Discussion

Business Cycle during Structural Change: Arthur Lewis' Theory from a Neoclassical Perspective.

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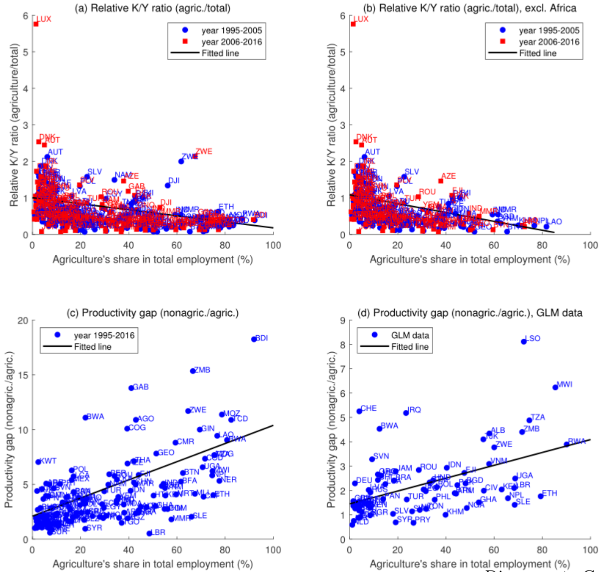
Summary I.

Observed:

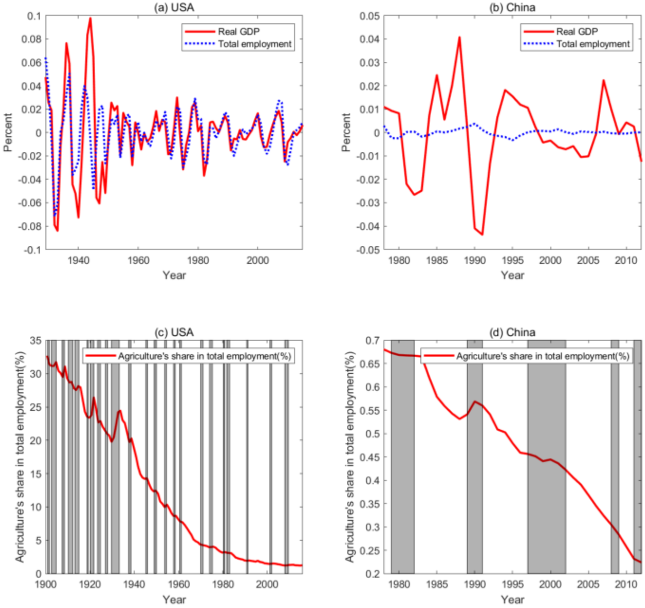
- BC in develping countries differ systematically from BC in mature countries
- Countries with declining agriculture sector:
  - smooth *aggregate* employment fluctuations
  - strong, procyclical labor reallocation between agriculture & non-agriculture
  - decline in agriculture accelerates during booms
- Developed countries:
  - Procyclical aggregate employment
  - Acyclical agricultural employment

Summary I.

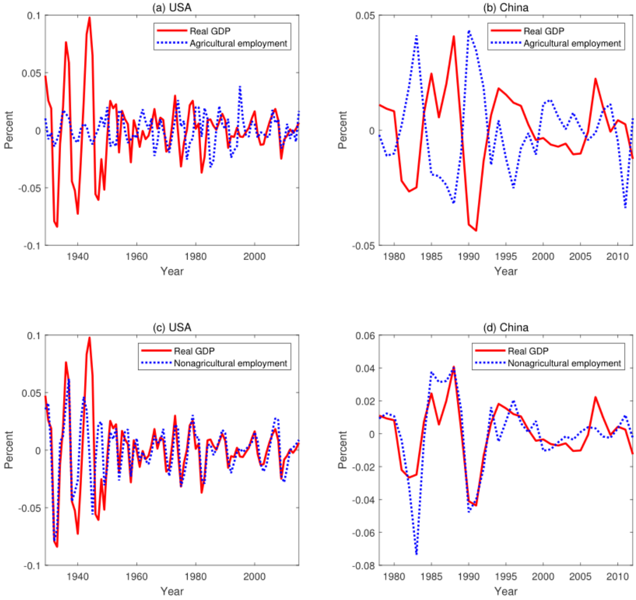
Figure 2: Modernization of agriculture: cross-country evidence



Summary I.


(a) USA
Real GDP
Total employment
Percent
Year
(b) China
Real GDP
Total employment
Percent
Year
(c) USA
Agriculture's share in total employment(%)
Agriculture's share in total employment(%)
Year
(d) China
Agriculture's share in total employment(%)
Agriculture's share in total employment(%)
Year

Summary I.



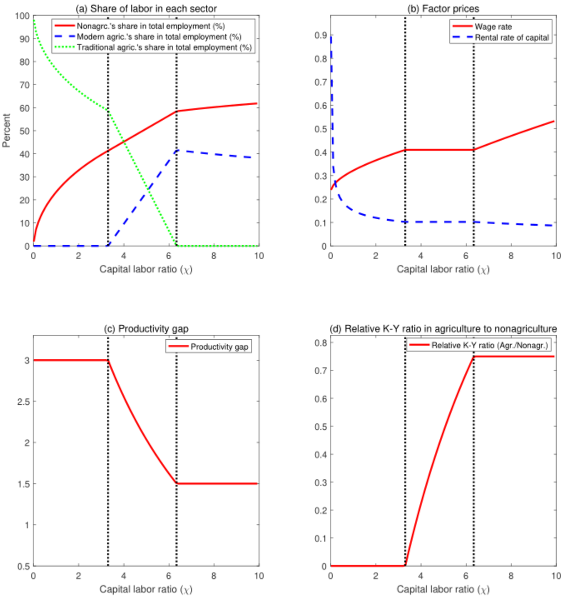
(a) USA
Real GDP
Agricultural employment
Percent
Year
0.1
0.05
0
-0.05
-0.1
1940
1960
1980
2000
(b) China
Real GDP
Agricultural employment
Percent
Year
0.05
0
-0.05
1980
1985
1990
1995
2000
2005
2010
(c) USA
Real GDP
Nonagricultural employment
Percent
Year
0.1
0.05
0
-0.05
-0.1
1940
1960
1980
2000
(d) China
Real GDP
Nonagricultural employment
Percent
Year
0.06
0.04
0.02
0
-0.02
-0.04
-0.06
-0.08
1980
1985
1990
1995
2000
2005
2010

Summary II.

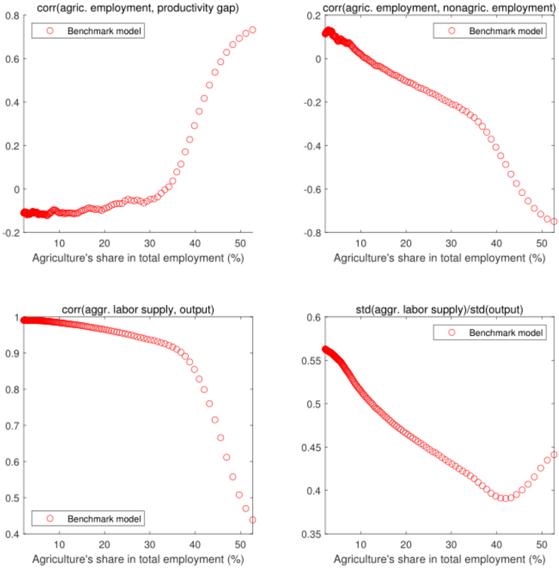
Proposed mechanism:

- 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
Nonagrc.'s share in total employment (%)
Modern agric.'s share in total employment (%)
Traditional agric.'s share in total employment (%)
Percent
Capital labor ratio (χ)
(b) Factor prices
Wage rate
Rental rate of capital
Capital labor ratio (χ)
(c) Productivity gap
Productivity gap
Capital labor ratio (χ)
(d) Relative K-Y ratio in agriculture to nonagriculture
Relative K-Y ratio (Agr./Nonagr.)
Capital labor ratio (χ)

Summary II.


corr(agric. employment, productivity gap)
Benchmark model
Agriculture's share in total employment (%)
corr(agric. employment, nonagric. employment)
Benchmark model
Agriculture's share in total employment (%)
corr(aggr. labor supply, output)
Benchmark model
Agriculture's share in total employment (%)
std(aggr. labor supply)/std(output)
Benchmark model
Agriculture's share in total employment (%)

Summary II: Features

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

*Storesletten: Department of Economics, University of Minnesota, 1925 Fourth Street S, Minneapolis MN, United States, kstoresl@umn.edu. Zhao: National School of Development, Peking University, No.8 Yiheyuan Road, Haidian District, Beijing, China, zhaobo@nsd.pku.edu.cn. Zilibotti: Department of Economics, Yale University, fabrizio.zilibotti@yale.edu, 28 Hillhouse Ave., New Haven CT, United States. We thank Huihuang Zhu and Pariroo Rattan for excellent research assistance. We also thank seminar participants at the 2016 Annual Meeting of the Program of Growth and Institutions at Tsinghua University, 2017 Midwest Macro Conference, 2017 European Economics Association Annual Meeting, 2019 Annual Conference on Macroeconomics Across Time and Space at the Federal Reserve of Philadelphia, 2019 Cowles Macroeconomics Conference at Yale University, 2019 ABFER Annual Conference (sessions on Asian Economic Transformation) at Singapore, 2019 QMUL CEPR Conference, Arizona State University, Brown University, Central University of Finance and Economics, Copenhagen Business School, Danmarks Nationalbank, East China Normal University, Emory University, Federal Reserve Bank of Minneapolis, Federal Reserve Bank of Philadelphia, Fudan University, IIES Stockholm University, Interamerican Development Bank, Paris School of Economics, Peking University, Shanghai Jiao Tong University, Shanghai University of Finance and Economics, University of California at Berkeley, University of California at San Diego, University of Oslo, University of Pennsylvania, University of Wienna, and Yale University. We are especially indebted to Chaoran Chen and Andrew Glover who acted as discussants 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 ϵ_t, measurement errors ν_t, parameters θ,
- Use particle filter to get $\mathcal{L}(\theta) = Prob\left(\{z_t\}_0^T | \theta\right)$
- Assign priors $p(\theta)$
- Estimate θ by sampling from posterior $p\left(\theta | \{z_t\}_0^T\right)$
- 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!