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**Impacts of Climate Change and Extreme Weather on U.S. Agricultural Productivity
Growth¹**

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Abstract

We employ state panel data for the period 1961-2004 to identify the role of climate change on U.S. agricultural productivity growth using a stochastic production frontier method. We examine the patterns of productivity changes and weather variations across regions and over time. Climate variables are measured using temperature humidity index (THI) load and Oury index at both their means and the degree of deviation from their historical norm (shocks). We also incorporate irrigation ratio and local public goods—R&D, extension, and road infrastructure—to capture the effects of specific state characteristics and to check for the robustness of the estimates of climate variables' impacts. Results indicate that higher THI load can drive farm production from its best performance using given inputs and best technology. On the other hand, a higher Oury index, irrigation ratio, local R&D, Extension, and road density can drive state overall farm production closer to the production frontier. In addition, weather “shock” variables seem to have more consistent and robust impacts in explaining technical inefficiency than do level variables.

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

Impacts of Adverse Weather on U.S. Agricultural Productivity Growth

According to USDA's U.S. agricultural productivity statistics, farm output was more than 2.5 times its 1948 level in 2011. With little growth in input use, total factor productivity (TFP) accounted for nearly all the farm output growth during that period. However, in the past four decades the frequency of adverse weather events has increased (Parry et al. 2007; Hatfield et al., 2014). Measured productivity growth fluctuated dramatically from time to time, reflecting a drop or slower growth in agricultural output. On the other hand, increasing global food demand and slowing growth in crop yields have led to soaring food prices in recent years, and have raised concerns about global food security. As one of the world's largest producers and consumers of agricultural commodities, sustainable agricultural productivity growth in the U.S. is critical to both domestic and global food security.

While research investment in agricultural science and farm input improvement is the major driver behind long-run productivity growth in the U.S., extreme weather can affect output growth, input use, and thus TFP estimates considerably. Unexpected drought, flooding, or heat stress could either cause declines in crop and livestock production, or raise production cost by adding more labor, energy (for cooling or heating systems), or intermediate goods due to weeds, diseases, insect pests, etc. These changes can drive farmer's performance from the production frontier and at least temporarily increase technical inefficiency.

Literature has shown 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). While moderate warming could benefit crop and pasture yields in temperate regions, further temperature increase could reduce crop yields in all regions (Carter et al., 1996; Tubiello and Rosenzweig, 2008; among others). On the other hand, weather extremes could also cause disease outbreaks patterns 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 could 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 based on a stochastic frontier estimate. Yet, most of these studies are focused on a single sector or commodity, i.e. either crops or livestock. When addressing the impacts of climate change on overall farm sector production or productivity growth, many studies rely on simulation methods. There is a lack of empirical study on how climate changes affect sector-wide productivity.

While projecting how climate change could affect agricultural production and food availability could provide useful information for current policy decisions, it can benefit from a better understanding on how climate changes affected farm production and productivity growth in the past. Empirical studies can rely on either time series data or cross-sectional data. The latter could contain information regarding geospatial differences. Yet, the statistical results may be biased if regionally specific characteristics are not taken into account, such as irrigation areas (Schlenker, Hanemann and Fisher, 2005). The advantage of time series study is that it captures the impacts of climate change and the farmers' adaption to these changes over time. Yet, it could fail to capture

varied effects across regions. Panel data, on the other hand, can preserve both desired features and avoid their weaknesses.

Therefore, the purposes of this study is three-fold: first, we examine how climate changes in the U.S., based on historical and cross-regional weather data; second, we examine how climate change and extreme weather affect agricultural productivity growth through their impacts on technical inefficiency; third, we compare the effects of different climate variables in explaining technical inefficiency using both level and shock (the degree of deviation from its historical norm) climate indexes. To achieve these goals, we employ state panel data for the period 1961-2004. We construct implicit quantities for agricultural outputs and inputs. We construct climate indexes that can capture the climate's impacts on livestock (THI load) and crops (Oury index). In addition to the level of the indexes we also construct climate shock variables that capture deviation from climate norms and represent a degree of extreme weather. This study is the first to analyze the impacts of both heat stress and temperature-adjusted precipitation weather variations on technical inefficiency for aggregate production at the state level. The results could shed light on how climate change and extreme weather affects U.S. agricultural productivity growth.

Measurement of technical inefficiency

Leibenstein (1966) first used the term “x-efficiency” to represent the effectiveness when a given set of inputs are used to produce outputs. A firm is said to be technical-efficient if it can produce the maximum output possible given the best technology and resources it employs. If the firm cannot achieve its best performance then x-inefficiency occurs. In general, the concept of

technical efficiency refers to producers' choices to allocate resources to obtain the maximum possible output from given inputs, or to produce a certain level of outputs using the minimum possible inputs.

Although researchers have used climate variables along with other input variables or policy variables in a production function to test for those impacts on crop yield, livestock production, or productivity growth directly (Zhang and Carter, 1997; Compas and Che, 2006; among others), the use of inputs could be endogenous on climate variable. There are a few studies that have modeled weather impacts as factors that affect productivity (or production) through its impacts on technical inefficiency (Key and Sneering, 2014; among others). By employing a stochastic production frontier approach, climate variables are incorporated as determinants of a one-sided error that drive farm production from its production frontier.

Following Aigner, Lovell, and Schmidt (1977), Meeusen and van den Broeck (1977), Bassete and Coelli (1995), and Key and Sneering (2014) we form the stochastic frontier production model as:

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

where q_{it} is the aggregate output quantity of state i at time t , and $f(\mathbf{x}_{it}, \boldsymbol{\beta})$ is the maximum quantity that can be produced with a vector of quantity of inputs \mathbf{x}_i at time t , $\boldsymbol{\beta}$ is a vector of unknown parameters to be estimated. Production can deviate from this deterministic frontier because of exogenous factors, such as adverse weather events. 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 assumed to

be normally and independently distributed, with zero mean and constant variance σ_v^2 . u_{it} is assumed to be half-normally and independently distributed, with a truncation at zero of the normal distribution with mean $\mathbf{z}_{it}\boldsymbol{\gamma}$, variance σ_u^2 . The technical inefficiency effects u_{it} is assumed to be affected by a vector of exogenous variables \mathbf{z}_{it} , such as climate variables and specific regional characteristics that could affect the ability of adapting the best technology at time t given its inputs level. $\boldsymbol{\gamma}$ is a vector of parameters to be estimated. If $u_{it}=0$, then state i is at the production frontier and is technical efficient. If $u_{it}>0$ then state i is deviated from the frontier, and is technical inefficient while v_{it} is a random error and could be positive or negative.

Production can deviate from this deterministic frontier because of exogenous factors, such as adverse weather events. v_{it} , could be positive or negative, or because of productive inefficiency u_{it} , which reduces output ($u_{it}\geq 0$).

Once technical inefficiency is estimated, technical efficiency (TE) can be computed as:

$$TE_{it} = \exp(-u_{it}) \quad (2)$$

In this study the stochastic frontier production function to be estimated is

$$\ln y_{it} = \beta_0 + \sum_{k=1}^K \beta_k \ln x_{kit} + \beta_t t + \sum_{j=1}^J \beta_j D_j + \sum_{m=1}^N \beta_m D_m + v_{it} - u_{it} \quad (3)$$

and y is an implicit quantity of state total output, x 's are inputs, including labor, capital, land, and intermediate goods, t is a time trend, D_j 's are state dummy variables ($j=1 \dots 47$), and D_m 's are time dummy variables ($m=1 \dots 43$) to capture cross-state, time-invariant, unobserved heterogeneity.

Equation (3) can be viewed as a linearized form of the Cobb-Douglas production function.

Following Battese and Coelli (1995) and Alvarez et al. (2006) we estimate an inefficiency variance regression model simultaneously with equation (3), i.e.

$$\ln \sigma_{uit}^2 = \gamma_0 + \sum_{n=1}^N \gamma_n z_{nit} + \omega_{it} ; \omega_{it} \sim N(0, \sigma_{\omega}^2) \quad (4)$$

z's include climate variables—THI load (for livestock) and aridity index (for crops, we apply Oury index in this study), in their mean or “shock” (the unit of standard deviation from its historical norm) estimate. We also include local public goods or infrastructure variables, such as irrigation ratio, R&D stock, extension, and road density variables in separate models to test for the robustness of the impacts of our climate variables. The stochastic frontier is estimated by a maximum likelihood (ML) procedure.

Data Sources and Measurement

In our study we employ agricultural output, as well as inputs of labor, capital, land, and intermediate goods at state level to form the stochastic frontier production function. To identify the impacts of climate changes on technical inefficiency changes we construct climate variables that can capture either the influences on crops or livestock production. In addition, we have incorporated some local public goods variables, such as irrigation ratio, R&D, extension, and roads infrastructure to test for the robustness of our estimates of the impact of climate changes.

Agricultural outputs and inputs

We construct state-specific aggregates of output and capital, labor, intermediate goods, and land inputs as implicit quantities based on the Törnqvist indexes approach over detailed output and

input information. Indexes of output are formed by aggregating over agricultural goods and services using revenue-share weights based on shadow prices. The changing demographic characteristics of the agricultural labor force are used to construct a quality-adjusted index of labor input. Similarly, much asset-specific detail underlies the measure of capital input. The construction of a measure of capital input begins with estimating the stock of capital for each component of capital input. For depreciable assets, the capital stocks are the cumulation of past investments adjusted for discards of worn-out assets and loss of efficiency of assets over their service life. Indexes of capital input are then formed by aggregating over the various capital assets using cost-share weights based on asset-specific rental prices. The land stock is adjusted by quality differences across counties and states.

Törnqvist indexes of energy consumption are calculated for each state by weighting the growth rates of petroleum fuels, natural gas, and electricity by their shares in the overall value of energy inputs. Fertilizers and pesticides are also important intermediate inputs, but their data require adjustment since these inputs have undergone significant changes in input quality. We estimate price indexes for fertilizers and pesticides using hedonic methods. The corresponding quantity indexes are formed implicitly by taking the ratio of the value of each aggregate to its hedonic price index. A Törnqvist index of intermediate input is calculated for each state by weighing the growth rates of each category of intermediate inputs by its value share in the overall value of intermediate inputs.

Finally, following Caves, Christensen, and Diewert (1982), we construct output and input measures that have spatial as well as temporal integrity. The result is panel data that can be used for both cross section and time series analysis. A full description of the underlying data sources

and aggregation procedures can be found in Ball et al. (1999) and on the USDA-ERS (2013) website.

Climate variables

Since our purpose is to evaluate 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 more affected by precipitation and temperature during the growing seasons. To suit our purpose we construct two different weather indexes—temperature-humidity index (THI), a combined measure of temperature and relative humidity, and Oury index, an aridity index that combines temperature and precipitation information, at both its year mean level and its deviation from the norm based on historical weather data drawn from the Parameter-elevation Regressions on Independent Slopes Model (PRISM, 2013). Since PRISM extrapolates between weather stations to generate climate estimates for each 4km grid cell in the U.S. (see <http://www.prism.oregonstate.edu/> for details) 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:

$$THI = (\text{dry bulb temperature } ^\circ C) + (0.36 * \text{dew point temperature } ^\circ C) + 41.2 \quad (5)$$

When animal stress is above a certain THI threshold, productivity can decline. 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 temperatures (dry bulb temperatures) and the dew point information from PRISM. Following engineering research, St-Pierre, Cobanov and Schnitkey (2003) and Key and Sneeringer (2014) estimate a THI load, which refers to the number of hours that the location has a THI above the threshold. To estimate the THI load, 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 above threshold and the degree to which THI is over the threshold (See Key and Sneering (2014) appendix for details).

We employ a threshold of 70 (dairy) to capture the possible impacts for all livestock, although poultry could have a higher threshold of 78 (St-Pierre, Cobanov and Schnitkey, 2003). The THI was calculated first by month then weighted by the number of days in each month. Next the monthly calculations were summed to the year, and finally, yearly totals were aggregated by state, based on an animal unit's weighting scheme. Weights used in the THI estimates are the county-level animal unit counts from the 2002 NASS Census of Agriculture (Census of Agriculture 2002). Unique PRISM cell data were spatially intersected with counties so that every THI value was associated with a county, and could therefore be weighted by the animal counts in the final estimates.

“Weather” is a critical factor influencing the production of crops. While precipitation and temperature are mostly considered in previous studies due to lack 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:

$$W_s = \frac{P_s}{1.07T_s} \quad (6)$$

where W represents the aridity index (Oury index), s is the month ($s=1 \dots 12$), P is the total precipitation for month s in millimeters; and T_s is the mean temperature for month s in degrees centigrade. The Oury index can be viewed as rainfall normalized with respect to temperature. We draw data from monthly PRISM, weighted by a set of cropland density at county level to construct a state level Oury index. The cropland weights were developed by summing the cropland pixels from the National Land Cover Database 2006 (NLCD 2006) by the same extent and cell size as the PRISM climate grids (roughly 4 km), giving a one- for- one match of the Oury index value to its corresponding cropland pixel count. 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 growing season months—April through August (an approximation of the growing season)—were considered for the Oury aridity index. Both THI and Oury measures were generated for a 30-year normal

spanning from 1941 to 1970 as well as measures for individual years from 1961 to 2004 (our study period).

Irrigation variable

We construct an irrigation ratio variable to capture the positive impact of irrigation systems on crop production. The crop land area and irrigation land area are available at census years (USDA-NASS, 2013) at the state level. We employ a cubic spline technique to interpolate the information between census years. The expanded irrigation areas and crop land areas are used to construct a panel of irrigated ratio across states and over time.

Local public goods

To capture specific state level characteristics that could also have impacts on the state's technical inefficiency (Rada, Buccola, and Fuglie, 2010) we draw data on R&D stock, extension, and roads from Wang et al. (2012). Wang et al. (2012) used a trapezoidal-weight pattern proposed by Huffman and Evenson (2006) to construct R&D stocks from R&D expenditures. The annual agricultural research expenditure data and the research price index used to deflate expenditures are provided by Huffman (2009). Our 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 using total road miles excluding local (e.g. city street) miles for each state divided by total land area.

Patterns of state productivity growth and climate changes

Table 1 provides a summary table of state level TFP growth during 1960-2004 (USDA, 2013), 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 within the Northeast region tend to have a higher ratio in 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 much drier condition that could lower crop production. If the Oury index is lower than 20, it indicates drought conditions, and if the Oury index is less than 10, it is implied as "desertlike" (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 than its level variation as farmers may have expected the climate changes based on past experience. 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. Yet, it is the unexpected weather changes that result in either a waste of inputs when crops cannot be harvested due to an extreme weather event or 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 farmers expect dramatic variation from year to year in advance, they may have already invested in irrigation facility to dampen the impacts of climate changes on farm production.

TFP growth usually moves 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 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, as well as the THI indexes in 1983 and 1995 across state. When compared with the Oury index, however, it has less variation over time. Yet, 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 condition, then the impacts of extreme weather on farm production could decline. Figure 6 shows irrigation ratio changes over time. In general, Pacific regions and mountainous regions have more intensive irrigation systems than other regions.

Impact of climate change on technical inefficiency

We present the empirical results on how climate variables as well as irrigation ratios and other local public goods affect overall technical inefficiency in table 2 and table 3. The climate variables incorporated in table 2 are THI mean and Oury mean variables. The climate variables incorporated in table 3 are THI shock and Oury shock variables, which are measured as units of standard deviation from their normal means. Model 2 and 4 take into account other local public goods variables to capture state characteristics and test for the robustness of the impacts of climate variables on overall state technical inefficiency.

(Insert Table 2 and Table 3 here)

Results of the stochastic frontier inefficiency estimation indicate that higher THI load can drive farm production from its best performance. However, a higher Oury index, irrigation ratio, local R&D, Extension, and road density could drive state overall farm production to its best performance using given inputs and the best technology. The signs of the coefficients are as expected. The estimates of impacts of the weather indexes on state technical inefficiency seem to be robust. While the signs of THI load are both positive in Model 1 and 2, the estimate without incorporating local public goods (Model 1) is not statistically significant. Yet, using “shock” variable in Model 3 and 4, the stronger THI load shock leads to technical inefficiency significantly no matter whether the local public goods variables are incorporated or not. The coefficient estimates of climate variables from Model 3 and 4 are also much closer than those from Model 1 and 2. It seems using weather shocks variables can provide much more robust results than using the level variables. Interestingly, while the magnitude for the impacts of means and shocks of climate variables are quite different, they are more similar for other local variables.

Since R&D, Extension, and Road density variables are all in natural log (Ln) form, it indicates that a one percent increase in road density and extension capacity may have higher impacts on improving technical inefficiency than R&D. It implies that while public R&D stock could contribute significantly to long-run technical changes by pushing up the production frontier, its impact on inefficiency improvement could be less than other public goods. On the other hand, the Extension activity and intensified road infrastructure can help to disseminate knowledge, reduce transportation cost, and therefore improve technical inefficiency further.

Summary and Conclusions

We examine the patterns of productivity changes and climate changes across regions and over time. We employ a state panel data for the period of 1960-2004 to identify the role of climate changes on U.S. agricultural productivity growth by employing a stochastic frontier production frontier method. Climate variables are measured using the THI load and Oury index at both their means and the degree of deviation from the historical norm (1941-1970) at the state level. We also incorporate the irrigation ratio and the measures of local public goods—R&D, extension, and road infrastructure—to capture the effects of specific state characteristics and to check for the robustness of the estimates of climate variables' impacts.

The state production data and weather information show noticeable variations across and within production regions. Yet, some regions seem to have faster overall TFP growth rate, such as 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, the higher Oury index, irrigation ratio, local R&D, Extension, and road density can drive state overall farm production closer to its best performance using given inputs and the best technology. Although the relative level of THI and Oury index could result in geospatial differences in technical inefficiency, the unexpected climate “shock”, such as extreme weather, seems to have more robust impacts than its level variation. It could be because farmers expect some degree of weather variations based on past experience and have made preparations. Therefore, it is the unexpected climate changes (shocks) that result in either waste, an increase use of input, or a drop in production.

While most studies evaluating the impacts of climate change are focused on a specific crop or livestock commodities, it is also important to identify the impact climate change has on overall productivity growth through its impacts on technical inefficiency. The results could help us further understand the sources and differences of productivity growth at the state level.

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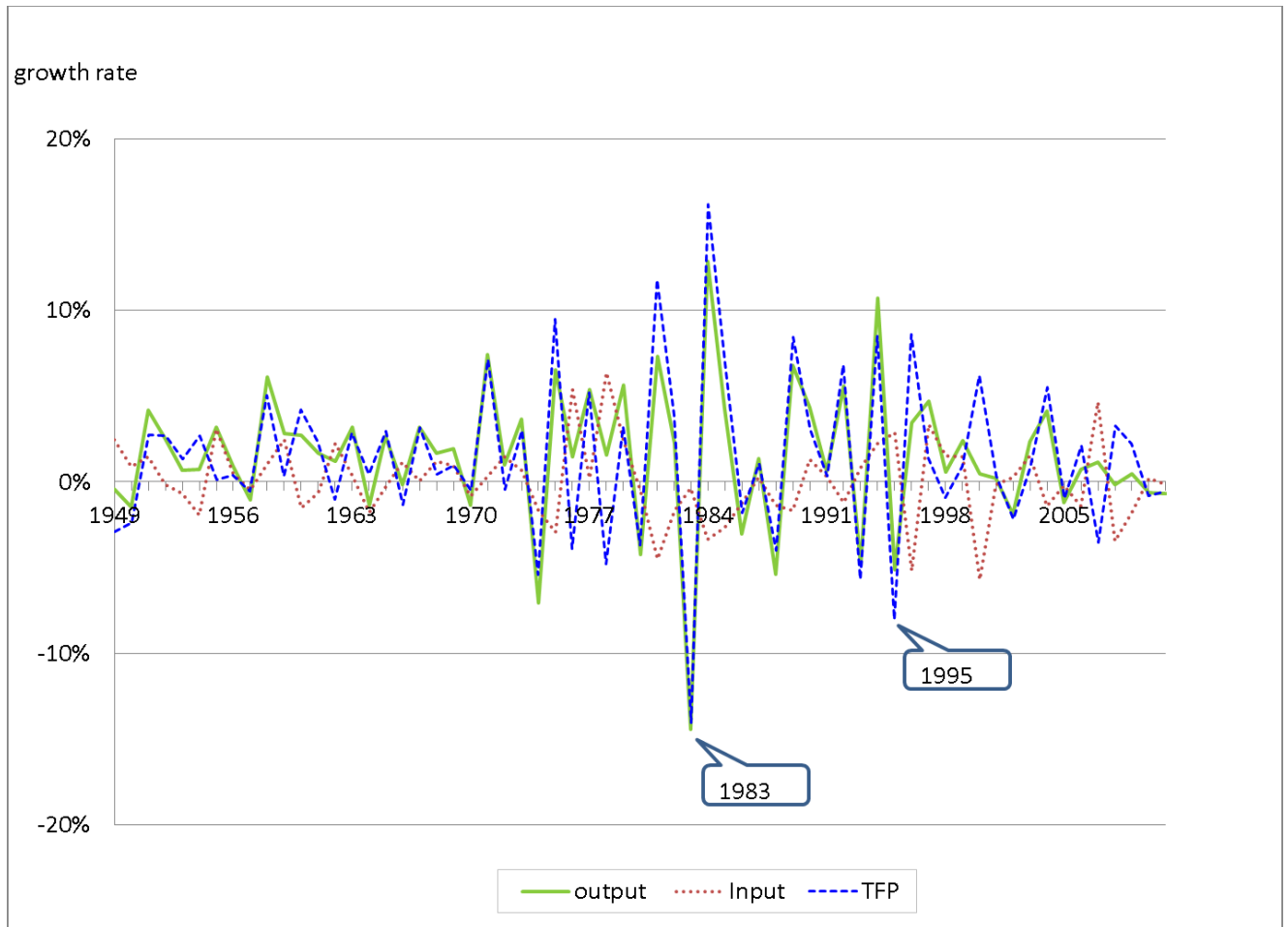
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Yu and Babcock (1992) More Drought Tolerant?

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

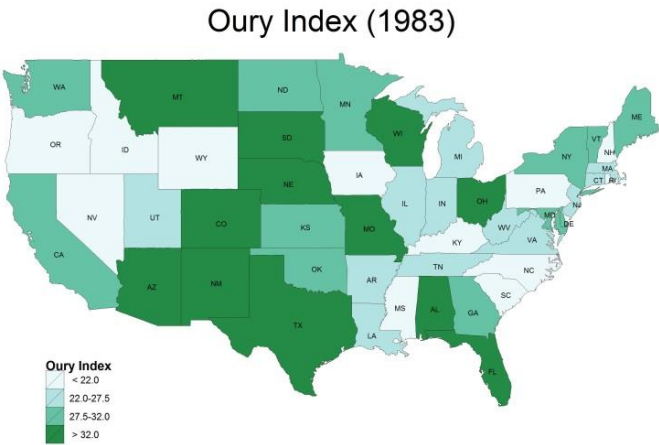
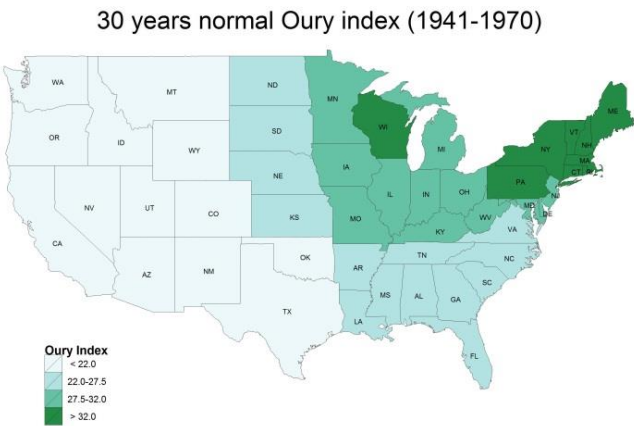


Data source: USDA and authors' calculation

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

Panel A

Panel B



Panel C

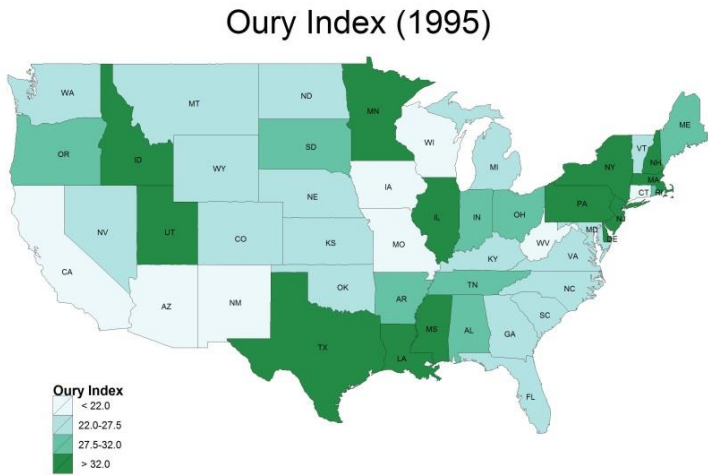


Figure 3. The climate shocks comparison using Oury Index: 1983 vs. 1995

Panel A

Panel B

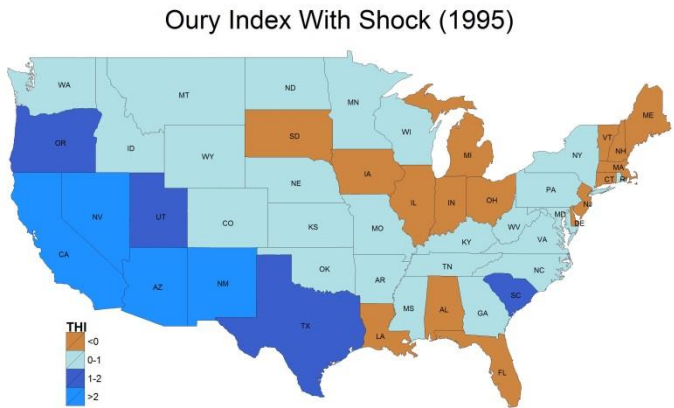
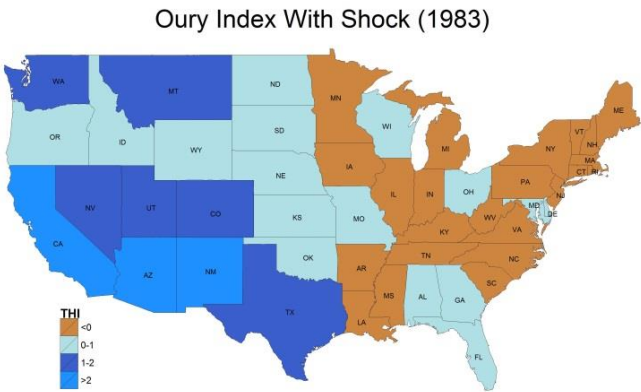
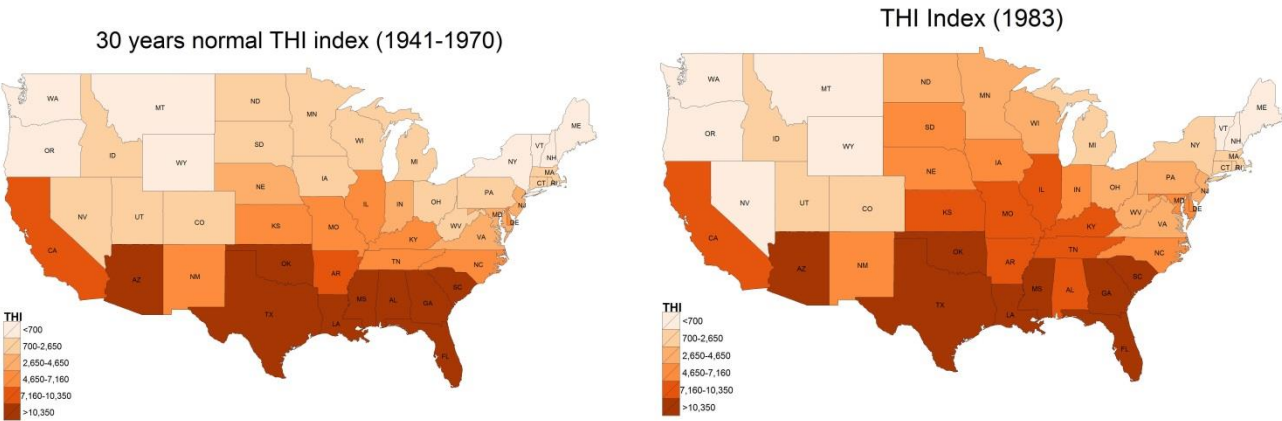


Figure 4. THI load comparison, the norm, 1983, and 1995

Panel A.

Panel B



Panel C

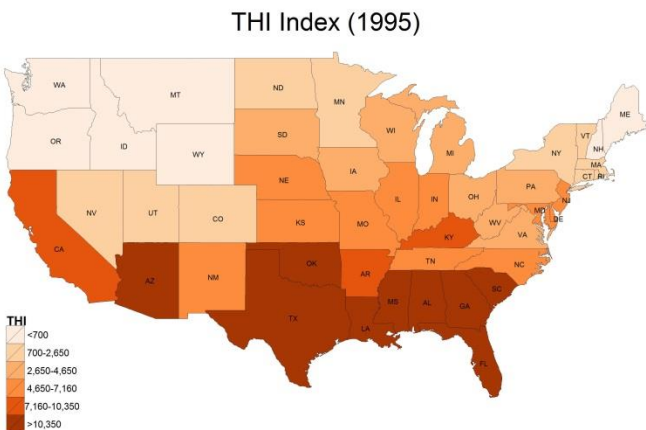


Figure 5. The climate shocks comparisons using THI load Index: 1983 vs. 1995

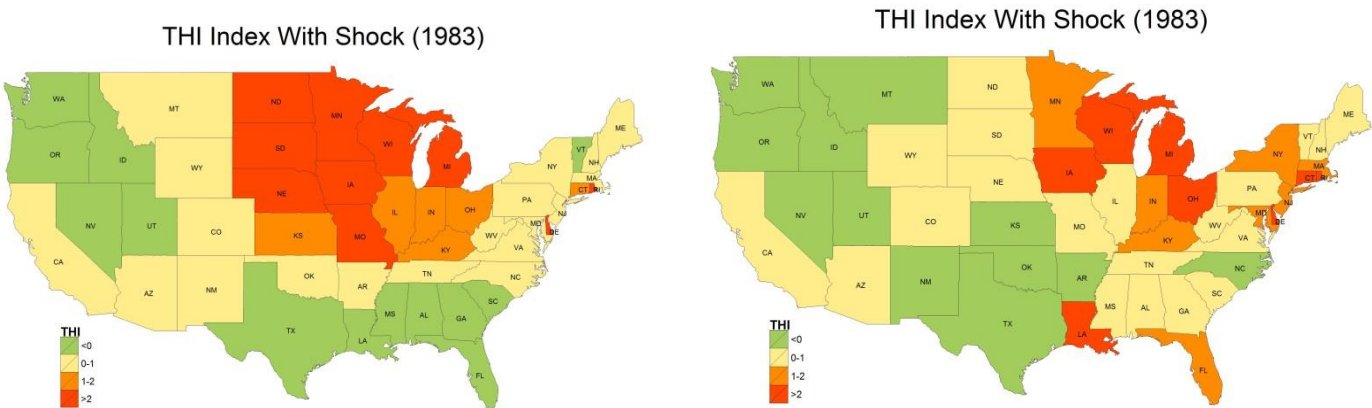


Figure 6. Irrigation ratio at census year

Irrigation Ratio Over Time

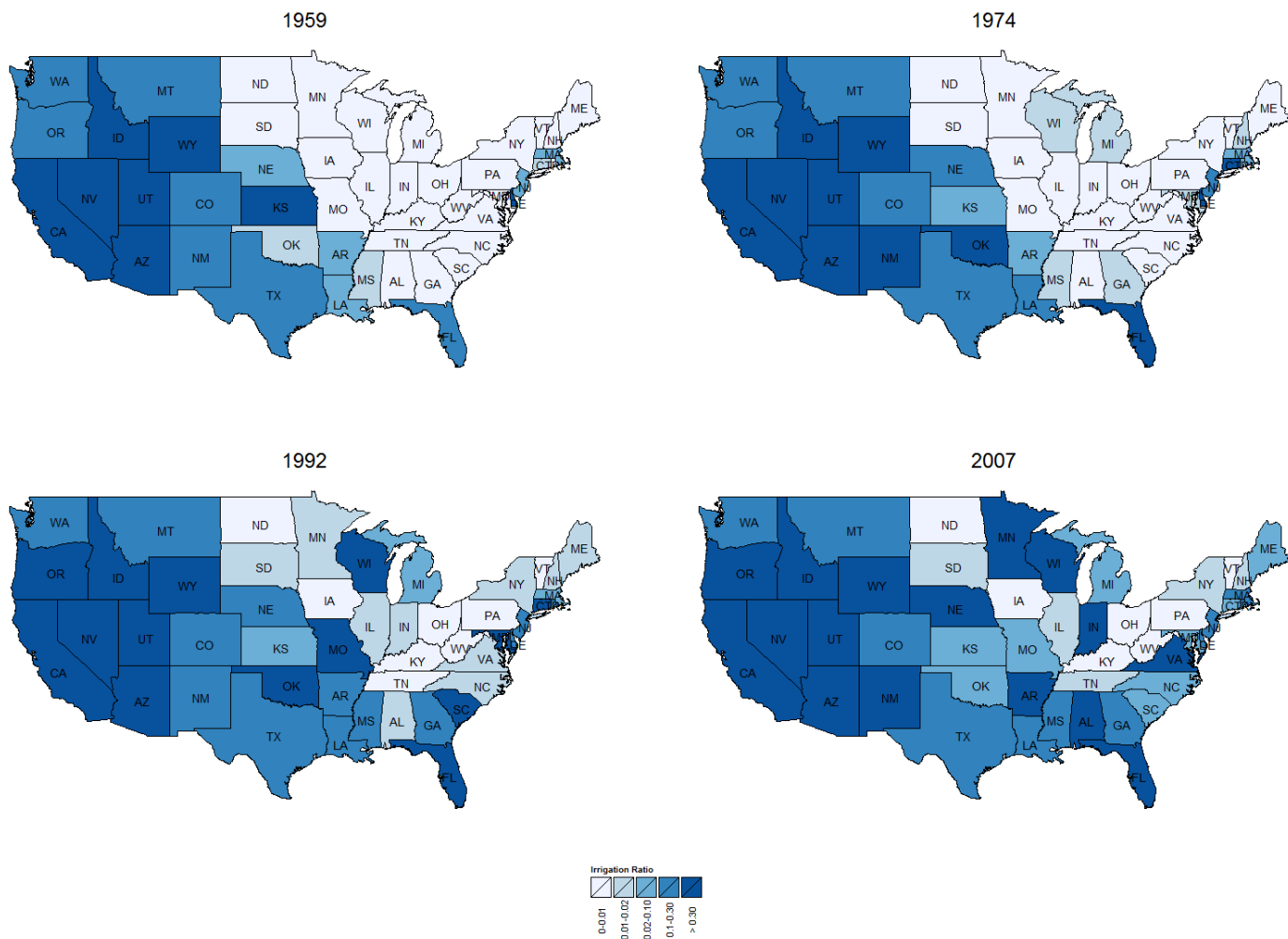


Table 1 State characteristics on productivity growth and climate indexes

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

Data source: Authors' calculation

Table 2 Technical inefficiency determinants (I)

Dependent variable: $\ln \sigma^2_{u, it}$	Coefficients	standard deviation	p> z
Model 1			
THI load	0.00002	0.00002	0.191
Oury index	-0.02566	0.00598	0.000
Irrigation ratio	-1.61679	0.55987	0.004
Constant	-4.51806	0.17359	0.000
Model 2			
THI load	0.00006	0.00002	0.001
Oury index	-0.02005	0.00656	0.002
Irrigation ratio	-2.87403	0.83239	0.001
R&D	-0.38697	0.13491	0.004
Extension	-0.62426	0.16819	0.000
Road	-0.87694	0.23835	0.000
Constant	-2.42410	2.12695	0.254

Note: R&D, Extension, and Road are in natural log term.

Table 3 Technical inefficiency determinants (II)

Dependent variable: $\ln \sigma^2_{u, it}$	Coefficients	standard deviation	p> z
Model 3			
THI load shock	0.308766	0.0572208	0.000
Oury index shock	-0.1831757	0.0852158	0.032
Irrigation ratio	-1.421067	0.7353514	0.053
Constant	-5.271049	0.210577	0.000
Model 4			
THI load shock	0.3071805	0.0585066	0.000
Oury index shock	-0.182993	0.0849239	0.031
Irrigation ratio	-2.219217	0.7363569	0.003
R&D	-0.3317824	0.1238919	0.007
Extension	-0.4784294	0.1775977	0.007
Road	-0.798406	0.2115199	0.000
Constant	-2.773977	1.831444	0.130

Note: R&D, Extension, and Road are in natural log term.