Climate Variability and Agricultural Productivity: Evidence from Southeastern US

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Introduction

- The value of climate forecasts can be defined and evaluated in different ways.
- Most studies have focused on the potential effect of climate information on the **financial performance** (revenues, profit, etc.) of a farm.
- However, the use of **economic performance** measures, such as productivity, input substitution, inefficiency, etc., have received much less attention in the literature.

Introduction

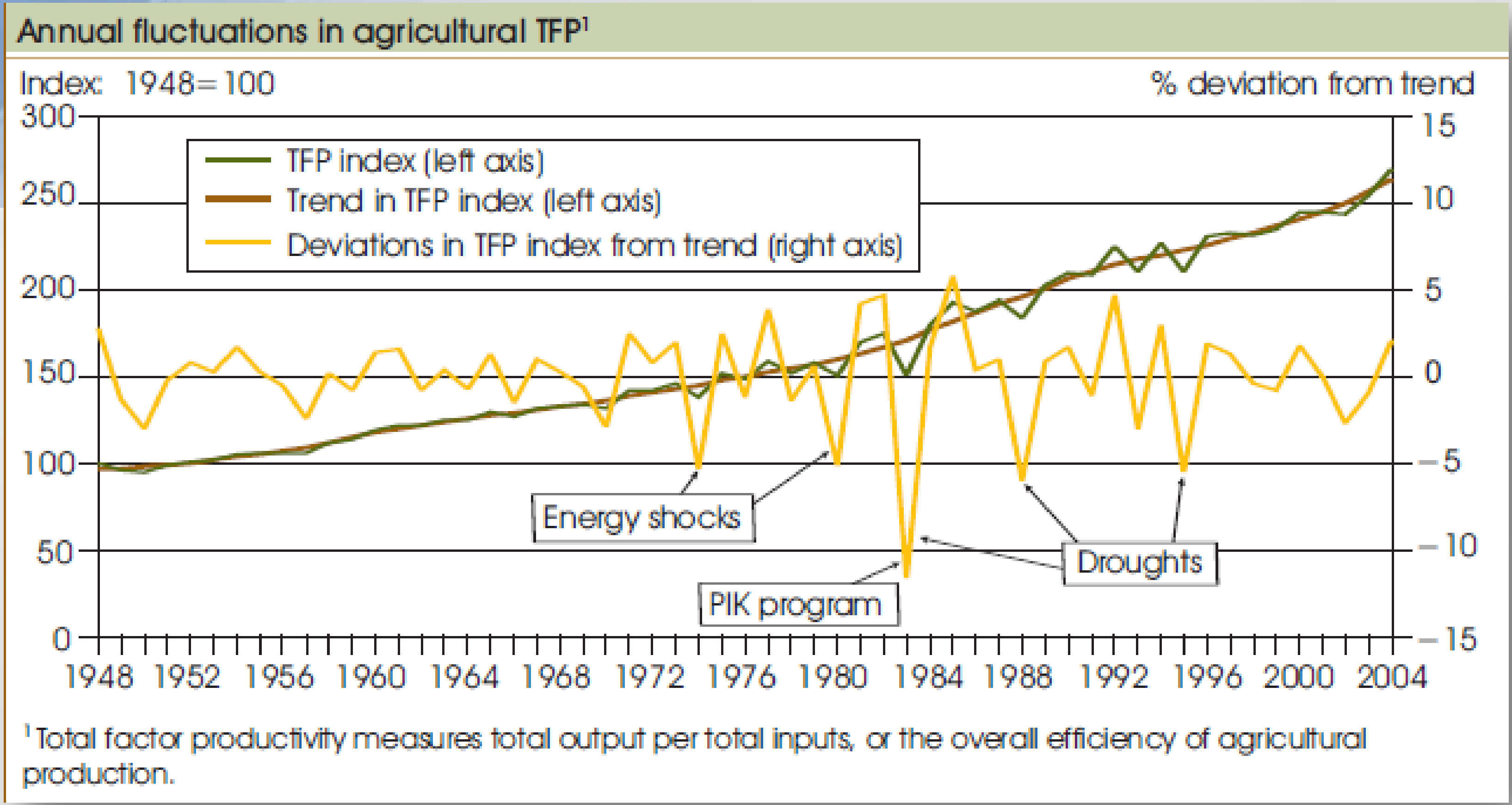
- Farm **productivity** and **efficiency** are important from a **practical** as well as from a **policy** point of view.
- **Farmers** could use this information to improve their performance.
- **Policymakers** could use this knowledge to identify and target public interventions to improve farm productivity and farm income.

Introduction

- A review of the agricultural **productivity** and **efficiency** literature reports few studies include climate in their models (Bravo-Ureta et al., 2007)
- Researchers have omitted climate from their empirical models by arguing that such variability is beyond the control of the producers; therefore, it should be treated as a random variable.
- However, some argue that climate variability is not a pure random variable (Demir and Mahmud, 2002).

Introduction

- Historical differences in climatic conditions are known with a reasonable degree of certainty.
- Advances in climate forecasting and the ability to predict climate fluctuations provide opportunities to improve farm management.
- Thus, omission of climate variables may lead to an inadequate representation of the production model.



Main drops in productivity

1) Global energy crises of 1974 and 1979,
2) Serious droughts in 1983, 1988 and 1995, and
3) Agricultural policy intervention (in 1983 the Federal Government encouraged farmers -using the Payment-In-Kind, or PIK program- to reduce crop production to lower accumulated government-held commodity surpluses).

Objectives

The overall purpose of this study is two-fold:

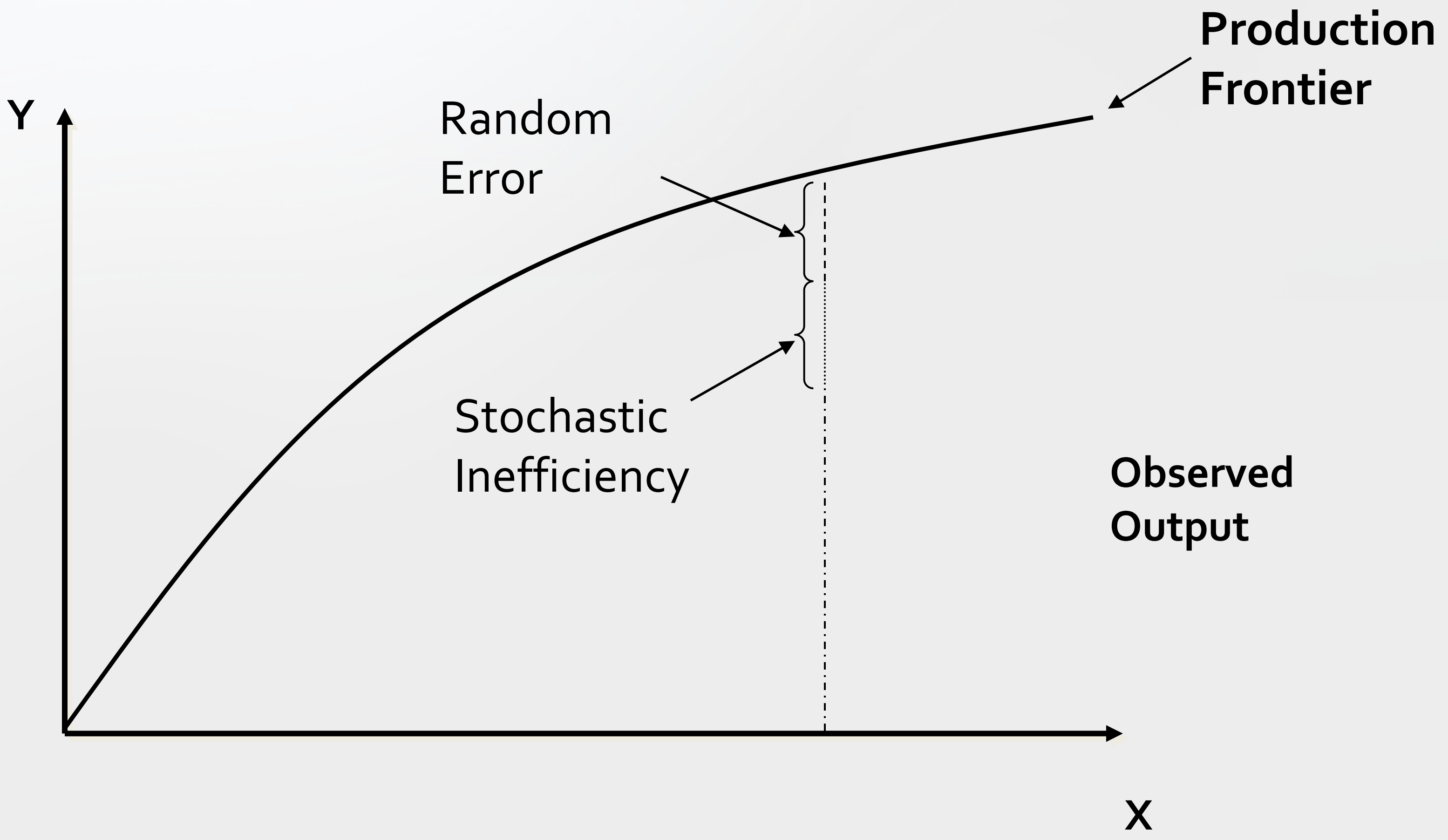
- The 1st goal of this study is to measure the effect of climatic variability on **Agricultural Productivity** and **Efficiency** using aggregate data and the Southeast US as a case of study.

- The 2nd goal is measure the **value of climate information** on the **efficiency** of US agriculture.

Methodology

- We implement the **Stochastic Production Frontier (SPF)** analysis, which is based on an econometric (parametric) specification of a production frontier.
- **Frontier function** provides the shape of the technology for the best performing decision making units.
- The frontier approach allows us to evaluate the effective gap between **current farm productivity** and the **potential productivity** level given the existing technology in a particular region.
- SPF is designed to incorporate stochastic disturbances into the model.

Stochastic Production Frontier: A Graphical Representation



Empirical model

Translog SPF

$$\ln VA_{it} = \alpha + \sum_j \beta_j \ln x_{jit} + \frac{1}{2}\sum_j \sum_k \beta_{jk} \ln x_{jit} \ln x_{kit} + \gamma_t \sum_N C_n + \delta_t T + \frac{1}{2}\delta_t T^2 + v_{it} - u_{it}$$

where ***VA**$_{it}$* is the agricultural value-added for the State ***i*** in year ***t;*** ***x*** are the inputs: **cultivated land** (A), **labor** (L) and **capital** (K); **C** is a set of climate variables (Seasonal rainfall and seasonal max temperature); and **T** is a time trend. The error term is composed of two terms, *v* (stochastic shocks) and *u* which captures the technical inefficiency (TI) relative to the stochastic frontier.

$$\mathrm{TE}_i = \exp\left(-\mathrm{E}\left[u_i \middle| \varepsilon_i\right]\right).$$

Empirical model

To evaluate the effect of climate information on TE, we regress the TI scores against selected climatic indexes

$$\mu_i = \alpha_0 + \sum_{n=1}^{m} \alpha_n I_{ni} + e_i$$

where μ_i is the inefficiency effect, I_{ni} is a vector of climate information variables (ENSO, PP, Drought), the α_s are unknown parameters and e_i is random noise.

Data

- Were collected from the USDA-ERS.
- We construct a state-by-year panel, covering 5 contiguous states in the SE US over 46 years from 1960-2006 inclusive.
- Ball et al (2001) was follow to account for differences in quality and value of inputs and outputs.

Results (climate biased)

- We estimated 4 alternative models:
  - **Model 1** does not include any climatic variables.
  - **Model 2** includes climatic variables only in the inefficiency function with neutral effects.
  - **Model 3** is a non-neutral specification with climatic variables in the inefficiency function.
  - **Model 4** is a non-neutral specification with climatic variables in the production frontier and the inefficiency function (**Full specification**).

Results (climate biased)

- Three separate null hypotheses were tested using the likelihood ratio test (LRT):
  - The null hypothesis that all production coefficients associated with the climatic variables are zero is strongly rejected.
  - The null hypothesis that all efficiency coefficients associated with the climatic variables are zero is strongly rejected.
  - Based on a LRT Model 4 (full representation) is the best representation for the data .

Elasticities

- It tells how much the level of production changes when we change one of the parameter in the SPF

Table 1. Elasticities of mean output and returns to scale with and without environmental variables inputs

Variables	Without Environmental Variables	With Environmental Variables
Land	0.20	0.68
Labor	0.54	0.35
Capital	0.72	0.12
Return to Scale	*1.46*	*1.15*

- The introduction of climate variable significantly affects the elasticity of inputs.
- RTS decreases by including climate

Ranking by level of productivity

USDA/ERS Official Ranking

State	Rank in 2004
California	1
Florida	2
Iowa	3
Illinois	4
Delaware	5
Idaho	6
Indiana	7
Rhode Island	8
Georgia	9
Massachusetts	10
Arizona	11
Arkansas	12
North Carolina	13
Connecticut	14
Oregon	15
New Jersey	16
Maryland	17
Minnesota	18
Ohio	19
Alabama	20
Nebraska	21
Maine	22
Washington	23
New York	24
Mississippi	25
South Carolina	26

Without Including Climate variability

State	Ranking
Florida	1
Georgia	2
N. Carolina	3
Alabama	4
S. Carolina	5

Including Climate Variability

State	Ranking
Florida	1
Georgia	2
N. Carolina	3
S. Carolina	4
Alabama	5

Results (the value of climate information)

- We estimated 5 alternative models
  - **Model 1**: Knowing that the cropping season is either **El Niño** or **La Niña**
  - **Model 2**: Knowing that the cropping season is not normal (**Neutral**)
  - **Model 3**: Knowing the predicted annual **rainfall** and **average MAX TEMP**
  - **Model 4**: Knowing the predicted seasonal **rainfall** and **MAX TEMP**
  - **Model 5**: Knowing that the cropping season is not normal (neutral) and the predicted seasonal **rainfall** and **MAX TEMP**

Results (the value of climate information)

	El Niño	La Niña	Enso	Annual Rainfall	Summer Rainfall	Spring Rainfall	Average Max T°	Summer Max T°	Spring Max T°
Model 1	+	-							
Model 2			+						
Model 3				**+*** **			+		
Model 4					**+*** **	**+*** **		**+***	+
Model 5			+	**+*** **			+		

***, p>0.01; **, p>0.05, *, p>0.1

Conclusions

- Productivity and efficiency studies on agriculture using regional data tend to ignore environmental effects, assuming that such variables are random.
- But it is found that agricultural production is under the influence of variations of climatic variables that are location-specific.
- If these environmental variables are ignored, it may cause improper specification of the TIE in models of agricultural production.
- Results shows that climatic variables affect directly and indirectly through interactions, mean output elasticities, economies to scale and technical efficiencies.

Conclusions

- When the climatic conditions are taken into account, States at locations with relatively unfavorable environmental conditions, are able to gain in terms of TE.
- Significant changes are observed in the size and spread of TE scores when climatic variables are incorporated in the production and ineficiency functions.
- The effect of **Climate Information** on agricultural efficiency present mixed results.
  - Non-significant results were found when **ENSO** was used as the climate indexes.
  - However information on **seasonal rainfall** and **Max Temp** display a positive and significant effect on reducing the inefficiency in this sector.

Work in progress

- Re estimate this model by production sectors (**crops**, **livestock** and **forestry**) and check the impact of climate variability and information by sector.
- Estimate the elasticity of climate information on TE.
- Conduct a sensitivity analysis of the impact of seasonal rainfall and max temp forecasts on TE

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