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Impacts of Climate Change and Extreme Weather on U.S. Agricultural Productivity: Evidence and Projection[1]

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Abstract

Under climate change, the average daily temperature and the frequency of extreme weather occurrences are expected to increase in the United States. This paper employs a stochastic frontier approach to examine how climate change and extreme weather affect U.S. agricultural productivity using 1940-1970 historical weather data (mean and variation) as the norm. We have four major findings. First, using temperature humidity index (THI) load and Oury index for the period 1960-2010 we find each state has experienced different patterns of climate change in the past half century, with some states incurring drier and warmer conditions than others. Second, the higher the THI load (more heat waves) and the lower the Oury index (much drier) will tend to lower a state's productivity. Third, the impacts of THI load shock and Oury index shock variables (deviations from historical norm fluctuations) on productivity are more robust than the level of THI and Oury index variables across specifications. Fourth, we project potential impacts of climate change and extreme weather on U.S. regional productivity based on the estimates. We find 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 other regions, using 2000-2010 as the reference period.

Key words: U.S. agricultural productivity, technical inefficiency, stochastic frontier, climate change, extreme weather, THI load, Oury index

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Impacts of Climate Change and Extreme Weather on U.S. Agricultural Productivity: Evidence and Projection

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 cost when producers try to mitigate the heat stress on animals or drought effects on crop production. It can also widen the distance between observed production and the feasible production frontier, and lower productivity estimates. According to USDA agricultural productivity statistics (USDA, 2015), in 2013 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, mostly adverse weathers. Since there is a growing consensus that climate change is occurring and the average daily temperature and the frequency of extreme weather are likely to increase in the future (IPCC, EPA, NASA, 2015), how climate change or weather fluctuation affect agricultural productivity or economic activity have gained much attention in recent studies.

In literature "weather" is usually used to address short-term variation of temperature or precipitation while "climate change" is usually referred to as the average level changes 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., Cobanov, and Schnitkey, 2003; Schlenker and Roberts, 2009; Lobell, Schlenker, and Costa-Roberts, 2011; Hatfield et al. 2014; St-Pierre, Cobanov and Schnitkey, 2003; and Key and Sneeringer, 2014). A second body of work focusses on adaptive response at the individual/frrm 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; 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. They are usually done by quantifying the effects of climate/weather changes on aggregate economic performance using country/regional level data (e.g., Sachs and Warner, 1997, Dell, Jones, and Olken, 2009, Dell et al., 2012) or sectoral data (e.g., Malcom et al., 2012; Hatfield et al., 2014; Marshall et al., 2015).

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 scenarios analysis, especially in agricultural study. 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 phenomenon. Empirical studies can rely on either time series data or cross-sectional data. Although the latter contain 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). The advantage of incorporating time series is that it captures the impacts of climate change and the farmers' adaption to these changes over time. Nevertheless, it could fail to capture varied effects across regions. Panel data, on the other hand, can preserve both desired features and avoid their weaknesses and has become a preferred approach in recent studies.

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 increase can reduce crop yields in all regions (Carter et al., 1996; Lobell and Asner, 2003; Schlenker and Roberts, 2006; Tubiello and Rosenzweig, 2008.) In addition, some studies suggest that higher variance in climate conditions lead to lower average crop yields and greater yield variability (McCarl, Villaviencio, and Wu, 2008; Semenov and Porter, 1995; Ferris et al., 1998; among others). Weather extremes can also cause disease outbreaks and impact agricultural production (Yu and Babcock, 1992; Anyamba et al., 2014). In livestock studies, evidence indicates that when animals' thermal environment is altered due to climate change it could affect animal health and reproduction. 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 temperature humidity index (THI) could help to explain the technical inefficiency of dairy production based on a stochastic frontier estimate. In an aggregate economy study, Dell, Jones, and Olken (2012) uses historical cross-countries data to identify the relationship between temperature shocks and economic growth. They find climatic effects vary across countries with different economic development stage. They suggest that in the long run, countries may adapt to a particular temperature, mitigating the short-run economic impacts.

In light of recent development in the literature, in this paper we use state panel data to study the impact of climate change and extreme weather on U.S. agricultural productivity empirically, from the entire farm sector aspect (including both crop and livestock production.) One major challenge on quantifying climatic effects on the aggregate sector is constructing appropriate climatic variables. Although Dell, Jones, and Olken (2012) uses historical fluctuations in temperature within countries to identify its effects 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. Scientific literature suggests that a heat stress that exceeds livestock's optimal thermoneutral zone (THI load) can reduce fertility, feed efficiency, weight gain, etc. (NRC, 1981; Fuquay 1981; Hansen et al., 2001, and West 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 from the literature we use historical temperature, humidity, and precipitation data to form a temperature-humidity-index (THI) and an Oury index (an aridity index) to construct desired climatic variables that can either reflect the annual changes in average weather outcome (mean level of THI and Oury indices) or capture the unexpected extreme weather effects (shocks of THI and Oury indies that measure the degree of deviations from their respective historical (1941-1970) annual variations).

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

In this study we have four major findings. First, using THI load and Oury indices we find the patterns of climate change varied from region to region in the last half century (1960-2010) with some states becoming drier or warmer while some states have little changes on average but have become more volatile in more recent years. Second, using mean level of THI and Oury indices we find that higher THI load and lower Oury index (much drier condition) will lower a state's productivity. However, the results become insignificant when more state characteristic variables are incorporated in the model specifications. Third, 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. It suggests that over the long run each state has gradually adapted to state-specific climate condition (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 U.S. 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 2000-2010 as the reference period.

This paper is the first empirical study, we believe, to estimate the climatic effect on 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 overall 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 and 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 paper as follows: Section 1 introduces the empirical approach. Section II describes the data and variables, and provides descriptive statistics. Section III presents the empirical results and discussion. Section IV reports the projection of regional productivity based on climate change scenarios. Section V provides concluding remarks.

I. Empirical Framework

Among the literature discussing climate and its economic impacts, some studies incorporate climate variables along with other input variables in one production function to test for the climatic effects on crop yield, livestock production, or productivity growth. However, input use can be endogenous on the climate variable as producers may try to mitigate output losses by increasing their expense on capital, energy, labor, or other intermediate inputs. To resolve this problem there are a few studies that model weather variables as factors impacting technical inefficiency (e.g., Key and Sneering, 2014). In a study of climatic effect on U.S. 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 technology similar to what other operators in different regions have are available to them. The study employs a stochastic production frontier approach in its estimates where climate variables are incorporated as determinants of a one-sided error that drive 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 U.S. regional agricultural productivity.

The stochastic frontier approach was first developed by Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Brocck (1977) and has been applied to numerous studies. In earlier applications, researchers tried to explain those inefficiency effects by conducting a two-stage approach that requires predicting the inefficiency effects first, then running a regression model that relates the inefficiency effects 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. Bassete 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) has 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 1960-2004. 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:

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

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 of adopting the best technology given its inputs level.

$$\sigma_{ui}^2 = exp(\boldsymbol{z}_i' \gamma) \qquad (2)$$

Therefore, $\boldsymbol{z}_i$ affect 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 formulas:

$$TE_{it} = \frac{y_i}{\exp(f(\boldsymbol{x_{it}}, ß) + v_{it})} = exp(-u_{it}) \quad (3)$$

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 as follows:

$$\ln y_{it} = ß_0 + \sum_{k=1}^{K} ß_k ln\, x_{kit} + ß_t t + \sum_{j=1}^{J} ß_j D_j + \sum_{m=1}^{N} ß_m D_m + v_{it} - u_{it} \quad (4)$$

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 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…47), and $\boldsymbol{D_m}$*'s* are time dummy variables (m=1..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 overall knowledge stock that are not captured by the time trend but could have shifted the overall production frontier unevenly across years. Equation (4) can be viewed as a log-linearized form of the Cobb-Douglas (C-D) production function[3]. We estimate an inefficiency variance

[3] While translog form is a more flexible form, given that the preferred curvature condition cannot hold globally using this form we chose the C-D functional form to approximate the underlying technology of the production frontier in this study.

regression model simultaneously with equation (4), i.e.

$$ln\sigma_{uit}^2 = \gamma_0 + \sum_{n=1}^{N} \gamma_n z_{nit} + \omega_{it}\ ;\ \omega_{it} \sim N(0, \sigma_\omega^2) \qquad (5)$$

z's include climate variables, irrigation-ready land density that may help to mitigate the impacts of adverse weather, and other control variables that capture the heterogeneity of individual state.

We include various forms of climate variables in our estimation, including THI load (for livestock) and Oury index (an aridity index for crops), in their mean or "shock" (the unit of standard deviation from its historical norm) measures. We also include state—specific characteristics 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; Rada et al., 2012; Wang et al., 2015; and Jin and Huffman, 2015 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.

II. Variables, Data Sources, and Descriptive Analysis

In this paper 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 either the impacts on crops or livestock production. We also construct irrigated land area ratio and other local public goods variables—R&D, extension, capacity and roads density—as control variables to test for the robustness of the climatic effects on state inefficiency.

Agricultural output and inputs

We draw state-specific aggregates of output and capital, labor, intermediate goods, and land inputs from USDA's state productivity accounts. Agricultural output and four inputs are implicit quantities measurement based on the Törnqvist indexes 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-ERS (2016) website.

Climate variables

Since our purpose is to estimate an overall impact of climate changes on the agricultural sector we need to consider climate 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-around 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 (Deschenes, and Greenstone (2007), Schlenker and Roberts (2006), and 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 temperature-humidity index (THI), a combined measure of temperature and relative humidity that has been shown to have significant impacts on livestock production; and one is the Oury index, an aridity index that combines temperature and precipitation information that can capture more impact 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 dataset produced by Oregon State University's PRISM[4] climate group (Daly et al. 2008). Since PRISM extrapolates between weather stations to generate climate estimates for each 4km grid cell in the U.S. 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:

$$THI=(dry\ bulb\ temperature\ ^{o}C) + (0.36*dew\ point\ temperature\ ^{o}C) + 41.2 \qquad (6)$$

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 THI is above threshold[5] (See Key and Sneering (2014) appendix for details). To construct state-level

[4] The PRISM Climate Group gathers climate observations from a wide range of monitoring networks, applies sophisticated quality control measures, and develops spatial climate datasets to reveal short- and long-term climate patterns. The PRISM data can be accessed at http://www.prism.oregonstate.edu.
[5] We employ a THI load threshold of 70 for dairy cow, as it is the least threshold among a broad category of livestock production (St-Pierre, Cobanov and Schnitkey, 2003).

THI load we aggregate up the county-level[6] monthly calculations to the state-level using county animal units derived from the Census of Agriculture (USDA, 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 aridity index in identifying the relationship between crop production and weather. Oury argued that it is hard to define a meaningful relationship between crop production and 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 idex), *s* is the month (s=1…12), *Ps* is the total precipitation for month s in millimeters; and *Ts* 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 National Land Cover Database 2006 (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.

[6] 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.

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 normal spanning from 1941 to 1970 and for individual years from 1961 to 2004 (our study period).

Irrigation-ready land density (irrigation ratio) variable

Irrigation infrastructure can help to mitigate the impact of adverse weather. We construct an irrigation-ready land density (irrigation ratio thereafter) variable to capture the impact of irrigation system availability in production. The variable is constructed as the ratio of land area with irrigation system to total cropland area. The cropland area and land area with irrigation system are available for census years (USDA-NASS, 2013) on the state level. 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-ready density (irrigation ratio) variable across states and over time.

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 R&D stock, extension, and roads (Rada, Buccola, and Fuglie, 2010, Wang et al., 2015). The annual agricultural research expenditure data and the research price index used to deflate expenditures are provided by Huffman (2009). Extension variable is a measure of extension capacity calculated as total full-time equivalent (FTE) extension staff divided by the land areas. Data on FTEs by state were drawn from the Salary Analysis of the Cooperative Extension Service from the Human Resource Division at the

USDA. Road infrastructure is a road density index constructed by dividing total road miles excluding local (e.g. citystreet) miles with total land area.

III. Patterns of state productivity growth and climate changes

Table 1 provides a summary table of state level TFP growth during 1960-2004[7] (USDA, 2015), as well as the mean and standard deviation of the normal THI index and Oury index over the historical period 1941-1970. In general, TFP growth varied across USDA's production regions and within the region. Still, some regions seem to have an overall higher TFP growth, such as Northeast, Corn Belt, and Delta regions, than others during the study period. Given the variances in geo-climate condition 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 "desertlike" state (Carter and Zhang, 1997).

(Insert table 1 here)

While the relative level of THI and Oury index 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 changes to be similar to the past.

[7] USDA's state productivity indexes only cover the period 1960-2004.

Farmers could have already invested in appropriate facilities, such as irrigation systems or cooling systems, in areas with low Oury index or high THI load. It is the unexpected weather changes that result in the inefficient inputs use as yields decline (or a waste of inputs when crops cannot be harvested due to an extreme weather event), as well as a decrease in livestock production due to unexpected heat stress. According to table 1, some regions may have much higher variation in their Oury index than in their THI index, such as the Mountain and Pacific regions. If famers expect dramatic variation from year to year in advance, they may have already invested in an irrigation system to damper the impacts of climate changes on farm production.

TFP growth estimates usually move closely with output growth. In 1983 and 1995, the dramatic impacts from adverse weather events caused significant drops in both output and TFP (figure 1). In figure 2 we map the normal Oury index, based on 1941-1970 data, and Oury indexes in 1983 and 1995 at the state level. We find that Oury index varied for many states in 1983 and 1995 while the shocks (figure 3) from its norm show a different picture regarding climate changes.

(Insert Figure 1, Figure 2, and Figure 3 here)

Figure 4 presents the normal THI load (1941-1970), 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 5) we may find that there are noticeable differences over the years.

(Insert Figure 4 and Figure 5 here)

If bad weather is expected and farmers invested in facilities to reduce the potential damage from adverse weather conditions, then the impacts of extreme weather on farm production could decline. Figure 6 shows irrigation density changes over time. In general, pacific regions and mountainous regions have more intensive irrigation systems than other regions.

(Insert Figure 6 here)

IV. Empirical results

We first estimate equation (4) and test the hypothesis of no inefficiency effects that H_0: $\sigma_u^2 = 0$, against the alternative hypothesis of H_1: $\sigma_u^2 > 0$. The result shows that the null hypothesis is rejected at the 1% level indicating 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 alternative weather variables and model specifications as a robustness check. Empirical results of both production regression and inefficiency determinants regression are presented in table 2. Model 1 and 2 evaluate climatic effects on state inefficiency by only including weather variables and irrigation density variable as inefficiency determinants. Besides weather variables and irrigation ratio variable, Model 3 and 4 also incorporate state specific variables—public R&D stock, extension capacity, and road density variables—as control variables to check the robustness of the estimated climatic impacts on state inefficiency. The differences between Model 1 and 2 and between Model 3 and 4 are the measures of weather variables. Model 1 and 3 use mean levels of THI and Oury indexes while Model 2 and 4 use THI shocks and Oury index shocks as weather variables. Since outputs and inputs are all in natural logarithmic terms, the input coefficients can be interpreted as the output elasticity for individual inputs. According to the estimates of production function on the top section of table 2, 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 0.07-0.08. Since the hypothesis of constant return to scale is rejected, we can infer a decreasing return to scale with input coefficients totaling to less than one.

(Insert Table 2 here)

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 THI load becomes insignificant in Model 1. According to the results, a single unit increase in THI load could result in a worse inefficiency, with 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 Oury index (drier condition) could cause further inefficiency, with 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 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 THI load will result in about a 0.3 percent deterioration in the inefficiency term while a unit of negative shock (drier condition) will result in about a 0.18 percent deterioration in the inefficiency term.

The results show that the 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 condition. 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 ratio 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-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 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% 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 to disseminate knowledge, reduce transportation cost, 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 7. We find that over the study period, California ranks first in efficiency, 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 its state-specific characteristics such that even with similar weather patterns and natural resources productivity can differ significantly[8].

(Insert Figure 7 here)

V. Potential Impacts of Future Climate Change on U.S. 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, and increasing incidences of extreme weather. Key and Sneeringer (2014) project the potential impacts of climate changes on U.S. dairy production in 2030 based on four

[8] 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 absent significant new capital investment California may not be as efficient as in the past.

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 2010-2030 ranges from 0.65^{o}C to 1.38^{o}C. According to EPA[9], earth's average temperature has risen by 0.83°C over the past century, and is projected to rise another 0.3 to 4.8°C over the next hundred years. According to the U.S. Global Change Research Program Report (USGCRP 2014)[10], the overall temperatures will continue to warm over the century in the U.S. with a projected average increase by the end of the century of approximately 3.9 to 6.1° C under the high emission scenario and 2.2 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;

[9] See https://www3.epa.gov/climatechange/basics/ for more details.

[10] Established under the Global Research Act of 1990, the U.S. 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 3rd 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.

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 1940-70 levels.

We estimate the production response as if there are no changes in prices, input use, technology, or farm practice[11]. The projections are conducted using Model 4 estimates where weather variables are shocks of THI load and Oury index with state-specific control variables kept constant as in the following equation:

$$ln\sigma_{uit}^2 = \gamma_0 + \gamma_1 z_{THI_{shock},it} + \gamma_2 z_{Oury_{shock},it} + r_3 z_{irrigation\ ratio,it} + r_4 lnRD_{it} + r_5 lnET_{it} + r_6 lnRO_{it} + \omega_{it}\ ;\ \omega_{it} \sim N(0, \sigma_\omega^2) \qquad (7)$$

- 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 (Shumway et al. 2015, Huang, Wang, and Wang, 2015; Marshall et al. 2015; Heisey and Day-Rubinstein 2015). Therefore, the unexpected same degree change in temperature and precipitation may have different impacts on 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 (7) with respect to temperature changes as follows:

[11] This is 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 producer.

$$\frac{\partial ln\sigma_{ui}^2}{\partial T} = \frac{\partial ln\sigma_{ui}^2}{\partial Z_{THI_{shock},i}}\frac{\partial Z_{THI_{shock},i}}{\partial T} + \frac{\partial ln\sigma_{ui}^2}{\partial Z_{Oury_{shock},i}}\frac{\partial Z_{Oury_{shock},i}}{\partial T}$$

$$=\gamma_1 * \frac{\partial Z_{THI_{shock},i}}{\partial T} + \gamma_2 * \frac{\partial Z_{Oury_{shock},i}}{\partial T} \quad (8)$$

The impact of precipitation changes on state inefficiency can be derived by taking the first derivative of equation (7) with respect to precipitation changes as follows:

$$\frac{\partial ln\sigma_{ui}^2}{\partial P} = \frac{\partial ln\sigma_{ui}^2}{\partial Z_{Oury_{shock},i}}\frac{\partial Z_{Oury_{shock},i}}{\partial P}$$

$$=\gamma_2 * \frac{\partial Z_{Oury_{shock},i}}{\partial P} \quad (9)$$

The total impact of projected temperature changes and precipitation changes is the sum of equations (8) and (9):

$$\frac{\partial ln\sigma_{ui}^2}{\partial T} + \frac{\partial ln\sigma_{ui}^2}{\partial P} = \gamma_1 * \frac{\partial Z_{THI_{shock},i}}{\partial T} + \gamma_2 * \left(\frac{\partial Z_{Oury_{shock},i}}{\partial T} + \frac{\partial Z_{Oury_{shock},i}}{\partial P}\right) \quad (10)$$

We predict the potential impacts of three climate change scenarios in the 2030s on state production inefficiency using the average weather conditions during 2000-10 as the baseline. The results are reported in table 3 and are grouped by production region (see notes in table 3 for region details). All regions will move further away from the production frontier with increasing temperature and declining precipitation. On average, a 1^{o} C increase in temperature will cause the production efficiency to decrease by 0.38 % in Pacific region and by 1.31% in Delta region relative to the 2000-10 mean inefficiency level ($ln\sigma_u^2$) (see table 3). When temperature increases by 2^{o}C the production efficiency will decrease further, ranging from by 0.73 % in Pacific region to 3.23% in Delta region relative to the 2000-10 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^{o}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 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.

(Insert table 3 here)

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 program) 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.

VI. Summary and Conclusions

This paper employs state panel data for the period of 1960-2004 to identify the role of climate change on U.S. agricultural productivity using a stochastic frontier production frontier 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 (during 1941-1970) at the state level. We also incorporate the irrigated land area ratio and the measures of local public goods—R&D, extension, and road infrastructure—to capture the effects of state characteristics and to 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 higher THI load can drive farm production away from its best performance. However, higher Oury index, irrigated land area ratio, local R&D, Extension, and road density can enhance state farm production and move it closer to the production frontier. Although the relative level of 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 input, 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 overall agricultural productivity by region 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.

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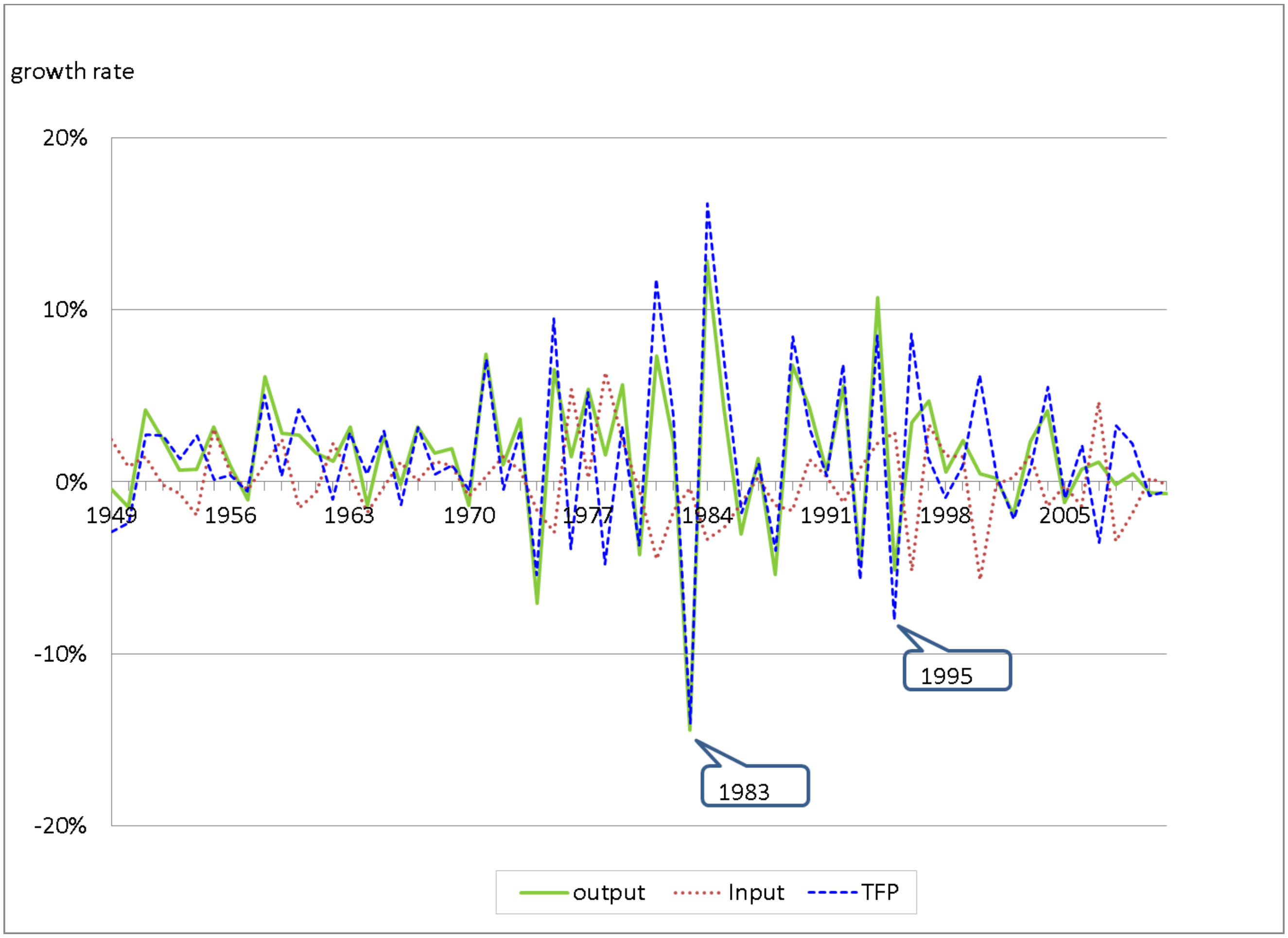
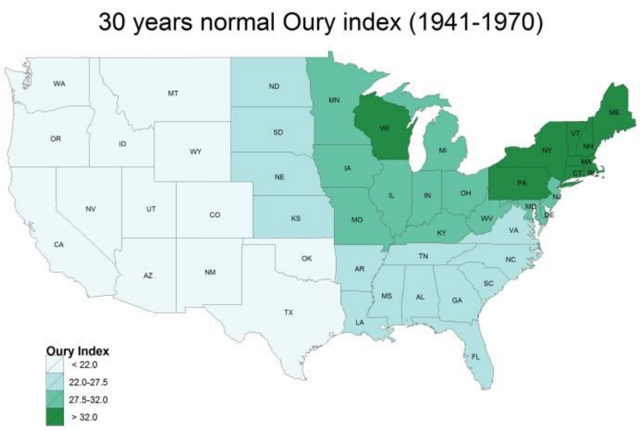
Figure 1 U.S. agricultural TFP growth moved closely with output growth (1948-2011)



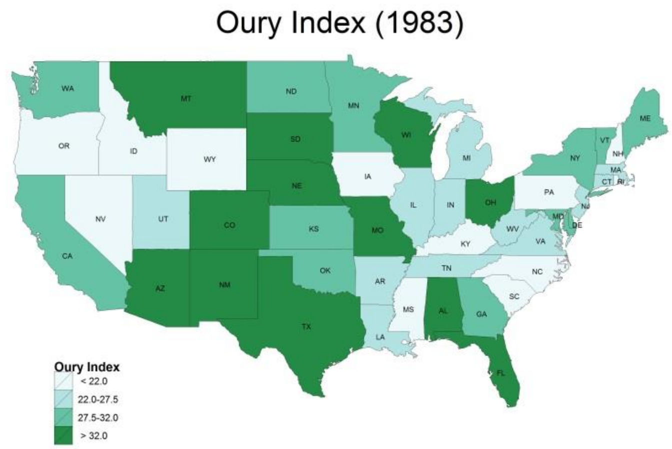
Data source: Authors' calculation

Figure 2. Oury index comparison, the norm (1941-1970), 1983, and 1995

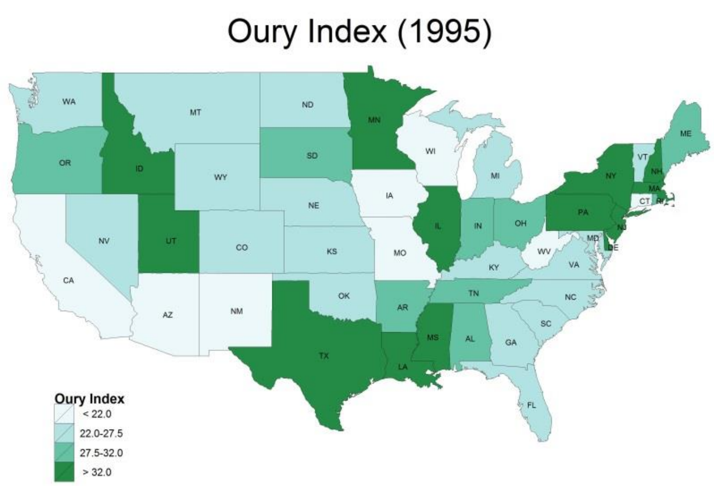
Panel A



Panel B



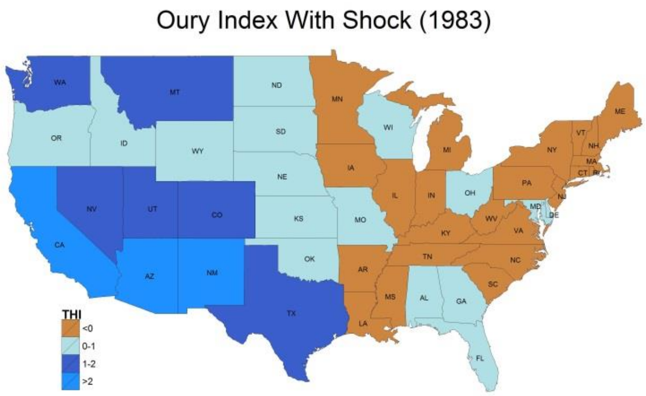
Panel C



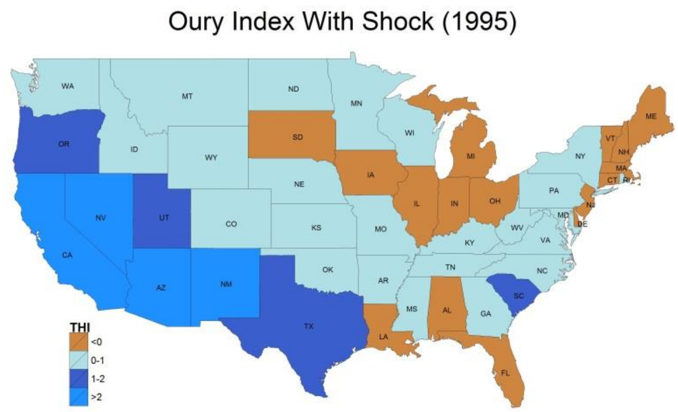
Source: Authors' calculation

Figure 3. The climate shocks comparison using Oury Index: 1983 vs. 1995

Panel A



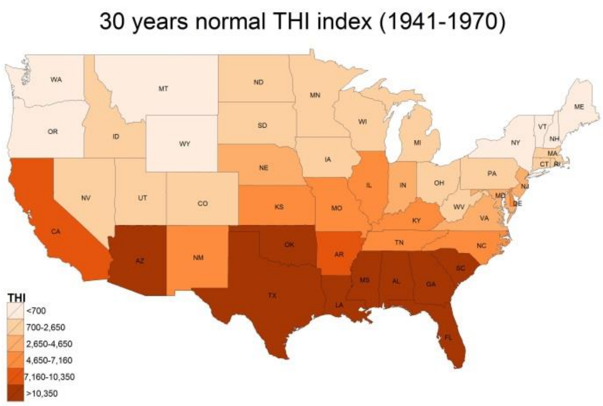
Panel B



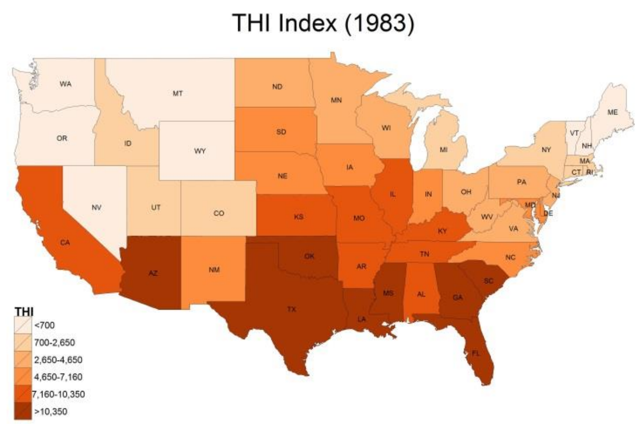
Source: Authors' calculation

Figure 4. THI load comparison, the norm, 1983, and 1995

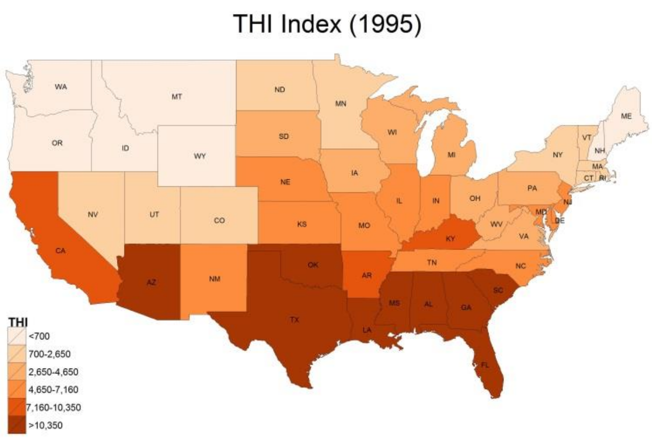
Panel A.



Panel B



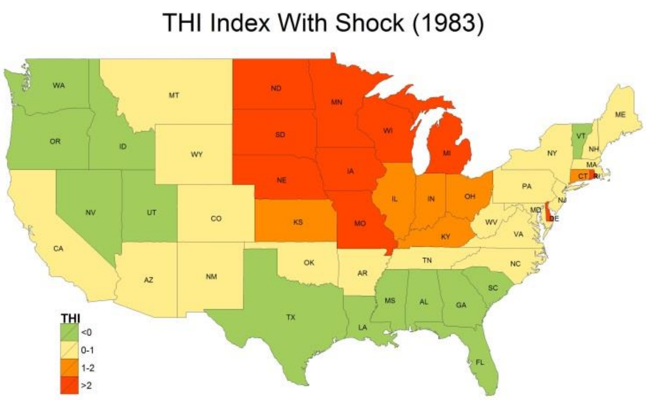
Panel C



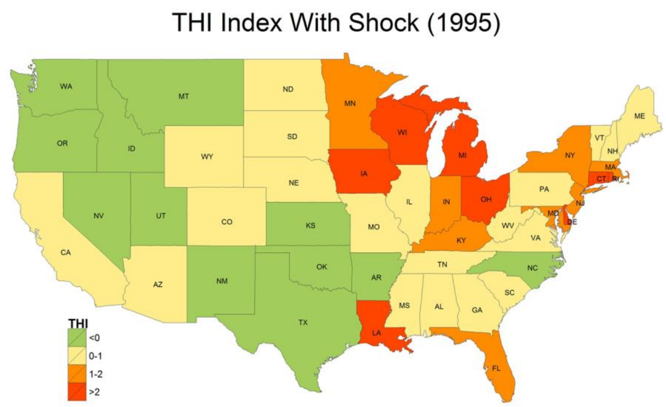
Source: Authors' calculation

Figure 5. The climate shocks comparisons using THI load Index: 1983 vs. 1995

Panel A

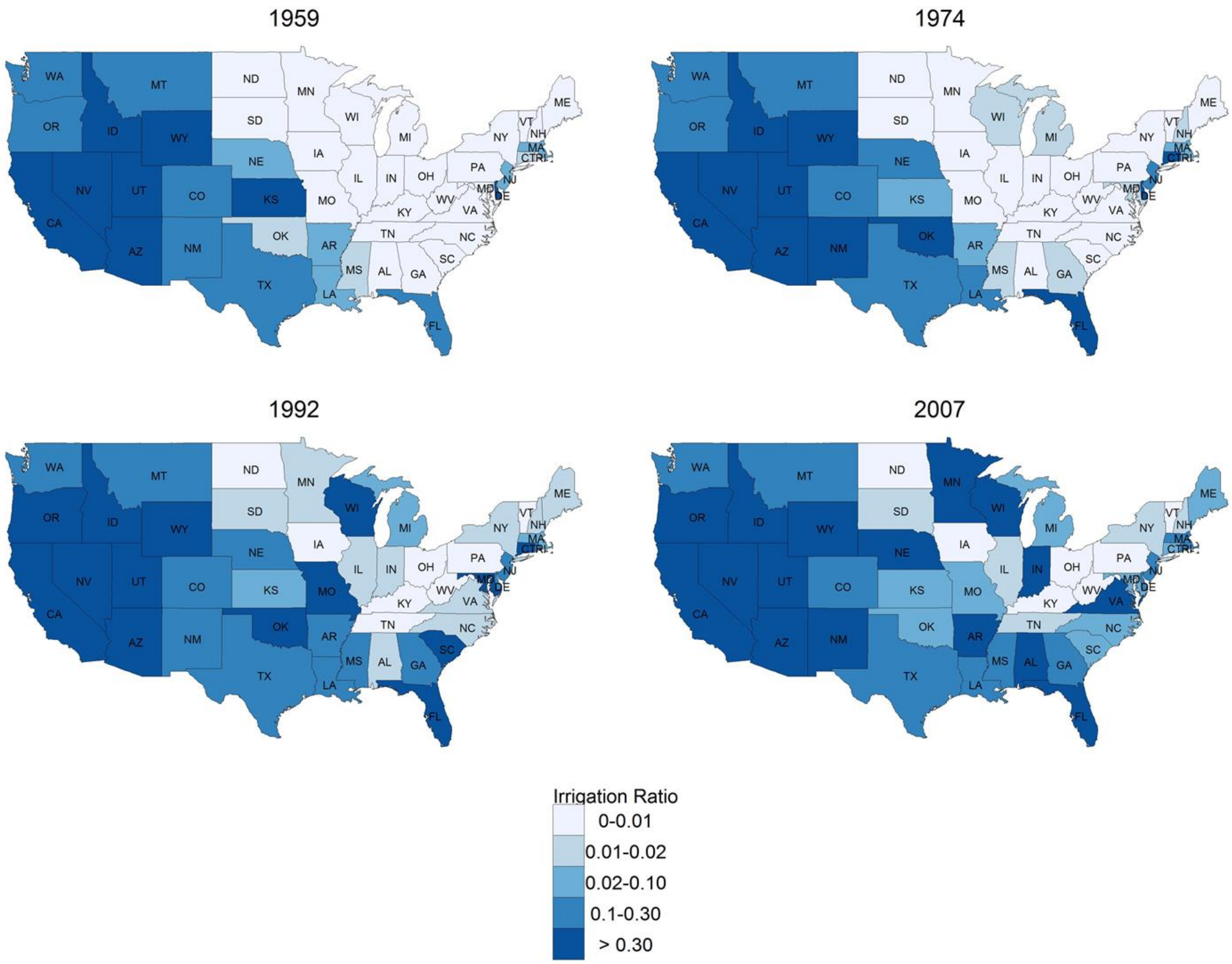


Panel B



Source: Authors' calculation

Figure 6. Ratios of irrigated land area to total crop land area (irigation ratio) at census year



Source: Author’s calculation using data from Agricultural Census

Note: irrigation ratio indicates ratios of irrigated land area to total cropland area.

Figure 7 Box and Whiskers Plots of State Efficiency Estimates and Rankings Based on Model 4

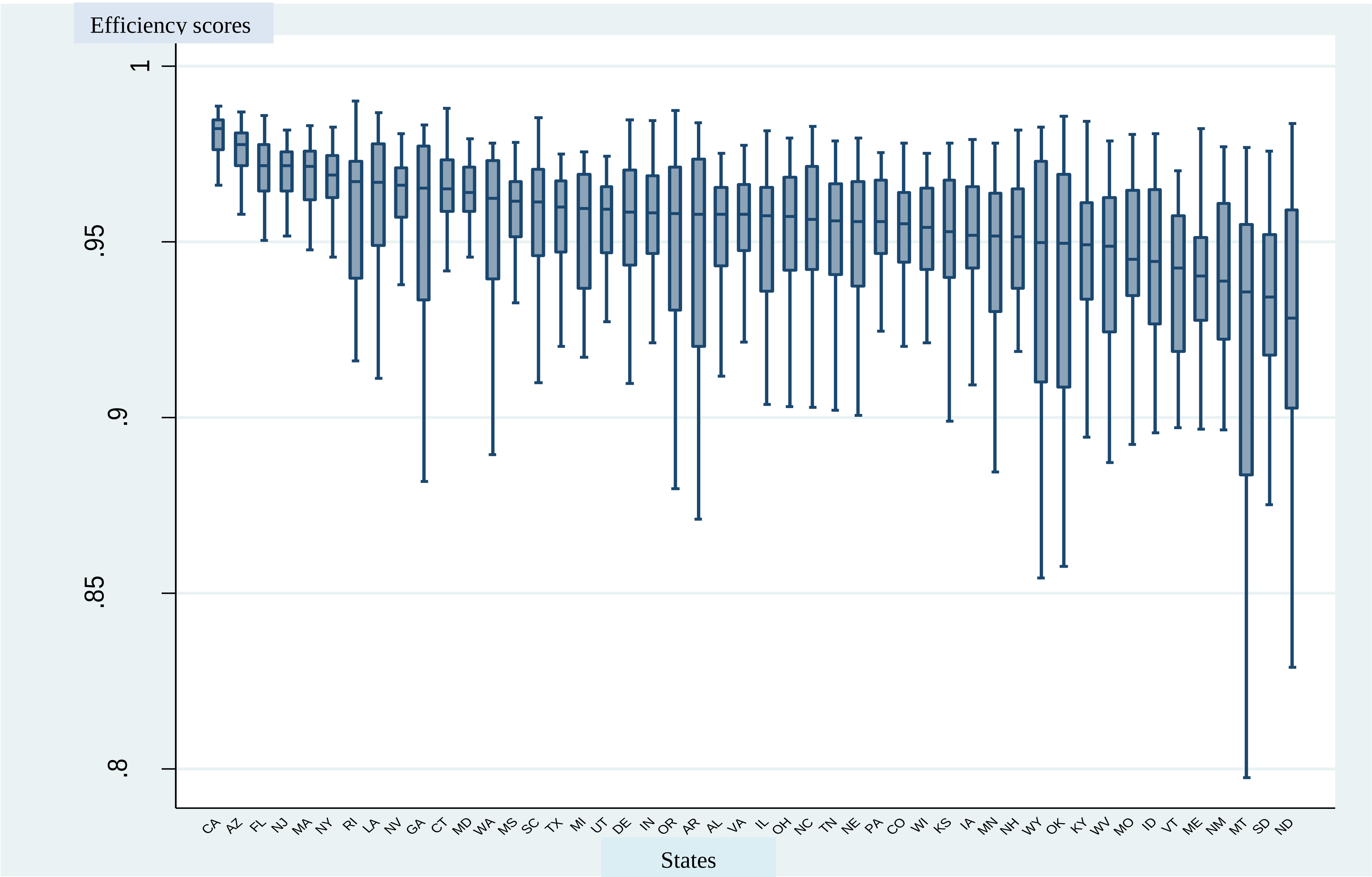


Table 1 State characteristics on productivity growth and climate indexes

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	1055.67	369.43	34.96	21.85
	Delaware	1.80	2.65	4852.78	434.19	27.60	15.90
	Maine	1.90	0.67	334.10	288.76	35.54	21.02
	Maryland	1.83	1.68	3854.23	1219.64	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	3036.90	1343.49	30.95	19.14
	New York	1.48	2.28	631.08	425.65	33.22	19.19
	Pennsylvania	1.81	1.55	2132.22	1176.03	34.03	20.20
	Rhode Island	2.48	0.57	1082.13	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	1337.86	565.03	29.15	18.46
	Minnesota	1.86	0.98	1316.14	541.74	30.48	16.84
	Wisconsin	1.59	1.77	1278.79	554.74	32.64	17.61
Corn Belt	Illinois	1.96	0.65	4700.84	2053.02	29.33	19.38
	Indiana	2.28	0.47	3333.96	1300.01	31.05	20.07
	Iowa	1.87	0.72	2464.54	683.11	31.38	18.19
	Missouri	1.62	1.10	6959.88	824.95	29.46	19.86
	Ohio	2.16	0.73	2483.27	756.51	30.19	18.40
Northern Plains	Kansas	1.05	1.03	7067.55	1509.53	23.00	17.48
	Nebraska	1.60	0.93	4244.28	920.75	25.68	17.53
	North Dakota	1.90	1.47	1135.88	362.00	24.17	16.20
	South Dakota	1.51	0.96	2385.50	887.56	24.89	16.98
Appalachian	Kentucky	1.61	0.88	6493.57	1190.49	27.85	15.95
	North Carolina	1.84	1.33	6815.53	2358.49	26.89	13.18
	Tennessee	1.13	0.88	7085.80	1830.86	26.26	15.92
	Virginia	1.53	3.29	3616.45	1769.74	26.63	13.68
	West Virginia	1.29	1.91	2409.00	1605.48	31.13	16.45
Southeast	Alabama	1.32	2.43	12354.32	2545.32	25.34	16.03
	Florida	1.44	0.33	20328.13	1819.72	26.73	13.90
	Georgia	1.91	1.56	12544.53	2573.72	23.97	13.49
	South Carolina	1.61	0.73	11534.97	1927.22	24.26	12.62
Delta	Arkansas	1.93	0.79	9604.32	2283.24	25.33	19.22
	Louisiana	1.93	0.68	16369.98	656.32	24.58	16.22
	Mississippi	1.98	1.03	14649.88	1650.05	23.81	16.65
Southern Plains	Oklahoma	0.58	1.54	12017.31	1660.94	22.00	18.92
	Texas	1.14	1.31	14224.99	3888.87	15.41	14.57
Mountain	Arizona	1.53	1.14	15465.14	3681.95	2.37	4.08
	Colorado	1.10	1.58	1537.62	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	1259.17	722.29	7.12	9.04
	New Mexico	1.44	0.46	5982.29	2428.52	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	7412.25	6012.63	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

Table 2 Stochastic frontier models estimates with alternative inefficiency determinants

variables	Model 1			Model 2			Model 3			Model 4		
	coefficient	t-ratio		coefficient	t-ratio		coefficient	t-ratio		coefficient	t-ratio	
lny												
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 σ_v^2 (noise)												
constant	-5.8828	-59.40	***	-5.8048	-52.68	***	-5.8232	-71.97	***	-5.8362	-66.84	***
ln σ_u^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	2679			2698			2713			2726		
$X^2(95)$	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

Table 3. Potential Impacts of Climate Changes and Extreme Weather on Regional Productivity in 2030-2040: Scenario Analysis

(Relative to 2000-2010 mean inefficiency level ($ln\sigma_u^2$))

Regions	Temperature increases by 1oC			Temperature increases by 2oC			Temperature increases by 2oC; precipitation declines by 1 inch		
	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

Sources: Authors' calculation
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.