Theoretical Production Restrictions and Measures of Technical Change in U.S. Agriculture

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Applied Production Analysis

Simple functional forms fully consistent with economic theory

Vs.

Flexible functional forms not fully consistent with economic theory

Recent example: Andersen, Alston, and Pardey (JPA 2012)

Output Elasticity wrt Labor:
- Cobb-Douglas: +, not statistically significant
- Translog: -, statistically significant.
Identifying the Problem

• If econometric estimates not fully consistent with economic theory…

• How robust are economic analyses and policy recommendations based on such estimates?

Problem: Lack of Counterfactuals
Main Goal

Investigate the consequences of failing to impose concavity and monotonicity in estimation on a flexible functional form of U.S. ag production:

• Pdfs of parm. estimates
• Characterization of production technology
Additional Contributions

- Technical Change estimates by State
- Technical Change vs. USDA’s TFP
- Advocate for Bayesian estimation of flexible forms
Main take-home message

• Imposing concavity and monotonicity in estimation changes the characterization of U.S. agricultural technology.
The Model

• **Production function**: Generalized Quadratic

\[ f(X, t) = \beta_0 + \sum_{i=1}^{n} \beta_i x_i + \beta_t t + \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \beta_{ij} x_i x_j + \sum_{i=1}^{n} \beta_{ti} x_i t + \frac{1}{2} \beta_{tt} t^2 \]

\[ \beta_{ij} = \beta_{ji} \]

• **Concavity**: max eigenvalue of \( H \leq 0 \)

\[ H \equiv \nabla^2 f(X) = \begin{bmatrix} \beta_{11} & \cdots & \beta_{1n} \\ \vdots & \ddots & \vdots \\ \beta_{1n} & \cdots & \beta_{nn} \end{bmatrix}, \]

• **Monotonicity**:

\[ \text{MPP}_{X_i} = \frac{\partial f(X, t)}{\partial x_i} = \beta_i + \sum_{j=1}^{n} \beta_{ij} x_j + \beta_{ti} t \geq 0. \]
The Model

• **Weak Essentiality:**

\[ f(0_n, t) = \beta_0 + \beta_t t + \frac{1}{2} \beta_{tt} t^2 = 0 \]

Does not hold with a time trend.
<table>
<thead>
<tr>
<th>Alternative Models</th>
<th>Conditions Imposed in Estimation</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Concavity</td>
</tr>
<tr>
<td>M1: Unrestricted</td>
<td>no</td>
</tr>
<tr>
<td>M2: Concavity</td>
<td>YES</td>
</tr>
<tr>
<td>M3: Mon@Mean</td>
<td>no</td>
</tr>
<tr>
<td>M4: Conc+Mon@Mean</td>
<td>YES</td>
</tr>
<tr>
<td>M5: Mon@All</td>
<td>no</td>
</tr>
<tr>
<td>M6: Conc+Mon@All</td>
<td>YES</td>
</tr>
</tbody>
</table>
Data

- USDA panel dataset on U.S. agricultural production (Ball et. al. 2004)
- 1 aggregate agricultural output
- 3 variable inputs: capital, labor, and materials
- 48 states
- 45 years: 1960-2004
Data (cont’d)

• Output: livestock, dairy, poultry, eggs, grains, oilseeds, cotton, tobacco, fruit, vegetables, nuts, and other miscellaneous outputs

• Capital: service flows of real estate, durable equipment and stocks of inventories.

• Labor: quality-adjusted amount of hired and self-employed labor.

• Materials: fertilizers, pesticides, energy and other miscellaneous inputs.
## Descriptive Statistics (million $ 1996)

<table>
<thead>
<tr>
<th>Implicit Quantity Index</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Output</td>
<td>3,845.8</td>
<td>3,937.5</td>
<td>42.9</td>
<td>31,595.5</td>
<td>2,160</td>
</tr>
<tr>
<td>Materials</td>
<td>1,761.2</td>
<td>1,635.9</td>
<td>12.9</td>
<td>9,451.8</td>
<td>2,160</td>
</tr>
<tr>
<td>Capital</td>
<td>662.0</td>
<td>591.4</td>
<td>7.4</td>
<td>3,330.6</td>
<td>2,160</td>
</tr>
<tr>
<td>Labor</td>
<td>1,971.8</td>
<td>1,742.1</td>
<td>18.2</td>
<td>9,476.4</td>
<td>2,160</td>
</tr>
</tbody>
</table>

Source: USDA
Estimation of Models 1-6

- 2 versions of M1-M6: AR(0), AR(1)
- Monte Carlo Markov Chain methods in R
- 4 chains of 5 million draws per chain
- First half of each chain discarded (burn-in)
- To avoid high correlation across sets of parameter estimates, only 1 every 5,000 ordered sets of par. est. is used
- 2,000 simulated values for each parameter
Likelihood: 95% Credible Intervals

AR(1)
LikelihoodP: 95% Credible Intervals for M1-M6 AR(1)
95% Credible Intervals for $\rho$'s
Example: bivariate posterior pdfs of $\beta_M$ and $\beta_{MM}$

Not Concave

Not Concave
Concavity & Monotonicity

Concavity (Max Eig $\leq 0$)

Monotonicity in Capital (MPP $\geq 0$)

Max Eigenvalue: 95% CI

$MPP_k$: 95% CI

CONCAVITY & MONOTONICITY IN CAPITAL ONLY HOLD FOR M4 & M6
Monotonicity in Labor

\[ MPP_l: 95\% \text{ CI} \]

Monotonicity in Materials

\[ MPP_m: 95\% \text{ CI} \]

MONOTONICITY IN LABOR & MATERIALS HOLDS FOR M1-M6
Output Elasticity wrt Capital

$$\varepsilon_k = \frac{MPP_k \times \text{mean}(K)}{\text{mean}(Y)}$$
Output Elasticity wrt Labor

$$\varepsilon_l = \frac{MPP_l \times \text{mean}(L)}{\text{mean}(Y)}$$

<table>
<thead>
<tr>
<th>Model</th>
<th>Mean Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>M1: Unrest+AR(1)</td>
<td>0.12</td>
</tr>
<tr>
<td>M2: Conc+AR(1)</td>
<td>0.15</td>
</tr>
<tr>
<td>M3: Mon@Mean+AR(1)</td>
<td>0.11</td>
</tr>
<tr>
<td>M4: Conc+Mon@All+AR(1)</td>
<td>0.14</td>
</tr>
<tr>
<td>M5: Mon@All+AR(1)</td>
<td>0.13</td>
</tr>
<tr>
<td>M6: Conc+Mon@All+AR(1)</td>
<td>0.14</td>
</tr>
</tbody>
</table>
Output Elasticity wrt Materials

\[ \varepsilon_m = MPP_m \times \frac{\text{mean}(M)}{\text{mean}(Y)} \]
Elasticity of Scale

\[ \varepsilon = \varepsilon_k + \varepsilon_l + \varepsilon_m \]

DECREASING RETURNS TO SCALE
Technical Change

$$TC = \frac{\partial f(X,t)}{\partial t} = \beta_t + \sum_i \beta_{ti} \bar{x}_i + \beta_{tt} \bar{t}$$

1.33% 1.32% 1.36% 1.34% 1.46% 1.48%

M1: Unrest+AR(1)  M2: Conc+AR(1)  M3:Mon@Mean+AR(1)  M4:Conc+Mon@All+AR(1)  M5:Mon@All+AR(L)  M6:Conc+Mon@All+AR(L)

TC at Mean Input Values
So... M4 or M6? Calculated MMPs with mean parameter estimates from M4 and all input values

% Sample where Monotonicity does NOT hold

- 50% Mon. in Capital
- 16% Mon. in Labor
- 5% Mon. in Materials

Preferred Model M6: Conc.+Mon@All+AR(1)
M6: Technical Change

- TC Not Hicks-neutral: $\beta_{tL}, \beta_{tM} > 0 ; \beta_{tK} < 0$ (all statistically significant at 5%)

- Disembodied TC explains 1.48% of annual growth in ag output over 1960-2004

- Top 3 states: Colorado (1.82%), Oklahoma (1.80%), Missouri (1.77%)

- TC very variable across states and decades
M6: Catch-up in Tech. Change

• Median TC per state in the 2000s vs. Median TC per state in the 1960s:
  • Slope coefficient -0.27
  • P-value <0.1%
  • Rsquare = 0.824
Technical Change vs TFP Growth 1960-2004

- TFP Growth Ranking: CO 45th, OK 48th, MO 27th
- Correlation between state rankings in TC and TFP growth: -0.50
- Correlation between average annual rates of TC and TFP growth: -0.41
- Differences: technical and allocative efficiency? Translog vs. Quadratic?
Concluding Remarks: Methodology

• Recovered technology from unrestricted model neither concave nor monotonic.
• Both conditions must be imposed in estimation to perform meaningful economic analyses
• How monotonicity is imposed matters
• Bayesian methods allow to impose constraints at all data points
Concluding Remarks: Policy

• Decreasing Returns to Scale:
  a) support recommendation to account for crop insurance subsidies to avoid upwardly biased TFP estimates (Shumway et.al. 2016)
  b) Call into question assumption of CRS in calculation of TFP at the national level.
  c) Extent of concentration in ag production limited by DRS
Next steps

• Similar analysis using Translog (underlying functional form in USDA’s TFP measurement)

• Effect of capital utilization bias (Andersen, Alston, Pardey. JPA 2012)
Thank you for your attention!

Comments/Questions?

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