Estimating the Effects of Weather and Climate Change on Agricultural Productivity

presented by

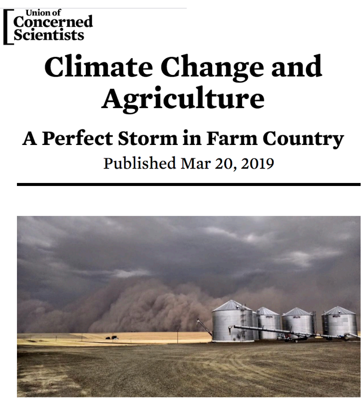
C.J. O'Donnell

Centre for Efficiency and Productivity Analysis
School of Economics, University of Queensland, Australia

in an

AARES Federal Webinar

18 November, 2020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Climate Change and Agriculture

A Perfect Storm in Farm Country

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Farming productivity puzzle a serious challenge

David Gregory-Kumar
Science, Environment & Rural Affairs Correspondent

18 January 2018

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Some Relevant Literature

- Anand and Khetarpal (2015) use a biophysical simulation model to examine the effects of changes in surface air temperatures on wheat yield per hectare.
- Nastis et al (2012) use OLS and a CRS production function to estimate the effects of changes in temperature and precipitation on land productivity.
- Ortiz-Bobea et al (2020) use a simple regression model to estimate the effects of changes in temperature and precipitation on a Törnqvist TFP index.
- Salim and Islam (2010) use a vector error correction model to estimate the effects of changes in rainfall on a Törnqvist TFP index.
- Hughes et al (2011) use a stochastic production frontier model to construct a climate effects index, which they then use to deflate a Fisher TFP index.
- Sabasi and Shumway (2018) use an SUR model to estimate the effects of changes in temperature and precipitation on an Lowe TFP index and DEA estimates of its components.
- Njuki et al (2018a) and Njuki et al (2018b) use stochastic production frontier models to estimate the effects of changes in temperature and precipitation on mulltiplicative TFP indexes.

This Paper

The basic premise of this paper is that changes in weather and climate affect agricultural inputs and outputs (and therefore TFP) in two ways: (1) realisations of weather variables affect the outputs that can be produced using predetermined inputs, and (2) expectations about weather and climate variables affect the input and planned output choices of managers.

The paper is divided into three sections:

1. Defining (Changes in) TFP
2. Measuring Changes in TFP
3. Explaining Changes in TFP

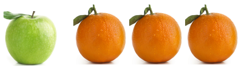
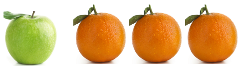
1. DEFINING (CHANGES IN) TFP

- Jorgenson and Griliches (1967, REStud): "The rate of growth of total factor productivity is defined as the difference between the rate of growth of real product and the rate of growth of real factor input" (p.250).
- Schreyer (2001) "Productivity is commonly defined as a ratio of a volume measure of output to a volume measure of input use . . . there is no disagreement on this general notion" (p.11)
- Hughes et al (2011) "[TFP] is simply the ratio of total or aggregate output to total or aggregate input . . . It is primarily concerned with the quantities of outputs and inputs" (p.6)
- O'Donnell (2018)". . . measures of productivity change are defined as measures of output quantity change divided by measures of input quantity change"(p.11).

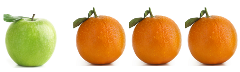
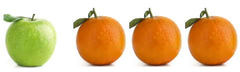
2. MEASURING CHANGES IN TFP

Computing measures of output and input quantity change (and therefore TFP change) involves assigning numbers to baskets of outputs and inputs. Measurement theory says that so-called index numbers must be assigned in such a way that the relationships between the numbers mirror the relationships between the baskets.

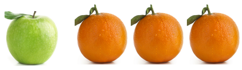
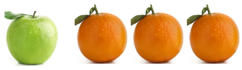
Quantity Index Numbers

Basket	Contents	
A		?
B		?
D		?
E		?

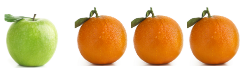
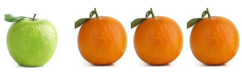
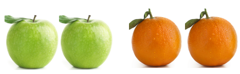
Quantity Index Numbers

Basket	Contents	
A		1
B		?
D		?
E		?

Quantity Index Numbers

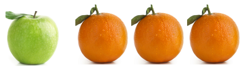
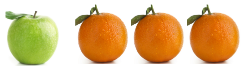
Basket	Contents	
A		1
B		?
D		?
E		2

Quantity Index Numbers

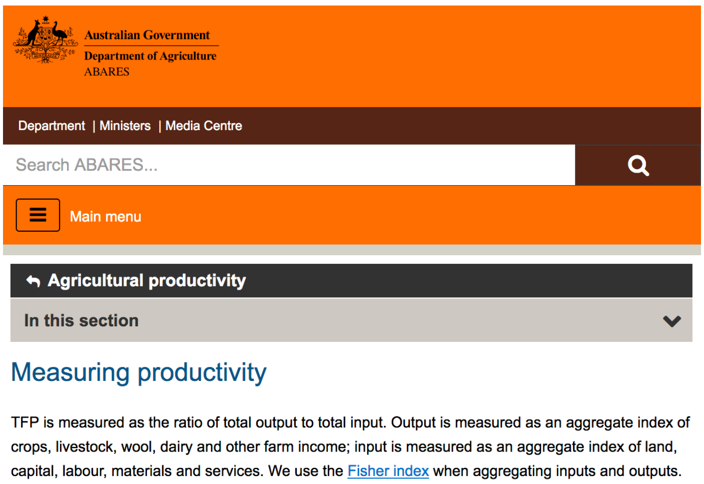
Basket	Contents	Lowe
A		1
B		2.034
D		?
E		2

$0.483 \times 1 + 0.512 \times 3 = 2.034$; these weights imply that oranges are $0.512/0.483 - 1 = 7.1\%$ more valuable than apples

Quantity Index Numbers

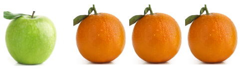
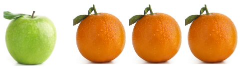
Basket	Contents	Lowe
A		1
B		2.034
D		2.034
E		2

Quantity Index Numbers

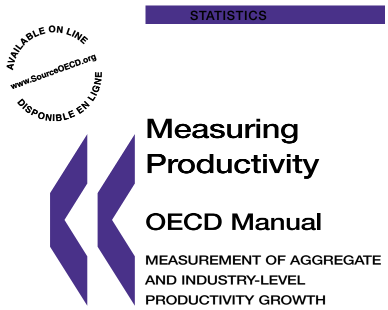


https://www.agriculture.gov.au/abares/research-topics/productivity/measuring-productivity

Quantity Index Numbers

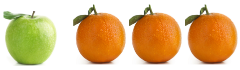
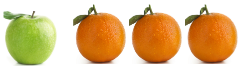
Basket	Contents	Lowe	Fisher
A		1	1
B		2.034	1.604
D		2.034	2.330
E		2	2

Quantity Index Numbers



“[The] economics literature as well as the SNA93 are quite unanimous in this respect: for inter-temporal comparisons, changes over longer periods should be obtained by chaining: i.e., by linking the year-to-year-movements” (Schreyer, 2001, p.83)

Quantity Index Numbers

Basket	Contents	Lowe	Fisher	Chained Fisher
A		1	1	1
B		2.034	1.604	1.604
D		2.034	2.330	3.684
E		2	2	2.739

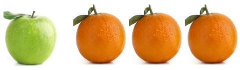
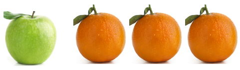
Quantity Index Numbers

The Economic Journal, **92** (*March* 1982), 73–86
Printed in Great Britain

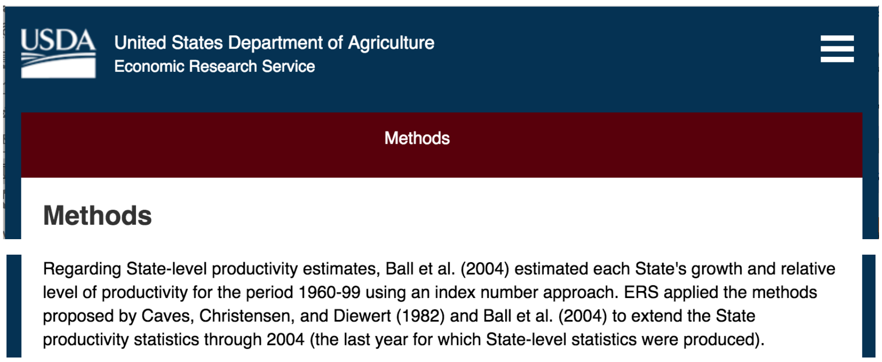
MULTILATERAL COMPARISONS
OF OUTPUT, INPUT, AND PRODUCTIVITY
USING SUPERLATIVE INDEX NUMBERS*

Douglas W. Caves, Laurits R. Christensen and W. Erwin Diewert

"[Our] indexes provide transitive multilateral comparisons that maintain a high degree of characteristicity. . . . The superlative multilateral indexes that we have proposed are very attractive for cross section comparisons and for panel data comparisons, but they are not necessarily preferable to chain-linked bilateral indexes for time series comparisons." (Caves et al, 1982, p. 84)

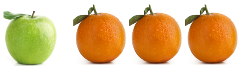
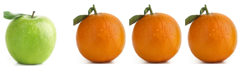
Basket	Contents	Lowe	Fisher	Chained Fisher	EKS
A		1	1	1	1
B		2.034	1.604	1.604	1.675
D		2.034	2.330	3.684	2.297
E		2	2	2.739	1.987

EKS = Elteto-Koves-Szulc



https://www.ers.usda.gov/data-products/agricultural-productivity-in-the-us/methods/

Quantity Index Numbers

Basket	Contents	Lowe	Fisher	Chained Fisher	EKS	Implicit EKS
A		1	1	1	1	1
B		2.034	1.604	1.604	1.675	1.675
D		2.034	2.330	3.684	2.297	2.297
E		2	2	2.739	1.987	1.987

EKS = Elteto-Koves-Szulc

Proper Quantity Indexes

In O'Donnell (2016, 2018), an output quantity index that compares q_{it} with q_{ks} is defined as any variable of the form

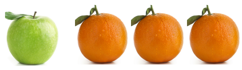
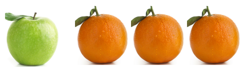
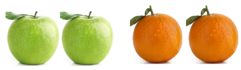
$$QI(q_{ks}, q_{it}) = Q(q_{it})/Q(q_{ks})$$

where $Q(.)$ is any nonnegative, nondecreasing, linearly-homogeneous, scalar-valued aggregator function. If outputs are positive, then all indexes of this type satisfy a set of basic axioms listed in O'Donnell (2016, 2018) (e.g., proportionality, transitivity). An output index is said to be proper if and only if it satisfies all of these axioms.

The same ideas carry over to input quantity indexes.

All proper quantity index numbers are consistent with measurement theory. The class of proper quantity indexes includes various additive, multiplicative, primal, dual and benefit-of-the doubt indexes.

Quantity Index Numbers

Basket	Contents	Lowe	AEW	MEW	GY	MOLS	BOD
A		1	1	1	1	1	1
B		2.034	2	1.732	1.812	1.627	2.2
D		2.034	2	1.732	1.812	1.627	2.2
E		2	2	2	2	2	2

AEW = additive with equal weights; MEW = multiplicative with equal weights; GY = geometric Young;
MOLS = multiplicative with OLS weights; BOD = benefit-of-the-doubt.

Proper TFP Indexes

In O'Donnell (2016, 2018), a total factor productivity (TFP) index is said to be proper if and only if it can be written as the ratio of a proper output quantity index divided by a proper input quantity index. This paper measures output and input change (and therefore TFP change) using a multiplicative index.

Multiplicative TFP Indexes

Multiplicative output and input indexes are constructed using aggregator functions of the form

$$Q(q_{it}) \propto \prod_{n=1}^{N} q_{nit}^{a_n} \qquad \text{and} \qquad X(x_{it}) \propto \prod_{m=1}^{M} x_{xit}^{b_m} \tag{1}$$

where $a_1, \ldots, a_N$ are any nonnegative output weights that sum to one and $b_1, \ldots, b_M$ are any nonnegative input weights that sum to one. The associated index that compares the TFP of firm i in period t with the TFP of firm k in period s is

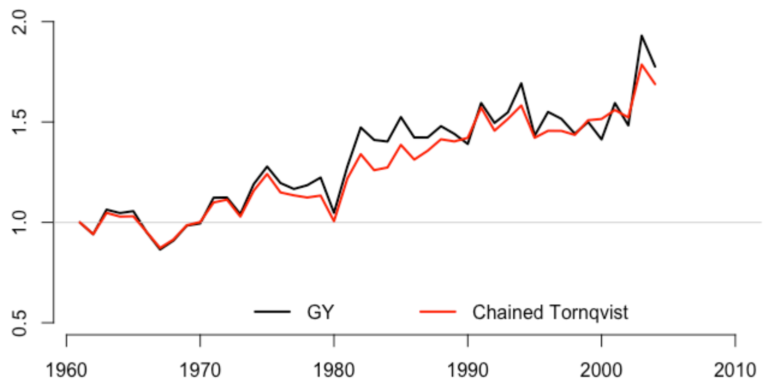
$$TFPI^M(x_{ks}, q_{ks}, x_{it}, q_{it}) \equiv \prod_{n=1}^{N} \left(\frac{q_{nit}}{q_{nks}}\right)^{a_n} \prod_{m=1}^{M} \left(\frac{x_{mks}}{x_{mit}}\right)^{b_m}. \tag{2}$$

Special cases include the GDF-based index defined by Silva Portela and Thanassoulis (2006, Eq. 4) and the geometric Young (GY) index defined by O'Donnell (2016, Eq. 5).

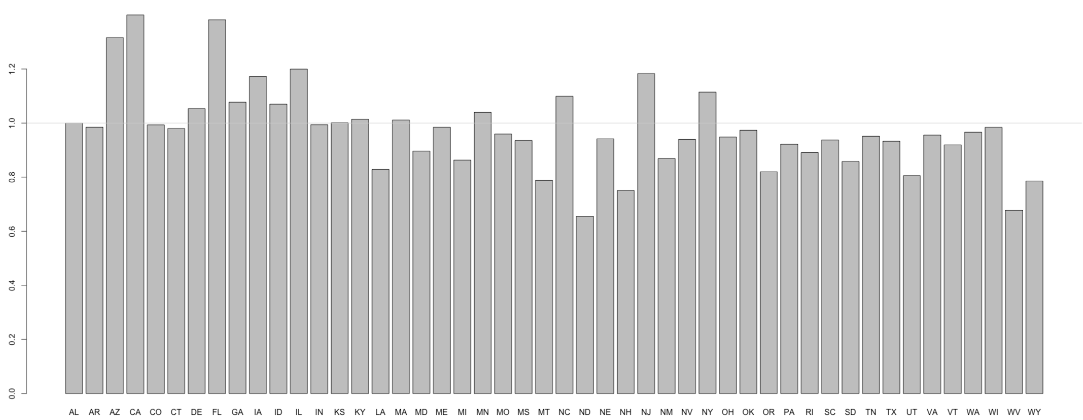
TFP Change in US Agriculture

- USDA farm production data
- 48 states
- 44 years from 1961 to 2004
- q_{it} = (livestock, crops, other outputs)'
- x_{it} = (capital, land, labour, materials)'
- $a = \bar{r}$ = (0.463, 0.484, 0.043)' ($\Rightarrow$ GY index)
- $b = \bar{s}$ = (0.132, 0.095, 0.264, 0.509)' ($\Rightarrow$ GY index)

TFP Change in Alabama Agriculture (AL 1961 = 1)



TFP Change in US Agriculture in 1961 (AL 1961 = 1)



3. EXPLAINING CHANGES IN TFP

To explain changes in productivity, we need to explain changes in output and input quantities. Economists have many behavioural models that can be used for this purpose.

This paper considers a behavioural model that accounts for weather uncertainty (i.e., uncertainty about day-to-day atmospheric conditions), climate uncertainty (i.e., uncertainty about average atmospheric conditions over a long period of time) and output price uncertainty.

Maximising Expected Profit

Assume that inputs and outputs are chosen/determined in two steps:

1. At the beginning of the production period, the managers of price-taking firms choose (variable) inputs and planned outputs to maximise expected profits in the face of uncertainty about output prices and one or more characteristics of the production environment (e.g., rainfall).
2. After inputs have been chosen and characteristics of the production environment have been realised, managers seek to maximise the outputs that can be obtained using their chosen inputs in their given production environment.

Explaining Changes in TFP

If Step 2 is true, then the relationship between outputs, inputs and environmental variables can be written in the form

$$\ln Q(q_{it}) = \alpha_i + \sum_{h=1}^{H} \lambda_h d_{hit} + \sum_{j=1}^{J} \delta_j \ln z_{jit} + \sum_{m=1}^{M} \beta_m \ln x_{mit} + v_{it} - u_{it} \quad (3)$$

where α_i is an unobserved fixed effect that accounts for nonstochastic time-invariant characteristics of the production environment (e.g., topography), d_{hit} is a function of t that allows for different rates of technical progress in different decades, z_{jit} is an exogenous characteristic of the production environment (e.g., rainfall), x_{mit} is a predetermined input, v_{it} represents functional form errors and other sources of statistical noise, and u_{it} denotes an output-oriented technical inefficiency effect. Equation (3) is a stochastic frontier model in which the explanatory variables are exogenous.

Explaining Changes in TFP

After some simple algebra, equation (3) can be rewritten as

$$Q(q_{it}) \prod_{m=1}^{M} x_{mit}^{-b_m} = \exp\left(\alpha_i + \sum_{h=1}^{H} \lambda_h d_{hit}\right) \left[\prod_{j=1}^{J} z_{jit}^{\delta_j}\right] \left[\prod_{m=1}^{M} x_{mit}^{\beta_m - b_m}\right] \exp(-u_{it}) \exp(v_{it}). \quad (4)$$

A similar equation holds for firm k in period s. Dividing one equation by the other yields:

$$TFPI^M(x_{ks}, q_{ks}, x_{it}, q_{it}) = \frac{\exp(\sum_{h=1}^{H} \lambda_h d_{hit})}{\exp(\sum_{h=1}^{H} \lambda_h d_{hks})} \left[\frac{\exp(\alpha_i)}{\exp(\alpha_k)} \prod_{j=1}^{J} \left(\frac{z_{jit}}{z_{jks}}\right)^{\delta_j}\right] \left[\prod_{m=1}^{M} \left(\frac{x_{mit}}{x_{mks}}\right)^{\beta_m - b_m}\right] \times \left[\frac{\exp(-u_{it})}{\exp(-u_{ks})}\right] \left[\frac{\exp(v_{it})}{\exp(v_{ks})}\right]. \quad (5)$$

The first term on the right would normally be viewed as an output-oriented technology index (OTI), the second term would normally be viewed as an output-oriented environment index (OEI), the third term would normally be viewed as an output-oriented scale-and-mix efficiency index (OSMEI), the next term is an output-oriented technical efficiency index (OTEI), and the last term is a statistical noise index (SNI).

TFP Change in US Agriculture

- USDA farm production data
- 48 states
- 44 years from 1961 to 2004
- $Q(q_{it})$ = GY aggregate output
- x_{it} = (capital, land, labour, materials)'
- z_{it} = (dd830, dd30, precipitation)'
- assume v_{it} is an independent $N(0, \sigma_v^2)$ random variable
- assume u_{it} is an independent $N^+(0, \sigma_u^2)$ random variable

Parameter Estimates

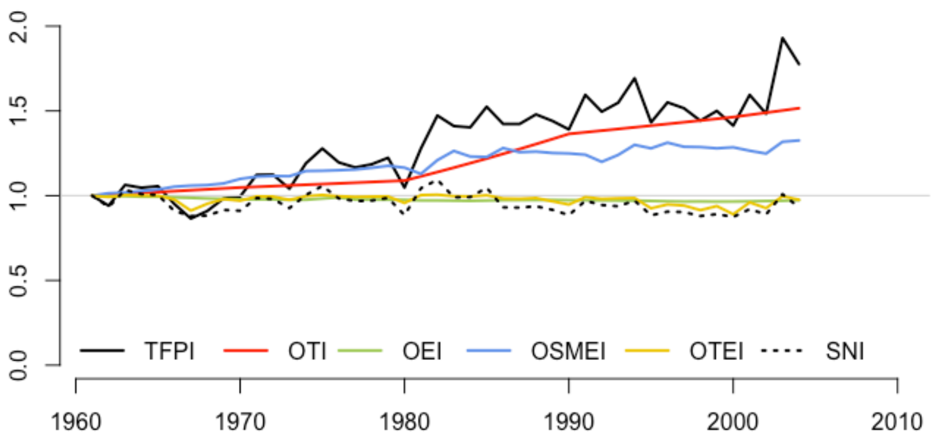
Coef.	Variable	ML	Bayes
α_1	AL	1.969**	1.926
:	:	:	:
α_{48}	WY	1.627*	1.603
λ_1	t in the 60s	0.005***	0.005
λ_2	t in the 70s	0.003	0.004
λ_3	t in the 80s	0.023***	0.023
λ_4	t in the 90s	0.007**	0.007
λ_5	t in the 00s	0.009	0.009
β_1	capital	0.153***	0.154
β_2	land	0.011	0.002
β_3	labour	0.105***	0.111
β_4	materials	0.580***	0.574
δ_1	dd830	0.002	0.020
δ_2	dd30	-0.016***	-0.017
δ_3	precipitation	0.006	0.000

***, **, * indicate significance at 1%, 5%, 10% level.

TFP Change in US Agriculture (AL 1961 = 1)

		TFPI	OTI	OEI	OSMEI	OTEI	SNI
AL	1961	1	1	1	1	1	1
AR	1961	0.985	1	1.332	0.960	0.923	0.834
AZ	1961	1.316	1	1.246	1.074	0.994	0.990
CA	1961	1.400	1	2.118	0.818	0.936	0.863
CO	1961	0.993	1	1.064	1.028	0.984	0.922
:	:	:	:	:	:	:	:
AL	2004	1.776	1.516	0.973	1.326	0.976	0.931
AR	2004	2.490	1.516	1.301	1.208	1.005	1.040
AZ	2004	2.460	1.516	1.246	1.265	0.998	1.031
CA	2004	2.873	1.516	2.080	0.920	0.997	0.993
CO	2004	1.844	1.516	1.032	1.225	0.988	0.973

TFP Change in Alabama Agriculture (AL 1961 = 1)



⇒ the effects of changes in weather on TFP have been relatively small.

Explaining Changes in OSME

If Step 1 is true, then the m-th input demand function can be written in the form

$$x_{mit} = \exp(\alpha_{mi} + \lambda_m t) \prod_{j=1}^{J} (z_{jit}^e)^{\delta_{mj}} \prod_{n=1}^{N} (p_{nit}^e)^{\phi_{mn}} \prod_{h=1}^{M} w_{hit}^{\xi_{mh}} \exp(e_{mit}) \quad (6)$$

where α_{mi} is an unobserved fixed effect that accounts for nonstochastic time-invariant characteristics of the production environment (e.g., topography), z_{jit}^e is the expected value of the j-th environmental variable, p_{nit}^e is the n-th expected output price, w_{kit} is an input price, and e_{mit} represents allocative inefficiency and statistical noise. Thus, the OSME component in (5) can be written as

$$\prod_{m=1}^{M} \left(\frac{x_{mit}}{x_{mks}} \right)^{\beta_m - b_m} = \prod_{m=1}^{M} \left[\frac{\exp(\lambda_m t)}{\exp(\lambda_m s)} \right]^{(\beta_m - b_m)} \prod_{m=1}^{M} \left[\frac{\exp(\alpha_{mi})}{\exp(\alpha_{mk})} \prod_{j=1}^{J} \left(\frac{z_{jit}^e}{z_{jks}^e} \right)^{\delta_{mj}} \right]^{(\beta_m - b_m)}$$
$$\times \prod_{m=1}^{M} \prod_{n=1}^{N} \left[\frac{p_{nit}^e}{p_{nks}^e} \right]^{\phi_{mn}(\beta_m - b_m)} \prod_{m=1}^{M} \prod_{h=1}^{M} \left[\frac{w_{hit}}{w_{hks}} \right]^{\xi_{mh}(\beta_m - b_m)} \prod_{m=1}^{M} \left[\frac{\exp(e_{mit})}{\exp(e_{mks})} \right]^{(\beta_m - b_m)}.$$

The terms on the right-hand side are a technology index (TI), an expected environment index (EEI), an expected output price index (EPI), an input price index (WI), and an allocative efficiency and statistical noise index (AESNI).

OSME Change in US Agriculture (AL 1961 = 1)

- $p_{it}^e = p_{i,t-1}$ = lagged GY output price index
- z_{it}^e = average of $z_{i,t-1}, \ldots, z_{i,t-10}$
- assume e_{mit} is an independent $N(0, \sigma_m^2)$ random variable

OLS Parameter Estimates

Coef.	Variable	Qty of capital	Qty of land	Qty of labour	Qty of materials
α_{m1}	AL	25.816***	11.863***	13.246***	21.697***
:	:	:	:	:	:
α_{m48}	WY	23.506***	12.890***	12.309***	19.527***
λ_m	t	-0.006***	-0.007***	-0.010***	0.011***
ϕ_m	E(output price)	-0.071	0.243***	-0.195***	0.047
ξ_{m1}	price of capital	-0.230***	0.230***	0.187***	0.027
ξ_{m2}	price of land	0.143***	-0.124***	-0.159***	-0.039***
ξ_{m3}	price of labour	-0.161***	0.016*	-0.243***	0.009
ξ_{m4}	price of materials	0.318***	-0.120***	0.410***	-0.044
δ_{m1}	E(dd830)	-1.532***	0.093	0.052	-0.904***
δ_{m2}	E(dd30)	-0.121***	-0.066***	-0.008	-0.142***
δ_{m3}	E(precipitation)	-0.192***	0.256***	0.125	-0.074

***, **, * indicate significance at 1%, 5%, 10% level.

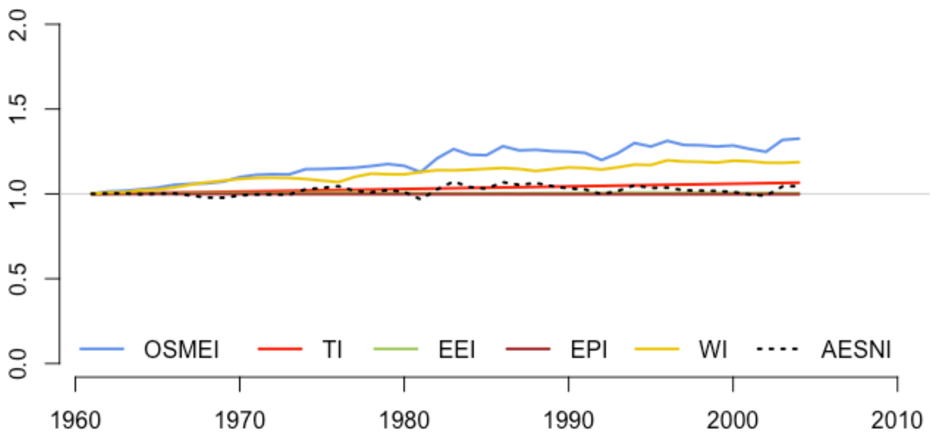
Bayesian Parameter Estimates

Coef.	Variable	Qty of capital	Qty of land	Qty of labour	Qty of materials
α_{m1}	AL	25.920	11.733	13.163	20.962
:	:	:	:	:	:
α_{m48}	WY	23.563	12.834	12.209	19.114
λ_m	t	-0.005	-0.005	-0.008	-0.000
ϕ_m	E(output price)	0.017	0.003	0.015	0.005
ξ_{m1}	price of capital	-0.249	0.167	0.143	0.165
ξ_{m2}	price of land	0.144	-0.119	-0.157	0.025
ξ_{m3}	price of labour	-0.169	0.006	-0.257	0.120
ξ_{m4}	price of materials	0.257	-0.057	0.255	-0.315
δ_{m1}	E(dd830)	-1.541	0.076	0.058	-0.795
δ_{m2}	E(dd30)	-0.116	-0.057	-0.008	-0.131
δ_{m3}	E(precipitation)	-0.227	0.318	0.113	0.047

OSME Change in US Agriculture (AL 1961 = 1)

		OSMEI	TI	EEI	EPI	WI	AESNI
AL	1961	1	1	1	1	1	1
AR	1961	0.960	1	0.978	1	1.020	0.963
AZ	1961	1.074	1	1.049	1	1.032	0.991
CA	1961	0.818	1	0.859	1	1.074	0.887
CO	1961	1.028	1	1.030	1	1.034	0.966
:	:	:	:	:	:	:	:
AL	2004	1.326	1.066	1.004	0.998	1.187	1.046
AR	2004	1.208	1.066	0.976	0.998	1.179	0.987
AZ	2004	1.265	1.066	1.054	0.998	1.143	0.987
CA	2004	0.920	1.066	0.853	0.998	1.182	0.858
CO	2004	1.225	1.066	1.024	0.998	1.155	0.974

OSME Change in Alabama Agriculture (AL 1961 = 1)



⇒ the effects of expectations about weather (i.e., climate change) on OSME have been relatively small.

CONCLUSION

- The first step in productivity analysis is to define exactly what is meant by the term productivity. If productivity is defined as a measure of output quantity divided by a measure of input quantity, then we cannot measure changes in productivity using conventional indexes (e.g., Fisher, Törnqvist, EKS, CCD). The class of proper indexes includes various additive, multiplicative, primal and dual indexes.
- If productivity is defined as a measure of output quantity divided by a measure of input quantity, then explaining changes in productivity involves explaining changes in output and input quantities. Economists have many models that can be used for this purpose.
- Changes in weather and climate affect agricultural inputs and outputs (and therefore productivity) in two ways: (1) realisations of weather variables affect the outputs that can be produced using predetermined inputs, and (2) expectations about weather and climate variables affect the input and planned output choices of managers.
- The empirical work in this paper is illustrative. More work could be done on the data (e.g,, measures of intra-seasonal variations in temperature and precipitation) and the SFA model (e.g., more flexible functional form) to reduce the amount of statistical noise.

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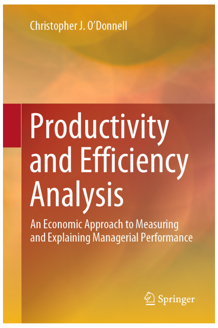

Read Ch. 3 for more details on proper (and improper) index numbers. Read Section 8.5.2 for more details on using stochastic frontier models to decompose proper TFP indexes. The book can be downloaded for free through libraries that subscribe to SpringerLink.

References I

Anand A, Khetarpal S (2015) Impact of climate change on agricultural productivity. In: Bahadur B, Raham M, Sahijram L, Krishnamurthy K (eds) Plant Biology and Biotechnology, vol I: Plant Diversity, Organization, Function and Improvement, Springer India

Caves D, Christensen L, Diewert W (1982) Multilateral comparisons of output, input, and productivity using superlative index numbers. The Economic Journal 92(365):73–86

Hughes N, Lawson K, Davidson A, Jackson T, Sheng Y (2011) Productivity pathways: climate-adjusted production frontiers for the Australian broadacre cropping industry. Research Report 11.5, Australian Bureau of Agricultural and Resource Economics and Sciences

Jorgenson D, Griliches Z (1967) The explanation of productivity change. The Review of Economic Studies 34(3):249–283

Nastis S, Michailidis A, Chatzitheodoridis F (2012) Climate change and agricultural productivity. African Journal of Agricultural Research 7(35):4885–4893

Njuki E, Bravo-Ureta B, O'Donnell C (2018a) Decomposing agricultural productivity growth using a random-parameters stochastic production frontier. Empirical Economics URL `https://doi.org/10.1007/s00181-018-1469-9`

Njuki E, Bravo-Ureta BE, O'Donnell C (2018b) A new look at the decomposition of agricultural productivity growth incorporating weather effects. PLOS One 13(2):e0192,432

References II

O'Donnell C (2016) Using information about technologies, markets and firm behaviour to decompose a proper productivity index. Journal of Econometrics 190(2):328–340

O'Donnell C (2018) Productivity and Efficiency Analysis: An Economic Approach to Measuring and Explaining Managerial Performance. Springer Nature, Singapore

Ortiz-Bobea A, Ault TR, Carrillo CM, Chambers RG, Lobell DB (2020) The historical impact of anthropogenic climate change on global agricultural productivity. arXiv:2007.10415 [econ.GN]

Sabasi D, Shumway C (2018) Climate change, health care access and regional influence on components of U.S. agricultural productivity. Applied Economics p DOI: 10.1080/00036846.2018.1489504

Salim R, Islam N (2010) Exploring the impact of R&D and climate change on agricultural productivity growth: the case of Western Australia. Australian Journal of Agricultural and Resource Economics 54(4):561–582

Schreyer P (2001) OECD Manual: Measuring Productivity: Measurement of Aggregate and Industry-Level Productivity Growth. Organisation for Economic Development and Cooperation, Paris

Silva Portela M, Thanassoulis E (2006) Malmquist indexes using a geometric distance function (GDF). Application to a sample of Portuguese bank branches. Journal of Productivity Analysis 25(1):25–41