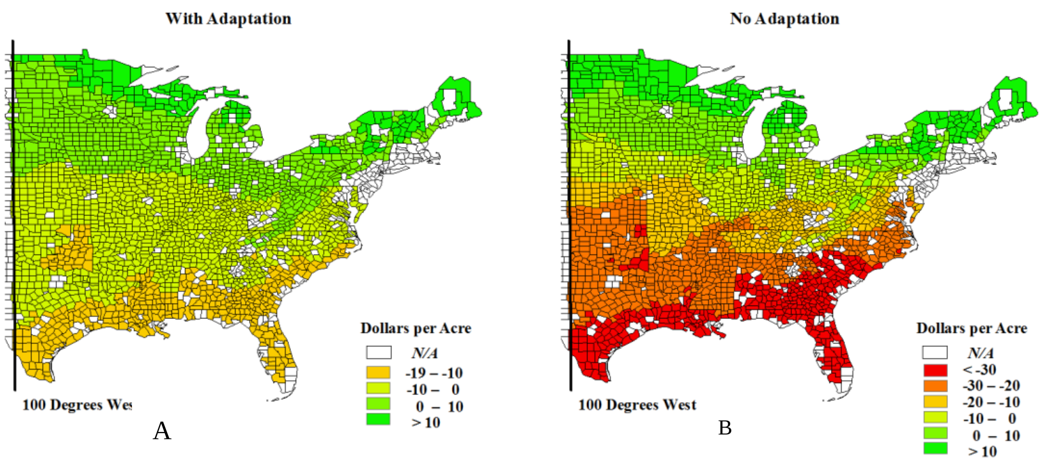

Figure 3-2: Geographic distribution of county-level effects of climate change by the end of this century under scenario CCSM4 RCP4.5

Notes: the left figure presents the effects that include adaptations and the right figure presents the effects without adaptations. The county-level effects are calculated by combining the estimated climate coefficients from model (1) and (2) with the predicted county-level climate changes. Here we take the predictions from climate model CCSM4 as an example; the geographic distributions of effects predicted from other climate models are quite similar. The sample includes 2155 rain-fed non-urban counties east of the 100º meridian. All values are expressed in 2012 constant dollars.

Finally, Figure 3-2 maps the geographic distribution of the climate change impact on agricultural profits. Taking the climate projection from the CCSM4 climate model as an example, we calculate the county-level impact with and without adaptations for each county in our study. From Panel B of Figure 3-2, we can see that warming will hurt the southern counties will lose but benefit the northern counties. However, if the effect of adaptation is taken into account, the losses by the southern counties would be smaller while the gains by northern counties would be larger, as is shown in Panel A. In particular, if predictions are made taking into account of adaptations, we find that no counties will lose more than 20 dollars per acre per year (Panel A). However, when adaptations are not taken into account, 863 southern counties are predicted to lose more than 20 dollars per year and 321 southern counties are predicted to lose more than 30 dollars (Panel B).

3.5. Concluding remarks

Having a good estimate of what the potential value of adaptation is would be useful from a policy perspective, especially for informing governments about the benefits of adaptation before they intervene in helping farmers to adapt. because numerous adaptation measures can potentially be applied by farmers, it is not feasible to estimate the total benefits of adaptation by first estimating the benefits accruing to each possible adaptation measure, and then aggregating these benefits up across all measures. It is also difficult to estimate the benefits of total adaptations by comparing two models in which one takes adaptation into account and another reflects the impact of climate change in the absence of any adaptive behavior. This is because the difference between these two models may also reflect the differences in specification, model assumptions, and the type of data that they are based upon. To reduce the chance of "comparing apples and oranges", this chapter propose an approach that identifies the value of adaptation by comparing the impact estimates from two panel models, where these models are the same except for the specification of the fixed effects that these models used.

We find that when taking into account of adaptation, climate change (under the *RCP4.5* climate change scenario) could cause the end-of-this-century agricultural profits per year to be 9% less than the current agricultural profits per year, or 3.18 billion dollars less per year in profits at the end of the century than what we currently observe (at 2012 constant values). If there are no adaptations, climate change could cause the end-of-this-century agricultural profits per year to be lower by 30%, or 10.56 billion dollars less per year, instead. Therefore, adaptation by farmers can help to offset about two-thirds of the potential overall damage from climate change when adaptation is absent. This conclusion is robust across a number of robustness checks that consider the implications of model specification, omitted variable bias, the influence of inventory and storage, and alternative climate change scenarios on the impact estimates.

There are several important caveats in explaining the empirical result. First of all, even though this chapter estimates that there are large potential benefits of agricultural adaptation to climate change, we do not suggest that the benefits can be exploited by farmers quickly and freely. This chapter only suggests that if famers can fully adaptation to a climate change, the benefit of adaptation could be significant. More specifically, we only suggest that, for example, facing a warming, farmers in a currently cold county of a state could be significantly benefit by mimicking the production behaviour of farmers currently in a hot county of the same state. However, adaptation may require significant investments and farmers may not adaptation to a climate change immediately.

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. In this case, the benefits of adaptation tend to be underestimated. Third, 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. Fourth, to avoid potential bias from irrigation, we follow the literature and use only data from US counties east of the 100º meridian. Hence, the results of this chapter apply to only the eastern US and not to the whole country. Finally, this chapter does not take into account the fertilization 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).

3.6. Appendix

A. An illustration of the remaining variation after different fixed effects are employed in a panel model

In Table 3-5, we demonstrate how a generic weather variable would be transformed by employing certain fixed effects in a climate change impact panel study. To simplify this discussion, we consider a balanced panel with two years and two counties. In Panel A of Table 3-5, we let w_{it} represent the weather realization of county i in year t, where $i, t \in (1,2)$. Each weather observation can be decomposed into three parts: the first part T_i represents the county i's climate (e.g. the long-term average temperature or precipitation), which has variations across counties; the second part d_t measures the inter-annual weather fluctuations that are common across counties in the same year but vary over time; the last part ε_{it} represents the county-specific weather shock. The within-county means and within-year means, which are used in the discussion below, are also reported in Panel A of Table 3-5.

Panel B of Table 3-5 shows the consequence of including the time fixed effect into a panel study on climate change, which is to transform the model by subtracting the yearly weather realizations of each county with the average weather across counties in the same year. Hence, when the time fixed effect is included, the common inter-annual weather fluctuation (d_t) will be filtered out by this transformation, and what remains in the weather variation will be attributed only to the county-specific climate (T_i) and the county-specific weather shock (ε_{it}). If the variation pertaining to the latter (ε_{it}) is small, the impact of the weather variable (when the time fixed effect is included) would then be identified mainly through cross-sectional climate differences (i.e. $T_1 - T_2$ or $T_2 - T_1$).

Table 3-5: the consequences of fixed effects on the climate change impact panel study

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

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

Panel C of Table 3-5 shows the consequence of including the county fixed effect into a panel study on climate change, which is to transform the model by subtracting the within-county mean from each county. Hence, what remains in the weather variation will be attributed only to the common inter-annual weather fluctuation (d_t) and the county-specific weather shock (ε_{it}). If the variation pertaining to the latter (ε_{it}) is small, the impact of the weather variable would then be identified mainly through inter-annual weather fluctuation (i.e. $d_1 - d_2$ or $d_2 - d_1$).

Finally, Panel D of Table 3-5 shows the consequence of including the county fixed effect along with the year fixed effect. This two-way fixed effect structure eliminates both cross-sectional differences in the climate (T_i) and the common inter-annual weather fluctuation (d_t). As a result, the climate change impact will be estimated mainly by exploiting the variation pertains to the county-specific weather shock (ε_{it}), which is extremely small as shown in Table 3-1.

B. Data sources and summary statistics

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

Agricultural production: we follow the literature to construct US county-level agricultural profits per acre from *Census of Agriculture* for the census years of 1982, 1987, 1992, 1997, 2002, 2007, and 2012. Agricultural profits are calculated as the difference between agricultural revenue and agricultural expenditure.[33] In this data source, agricultural revenue measures the before-taxes total market value of all agricultural products sold in a county during a particular year. These products include livestock, poultry, and other derivative products, as well as crops that include nursery and greenhouse crops and hay. Agricultural expenditure covers all variable

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

costs for agricultural production, farm business related interest paid on debts, and maintenance costs.

As a robustness check, we consider farmland value per acre as another measure of agricultural productivity.[34] 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.[35]

*Climate***:** the daily maximum temperature, minimum temperature and precipitation data from 1981 to 2012 are derived from Parameter-elevation Regressions on Independent Slopes Model (PRISM 2014). PRISM Climate Group provides 4×4 kilometre gridded daily data after the year of 1981 for the entire US, which is regarded as one of the most reliable small scale climatic data sets. County-level climate measures are calculated as the simple averages of the climate cells over the agricultural land within each county. This study follows the literature to construct the standard county-level measures of climatic variables: growing season degree-days (GDD), growing season harmful degree-days (GHDD) and growing season total precipitation (GTP) (Schlenker, Hanemann, and Fisher 2006, Deschênes and Greenstone 2007).

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

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

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

GHDD is calculated as the sum of degree-days above a harmful threshold. We set the threshold of harmful temperature as 32ºC. Thus, a day with a mean temperature (say $\bar{z}$) above 32ºC contributes $\bar{z} - 32$ harmful degree-days; otherwise, it contributes zero harmful degree-days (Ritchie and NeSmith 1991).[36] 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

[36] 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.

and RCP8.5)[37] are available from the NASA Earth Exchange Global Daily Downscaled Projections (NEX-GDDP) dataset.[38] Each model provides daily maximum temperature, minimum temperature and precipitation under various scenarios for the periods from 2006 to 2100, and with a spatial resolution of 0.25 degrees × 0.25 degrees (about 25 km × 25 km). Each model also provides simulated historical daily data from 1950 to 2005 for the same spatial resolution. Since point estimates based on a single climate projection can be misleading (Burke et al. 2015), to estimate the impact of climate change here, we use the climate projection for the medium scenario RCP4.5 from four of the most widely used CMIP5 models: *CCSM4*, *CESM1-BGC*, *CanESM2*, and *NorESM1-M*.[39]

Control variables: we follow the literature to use a set of county-level soil quality variables as controls. These data are from the National Resource Inventory and have been widely used. The soil quality controls include measures of soil salinity, sand content, clay content, K-Factor, flood risk, permeability, slope length, moisture in top soil, share of wetland and irrigated land.[40]

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

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

[39] 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 centres.

[40] 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 in the soil quality controls are interpolated. We also use county-level per capita income and population density as control variables for robustness check.

Irrigation water is 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 100º meridian, which account for a large proportion (71.6%) of US agricultural profits. Importantly, in these counties, farming largely relies on rainfall, as opposed to farming in the arid West that depends mainly on irrigation. As such, we will address the issue of unmeasurable irrigation differences by focusing on counties east of the 100º meridian.

We also exclude urban counties in this study as farming in these counties usually take place on a very small scale. Urban counties are defined as counties having a population density of more than 400 people per square mile (Schlenker, Hanemann, and Fisher 2005). We exclude counties with missing values during the sample years to form a balanced panel. In doing so, we are left with 2155 non-urban rain-fed sample counties across the seven census years. All profits and land prices are translated into 2012 dollars using the GDP implicit price deflator.

Table 3-6: A summary of agricultural production data

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

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

Table 3-6 summarizes the agricultural production data. Large non-linear variations in farmland prices and agricultural profits are observed during 1982–2012, but no obvious correlations can be found between them. The farmland areas remain almost constant, while agricultural expenses show an increasing trend.

Table 3-7: Summary Statistics of Climate Normal and Climate Predictions

	Growing Season:			
	Average temperature (°C)	GDD (°C)	GHDD (°C)	GTP (Inches)
Climate Normal				
	20.23	2272	0.11	23.50
	(3.25)	(558)	(0.43)	(3.60)
Predicted climatic changes by the end of this century under scenario RCP45:				
CCSM4	1.95	379	0.38	1.90
	(0.61)	(55)	(0.66)	(2.17)
CESM1-BGC	2.04	384	0.49	2.63
	(0.99)	(65)	(1.55)	(2.97)
CanESM2	2.27	583	1.47	0.41
	(0.50)	(74)	(3.01)	(1.61)
NorESM1-M	2.79	547	3.13	1.35
	(0.80)	(89)	(4.92)	(1.80)

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

Table 3-7 reports statistics of climate normal and climate projections (temperature and precipitation). County-level climate normal is calculated as a 20 year average of the climatic variable (i.e. average temperature, *GDD*, *GHDD* or *GTP*) from 1981 to 2000 for each county. The projected county-level climates based on various scenarios for each climate projection model (i.e. *CCSM4*, *CESM1-BGC*, *CanESM2* or *NorESM1-M*) are calculated by the following steps: **Step 1**: Map the gridded climate predictions from each climate projection model into each state to provide state-level climate predictions,[41] **Step 2**: Calculate state-level climate change predictions as the difference between the predicted 2081–2100 average and the simulated historical average of 1981–2000 based on each model, **Step 3**: Add the predicted state-level climate changes from Step 2 to the county-level climate normal to form county-level climate predictions for the end of this century.[42]

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

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

[42] 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).

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

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

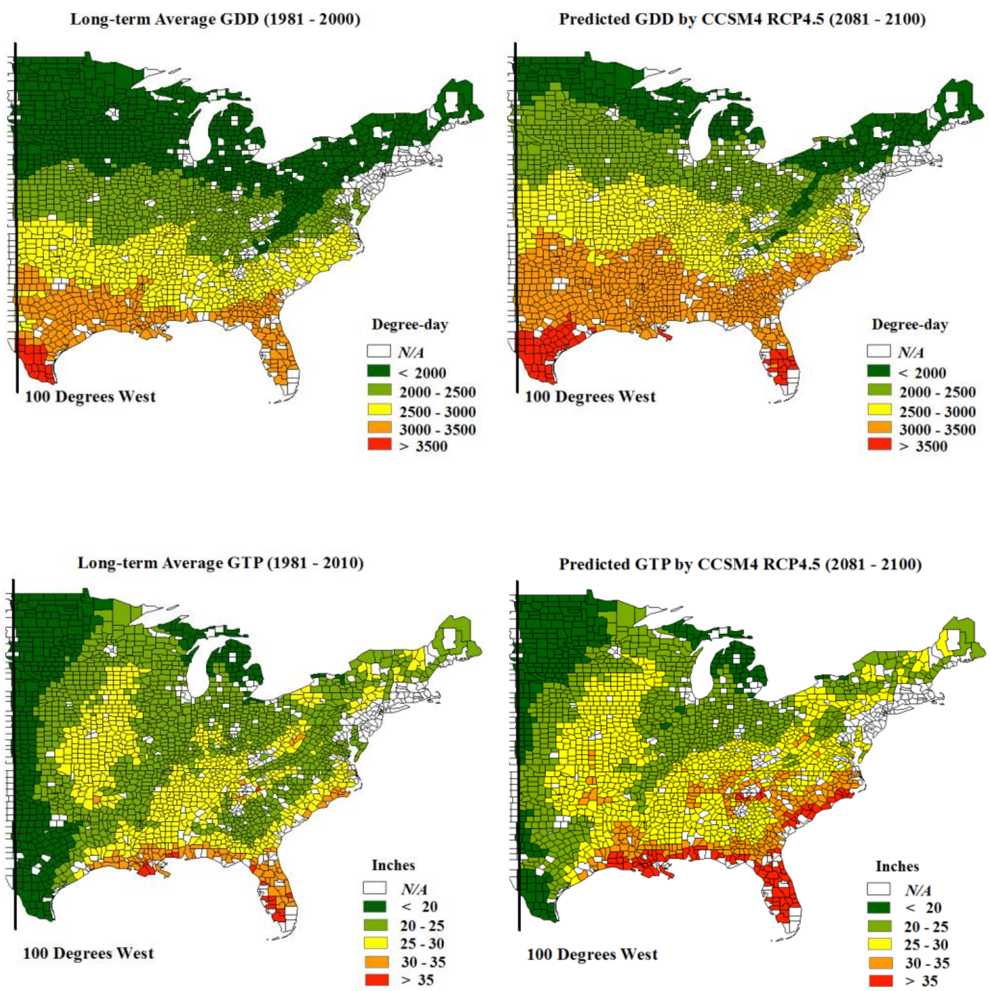

Figure 3-3: Geographic distributions of GDD and GTP for climate normal and scenario CCSM4 RCP4.5

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

Lastly, Figure 3-3 compares the geographic distribution of the climatic variables of climate normal with the distribution of predictions from the representative model CCM4 RCP4.5. The distributions of predictions from the other three models are quite similar. For the climate normal, the GDD is decreasing from southern counties to northern counties, and the GTP is decreasing from east counties to west counties. The predictions from CCSM4 RCP4.5 follow the same geographic pattern, but predict a hotter and wetter climate. We mapped distributions of the prediction from other climate models and find similar results.

C. A Bayesian learning simulation of the believed climate trend

This section argues that farmers may not fully recognize and adapt to the recent climate trends because large inter-annual weather fluctuations accompanied with it may obscure farmers' recognition of the climate trend. As shown in Figure 3-4, even though there are significant increasing trend in the yearly mean temperature in the United States from 1960 to 2010, the inter-annual temperature fluctuation is much larger than the warming trend.

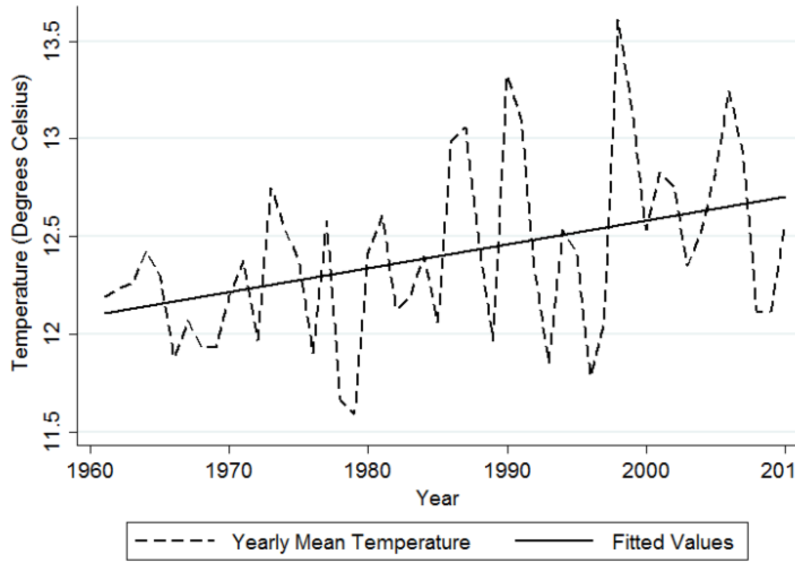

Figure 3-4: Yearly mean temperature fluctuations in the US, 1960–2010

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

This section provides a simple learning model to show that, even when there are obvious climate trend, farmers' perception of the trend is very limited. 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 the precision φ_t. In each period, they observe the realization of temperature s_t and update their belief to c_{t+1} using a weighted combination of prior belief and the realized temperature. Assume the variance (σ^2) of realized temperature is unchanged when mean temperature increases, and denote $\delta = 1/\sigma^2$. According to DeGroot (1970), for a sudden temperature increase, such as Δc, in the base year, the farmers' belief about mean temperature after T years is given by:

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

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

$$D = \frac{\Delta c}{1 + T\delta / \varphi_0} \tag{3.5}$$

We combine equation (3.5) with the empirical data as used in Figure 3-4 to draw a simulation of farmers' belief. Assume the initial precision of belief (φ_0) as the inverse of the variance of temperature during 1960-1970, which is a period before large temperature variance. Assume the temperature variance during 1970-2010 as σ^2. Then we can simulate the evolution of farmers' belief after a once for all, for example 5 °C, mean temperature rise in the base year. The result is shown in Figure 3-5. We find that, after 10 years only about 40 percent of the mean temperature rise 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 to recent climate trend is potentially quite limited.

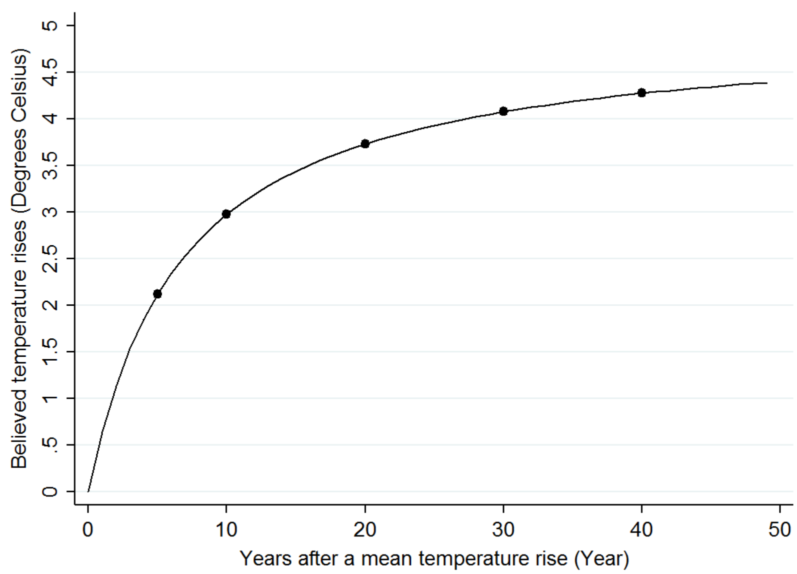

Figure 3-5: A simulation of farmers' believed "true" temperature rise after an assumed 5 °C temperature increase in the base year

Statement of Authorship for Chapter 4

Statement of Authorship

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Name of Principal Author (Candidate)	Kaixing Huang		
Contribution to the Paper	Performed analysis on all samples, interpreted data, wrote manuscript.		
Overall percentage (%)	75%		
Certification:	This paper reports on original research I conducted during the period of my Higher Degree by Research candidature and is not subject to any obligations or contractual agreements with a third party that would constrain its inclusion in this thesis. I am the primary author of this paper.		
Signature		Date	5 May 2016

Co-Author Contributions

By signing the Statement of Authorship, each author certifies that:

i. the candidate's stated contribution to the publication is accurate (as detailed above);
ii. permission is granted for the candidate in include the publication in the thesis; and
iii. the sum of all co-author contributions is equal to 100% less the candidate's stated contribution.

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Contribution to the Paper	Field survey design and implementation; helped in data interpretation and manuscript evaluation and improvement.		
Signature		Date	10/05/2016

Please cut and paste additional co-author panels here as required.

Chapter 4 : The Potential Benefits of Agricultural Adaptation to Warming in China in the Long Run

Abstract

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 a panel of household survey data from a large sample in rural China, the present chapter 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 chapter also finds that household-level capital intensity and farmland size have significant effects on farmers' adaptive capacities. (JEL Q15, Q51, Q54)

Keywords: climate change impact, agriculture, adaptation capability

4.1. Introduction

Estimating the potential impacts of climate change on agriculture is crucial for understanding food security issues and for assessing the potential costs associated with the effects of greenhouse gas emissions (Lobell and Asner 2003). However, any estimate of the impact of climate change is potentially biased if adaptation measures that are believed to determine the future severity of the impact of climate change on agriculture 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, e.g., Huang, Wang, and Wang 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 chapter 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, Nordhaus, and Shaw (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, Nordhaus, and Shaw (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.[43] The present study attempts to identify the value of long-run adaptations as a whole by a panel approach. In this approach, the value of adaptations is approximated by comparing the estimated damage from cross-sectional climate differences and the identified damage from inter-annual weather fluctuations.

Specifically, based on the key fact that inter-annual weather fluctuations are generally common across regions in the same year,[44] two types of panel models were developed: one depending on cross-sectional climate differences and the other on inter-annual weather fluctuations. Only the former model, that is, the model using cross-sectional climate differences, includes the benefit of adaptations. Thus, we hypothesized that the differences between the predicted impacts from these two models should reflect 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, Sygna, and Haugen 2004). Some other studies take an experimental or empirical approach to inferring

[43] 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.

[44] 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.

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, Wang, and Wang 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.

However, since previous studies lack an explicit estimate of the overall value of long-run adaptations, 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 chapter from previous studies. First, this chapter investigates the benefits of long-run adaptations of agriculture to climate change in China, while most previous studies examined the damage from climate change (see, e.g., Wang et al. 2009, Chen, Chen, and Xu 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 chapter 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.

4.2. 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. Funding was available for the field survey in eight of the 34 provinces and regions of China (see Figure 4-1). 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 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 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. 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.

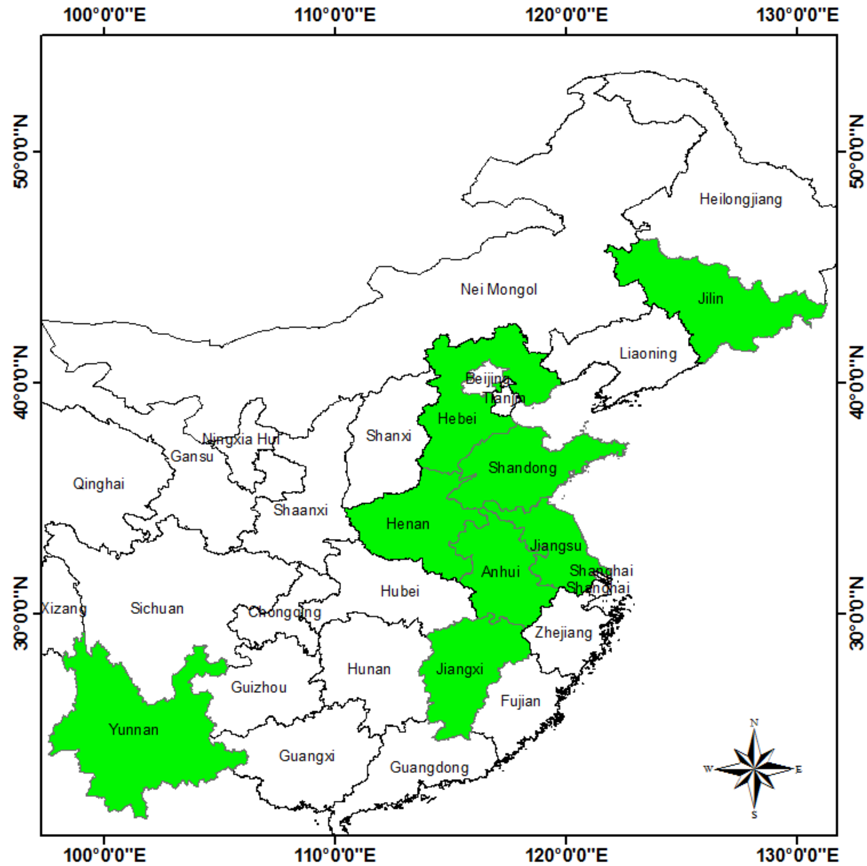

Figure 4-1: Sample provinces of the survey in China.

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 2733 households.

The farmlands in the survey are mainly used for crops and orchards.[45] The crop production and orchard data were collected separately. For land used for crop production, only the larger two 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 percent 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.[46] According to the survey, farmers usually plant multiple crops in sequence in a plot

[45] 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.

[46] 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.

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.[47] Finally, the profits per hectare were translated into US dollars (USD) using China's rural Consumer Price Indices (CPI) and 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.

[46] 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.

Table 4-1: 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
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) [†]
Education	Education of head of household (years)
Age	Age of head of household (years)
Other control variables	
Irrigation	Irrigation water used per year per hectare (m^3/ha)
Disaster loss	Loss per hectare caused by natural disasters (%)
Market access	Distance to the nearest market of production inputs (km)
Soil quality	County-level land quality measured by loam in the soil (%)[#]
Road density	County-level density of paved road and railway (km/km^2)[§]

†: 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.

#: Loam is a standard indicator of soil quality. Loam is considered ideal for agricultural uses because it retains nutrients well and retains 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/).

§: 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.

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 4-1, these characteristics include the capital intensity, labor intensity, and farmland size of the household; education level and age of the head of household; irrigation water used per hectare; agricultural loss per hectare caused by natural disasters; 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, 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 4-2.

Table 4-2: 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)	3472	999	1941	5688
Precipitation (mm/year)	1182	707	302	2866
Capital intensity (1000 USD/ha)	59.1	77.3	1.0	898.4
Land size (ha)	2.2	5.5	0.0	44.5
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
Irrigation (m^3 /ha)	2788	3287	0.0	14991
Disaster loss (%)	10.6	10.8	0.0	100.0
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 4-1.

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 was calculated as the sample average from all the meteorological stations within the county. For the nine sample counties in which meteorological stations were not available, we instead used climate data from the nearest meteorological station.[48]

Daily mean temperature and precipitation were used to construct values for county-level yearly degree-days (DD) and yearly total precipitation (TP).[49] DD measures cumulative exposure to temperatures of between 8°C and 32°C during the year. For example, a day with a mean temperature below 8°C contributes zero DDs, between 8°C and 32°C it contributes the difference between the mean and 8°C, and above 32°C it contributes 24 DDs. DD is the sum of daily measures across the calendar year. 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

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

[49] Some previous studies focusing on only one or several crops used 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.

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 periods 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.

Table 4-3: 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).

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.[50] Since point estimates depending on a single climate projection can be misleading (Burke et al. 2015),[51] we used the average prediction of the CMIP5 models in the following impact estimation. Table 4-3 reports the projected climate changes of scenarios RCP4.5 and RCP8.5. The projected yearly mean temperature rise is 2.7ºC and 5.2ºC 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.

4.3. 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, Nordhaus, and Shaw (1994), and inter-annual random weather fluctuations adopted by panel studies, such as in Deschênes and Greenstone (2007).[52] 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

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

[51] 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 Coupled Model Intercomparison Project," *Program for Climate Model Diagnosis and Intercomparison*, http://cmip-pcmdi.llnl.gov/cmip5/availability.html.

[52] "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, Jones, and Olken 2014).

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, Nordhaus, and Shaw 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 (4.1):

$$w_{it} = T_i + d_t + \varepsilon_{it} \tag{4.1}$$

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 differ 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.[53] 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 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 4-4), 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.

[53] Here, we assume the climate of a county T_i is constant for not too long 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 4-4: The magnitudes of inter-county climate variation and local weather shocks

Panel A. Percentage of counties with temperature variance below/above (°C):				
	±0.1	±0.2	±0.3	±0.4
Inter-county mean temperature variation	96.7	93.5	90.3	74.2
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
Inter-county total precipitation variation	96.7	93.5	83.9	64.5
County-specific precipitation shocks	18.3	5.4	4.3	2.1

Note: Temperature is measured by the yearly mean temperature (°C), while the 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 "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.

Table 4-4 shows the actual size of the variation pertaining to ε_{it} and T_i . We found that 74.2 percent 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 no counties had county-specific temperature shocks (ε_{it}) higher than 0.4°C (see Panel A of Table 4-4). The same result applied to precipitation, with 64.5 percent 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 percent of counties having local precipitation shocks (ε_{it}) of more than 400 mm (see Panel B of Table 4-4). 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 4-4, 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 4-4 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 (4.2), 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 total precipitation, and their quadratic terms; L_{ijt} is a vector of the farm and household characteristics as shown in Table 4-1, including capital intensity, land size, labor intensity, head of household education and age, irrigation, disaster loss, and market access; K_{jt} is a vector of the county-level soil quality and transportation controls as defined in the last two rows of Table 4-1; 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.[54] Thus, the coefficients of the climate variables

[54] 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.

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).

$$y_{ijt} = C_{jt}^{'}\alpha + L_{ijt}^{'}\beta + K_{jt}^{'}\gamma + \rho_{pt} + \mu_{ijt} \tag{4.2}$$

The model used to identify climate change impacts through inter-annual weather fluctuations is presented in equation (4.3). The settings for y_{ijt}, C_{jt}, L_{ijt}, and K_{jt} are the same as for equation (4.2). The only difference is in the use of fixed effects. Model (4.3) includes the county fixed effects τ_j to eliminate inter-county climate differences and does not use any type of time fixed effects, as these tend to eliminate most of the year-to-year weather fluctuations.[55] 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.

$$y_{ijt} = C_{jt}^{'}\alpha + L_{ijt}^{'}\beta + K_{jt}^{'}\gamma + \tau_j + \upsilon_{ijt} \tag{4.3}$$

By combining the estimates of the climate variables from models (4.2) and (4.3) with the climate change predictions, we were able to project the impacts with and without adaptations,

[55] 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).

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.[56] 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 distributions 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),

[56] 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.

while for regions with sufficiently warm temperatures, cultivation is strongly determined by the distribution of precipitation (Leemans and Solomon 1993).

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, Hu, and Yu 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 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, transportation, and the availability of ground water for irrigation 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, Jones, and Olken (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, irrigation, disaster loss, market access, land quality, and transportation.

4.4. Empirical results

The regression results are shown in Table 4-5. Columns 1a and 1b present the regression results from model (4.2) and model (4.3), respectively, using crop profits as the dependent variable, while columns 2a and 2b represent the regression results from model (4.2) and model (4.3), respectively, using the average profits of crops and orchards as the dependent variable.[57] 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 precipitation are all statistically insignificant, presumably because the control variables, especially the household-level detailed control for irrigation, and 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, Hanemann, and Fisher 2005). In the data, the agricultural production of 78.0 percent of households depends on irrigation, so control for irrigation is necessary. Even though we included a detailed measure of current irrigation water used, we don't have a good measure of the future availability of irrigation water. Hence, the

[57] The magnitudes of the estimated coefficients of model (4.2) and model (4.3) are not directly comparable because different fixed effects are used. However, as shown in the following, the impacts calculated from these coefficients are comparable.

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 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.

Table 4-5: Regression results of the effects of climatic variables and household characteristics on agricultural profits

Independent variables	Crop profits		Crop and orchard profits	
	(1a)	(1b)	(2a)	(2b)
Climate variables				
Degree-day (100 degrees/year)	200.99*	1,148.51***	183.21*	1,040.01***
	(107.10)	(188.95)	(87.25)	(221.23)
Degree-day^2	-3.20*	-15.29***	-3.03*	-13.48***
	(1.62)	(2.91)	(1.33)	(3.41)
Precipitation (100 mm/year)	76.04	-45.27	84.27	-39.00
	(70.09)	(39.82)	(70.67)	(46.62)
Precipitation^2	-2.44	2.66	-2.51	2.59
	(2.44)	(1.36)	(2.43)	(1.60)
Farm and household characteristics				
Capital intensity (1000 USD/ha)	14.60*	21.00**	19.97*	24.56**
	(6.28)	(9.05)	(8.67)	(10.60)
Capital intensity^2	-0.00***	-0.00**	-0.00**	-0.00*
	(0.00)	(0.00)	(0.00)	(0.00)
Land size (ha)	357.71**	344.45***	429.03**	445.74***
	(120.44)	(49.53)	(148.81)	(58.00)
Land size^2	-20.76*	-20.60***	-23.63*	-25.52***
	(9.75)	(3.91)	(11.73)	(4.57)
Labor intensity (days/ha)	2.41	1.33**	1.78	0.75
	(1.40)	(0.61)	(1.31)	(0.72)
Labor intensity^2	-0.00	0.00	-0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Education (year)	15.27*	15.89***	21.41**	21.30***
	(7.51)	(6.11)	(8.41)	(7.15)
Age (year)	1.03	-0.22	-0.68	-2.61
	(2.59)	(1.90)	(2.15)	(2.23)
Other controls				
Irrigation (m^3/ha)	0.04**	0.02***	0.05**	0.03***
	(0.02)	(0.01)	(0.02)	(0.01)
Disaster loss (%)	-37.23***	-36.50***	-36.74***	-36.05***
	(4.94)	(1.66)	(4.11)	(1.95)
Market access	-44.51**	-27.18***	-41.72**	-26.00***
	(16.19)	(6.86)	(15.59)	(8.03)
Soil quality control	27.85	-	32.27	-
	(21.92)		(22.44)	
Road density control	336.06	-	478.85	-
	(255.36)		(285.75)	
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	0.213	0.248	0.166	0.198

Note: The definitions of the variables are given in Table 4-1. 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.

We combined the estimated coefficients of degree-day and degree-day square of models (4.2) and (4.3) with the climate change scenarios to predict the impacts of warming with and without long-run adaptations, respectively. Row (1) of Table 4-6 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 median climate change scenario RCP4.5, the predicted changes in crop profits per hectare will be -163.7 USD and -370.6 USD with and without long-run adaptations, respectively. These damages correspond to 7.5 percent and 17.0 percent of the current mean annual profits per hectare in the sample area (see Table 4-2). Column (4) reports the percentage of damages that will be offset by long-run adaptations. Long-run adaptations will help to mitigate 55.8 percent and 56.1 percent 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 4-6: 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	-163.7 (92.7)	-370.6 (397.5)	26.5***	55.8
	RCP8.5	-908.0 (223.9)	-2069.7 (1019.4)	58.2***	56.1
Robustness tests					
(2) Including the effects of changes in precipitation	RCP4.5	-154.6 (119.9)	-313.1 (454.1)	17.6***	50.6
	RCP8.5	-842.8 (307.6)	-1981.1 (986.4)	57.6***	57.5
(3) Excluding household characteristics and soil controls in the regressions	RCP4.5	-217.9 (114.3)	-375.5 (394.1)	20.1***	42.0
	RCP8.5	-1208.9 (328.2)	-2095.1 (1022.3)	43.1***	42.3
(4) Using the profits from both crops and orchards as the dependent variable	RCP4.5	-169.9 (104.2)	-268.8 (408.6)	12.3***	36.8
	RCP8.5	-977.8 (184.5)	-1654.2 (774.6)	44.4***	40.9
(5) Using growing season climatic variables	RCP4.5	-144.0 (72.0)	-221.5 (454.1)	8.8***	35.0
	RCP8.5	-1041.5 (82.9)	-1559.9 (88.2)	222.8***	33.2

Note: Standard deviations are reported in parentheses. Significance levels are *** p <0.01, ** p <0.05, * p <0.1. See the text for further details.

Row (2) to row (5) of Table 4-6 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 biases. 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 4-1. 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 55.8 percent to 42.0 percent for scenario RCP4.5 and from 56.1 percent to 42.3 percent 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 percent, 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 4-6 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., 36.8 percent under scenario RCP4.5 and 40.9 percent under scenario RCP8.5).

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 35.0 percent for scenario RCP4.5 and to 33.2 percent for RCP8.5. The main conclusion remains that omitting long-run adaptations will dramatically overestimate the damages.

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 4-5, 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 4-1 and controlled for the mean temperature differences among counties. The significant regression coefficients are reported in equation (4.4)[58]:

$$\begin{aligned}\text{Adaptation\_value} = {} & 10.4^{***} \times \text{Capital\_intensity} - 2.3e^{-7***} \times \text{Capital\_intensity}^{2***} \\ & -65.5^{***} \times \text{Land\_scale} + 6.1^{***} \times \text{Land\_scale}^2 - 7.3^{**} \times \text{Age} - 0.01^{**} \times \text{irrigation} \\ & -4.4^{***} \times \text{Degree-day} + 0.001^{***} \times \text{Degree-day}^2\end{aligned} \tag{4.4}$$

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 values than temperate areas. This result is intuitive, because farmers in cold areas have more potential to

[58] 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.

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. For farmers with limited production capital, increases in capital intensity will raise their adaptive capacity. When production capital is quite abundant, further increases in capital intensity will reduce the value of adaptation, presumably due to decreasing returns from physical capital investment, but the negative effects are negligible (the coefficient of the square term is only $-2.3e^{-7}$). 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 a turning point. 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. However, once the land size is large enough, modern agricultural production methods such as mechanized agriculture production are available to reduce labor force constraints. Hence, for those areas with the possibility of significantly increasing their household-level farmland size, a government policy to increase farmland size would enhance adaptive capacity.

In addition, the age of the head of household also had a statistically significant negative effect on adaptation value. This could reflect the fact that old farmers have less adaptation ability than young farmers. Finally, agricultural production that depends more heavily on irrigation had lower adaptation values. This could be explained by the fact that irrigation is itself an adaptation, so currently irrigated farms might experience lower marginal benefits than currently non-irrigated farms from further irrigation improvements.

4.5. Conclusions

This chapter 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.

Chapter 5 : Concluding Remarks

Having a good understanding of the relationship between climate change and agricultural production can help policy makers to better anticipate issues concerning food security. However, although there is a growing econometric literature on this topic, there is also much disagreement on what exactly the effect of warming is: Whether it is positive or negative, or if there is an effect at all. Using a standard meta-analysis, Chapter 2 of the thesis identifies some potential sources of this disagreement using the estimates of the effect of warming on agricultural output from 130 primary studies.

The role of adaptation is central to the debate surrounding the impacts of climate change on agriculture. Understanding how much adaptation is likely to occur is central to any study of the impact of climate change and is also of paramount importance from the policy perspective. Chapter 3 of the thesis combines the basic idea of the traditional hedonic approach with the panel method proposed by Deschênes and Greenstone (2007), developing a panel framework that can be used to incorporate a full range of adaptations to climate change and to explicitly estimate the value of adaptation.

An even more interesting issue from the policy perspective is to identify and understand the determinants of farmers' adaptation capability, as that knowledge can support the design of effective adaptation policies. Using large-scale household-level survey data from rural China, Chapter 4 of the thesis employed the panel framework developed in Chapter 3 to identify the determinants of adaptation capability.

5.1. Souces of the heterogeneity in the climate change impact literature

Chapter 2 conducts a meta-analysis based on 130 primary econometric studies to better understand the conflict among the existing estimates of warming on agriculture. We carried out a broad and inclusive search of the rapidly growing econometric based literature that examines the effect of climate change on agricultural output. In all, we selected 130 papers based on several criteria.

The summary statistics of the primary studies suggest that (1) differences in model specification of the primary studies may account for different conclusions; (2) differences in certain study characteristics (e.g. the latitude of the region in which the study is based on) may also explain why the econometric estimates disagree; (3) the conflicting results could be due to publication bias, which refers to the fact that research with 'statistically significant' results tend to be published more often than those with 'negative' results. According to these summary statistics, 10 characteristics of primary studies were chosen as the independent variables in the meta-regression.

The meta-regressions find that 10 independent variables explain a significant proportion of the variation in the primary estimates. For example, the adjusted R^2 of 64.89% indicates that the 10 independent variables account for 64.89% of the variation in the primary estimates. Most of the independent variables are statistically significant. The location of the primary studies can influence the estimates of the effect of warming on crop yield. For instance, the coefficient of *latitude* is positive and statistically significant, which implies that studies based on higher latitude regions are more likely to report positive effects of warming than studies based on lower latitude regions.

Publication bias and biological differences in crops are also important in accounting for the disagreement among primary studies. Under the Publication Bias category, the coefficient on *research time* is positive and statistically significant, which implies that studies that are published more recently tend to report positive effects more frequently than those published earlier. The coefficient of *publication status* is negative and statistically significant, which means published papers or books are more likely than unpublished materials to report negative effects. Under the Biological Differences category, the significant coefficients on the dummies for *maize*, *soybean*, and *rice* but not *wheat* imply that the effects of warming can differ for different crops.

The specification of the econometric model has a strong influence on the eventual estimated effects of warming as well. Under the Model Specification category, the variables *measures of output*, *temperature measures*, and *data types* are all positive and statistically significant. To investigate the relative importance of model specification in explaining the disparity among the primary studies, we conducted a regression analysis for each sub-category of variables. Comparing the adjusted R^2 across the four sub-category regressions, we find that model specification has the strongest influence on the primary estimates. In particular, differences in model specification can explain 30% of the disagreement among primary studies, whereas 15% of the disagreement can be explained by biological differences in crops, 12.4% by regional differences, and 9.8% by publication bias.

Given that differences in model specification account for the largest share of the disagreement, we investigate the extent to which these studies could be reconciled if they had adopted a certain set of specifications. We find that if the primary studies use the yearly temperature measure and adopt the hedonic modelling approach, their estimates will have less dispersion and will tend to concur with the prediction from the simulation-based literature that warming will lead to positive effects on agriculture in the high latitudes but damages in the low latitudes.

5.2. The extent to which US agriculture will adapt to climate change

Understanding how much adaptation is likely to occur is central to any study of the impact of climate change on agriculture and is also of paramount importance from the policy perspective. However, an effective approach for evaluating the benefits of potential adaptations has not yet been developed. Chapter 3 of the thesis develops a panel framework to estimating the potential value of adaptation.

This panel framework depends on the basic idea that impacts identified through cross-sectional climate differences should include the benefit of a full range 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 the adaptations to long-run climate change since farmers have only limited *ex-post* adjustments in response to random year-to-year weather fluctuations, and this short-run response is not seen as adaptation to climate change. Two types of panel model were developed to estimate the potential impacts of climate change. One depended on cross-sectional climate differences and the other on inter-annual weather fluctuations. Only the former model, that is, the model using cross-sectional climate differences, included the benefit of adaptations. Hence, the differences between the predicted impacts from these two models should reflect the value of a full range of adaptations.

To estimate the climate change impacts on US agriculture and the potential values of adaptation, this study combines this panel framework with a panel of county-level agricultural production, climate, and other socio-economic and geophysical data for 2155 US counties east of the 100° meridian. We follow the literature to construct US county-level agricultural profits and farmland value per acre from the *Census of Agriculture* for the census years of 1982, 1987, 1992, 1997, 2002, 2007, and 2012. The daily maximum temperature, minimum temperature, and precipitation data from 1981 to 2012 are derived from the Parameter-elevation Regressions on Independent Slopes Model (PRISM). We also use the latest high-resolution climate predictions from general circulation model (GCM) runs conducted under the Coupled Model Intercomparison Project Phase 5 (CMIP5).

The econometric estimations conclude that, for estimates from the model that includes adaptations, the overall impacts on agricultural profits are negative but generally quite small. The changes in agricultural profits from climate predictions per year and by the end of this century are, in billions of 2012 constant USD, -1.27 (-3.6%, CCSM4), -1.57 (-4.4%, CESM1-BGC), -4.63 (-12.3%, CanESM2) and -5.52 (-15.6%, NorESM1-M). On the other hand, the model that does not include adaptations predicts relatively large falls in agricultural profits, ranging from USD -5.96 (-16.8%) to -16.14 (-45.7%) billion for different climate predictions. The average impacts of these four climate predictions are 9% with adaptations and 30% without adaptations.

We calculate the benefit of adaptation as the difference between estimates of the models with and without adaptations. The benefit of adaptation ranges from USD 4.69 to 10.62 billion per year, and this benefit increases with the level of predicted warming. Adaptations will help to offset 78.7%, 78.2%, 66.3% and 65.8% of potential output loss from the predicted climate change given by CCSM4, CESM1-BGC, CanESM2 and NorESM1-M, respectively. On average, adaptation is estimated to reduce 72.4% of the overall predicted damages from climate change. Hence, omitting adaptation from models will dramatically overestimate the impacts.

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

5.3. Determinants of farmers' adaptation capability in rural China

Understanding the determinants of farmers' adaptation capability is of paramount importance from a policy perspective, especially for developing countries where agricultural production is potentially most vulnerable to climate change. However, most of the adaptation study involved the hedonic approach proposed by Mendelsohn, Nordhaus, and Shaw (1994), which implicitly includes adaptations in its climate change impact estimation. The benefits of adaptations cannot be explicitly evaluated by this approach. In addition, most of the farm-level studies explain the responses to weather fluctuations as adaptations, so interpretation of these studies might have precluded some of the potential benefits of long-term adaptation from adjusting ex ante production behaviors.

Therefore, an approach to identifying the benefits of a full range of adaptations without examining individual adaptation measures would be valuable. The value of examining the full range of adaptations as a whole 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. However, this is not yet possible, as an effective approach to evaluating the benefits of a full range of adaptations has not been developed. The present study attempts to identify the value of a full range of adaptations using the panel approach proposed in Chapter 3.

In this approach, the value of adaptations was approximated by comparing the damages estimated from cross-sectional climate differences and the damages identified from inter-annual weather fluctuations. Specifically, based on the key fact that inter-annual weather fluctuations are generally common across regions in the same year, two types of panel model were developed: one depended on cross-sectional climate differences, and the other on inter-annual weather fluctuations. Only the former model, that using cross-sectional climate differences, included the benefit of adaptations. Thus, we hypothesized that the differences between the predicted impacts from these two models should reflect the value of a full range of long-term adaptations.

By combining this panel framework with a panel of large-scale household-level survey data from rural China, the present study not only predicts the potential damage of global warming on agricultural profits with farmers' adaptations applied, but also explicitly approximates the potential value of a full range of long-term adaptations. We find that agricultural profits increase with climate variables up to a turning point, after which they decline. In addition, most of the farm and household characteristics have statistically significant effects on agricultural profits. For example, labor intensity has a negative and statistically significant effect on agricultural profits. A potential explanation for this is that because labor is abundant in rural China, higher labor input will drive down the marginal labor output. The effect of capital intensity is positive and statistically significant, which implies that increased capital input per hectare will enhance agricultural profits per hectare. This reflects the fact that production capital is scarce in rural China. Finally, agricultural profits increase significantly with the volume of irrigation water used and decrease with losses caused by natural disasters.

We combined the estimated coefficients from the econometric models with the climate change scenarios to predict the impacts of *warming* with and without adaptations, respectively. We found that the model that did not include adaptations predicted twice as much damage as the model that included adaptations for both scenarios. If we include adaptations, by the end of this century, the predicted changes in agricultural profits per year, per hectare, will be USD -196.9 billion (scenario RCP4.5) and USD -996.3 billion (scenario RCP8.5), which corresponds to 8.4% and 42.5% of the current mean annual profits per hectare in China, respectively. In addition, relatively large standard deviations for the estimated damages are found, implying that there are significant regional differences in the impacts of warming.

As expected, the model without long-term adaptations consistently predicted much higher impacts than the model with adaptations, and furthermore, the value of adaptation increased almost linearly with warming. The values of adaptations ranged from USD 225.8 billion to USD 1512.8 billion per hectare per year (in 2010 constant dollars). Interestingly, we found that, for various degrees of warming, long-term adaptations will always help to offset about 50% of the damages predicted by the model that does not include long-term adaptations.

More importantly, the regression coefficients of farm and household characteristics implied that labor intensity and capital intensity have a statistically significant positive effect on the adaptation value. Farmers with higher labor and capital intensity will be good at adaptation. However, the farmers' education level had a negative effect on adaptation value. A possible explanation is that educated people have higher opportunity costs of adaptation. In addition, the age of the household head also had a statistically significant negative effect on the adaptation value; this may reflect the fact that old farmers have less adaptation ability than young farmers. Finally, agricultural production that depends more heavily on irrigation had lower adaptation values.

5.4. Policy recommendations

Food security is at increasing pressure owing to diminishing returns from technological advances and world population growth; yet, changes in climate may make the situation even worse. To address this threat, policy makers need to be informed by robust empirical evidence on the effect that global warming has on agricultural production. Understanding how much adaptation is likely to occur is central to any study of the impact of climate change on agriculture and is also of paramount importance from the policy perspective. The role of adaptation is central to the debate surrounding the impacts of climate change on agriculture. Even more interesting from a policy perspective are the determinants of adaptation capability, because identifying the determinants of farmers' adaptation capabilities can support the design of effective adaptation policies.

To illustrate the importance of including adaptations in the climate change impact study, this thesis develops a panel framework that can be used both to incorporate a full range of adaptations to climate change and to explicitly estimate the value of adaptation. Combining this framework with empirical data from the United States and China we find that, if the potential adaptations are taken into account, the overall impact of climate change on the agricultural production of these two countries is quite small. The overall fall in US agricultural profits will be about 9% per year by the end of this century, and the potential impact of climate change on agricultural profits in China will be about 8.4% annually.

If adaptations are omitted or farmers cannot adapt to the climate change, however, the overall damage will be much higher: 30% of profits in the United States and 18% in China. Therefore, improving farmers' adaptation capabilities will be crucial in reducing the damage caused by climate change from a policy perspective. The empirical study in Chapter 4 found that increasing farm-level labor and capital intensities will significantly enhance farmers' adaptation capabilities, presumably because adaptation requires a large amount of labor and capital input. Hence, a government policy providing incentives for farmers to invest more time in managing their farms will lead to a higher adaptation level and less damage due to climate change. In addition, a government policy with the target of improving the capital intensity of agricultural production will also enhance farmers' adaptation capabilities and reduce the overall damage from climate change.

5.5. Limitation and further studies

In Chapter 2 of the thesis, a standard meta-analysis is applied to identify some potential sources of the disagreement among econometric studies concerning the climate change impacts on agriculture. However, because studies summarized in the meta-analysis usually utilize different units, we can only use the z-value of the marginal effect of warming at the mean as the meta-dependent variable. Even though using the z-value as the meta-dependent variable helps to make primary studies comparable, much useful information is omitted. For example, if we can use the coefficients of climate variables as the meta-dependent variable, the global-level overall impacts of climate change can be identified by the meta-analysis. Efforts to adjust the units of primary studies and to make the coefficients from primary studies comparable will lead to a more sophisticated meta-analysis that can provide further policy recommendations.

The panel method proposed in Chapter 3 provides a potential method for identifying the value of adaptations under climate change. Even though this method has the advantage of identifying adaptations, it is potentially vulnerable to omitted variables. Although the inter-annual fluctuations that are common across counties and the time-invariant differences among states are well controlled by the fixed effects, we do not control for inter-county differences within each state. In order to account for the inter-county unobservable differences, county-fixed effects are applied in previous studies. 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. We conducted numerous tests to ensure the omitted variables would not cause significant biases in our estimation; however, further studies developing an approach that avoids the omitted variables biases would be valuable.

Another potential bias of our study in Chapter 3 comes from the measurement error of agricultural profits data. A potential concern of using annual agricultural profits as the dependent variable is the potential bias results from yearly storage and inventory adjustments. The annual profits data from the US 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 the next year, or part of this year's profits might come from last year's production. In further studies, developing a way to adjust the bias derived from the agricultural profits data will help to provide more precise estimates of climate change impacts and the value of adaptations.

In addition, there are several important caveats in explaining the empirical result of Chapter 3. First, this study does not take into account the fertilization effects of higher CO_2 concentration. In fact, evidence from agronomic experiments suggests 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. Second, in this partial equilibrium analysis, agricultural prices are assumed to be constant under climate change. This assumption is reliable if most of the negative effects in currently hot areas are offset by the positive effects in currently cold regions. Otherwise, agricultural prices will rise, resulting in a smaller overall profit loss. Third, to avoid potential bias from irrigation, we follow the literature and use only data from US counties east of the 100º meridian. Hence, the results of this chapter apply only to eastern US and not to the whole country. Fifth, the potential benefits from technological advancements induced by climate change are not included in the adaptation benefit estimation. Previous studies show that technological advancements may play an important role in agricultural adaptation to climate change (Emerick et al. 2016). Consequently, this study estimates only the lower boundary of adaptation benefits.

Finally, the conclusions of Chapter 4 depend heavily on the sample areas. Based on a panel of household survey data from rural China, Chapter 4 adopts the panel approach developed in Chapter 3 to estimate the potential benefits of adaptation and to identify the determinants of farmers' adaptation capability. In the survey, only 31 counties in eight sample provinces were selected to represent the various agricultural systems in China. However, provinces and counties in China different dramatically in conditions of agricultural production, such as the irrigation water availability, soil quality, and transportation costs. Further studies that expand the sample areas should lead to more reliable conclusions.

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