Discussion
by K. Storesletten, B. Zhao, & F. Zilibotti

Discussant: Gregor Boehl

Uni Bonn

Konstanz Seminar 2022
Summary I.

**Observed:**

- BC in developing countries differ systematically from BC in mature countries.

- Countries with declining agriculture sector:
  - smooth *aggregate* employment fluctuations
  - strong, procyclical labor reallocation between agriculture & non-agriculture
  - decline in agriculture accelerates during booms

- Developed countries:
  - Procyclical aggregate employment
  - Acyclical agricultural employment
Summary I.

Figure 2: Modernization of agriculture: cross-country evidence
Summary I.
Summary I.

(a) USA

(b) China

(c) USA

(d) China

Discussant: Gregor Boehl 1/7
Proposed mechanism:

- Modernization of agricultural sector is key
- Capital intensive modern agricultural sector crowds out labor intensive traditional agriculture
- TFP relocates workers out of traditional agricultural sector, causing boost in productivity but not in employment
- TFP drives BC and changes how TFP drives BC
Summary II.

(a) Share of labor in each sector
- Nonagric.'s share in total employment (%)
- Modern agric.'s share in total employment (%)
- Traditional agric.'s share in total employment (%)

(b) Factor prices
- Wage rate
- Rental rate of capital

(c) Productivity gap
- Productivity gap

(d) Relative K-Y ratio in agriculture to nonagriculture
- Relative K-Y ratio (Agr./Nonagr.)
Summary II.

Discussant: Gregor Boehl
The ingredients:

1. Strong empirical section
2. Continuous time model:
   ▶ Nice closed form expressions
   ▶ Estimation
3. Discrete time model for quantitative exercises
4. International evidence as a robustness exercise
The history of the paper

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- Convincing mechanism, but validation difficult
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Estimation I.

What you do:
- Method of simulated moments
- Using the deterministic model
- Targeting ratios in the data at given points in time (i.e. indirect inference)
- 13 parameters for 16 ratios

Potential problems with MSM/IF:
- Are parameters identified by the given ratios?
- Deterministic model $\rightarrow$ no asymptotics $\rightarrow$ no standard deviations
- Are estimates independent of initial values?

Somewhat easy fix: approximate Bayesian computation (ABC)

But: Do we actually need an estimation exercise here?
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Estimation II.: Bayesian way

What you could do:

- **Problem:** no balanced growth path, model essentially nonlinear
- Take discrete time transition function \( x_t = f(x_{t-1}, \epsilon_t; \theta) \)
- Observation function \( z_t = g(z_t) + \nu_t \)
- State \( x_t \), shocks \( \epsilon_t \), measurement errors \( \nu_t \), parameters \( \theta \)
- Use particle filter to get \( \mathcal{L}(\theta) = Prob \left( \{ z_t \}_0^T | \theta \right) \)
- Assign priors \( p(\theta) \)
- Estimate \( \theta \) by sampling from posterior \( p ( \theta | \{ z_t \}_0^T ) \)
- Estimate \( \tilde{\theta} \subset \theta \) which nests model of Herrendorf. Do Bayesian model comparison
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Recommendation

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Publish as is.
Thank you for your attention!