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Impacts of Climate Change and Extreme Weather on US Agricultural Productivity
Evidence and Projection

Sun Ling Wang, Eldon Ball, Richard Nehring,
Ryan Williams, and Truong Chau

In the past four decades, the frequency of adverse weather events has increased (Parry et al. 2007; IPCC 2007; Hatfield et al. 2014). Bad weather can result in higher unit-production costs when producers try to mitigate heat stress on animals or drought effects on crops. It can also widen the distance between observed production and the feasible production frontier and lower productivity estimates. According to USDA's US agricultural productivity statistics (USDA-ERS 2017), in 2015, farm output was more than 2.7 times its 1948 level. With little growth in input use, the growth of total factor productivity (TFP) accounted for nearly all output growth during that period. However, TFP growth rates fluctuate considerably from year to year in response to transitory events (see Wang et al. 2015 for discussion), mostly adverse weather. Since there is a growing consensus that climate change is occurring and the average daily temperature and the frequency of extreme

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weather are likely to increase in the future (IPCC 2007; EPA 2018; NASA 2018), the likely effects of climate change or weather fluctuations on agricultural productivity have gained much attention in recent studies.

In the literature, "weather" is usually used to denote short-term variations in temperature or precipitation, while "climate change" refers to changes in average levels of weather outcomes (e.g., degree of temperature) that cover a long period of time. While climate change and weather variation are two different issues, one phenomenon of climate change is the increasing frequency of weather shocks (extreme weather). Therefore, it is critical to consider the case of extreme weather in addressing the effect of climate on agricultural productivity.

There are three major streams of literature studying the relationship between climate change / weather effect and economic activities. One body of work focuses on biophysical impacts through examining the relationship between climatic factors and individual commodity production or productivity, such as weather and crop yield or livestock production (e.g., St-Pierre, Cobanov, and Schnitkey 2003; Schlenker and Roberts 2009; Lobell, Schlenker, and Costa-Roberts 2011; Paltasingh, Goyari, and Mishra 2012; Mukherjee, Bravo-Ureta, and Vries 2012; Hatfield et al. 2014; Key and Sneeringer 2014; Burke and Emerick 2016). A second body of work focuses on adaptive response at the individual/firm level through evaluating how an individual farm/firm/person reacts to climatic impacts, such as a farmer's behavior under uncertainty (risk management, see Schimmelpfennig 1996; Kim and Chavas 2003; Di Falco and Veronesi 2013; Yang and Shumway 2015.) The third stream of literature addresses impacts at a regional/national/sectoral scale, considering both biophysical effects and adaptation or other economic impacts (e.g., land values, see Mendelsohn, Nordhaus, and Shaw 1994; agricultural profit, see Deschênes and Greenstone 2007; economic growth, see Dell, Jones, and Olken 2012). They are usually done by quantifying the effects of climate/weather changes on aggregate economic performance using country- and regional-level data (e.g., Mendelson, Nordhaus, and Shaw 1994; Sachs and Warner 1997; Dell, Jones, and Olken 2009, 2012) or sectoral data (e.g., Malcom et al. 2012; Hatfield et al. 2014; Marshall et al. 2015; Liang et al. 2017).

In the literature on identifying climatic impacts on aggregate economic performance, researchers either employ an empirical approach based on historical data or utilize simulation techniques to project economic responses to climate/weather shocks based on baseline projections and scenario analysis, especially in agricultural studies. While projecting climatic impacts can be useful for informing policy or making policy recommendations, empirical studies can help identify the relationship between climate/weather and economic activities and provide statistical evidence in explaining economic phenomena. Empirical studies can rely on either time-series data or cross-sectional data. The advantage of using time-series data is that they capture the impacts of climate change and the farmers' adaption to these changes over time. Nevertheless, they could fail to capture varied effects across regions. Notwithstanding, while the cross-sectional data approach contains information on geospatial differences, the statistical results may be biased if regionally specific characteristics are not taken into account, such as irrigation areas (Schlenker, Hanemann, and Fisher 2006). Panel data, on the other hand, can both preserve desired features of time-series and cross-sectional analyses and avoid their weaknesses, and it has become a preferred approach in recent studies.

The literature on the impact of climate change on crop production has shown that while moderate warming may benefit crop and pasture yields in temperate regions, further temperature increases can reduce crop yields in all regions (Carter et al. 1994; Lobell and Asner 2003; Tubiello and Rosenzweig 2008; Schlenker and Roberts 2009). In addition, some studies suggest that higher variance in climate conditions leads to lower average crop yields and greater yield variability (Semenov and Porter 1995; Ferris et al. 1998; McCarl, Villaviencio, and Wu 2008; among others). Weather extremes can also cause disease outbreaks and influence agricultural production (Yu and Babcock 1992; Anyamba et al. 2014). In livestock studies, evidence indicates that when an animal's thermal environment is altered due to climate change, the animal's health and reproduction can be affected. The feed conversion rate can also be affected (St-Pierre, Cobanov, and Schnitkey 2003; Morrison 1983; Fuquay 1981). Mukherjee, Bravo-Ureta, and Vries (2012) and Key and Sneeringer (2014) indicate that an increase in a temperature humidity index (THI) could help explain the technical inefficiency of dairy production based on stochastic frontier estimates. In an aggregate economy study, Dell, Jones, and Olken (2012) use historical cross-country data to identify the relationship between temperature shocks and economic growth. They find that climatic effects vary across countries with different economic development stages. They suggest that in the long run, countries may adapt to a particular temperature, mitigating the short-run economic impacts.

In light of recent developments in the literature, in this chapter we use state panel data to study the impact of climate change and extreme weather on US agricultural productivity empirically, for the entire farm sector (including both crop and livestock production). One major challenge in quantifying climatic effects on the aggregate sector is constructing appropriate climatic variables. While Dell, Jones, and Olken (2012) use historical fluctuations in temperature within countries to identify impacts on aggregate economic outcomes and find significant results, our climate variables are not limited to temperature and also include precipitation and humidity estimates, as precipitation is relevant to crop production. The scientific literature suggests that a heat stress that exceeds livestock's optimal thermoneutral zone (THI load) can reduce fertility, feed efficiency, weight gain, and so on (NRC 1983; Fuquay 1981; Hansen and Aréchiga 1999; West, Mullinix, and Bernard

2003). THI load has been shown to be an effective measure in evaluating the environmental effects on livestock. The Oury index, on the other hand, is an aridity index that combines temperature and precipitation in the measurement and is effective in connecting climatic effects to crop growth (Oury 1965; Zhang and Carter 1997). A lower Oury index indicates drier conditions that would be less favorable to crop production. Drawing upon the prior literature, we use historical temperature, humidity, and precipitation data to form a THI and an Oury index (an aridity index). The mean levels of THI and Oury indexes reflect changes in annual weather outcomes for individual states over the study period. Shocks of THI and Oury indexes, which measure the degree of unexpected deviations from their historical (1941 to 1970) means, are used to capture the unexpected extreme weather effects.

We use constructed weather variables and aggregate economic data within states to examine the relationships between climatic variables and regional agricultural productivity. Given that there may be spatial heterogeneity, we also include state characteristic variables—including irrigated area, state-level R&D, extension, and road infrastructure—in alternative model specifications in addition to using a fixed-effect approach. We further conduct scenario analyses to project how future temperature and precipitation changes, under climate-change expectations, affect agricultural productivity using 2000 to 2010 as the reference period.

In this study, we have four major findings. First, using the THI load and Oury indexes, we find that the patterns of climate change varied from region to region in the last half century (1960 to 2010), with some states becoming drier or warmer, while some states have little change on average but have become more volatile in more recent years. Second, using mean levels of THI and Oury indexes, we find that a higher THI load and lower Oury index (much drier condition) will lower a state's productivity. However, some estimated coefficients become insignificant when more state characteristic variables are incorporated into the estimation. Third, when using THI shock and Oury shock variables, the results are more robust across model specifications in both signs and coefficient estimates. Positive THI shocks and negative Oury shocks will lower state technical efficiency. This suggests that over the long run, each state has gradually adapted to state-specific climate conditions (the average level of temperature and precipitation and the degree of weather fluctuations). It is the unexpected weather shocks that are affecting regional productivity more profoundly. Fourth, using weather shock variables, we project potential impacts of increasing temperature and extreme weather (the expected climate-change phenomenon) on US regional productivity. Results show that the same degree changes in temperature or precipitation will have uneven impacts on regional productivities, with Delta, Northeast, and Southeast regions incurring much greater effects than the other regions, using 2000 to 2010 as the reference period.

This chapter is the first empirical study, we think, to estimate the climatic effect on regional agricultural productivity from the perspective of the entire farm sector, including both livestock and crop production. The study adds new insight into identifying the climatic effects on aggregate agricultural productivity. Our evidence suggests that weather shocks have more consistent and profound impacts on regional productivity when each state faces its particular weather condition. The diverse weather impacts on regional productivity from the same degree of changes in temperature or precipitation suggest the need for state-specific research programs to help producers manage their own climatic situations and future challenges.

We organize the remainder of the chapter as follows: Section 2.1 introduces the empirical approach. Section 2.2 describes the data and variables and provides descriptive statistics. Section 2.3 presents patterns of state productivity growth and climate changes. Section 2.4 the empirical results and discussion. Section 2.5 reports the projection of regional productivity based on climate change scenarios. Section 2.6 provides concluding remarks.

2.1 Empirical Framework

In the literature on climate and its economic impacts, some studies incorporate climate variables along with other input variables in one production function to test for climatic effects on crop yield, livestock production, economic performance, or productivity growth. There are also studies that model weather variables as factors that impact technical inefficiency but aren't in the production equation (see Key and Sneeringer 2014, for example). In a study of climatic effects on US dairy productivity, Key and Sneeringer (2014) assert that operators in a region under adverse weather conditions will operate further from the production frontier (i.e., be less technically efficient) even when they have technology similar to that of other operators in different regions. That study employed a stochastic frontier production approach in its estimates, where climate variables were incorporated as determinants of a one-sided error that drove farm production from its production frontier. In this study, we employ the same approach to evaluate the potential impacts of climate change and extreme weather on US regional agricultural productivity. To validate our choices of model specifications and weather variables, we also perform out-of-sample validation tests. We divide the data set into estimation sets (80 percent of observations, from 1961 to 1995) and validation sets (20 percent of observations, from 1996 to 2004) to evaluate forecasting performances among various model specifications and alternative weather variables (see table 2A.1 in the appendix to this chapter for examples). The likelihood-ratio (LR) test results at the bottom of table 2A.2 indicate that we reject the hypothesis of no inefficiency for all estimated stochastic frontier models. The results show that utilizing THI and Oury indexes as determinants of a one-sided inefficiency term along with other external control variables under the stochastic frontier model setup leads to better forecast performances. The mean standard errors of predictions of those models are the lowest among estimated models (see table 2A.2 for details).

2.1.1 Stochastic Frontier Production Function

The stochastic frontier approach was first developed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977) and has been applied to numerous studies. In earlier applications, researchers tried to explain those inefficiency effects by conducting a two-step approach that requires predicting the inefficiency scores first and then running a regression model that relates the inefficiency scores and the explanatory variables in a second step. Using cross-section data, Kumbhakar, Ghosh, and McGuckin (1991), Reifschneider and Stevenson (1991), and Huang and Liu (1994) later proposed models that allow the estimation of technical inefficiency effects with parameters simultaneously estimated in the stochastic frontier function and inefficiency model. Battese and Coelli (1995) further proposed a model to estimate the technical inefficiency effects in a stochastic frontier production function for panel data. Since Wang and Schmidt (2002) have theoretically explained that two-step procedures are biased, in this study we follow Key and Sneeringer (2014) to employ a one-step procedure to test the climatic effects on regional productivity using a state panel data of 48 contiguous states for the period from 1960 to 2004. Each state is treated as an individual producer facing its particular climate patterns, state-specific characteristics, and resources.

Under the stochastic frontier production function framework, the model can be expressed as

$$\ln(y_{it}) = f(\boldsymbol{x}_{it}, \boldsymbol{\beta}) + v_{it} - u_{it}, \tag{1}$$

where y_{it} is the observed aggregate output of state i at time t, and $f(\boldsymbol{x}_{it}, \boldsymbol{\beta})$ is the maximum output that can be produced with a technology described by parameters $\boldsymbol{\beta}$ (to be estimated) and a vector of inputs $\boldsymbol{x}_i$. The deviations (ε_{it}) from the frontier are composed of a two-sided random error (v_{it}) and a one-side error term ($u_{it} \geq 0$). v_{it} is a random error that can be positive or negative and is assumed to be normally and independently distributed, with a zero mean and constant variance of σ_v^2. u_{it} is assumed to be half-normally and independently distributed, $u_{it} \sim N^{+}(0, \sigma_u^2)$.

In a one-step approach, we assume the technical inefficiency component is heteroskedastic, that the variance σ_{ui}^2 depends on a vector of exogenous variables $\mathbf{z}_i$ and a set of parameters $\boldsymbol{\gamma}$ (to be estimated), such as climate variables and state-specific characteristics that can affect the individual state's ability to adopt the best technology given its input level:

$$\sigma_{ui}^2 = \exp(z_i'\boldsymbol{\gamma}). \tag{2}$$

Therefore, $\boldsymbol{z}_i$ affects the mean and variance of the inefficiency term u_i. If $u_i = 0$, then state i is at the production frontier and is technically efficient. If $u_i > 0$, then state i is deviated from the frontier and is technically inefficient. The technical efficiency of state i (TE_i) is defined as the ratio of the *ith* state's observed output to its feasible output (the maximum output it can produce with given inputs). Once the technical inefficiency u_i is estimated, technical efficiency (TE_{it}) can be obtained by the following formula:

$$(3) \qquad TE_{it} = \frac{y_i}{\exp(f(\boldsymbol{x}_{\mathbf{it}}, \beta) + v_{it})} = \exp(-u_{it}).$$

TE_{it} ranges between 0 and 1, with 1 being on the frontier. In this study, the empirical stochastic frontier production function to be estimated is

$$(4) \qquad \ln y_{it} = \beta_0 + \sum_{k=1}^{K} \beta_k \ln x_{kit} + \beta_t t + \sum_{j=1}^{J} \beta_j D_j + \sum_{m=1}^{M} \beta_m D_m + v_{it} - u_{it},$$

where y_i is an implicit quantity of state *i*'s total output; x_{ki}'s are implicit quantities of state *i*'s k inputs, including labor, capital, land, and intermediate goods; t is a time trend to capture natural technical changes driven by research and development from both public and private sectors (public R&D and private R&D) over time; $\boldsymbol{D}_j$'s are state dummy variables ($j = 1 \ldots 47$), and $\boldsymbol{D}_m$'s are time dummy variables ($m = 1 \ldots 43$) to capture cross-state, time-invariant, unobserved heterogeneity. The time dummy can also help reflect part of the development of technical change effects driven by the aggregate knowledge stock that are not captured by the time trend but could have shifted the production frontier unevenly across years. Equation (4) can be viewed as a log-linearized form of the Cobb-Douglas (C-D) production function.[1] We estimate an inefficiency variance regression model simultaneously with equation (4)—that is,

$$(5) \qquad \ln \sigma^2_{uit} = \gamma_0 + \sum_{n=1}^{N} \gamma_n z_{nit} + \omega_{it},$$

where ω_{it} is a disturbance term with standard normal distribution, z's include climate variables, irrigation-ready land density that may help mitigate the impacts of adverse weather, and other control variables that capture the heterogeneity of individual states.

We include various forms of climate variables in our estimation, including the THI load (for livestock) and the Oury index (an aridity index for crops), in their mean or "shock" (the unit of standard deviation from its historical

1. We choose the C-D functional form to approximate the underlying technology of the production frontier in this study because it is easy to interpret the estimated coefficients directly, and fewer parameters must be estimated.

norm) measures. We also include state-specific characteristic variables that may affect each state's technical efficiency, including R&D stock, extension capacity, and road density, as these variables are suggested to have impacts on state-level productivity in the literature (Alston et al. 2010; Wang et al. 2012; Jin and Huffman 2016, among others). We will explain how we construct those variables in the next section. The stochastic frontier is estimated by a maximum likelihood (ML) procedure.

2.2 Variables, Data Sources, and Descriptive Analysis

We employ a panel of state-level aggregate agricultural output, as well as inputs of labor, capital, land, and intermediate goods, to form the stochastic frontier production function. To identify the impacts of climate change on technical inefficiency changes, we construct climate variables that can capture the impacts on either crops or livestock production. We also construct measures of the share of irrigated land area and other local public good variables—R&D, extension, capacity, and road density—as control variables to test for the robustness of the climatic effects on state inefficiency.

2.2.1 Agricultural Output and Inputs

We draw state-specific aggregates of output and capital, labor, intermediate goods, and land input from the USDA state productivity accounts. Agricultural output and the four inputs are implicit quantity measurements based on the Törnqvist index approach over detailed output and input information. A full description of the underlying data sources and aggregation procedures can be found in Ball et al. (1999) and the USDA Economic Research Service (ERS) website (USDA-ERS 2017).

2.2.2 Weather Variables

Since our purpose is to estimate an overall impact of climate changes on the agricultural sector, we need to consider weather variables that have strong relationships with livestock or crops. However, there is no single measurement that can capture the weather impacts on both livestock and crops, as livestock production is more related to animals' year-round thermal environment, while crop production is affected by precipitation and temperature during the growing seasons. In addition, researchers have found nonlinear temperature effects for agriculture (Deschênes and Greenstone 2007; Schlenker and Roberts 2009). To meet our objective, we construct two different weather measures to capture their effects on either livestock or crops. One is the THI, a combined measure of temperature and relative humidity that has been shown to have significant impacts on livestock production, and another is the Oury index, an aridity index that combines temperature and precipitation information that can capture more impacts on crop production than a single measure of temperature or precipitation. We draw monthly temperature and precipitation data at the county level from a weather data set produced by Oregon State University's PRISM[2] Climate Group (Daly et al. 2008). Since PRISM interpolates between weather stations to generate climate estimates for each 4 km grid cell in the United States, we are able to link county-level weather information and agricultural production to construct climate variables that could explain climate variations across regions and over time.

Livestock scientists have found that livestock productivity is related to climate through a THI measure (Thom 1958; St-Pierre, Cobanov, and Schnitkey 2003; Zimbelman et al. 2009). THI can be measured using the following equation:

$$\text{(6)} \quad \text{THI} = (\text{dry bulb temperature °C}) + (0.36 \times \text{dew point temperature °C}) + 41.2.$$

When animal stress is above a certain THI threshold, productivity declines. Following St-Pierre, Cobanov, and Schnitkey (2003) and Key and Sneeringer (2014), we generate a minimum and maximum THI for each month and location based on minimum and maximum dry-bulb temperatures and dew-point data from PRISM. To estimate the THI load—the number of hours that the location has a THI above the threshold—we employ a method proposed by St-Pierre, Cobanov, and Schnitkey (2003) to estimate a sine curve between the maximum and minimum THI over a 24-hour period. We then estimate the number of hours and degree to which the THI is above threshold[3] (See Key and Sneering 2014 appendix for more details). To construct a state-level THI load, we aggregate up the county-level[4] monthly calculations to the state-level using county animal units derived from the Census of Agriculture (USDA-NASS 2002) as the weight.

Weather is a critical factor influencing the production of crops. While precipitation and temperature are mostly considered in previous studies due to lack of information on other factors such as sunshine and wind velocity, Oury (1965) recommended the use of an aridity index in identifying the relationship between crop production and weather. Oury asserted that it is hard to define a meaningful relationship between crop production and

2. The PRISM Climate Group gathers climate observations from a wide range of monitoring networks, applies sophisticated quality-control measures, and develops spatial climate data sets to reveal short- and long-term climate patterns. The PRISM data can be accessed at http://www.prism.oregonstate.edu.

3. We employ a THI load threshold of 70 for dairy cows, as it is the lowest threshold among a broad category of livestock production (St-Pierre, Cobanov, and Schnitkey 2003).

4. Climate estimates were limited only to cropland areas as defined by the combination of the Cultivated Crops and the Pasture/Hay classes in the National Land Cover Dataset (NLCD 2006). Therefore, it eliminates the effect of urban heat islands, mountains, etc.

weather based only on one weather factor, since they are interrelated. The proposed aridity index, which is termed the Oury index, is defined (Oury 1965; Zhang and Carter 1997) as

$$W_s = \frac{P_s}{1.07^{T_s}}, \tag{6}$$

where W represents the aridity index (Oury index), s is the month (s = 1 . . . 12), P_s is the total precipitation for month s in millimeters, and T_s is the mean temperature for month s in degrees Celsius. The Oury index can be viewed as rainfall normalized with respect to temperature. We draw county-level monthly temperature and precipitation data from PRISM to aggregate up to a state-level Oury index, using county cropland density drawn from the National Land Cover Database (NLCD 2006) as the weight. The NLCD cropland pixels are composed of the combination of NLCD classes 81 (pasture/hay) and 82 (cultivated crops), with the notion that pasture/hay is a potentially convertible land cover to cultivated crops. The cropland area in the weight data is therefore a representation of current and potential cultivated cropland.

While all months of the year were considered for the THI measures, only the primary growing season months, approximately April through August, were considered for the Oury aridity index. Both THI and Oury measures were generated for a 30-year span from 1941 to 1970 and for individual years from 1961 to 2004 (our study period).

To measure the impacts of unexpected weather shocks or potential weather extremes on regional productivity, we construct Oury shock and THI shock variables as

$$\text{Oury shock}_{i,t} = (\text{Oury}_{i,t} - \text{Oury}_{i,LR})/\text{Stdv of Oury}_{i,LR} \tag{7}$$

$$\text{THI shock}_{i,t} = (\text{THI}_{i,t} - \text{THI}_{i,LR})/\text{Stdv of THI}_{i,LR}, \tag{8}$$

where $\text{Oury}_{i,t}$ is the Oury mean of year t for state i, $\text{Oury}_{i,LR}$ is the long-run Oury mean for state i calculated using historical Oury mean data between 1941 and 1970, $\text{THI}_{i,t}$ is the THI load of year t for state i, $\text{THI}_{i,LR}$ is the long-run THI mean calculated using historical THI mean data between 1941 and 1970, and $\text{Stdv}_{i,LR}$ is the standard deviation of historical Oury means or historical THI means. Since each state has its unique weather variation pattern, a same-level change in Oury mean or THI mean may result in different Oury shock or THI shock estimates given that the long-run values of Oury mean, THI mean, and long-run standard deviations of those indexes vary from state to state. We suspect that even with the same degree of deviations from historical Oury mean (Oury_{LR}) or TH mean (THI_{LR}), some states may perform better than others if they have expected and adapted to a larger weather variation climatic pattern in the past.

We compared Oury and THI indexes with other potential weather variables (see table 2A.1 for examples) using out-of-sample validation tests. We report the mean standard errors of prediction statistics for each model in table 2A.2. Since the good weather index (dd830) has a "wrong" sign (negative) in most of the estimates, coefficients of Palmer index are mostly insignificant, and the bad weather index (dd30) has a similar result to the maximum temperature variable (see table 2A.1 for weather variable descriptions), we only report out-of-sample test results of those using maximum temperature, precipitation, Oury mean, THI mean, Oury shock, and THI shock weather variables (see table 2A.2). The results show that stochastic frontier model estimates with Oury and THI weather variables have better forecast performances among estimated models.

2.2.3 Irrigation-Ready Land Density (Irrigation Density) Variable

Irrigation infrastructure can help mitigate the impact of adverse weather. We construct an irrigation-ready land density (share of irrigated land area, irrigation density thereafter) variable to capture the impact of irrigation-system availability in production. The variable is constructed as the ratio of irrigated land area to total cropland. The cropland and irrigated land area are available for the census of agriculture years (USDA-NASS, 2013) for each state. We employ a cubic spline technique to interpolate the information between census years. The expanded irrigated areas and cropland areas are used to construct a panel of irrigation density variables across states and over time.

2.2.4 R&D, Extension, and Roads

To capture specific state characteristics that could have also impacted the state's technical inefficiency, we included state-level variables on public agricultural R&D stock, extension, and roads. Annual data on public agricultural research expenditures and a research price index used to deflate expenditures are provided by Huffman (see Jin and Huffman 2016 for data construction details.) The extension variable is a measure of extension capacity calculated as the total full-time equivalent (FTE) extension staff divided by the total number of farms. Data on FTEs by state were drawn from the Salary Analysis of the Cooperative Extension Service from the Human Resource Division at the USDA (USDA-NIFA). Road infrastructure is a road-density index constructed by dividing total road miles excluding local (e.g., city street) miles by total land area.

2.3 Patterns of State Productivity Growth and Climate Changes

We summarize state-level TFP growth from 1960 to 2004[5] (USDA-ERS 2017) as well as the mean and standard deviation of the normal THI index

5. USDA's state productivity indexes only cover the period of 1960 to 2004.

and Oury index over the historical period from 1941 to 1970 in table 2A.3 to provide some background information on state-specific characteristics. In general, TFP growth varied across and within USDA's production regions. Given the variances in geoclimate conditions and natural resources, states tend to have notable differences in their composition of livestock and crop production. For example, states in the Northeast region tend to have a higher ratio of livestock production, while the Corn Belt and Pacific regions tend to produce more crops than livestock. Usually, a higher THI indicates more intensive heat stress and can hinder livestock productivity growth. On the other hand, a lower Oury index indicates a much drier condition that would lower crop production. If the Oury index is lower than 20, it indicates a very dry situation that could be seen as a drought condition, and if the Oury index is less than 10, it implies a "desert-like" state (Zhang and Carter 1997).

While the relative THI and Oury index levels could result in geospatial differences in technical inefficiency, an unexpected climate "shock," such as extreme weather, could cause more of an impact, as farmers will have expected climate patterns to be similar to the past. Farmers could have already invested in appropriate facilities, such as irrigation systems or cooling systems, in areas with a low Oury index or high THI loads. It is the unexpected weather changes that result in inefficient input use as yields decline (or a waste of inputs when crops cannot be harvested) as well as a decrease in livestock production due to unexpected heat stress. According to table 2A.3, some regions may have much higher variation in their Oury index than in their THI index, such as the mountain and Pacific regions. If farmers expect dramatic variation from year to year in advance, they may have already invested in an irrigation system to dampen the impacts of climate changes on farm production.

TFP growth estimates usually move closely with output growth. According to ERS's US agricultural productivity accounts (USDA-ERS 2017), in 1983 and 1995, the dramatic impacts from adverse weather events caused significant drops in both output and TFP (see Wang et al. 2015 for more discussion). In figure 2.1, we map the normal Oury index ($\text{Oury}_{i,LR}$) (based on 1941–1970 data) and Oury indexes in 1983 and 1995 at the state level. We find that the Oury index varied for many states in 1983 and 1995, while the shocks (figure 2.2) from its norm show a different picture regarding climate changes.

Figure 2.3 presents the normal THI load ($\text{THI}_{i,LR}$) (based on 1941–1970 data) as well as the THI indexes in 1983 and 1995 across states. When compared with the Oury index, however, THI load shows less variation over time. Nevertheless, if we look at the maps of shock indexes in different years (figure 2.4), we may find that there are noticeable differences over the years.

If bad weather is expected and farmers invest in facilities to reduce the potential damage from adverse weather conditions, then the impacts of extreme weather on farm production could decline. Figure 2.5 shows

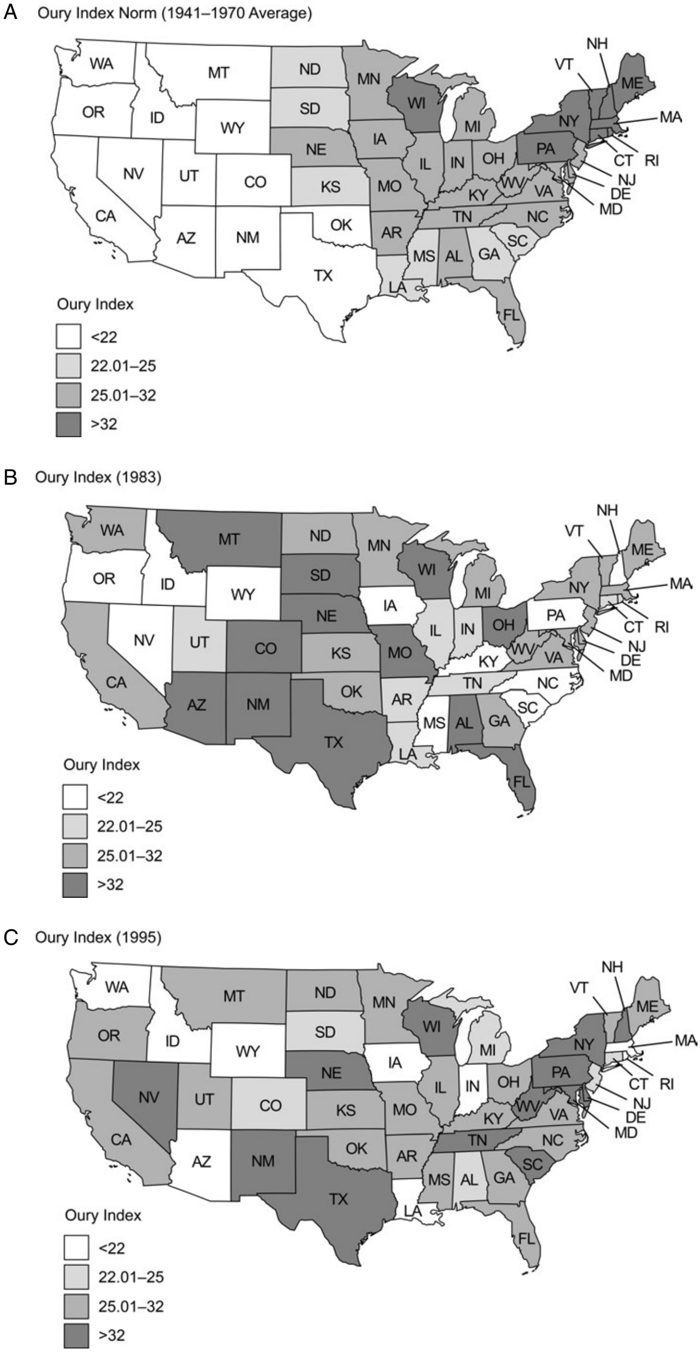

Fig. 2.1 Oury index comparison, the norm (1941 to 1970), 1983, and 1995
Source: Authors' calculation.

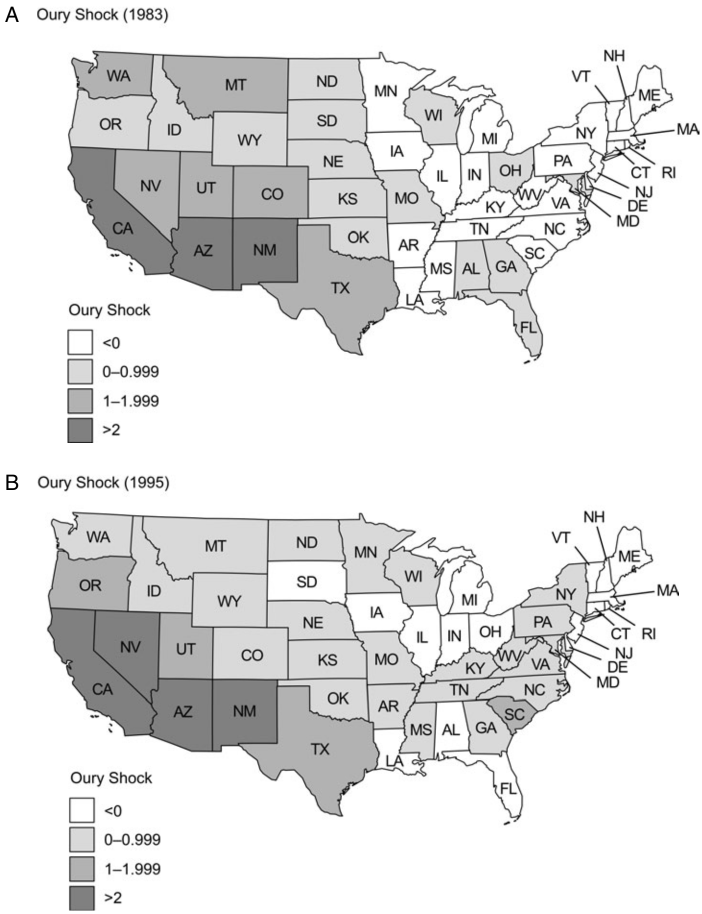

Fig. 2.2 The climate-shocks comparison using the Oury index: 1983 versus 1995
Source: Authors' calculation.

irrigation-density changes over time. In general, Pacific regions and mountainous regions have more intensive irrigation systems than other regions.

2.4 Empirical Results

We first estimate equation (4) and test the hypothesis of no inefficiency effect that $H_0 \colon \sigma_u^2 = 0$, against the alternative hypothesis of $H_1 \colon \sigma_u^2 > 0$. The L-R test result shows that the null hypothesis is rejected at the 1 percent significance level, indicating that the stochastic frontier approach is valid in our study. We then estimate the stochastic frontier model (equation [4]) and the inefficiency determinants regression model (equation [5]) simultaneously using alter-

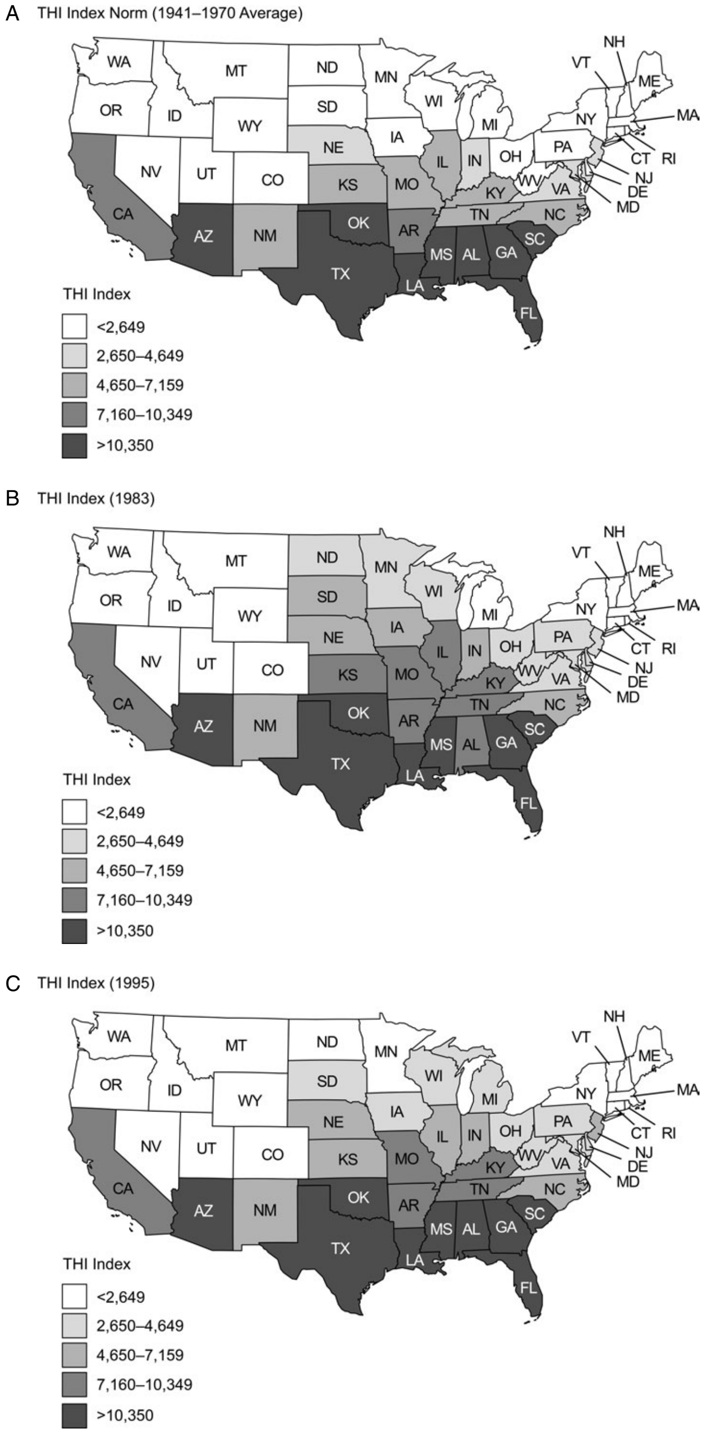

Fig. 2.3 THI load comparison, the norm, 1983, and 1995
Source: Authors' calculations.

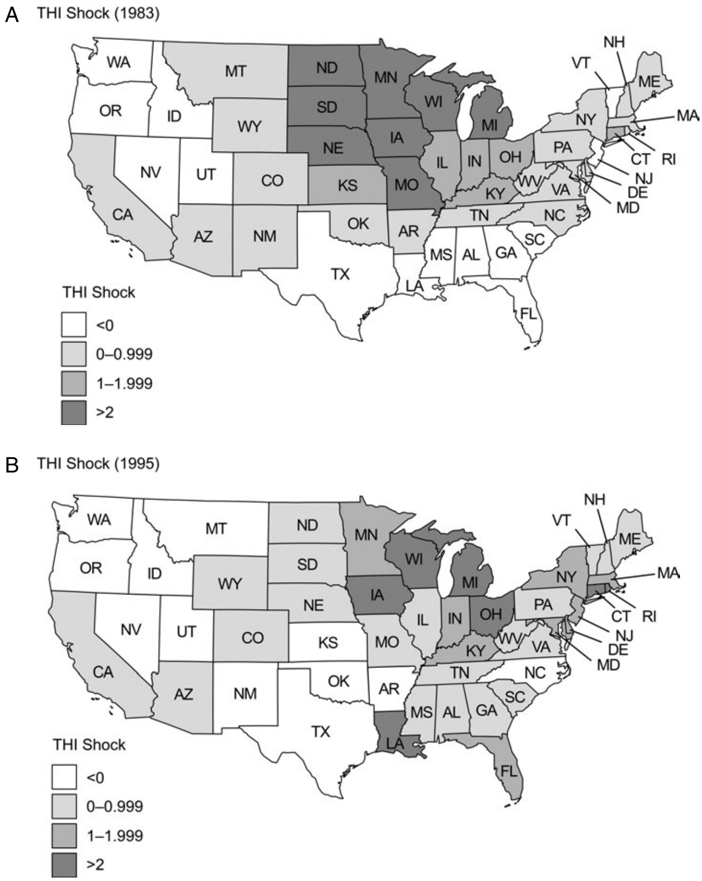

Fig. 2.4 The climate-shocks comparisons using the THI index: 1983 versus 1995
Source: Authors' calculation.

native weather variables and model specifications as a robustness check.[6] Empirical results of both production regression and inefficiency determinant regression are presented in table 2.1. Models 1 and 2 evaluate climatic effects on state inefficiency by including only weather and irrigation den-

6. There is a challenge estimating production functions given that inputs can be endogenous. While we have done some experiments using inputs from previous year (a common approach used in the literature) as an instrument in the estimation, we only report the results based on the output and input variables from the same year. There are two reasons behind this choice: first, the coefficients in the production function are similar given that input uses are rather stable from one year to another (not like output); second, we want to capture the concurrent effects so that the inefficiency component can capture both output changes and input changes (not endogeneity-adjusted) in the same year. Still, future studies can consider applying some other IV techniques (e.g., Levinsohn and Petrin 2003; Shee and Stefanou 2014; Amsler, Prokhorov, and Schmidt 2014) for comparison purpose.

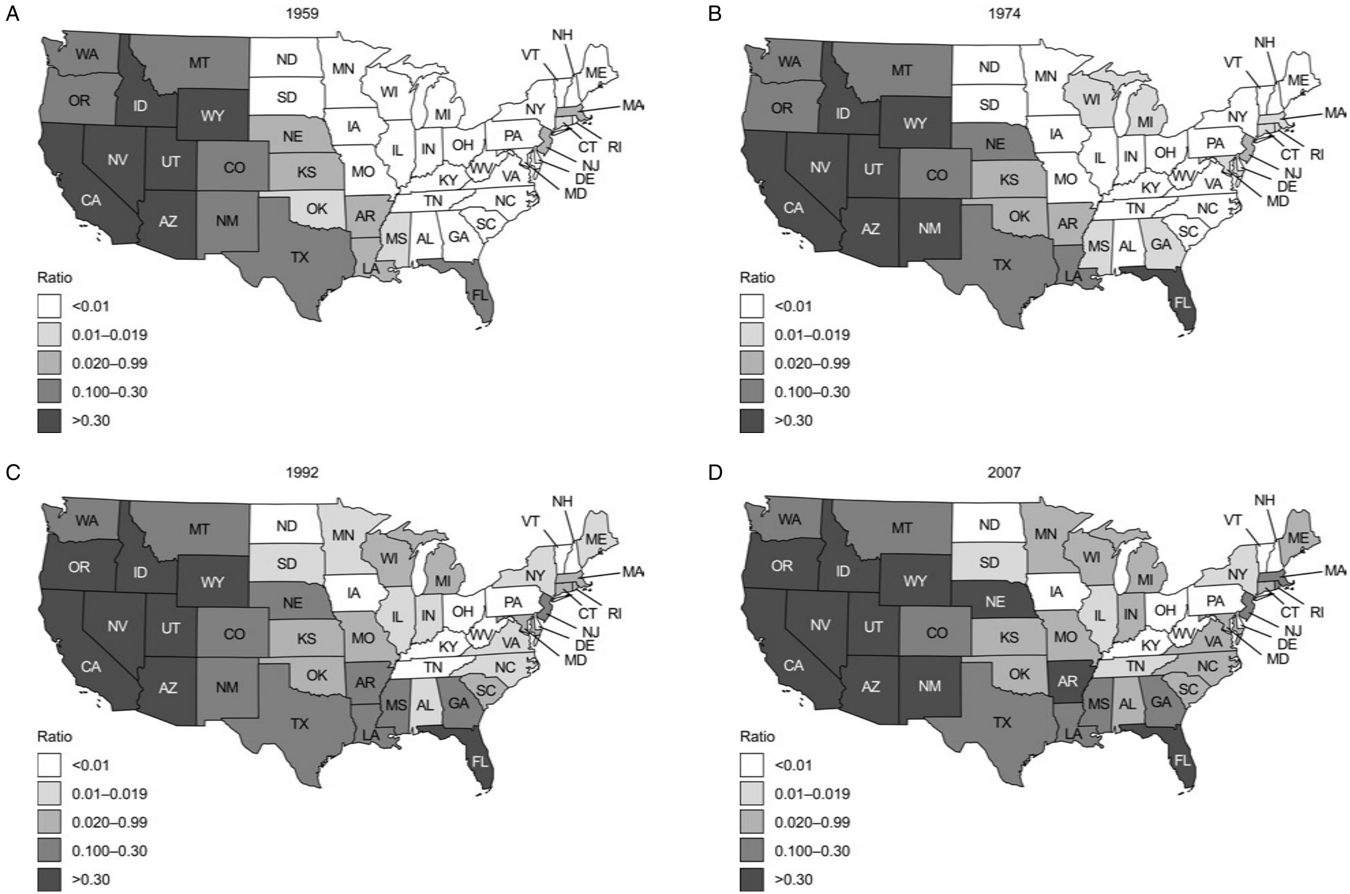

Fig. 2.5 Ratios of irrigation-ready land area to total cropland area (irrigation density) at census years
Note: "Ratio" indicates the share of irrigation-ready land area to total cropland area.
Source: Author's calculation using data from the agricultural census in various years.

sity variables as inefficiency determinants. Models 3 and 4 add state-specific variables—public R&D stock, extension capacity, and road density—as control variables to check the robustness of the estimated climatic impacts on state inefficiency. Models 1 and 3 use mean levels of THI and Oury indexes, while model 2 and 4 use THI shocks and Oury shocks as weather variables. Since outputs and inputs are all in natural logarithms, the input coefficients can be interpreted as output elasticities. According to the estimates of production function on the top section of table 2.1, the output elasticities for specific input across four models are consistent, with the output elasticity of intermediate goods at its highest, about 0.6, and capital's output elasticity at its lowest, about 0.07 to 0.08. Since the hypothesis of constant return to scale is rejected, we can infer a decreasing return to scale with input coefficients totaling less than one.

The signs of the coefficients of weather variables are as expected and consistent no matter the measures. Results of the inefficiency determinants regressions indicate that the combined effects of higher temperature and lower precipitation that result in a higher THI load or a lower Oury index measure can drive state production away from its best performance. However, without controlling for state-specific variables, the coefficient of the THI load becomes insignificant in model 1. According to the results, one unit increase in the THI load could result in a worse inefficiency, with the inefficiency term ($\ln \sigma_u^2$) increasing by 0.00002 percent in model 1 and 0.00006 percent in model 3. On the other hand, one unit decrease in the Oury index (drier conditions) could cause further inefficiency, with the inefficiency term increasing by 0.026 percent in model 1 and 0.02 percent in model 3. Using "shock" measures (units of standard deviations relative to historical norms) of the THI load and Oury index as weather variables in model 2 and model 4, the estimates are all significant, and the magnitudes of those coefficients are consistent between the two models. According to both models, a single unit shock of the THI load will result in about a 0.3 percent deterioration in the inefficiency term, while a unit of negative shock (drier conditions) will result in about a 0.18 percent deterioration in the inefficiency term.

The results show that the "unexpected" deviation from the state's historical norm in weather variations have more consistent impacts on state production efficiency than the mean-level changes of weather variables. It implies that farmers in a region with more temperature or precipitation variations may have adapted more to the environment by adopting technologies or practices that can mitigate the damages from adverse weather. For example, drier regions, such as California and Nevada, usually have higher irrigation-ready land density than other regions, and that may partially offset the negative impacts of bad weather. The negative coefficients of irrigation density indicate that a state with a higher density in irrigation-system-ready land areas tends to be closer to its best production performance when holding other factors constant. After controlling for state-

Table 2.1 **Stochastic frontier models estimates with alternative inefficiency determinants**

	Model 1		Model 2		Model 3		Model 4	
Variables	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio	Coefficient	t-ratio
ln y								
Technology (time trend)	0.0009	6.86***	0.0010	7.49***	0.0010	7.23***	0.0010	7.73***
ln(capital)	0.0813	4.10***	0.0775	3.96***	0.0705	3.59***	0.0785	4.11***
ln(materials)	0.5959	44.35***	0.5952	45.24***	0.5920	45.49***	0.5879	45.42***
ln(labor)	0.0982	10.60***	0.0998	10.98***	0.1089	11.57***	0.1079	11.66***
ln(land)	0.1124	6.55***	0.1055	6.25***	0.1083	6.23***	0.0995	5.80***
ln $\sigma_v'^2$ (noise)								
Constant	–5.8828	–59.40***	–5.8048	–52.68***	–5.8232	–71.97***	–5.8362	–66.84***
ln $\sigma_v'^2$ (inefficiency)								
Constant	–4.5181	–26.02***	–5.2706	–25.05***	–2.4305	–1.14	–2.7825	–1.52
THI load	0.00002	1.31			0.00006	3.38***		
Oury index	–0.0257	–4.29***			–0.0201	–3.06***		
THI load shock			0.3087	5.40***			0.3073	5.25***
Oury index shock			–0.1831	–2.15***			–0.1831	–2.15***
Irrigation density	–1.6170	–2.89***	–1.4210	–1.93***	–2.8771	–3.45***	–2.2217	–3.01***
lnR&D					–0.3867	–2.86***	–0.3314	–2.67***
lnExtension					–0.6245	–3.71***	–0.4787	–2.69***
lnRoad					–0.8779	–3.68***	–0.7994	–3.78***
State fixed effects	Yes		Yes		Yes		Yes	
Time fixed effects	Yes		Yes		Yes		Yes	
Log-likelihood	2,679		2,698		2,713		2,726	
X^2 (95)	16,400,000	prob > X^2 = 0	11,700,000	prob > X^2 = 0	15,900,000	prob > X^2 = 0	14,600,000	prob > X^2 = 0
Observations	2,112		2,112		2,112		2,112	

Source: Authors' calculation.

specific characteristics, the irrigation density's impacts on inefficiency are also larger in models 3 and 4.

The signs of the coefficient estimates of state-specific control variables—R&D stock, extension, road density—are consistent with the literature, wherein higher knowledge capital (R&D stock), extension capacity, and road density can enhance an individual state's productivity and push its production toward its best performance using given inputs and the best technology. Since R&D, extension, and road-density variables are all in natural log (Ln) form, a 1 percent increase in road density and extension capacity may have higher impacts on improving technical inefficiency than a 1 percent increase in local R&D stock. This implies that while public R&D stock can contribute to overall technical changes by pushing up the general production frontier for all states, its contribution in improving a local state's inefficiency may be less than that of other local public goods. The state extension activity and intensified road infrastructure can help disseminate knowledge, reduce transportation costs, and improve a state's technical efficiencies by catching up with others.

Based on the results from model 4, we estimate box and whisker plots of individual states' inefficiencies. The mean and distribution of states' inefficiency scores and rankings are presented in figure 2.6. We find that over the study period, California ranks first in productivity performance (least inefficiency), making it the most productive state among all 48 contiguous states. The top six most efficient states also include Arizona, Florida, New Jersey, Massachusetts, and New York. According to the predicted inefficiency scores, individual states' productivity is strongly affected by their state-specific characteristics such that even with similar weather patterns and natural resources, productivity can differ significantly.[7]

2.5 Potential Impacts of Future Climate Change on US Agricultural Production: Scenario Analysis

To estimate the heat-stress- and drought-related production losses attributable to climate change (mean level changes) and extreme weather (weather shock), we simulate the climate change projections in temperature and precipitation in the 2030s that result in various THI load and Oury index estimates. There are many global models projecting future climate changes, and while the magnitudes of future temperature or precipitation may be different from one projection to another, the direction of the projections consistently point toward more frequent heat waves, warmer temperatures,

7. The results could also imply that if the major federal/state water storage and allocation system that helped support the high-valued irrigated agricultural sector in California is not to be as resilient in future years under prolonged drought conditions due to an absence of significant new capital investment, California may not be as efficient as in the past.

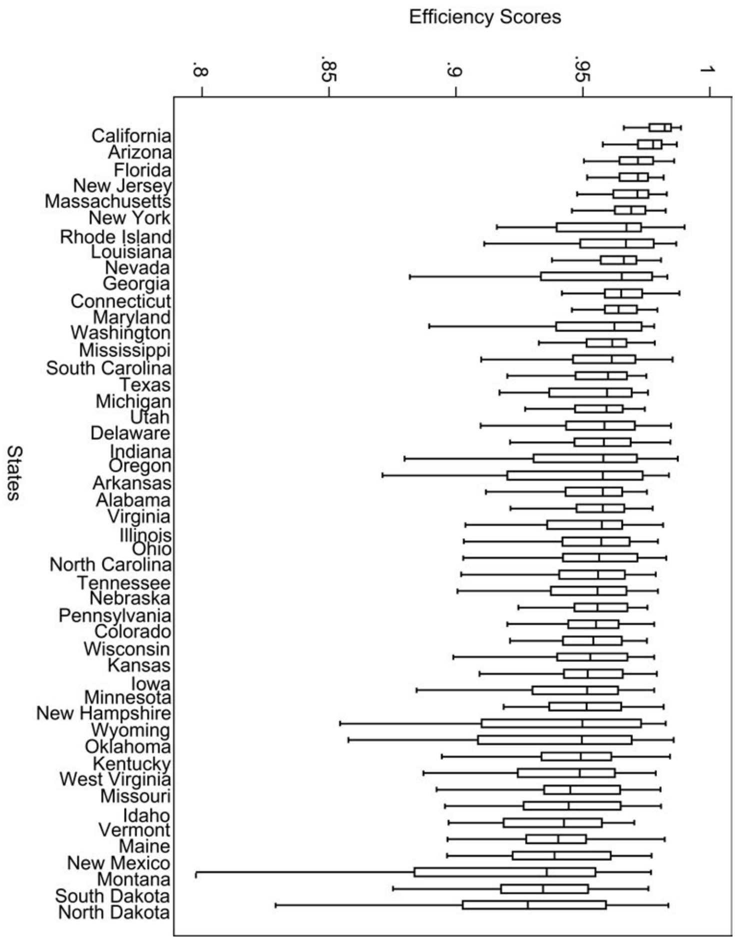

Fig. 2.6 Box and whiskers plots of state efficiency estimates and rankings based on model 4

and increasing incidences of extreme weather. Key and Sneeringer (2014) project the potential impacts of climate change on US dairy production in 2030 based on four climate-change scenarios drawn from the projections of four general circulation models—CNR, ECH, CSIRO, and MORPC (see Key and Sneeringer 2014 data appendix for details). Under their scenarios, temperature change during the period of 2010 to 2030 ranges from 0.65°C to 1.38°C. According to the Environmental Protection Agency,[8] earth's average temperature has risen by 0.83°C over the past century and is projected to rise another 0.3°C to 4.8°C over the next hundred years. According to the

8. See https://www3.epa.gov/climatechange/basics/ for more details.

US Global Change Research Program Report (USGCRP 2014),[9] the overall temperatures will continue to warm over the century in the United States, with a projected average increase by the end of the century of approximately 3.9°C to 6.1°C under the high-emission scenario and 2.2°C to 3.6°C under the low-emission scenario. We draw information from various projected trends in future temperature and precipitation changes to form three scenarios from mild to extreme. The scenarios are as follows:

Scenario 1: We assume a mild climate change during the growing season of the 2030s, with a 1°C increase relative to 1940–1970 temperature levels.
Scenario 2: We assume a more serious climate change scenario in the 2030s, with a 2°C increase relative to 1940–1970 temperature levels.
Scenario 3: We assume an extreme-weather scenario during the 2030s, with a 2°C temperature increase and one-inch decrease in monthly average precipitation relative to 1940–1970 levels.

We estimate the production response as if there are no changes in prices, input use, technology, or farm practices.[10] The projections are conducted using model 4 estimates, where the weather variables are shocks of the THI load and the Oury index with state-specific control variables kept constant as in the following equation:

$$(9)\quad \ln \sigma^2_{uit} = \gamma_0 + \gamma_1 z_{\mathrm{THI\_shock},it} + \gamma_2 z_{\mathrm{Oury\_shock},it} + r_3 z_{\mathrm{irrigation\_density},it} + r_4 \ln \mathrm{RD}_{it} + r_5 \ln \mathrm{ET}_{it} + r_6 \ln \mathrm{RO}_{it} + \omega_{it};\ \omega_{it} \sim N(0, \sigma^2_\omega).$$

Since each state has its own genuine pattern of historical climatic variations, each could have adjusted its farm production by adopting various production practices or technologies to adapt to the weather it is facing (Yang and Shumway 2015; Huang, Wang, and Wang 2015; Marshall et al. 2015; Heisey and Day-Rubenstein 2015). Therefore, the unexpected same-degree change in temperature and precipitation may have different impacts on an individual state's THI shock and Oury index shock estimates, resulting in varying effects on state production efficiency estimates. The impact of temperature changes on estimated state inefficiency can be derived by taking the first derivative of equation (9) with respect to temperature changes as follows:

9. Established under the Global Research Act of 1990, the US Global Change Research Program (USGCRP) has provided strategic planning and coordination to 13 participating federal agencies working to advance the science of global environmental change. The third National Climate Assessment, released by USGCRP in May 2014, is the most comprehensive and authoritative report on climate change and its impacts in the United States. See http://nca2014.globalchange.gov/ for more details.

10. This is the so-called dumb farmer (a naïve case) assumption (Mendelsohn, Nordhaus, and Shaw 1994; Key and Sneeringer 2014), where farm operators are assumed not to anticipate or respond to changing environmental conditions. The impacts may be reduced by allowing for some level of adaptation by the producer.

$$(10)\qquad \frac{\partial \ln \sigma_{ui}^2}{\partial T} = \frac{\partial \ln \sigma_{ui}^2}{\partial Z_{\text{THI\_shock},i}} \frac{\partial Z_{\text{THI\_shock},i}}{\partial T} + \frac{\partial \ln \sigma_{ui}^2}{\partial Z_{\text{Oury\_shock},i}} \frac{\partial Z_{\text{Oury\_shock},i}}{\partial T}$$
$$= \gamma_1 \times \frac{\partial Z_{\text{THI\_shock},i}}{\partial T} + \gamma_2 \times \frac{\partial Z_{\text{Oury\_shock},i}}{\partial T}.$$

The impact of precipitation changes on state inefficiency can be derived by taking the first derivative of equation (9) with respect to precipitation changes as follows:

$$(11)\qquad \frac{\partial \ln \sigma_{ui}^2}{\partial P} = \frac{\partial \ln \sigma_{ui}^2}{\partial Z_{\text{Oury\_shock},i}} \frac{\partial Z_{\text{Oury\_shock},i}}{\partial P} = \gamma_2 * \frac{\partial Z_{\text{Oury\_shock},i}}{\partial P}.$$

The total impact of projected temperature changes and precipitation changes is the sum of equations (10) and (11):

$$(12)\qquad \frac{\partial \ln \sigma_{ui}^2}{\partial T} + \frac{\partial \ln \sigma_{ui}^2}{\partial P} = \gamma_1 \times \frac{\partial Z_{\text{THI\_shock},i}}{\partial T} + \gamma_2$$
$$\times \left(\frac{\partial Z_{\text{Oury\_shock,i}}}{\partial T} + \frac{\partial Z_{\text{Oury\_shock},i}}{\partial P} \right).$$

We predict the potential impacts of three climate-change scenarios in the 2030s on state production inefficiency using the average weather conditions from 2000 to 2010 as the baseline. The results are reported in table 2.2 and are grouped by production region (see notes in table 2.2 for region details). All regions will move further away from the production frontier with increasing temperature and declining precipitation. On average, a 1°C increase in temperature will cause the production efficiency to decrease by 0.38 percent in the Pacific region and 1.31 percent in the Delta region relative to the 2000–2010 mean inefficiency level ($\ln \sigma_u^2$; see table 2.2). When temperature increases by 2°C, the production efficiency will decrease further, ranging from 0.73 percent in the Pacific region to 3.23 percent in the Delta region relative to the 2000–2010 mean inefficiency level ($\ln \sigma_u^2$).

The results imply that the impacts of temperature changes on production efficiencies are not linear and vary across regions. According to the coefficient of variation (CV) estimates, the weather impacts are more consistent within the Lake States region and the Northern Plains region than in other regions. While the temperature changes seem to cause a more serious impact on the Delta region, the variation is also the largest within that region. Several factors can cause these differences, including different historical climate patterns in those states and varying degrees of irrigation development. Under scenario 3 (extreme weather), the temperature increases by 2°C and precipitation decreases by 1 inch on average, and the impacts are more consistent for states within the same region, as the CV declines in almost

Table 2.2 **Potential impacts of climate changes and extreme weather on regional productivity in 2030–2040: Scenario analysis relative to 2000–2010 mean inefficiency level ($\ln \sigma_u^2$)**

	Temperature increases by 1°C			Temperature increases by 2°C			Temperature increases by 2°C; precipitation declines by 1 inch		
Regions	Mean	Standard deviation	CV	Mean	Standard deviation	CV	Mean	Standard deviation	CV
Appalachian	0.45	0.15	0.33	1.19	0.39	0.33	1.26	0.38	0.30
Corn Belt	0.68	0.35	0.51	1.73	0.77	0.45	1.80	0.77	0.43
Delta	1.31	0.93	0.71	3.23	2.48	0.77	3.28	2.48	0.75
Lake States	0.61	0.04	0.06	1.70	0.05	0.03	1.79	0.04	0.02
Mountain	0.41	0.24	0.58	0.91	0.30	0.32	1.04	0.31	0.30
Northeast	0.42	0.19	0.45	1.78	0.97	0.55	1.85	0.97	0.52
Northern Plains	0.66	0.11	0.16	1.66	0.31	0.19	1.74	0.32	0.19
Pacific	0.38	0.08	0.20	0.73	0.13	0.18	0.84	0.12	0.15
Southeast	0.77	0.25	0.33	1.85	0.68	0.37	1.92	0.68	0.35
Southern Plains	0.69	0.22	0.32	1.51	0.63	0.42	1.57	0.62	0.40

Notes: States according to region: Appalachian: WV, TN, NC, VA, KY; Corn Belt: OH, IA, MO, IN, IL; Delta: LA, AR, MS; Lake States: MN, MI, WI; Mountain: CO, UT, AZ, NM, WY, NV, ID, MT; Northeast: NH, PA, ME, MD, RI, MA, DE, CT, VT, NY, NJ; Northern Plains: ND, SD, KS, NE; Pacific: OR, CA, WA; Southeast: SC, AL, GA, FL; Southern Plains: TX, OK.

Sources: Authors' calculation.

all regions when compared to scenario 2 (medium weather impact). This indicates that extreme weather, which is beyond the expected climatic change pattern, can have more disastrous effects on all states.

Responses of agricultural productivity to climate change (mean level changes of Oury index and THI load) and extreme weather shocks (deviations from historical average variations of Oury index and THI load) can inform agricultural policy decisions. For example, while farmers are expected and sometimes observed to adapt to the shifting long-run climate pattern, Dell, Jones, and Olken (2014) argue that certain governmental agricultural support programs (such as subsidized crop insurance) could have reduced farmers' incentives to adapt. Therefore, there could be a tradeoff between reducing farmers' revenue risk and increasing agricultural productivity. The diverse weather impacts on regional productivity from a certain degree of temperature and precipitation changes suggest the need for state-specific research programs to help producers manage their state-specific climatic situations and future climate-change challenges. To help agriculture adapt to climate change, Heisey and Day-Rubenstein (2015) suggest the use of genetic resources to develop new crop varieties that are more tolerant to both abiotic and biotic stresses. However, they also indicate that given the public-goods characteristics of genetic resources, there can be obstacles for private research and development. Creating incentives for the private sector through intellectual property rules for genetic resources and international agreements governing genetic resource exchanges could promote greater use of genetic resources for climate-change adaptation.

2.6 Summary and Conclusions

This chapter employs state panel data from 1960 to 2004 to identify the role of climate change on US agricultural productivity using a stochastic frontier production function method. Climate/weather variables are measured using the THI load and Oury index at both their mean levels and the degree of deviation from the historical variation norms (from 1941 to 1970) at the state level. We also incorporate irrigated land area density and measures of local public goods—R&D, extension, and road infrastructure—to capture the effects of state characteristics and check for the robustness of the estimate of climate variable impact.

The state production data and climate information show noticeable variations across and within production regions. Some regions seem to have faster overall TFP growth—the Northeast, Corn Belt, and Delta regions—than others during the study period. Results indicate that a higher THI load can drive farm production away from its best performance. However, a higher Oury index, irrigated land area density, local R&D, Extension, and road density can enhance state farm production and move it closer to the production frontier. Although the relative levels of the THI and Oury index could result in geospatial differences in technical inefficiency, the unexpected extreme weather "shock" seems to have more robust impacts on estimated inefficiency, and this could be because farmers expect some degree of weather variation based on past experience and would have already made preparations. Therefore, it is the unexpected climatic shocks that result in either an increased use of inputs or a drop in production.

While most studies evaluating the climatic effect on agricultural productivity focus on specific crop or livestock commodities, it is also important to identify the climatic effect on regional agricultural productivity through its impacts on technical inefficiency. Responses of agricultural productivity to climate change at the state level can then inform state-specific agricultural policy decisions.

Appendix

Table 2A.1 Summary statistics of potential weather variables

Weather variables	Variable description	N	Mean	Std. dev.	Min.	Max.
dd830	Good-weather index: degree-days between 8°C and 30°C between March and August	2,112	1,804.25	512.06	920.45	3,098.31
dd30	Bad-weather index: degree-days when temperature is above 30°C between March and August	2,112	27.44	47.48	0.00	376.15
prec	Total precipitation in inches between March and August	2,112	8.01	3.65	0.48	18.61
max_5_8	Average max temperature between May and August	2,112	27.88	3.17	21.55	39.45
Palmer3_8	Palmer index between April and August	2,112	0.00	1.10	–4.11	5.98
THI_mean	Annual mean of THI load index	2,112	4,964.61	5,251.69	0.87	25,566.66
THI_mean_norm	Average THI mean between 1940 and 1970	2,112	5,044.42	5,165.42	195.48	20,328.13
THI_stdv_norm	Average THI dev between 1940 and 1970	2,112	1,306.33	1,099.55	223.34	6,012.63
THI_shock	(THI mean − THI norm) / THI_stdv_norm	2,112	–0.02	1.16	–6.12	8.72
Oury_mean	Annual mean of Oury index between March and August	2,112	25.34	10.93	0.51	58.91
Oury_mean_norm	Average Oury_mean between 1940 and 1970 between March and August	2,112	24.47	8.69	2.37	35.54
Oury_stdv_norm	Average Oury dev between 1940 and 1970 between March and August	2,112	16.32	3.78	4.08	24.66
Oury_shock	(Oury mean − Oury norm) / Oury_stdv_norm	2,112	0.25	1.34	–1.91	12.81

Source: Authors' calculation.

Table 2A.2 **Out-of-sample model specifications comparison**

	Linear regression models											
Model specifications	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
Weather variables												
Max temp. (5–8)	x			x			x			x		
Precipitation (3–8)	x			x			x			x		
Oury mean		x			x			x			x	
THI mean		x			x			x			x	
Oury shock			x			x			x			x
THI shock			x			x			x			x
Other variables												
Time, state fixed effects	x	x	x	x	x	x	x	x	x	x	x	x
External control variables				x	x	x				x	x	x
Input variables							x	x	x	x	x	x
Models												
Linear model	x	x	x	x	x	x	x	x	x	x	x	x
Stochastic frontier models												
A. No variable in the inefficiency term												
B. Only weather variables in the inefficiency term												
C. Weather and other control variables are all in the inefficiency term												
Mean standard errors of predictions	0.9055	0.9427	0.9206	0.8117	0.838	0.8235	0.5273	0.5453	0.5353	0.5114	0.5277	0.5193
L-R test H_0: $\sigma_u = 0$ (no inefficiency term)	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

(*continued*)

Table 2A.2 (continued)

	Stochastic frontier models (I)								
Model specifications	M13	M14	M15	M16	M17	M18	M19	M20	M21
Weather variables									
Max temp. (5–8)	x			x			x		
Precipitation (3–8)	x			x			x		
Oury mean		x			x			x	
THI mean		x			x			x	
Oury shock			x			x			x
THI shock			x			x			x
Other variables									
Time, state fixed effects	x	x	x	x	x	x	x	x	x
External control variables	x	x	x				x	x	x
Input variables				x	x	x	x	x	x
Models									
Linear model									
Stochastic frontier models									
A. No variable in the inefficiency term	x	x	x	x	x	x	x	x	x
B. Only weather variables in the inefficiency term									
C. Weather and other control variables are all in the inefficiency term									
Mean standard errors of predictions	0.7514	0.7542	0.7336	0.4985	0.5153	0.5055	0.4854	0.5004	0.4917
L-R test H_0: $\sigma_u = 0$ (no inefficiency term)	***	***	***	***	***	***	***	***	***

	Stochastic frontier models (II)								
Model specifications	M22	M23	M24	M25	M26	M27	M28	M29	M30
Weather variables									
Max temp. (5–8)	x			x			x		
Precipitation (3–8)	x			x			x		
Oury mean		x			x			x	
THI mean		x			x			x	
Oury shock			x			x			x
THI shock			x			x			x
Other variables									
Time, state fixed effects	x	x	x	x	x	x	x	x	x
External control variables	x	x	x	x	x	x	x	x	x
Input variables				x	x	x	x	x	x
Models									
Linear model									
Stochastic frontier models									
A. No variable in the inefficiency term									
B. Only weather variables in the inefficiency term	x	x	x	x	x	x			
C. Weather and other control variables are all in the inefficiency term							x	x	x
Mean standard errors of predictions	0.0286	0.0282	0.0346	0.0242	0.0242	0.0240	0.0234	0.0219	0.0215
L-R test H_0: $\sigma_u = 0$ (no inefficiency term)	***	***	***	***	***	***	***	***	***

Notes: "NA" indicates "not applicable," "***" indicates that according to the L-R test results, we reject the hypothesis of $\sigma_u = 0$ (no inefficiency term) at 1 percent significance level.

Sources: Authors' calculation.

Table 2A.3 State characteristics on productivity growth and climate indexes

Production region	State	TFP annual growth (%)	Livestock/crop ratio (1960–2004)	THI_mean_norm	THI_stdv_norm	Oury_mean_norm	Oury_stdv_norm
Northeast	Connecticut	2.20	1.04	1,055.67	369.43	34.96	21.85
	Delaware	1.80	2.65	4,852.78	434.19	27.60	15.90
	Maine	1.90	0.67	334.10	288.76	35.54	21.02
	Maryland	1.83	1.68	3,854.23	1,219.64	27.85	16.52
	Massachusetts	2.29	1.28	837.76	507.73	34.82	22.52
	New Hampshire	2.00	1.09	400.82	400.96	34.91	20.69
	New Jersey	1.67	1.47	3,036.90	1,343.49	30.95	19.14
	New York	1.48	2.28	631.08	425.65	33.22	19.19
	Pennsylvania	1.81	1.55	2,132.22	1,176.03	34.03	20.20
	Rhode Island	2.48	0.57	1,082.13	223.34	33.45	24.66
	Vermont	1.62	1.22	460.23	431.81	34.84	18.42
Lake States	Michigan	2.41	0.68	1,337.86	565.03	29.15	18.46
	Minnesota	1.86	0.98	1,316.14	541.74	30.48	16.84
	Wisconsin	1.59	1.77	1,278.79	554.74	32.64	17.61
Corn Belt	Illinois	1.96	0.65	4,700.84	2,053.02	29.33	19.38
	Indiana	2.28	0.47	3,333.96	1,300.01	31.05	20.07
	Iowa	1.87	0.72	2,464.54	683.11	31.38	18.19
	Missouri	1.62	1.10	6,959.88	824.95	29.46	19.86
	Ohio	2.16	0.73	2,483.27	756.51	30.19	18.40
Northern Plains	Kansas	1.05	1.03	7,067.55	1,509.53	23.00	17.48
	Nebraska	1.60	0.93	4,244.28	920.75	25.68	17.53
	North Dakota	1.90	1.47	1,135.88	362.00	24.17	16.20
	South Dakota	1.51	0.96	2,385.50	887.56	24.89	16.98

Appalachian	Kentucky	1.61	0.88	6,493.57	1,190.49	27.85	15.95
	North Carolina	1.84	1.33	6,815.53	2,358.49	26.89	13.18
	Tennessee	1.13	0.88	7,085.80	1,830.86	26.26	15.92
	Virginia	1.53	3.29	3,616.45	1,769.74	26.63	13.68
	West Virginia	1.29	1.91	2,409.00	1,605.48	31.13	16.45
Southeast	Alabama	1.32	2.43	12,354.32	2,545.32	25.34	16.03
	Florida	1.44	0.33	20,328.13	1,819.72	26.73	13.90
	Georgia	1.91	1.56	12,544.53	2,573.72	23.97	13.49
	South Carolina	1.61	0.73	11,534.97	1,927.22	24.26	12.62
Delta	Arkansas	1.93	0.79	9,604.32	2,283.24	25.33	19.22
	Louisiana	1.93	0.68	16,369.98	656.32	24.58	16.22
	Mississippi	1.98	1.03	14,649.88	1,650.05	23.81	16.65
Southern Plains	Oklahoma	0.58	1.54	12,017.31	1,660.94	22.00	18.92
	Texas	1.14	1.31	14,224.99	3,888.87	15.41	14.57
Mountain	Arizona	1.53	1.14	15,465.14	3,681.95	2.37	4.08
	Colorado	1.10	1.58	1,537.62	785.93	17.21	13.61
	Idaho	2.01	1.03	927.67	726.82	12.23	13.29
	Montana	1.38	0.69	235.59	384.94	18.53	15.18
	Nevada	1.24	0.30	1,259.17	722.29	7.12	9.04
	New Mexico	1.44	0.46	5,982.29	2,428.52	10.05	10.54
	Utah	1.55	1.88	860.60	790.21	10.46	11.34
	Wyoming	0.66	1.75	195.48	409.08	17.70	16.09
Pacific	California	1.66	0.48	7,412.25	6,012.63	3.61	8.93
	Oregon	2.58	0.50	355.74	490.08	12.26	15.34
	Washington	1.73	0.43	465.32	731.14	9.47	12.08

Source: Authors' calculation.

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