“Golden Ages”: A Tale of the Labor Markets in China and the United States

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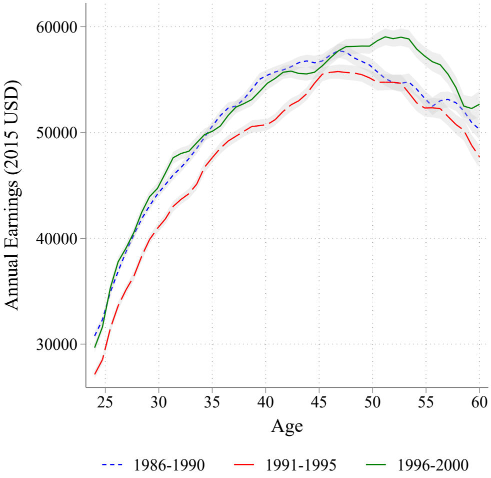
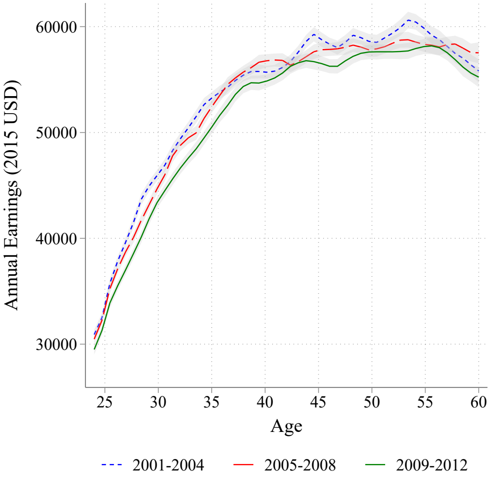
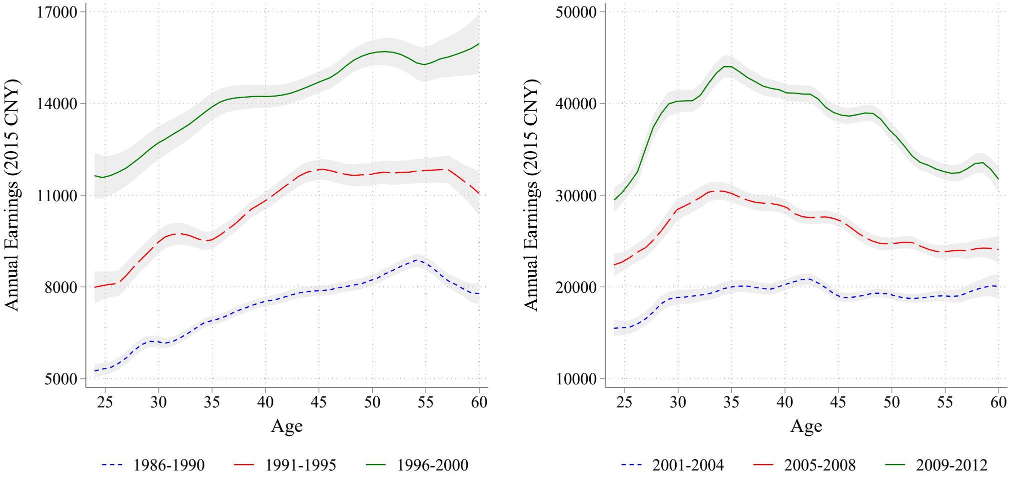
Cross-Sectional Age-Earnings Profiles: US

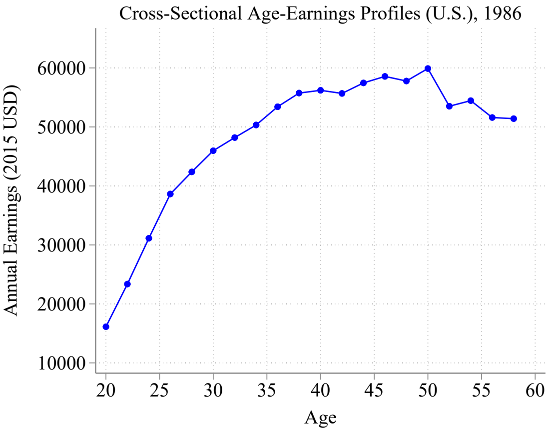


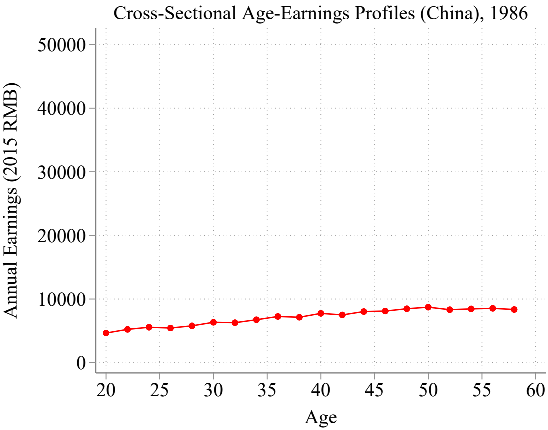


Cross-Sectional Age-Earnings Profiles: China

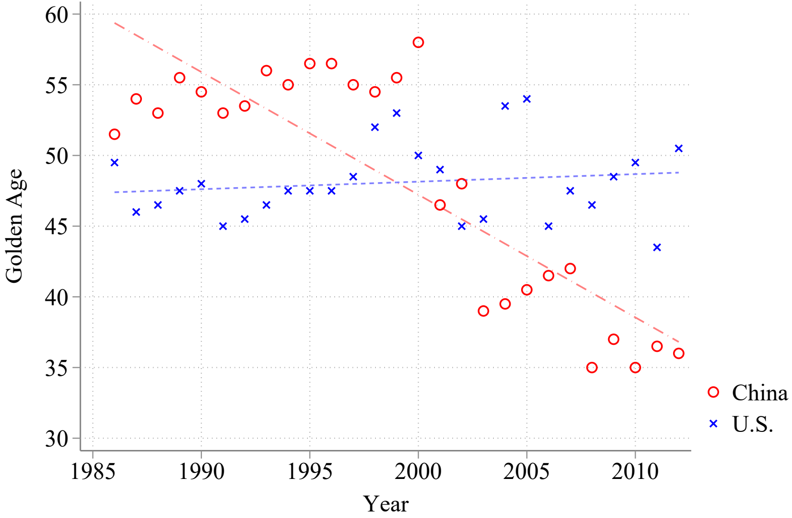


Evolution of Cross-Sectional Age-Earnings Profiles: US vs China

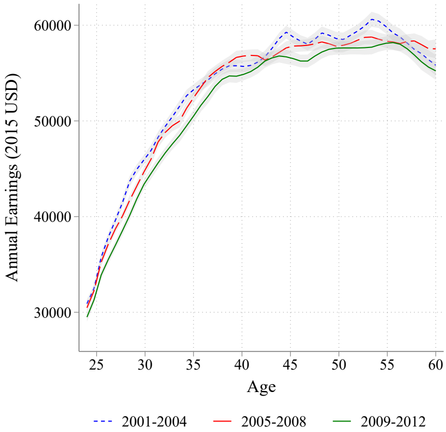


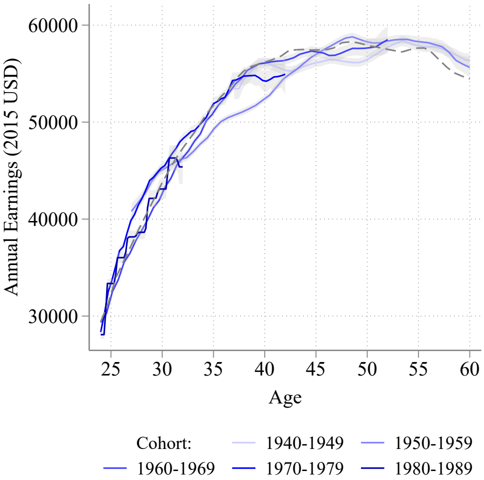


Evolution of Cross-Sectional "Golden Age": US vs China

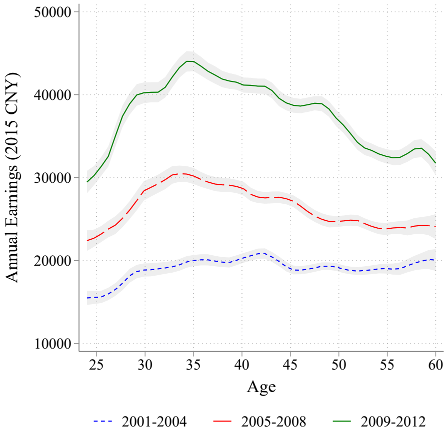


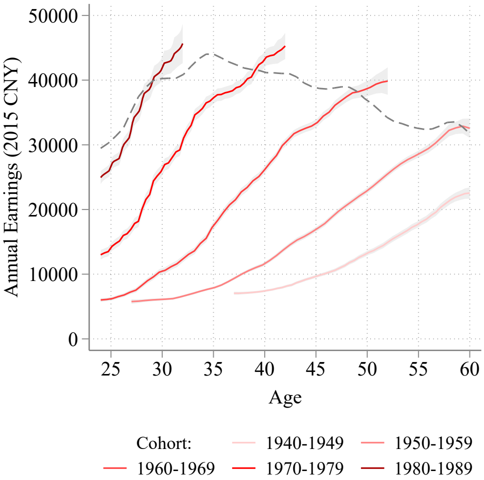
Cross-Sectional vs Life-Cycle Earnings Profiles: US





Cross-Sectional vs Life-Cycle Earnings Profiles: China





This Paper

- Empirics: stark differences in age-earnings profiles of US and China
  1. "Golden age" 55 $\to$ 35 in China but stable at 45 $\sim$ 50 in US
  2. Age-specific earnings grow drastically in China but stagnate in US
  3. Cross-sectional & life-cycle profiles differ in China but look similar in US

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- Methodology: decomposition framework for repeated cross-sections
  1. Experience effects: life-cycle human capital accumulation
  2. Cohort effects: inter-cohort human capital growth
  3. Time effects: human capital rental price changes over time

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  1. Experience effects: life-cycle human capital accumulation
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  3. Time effects: human capital rental price changes over time
- Applications: revisiting classical questions in macro/labor
  1. Growth accounting adjusting for human capital
  2. Skill-biased technological change

Framework

Framework

- Observed wage is: $\text{wage}_{i,t} = \text{HC price}_t \times \text{HC quantity}_{i,t}$, or in logs
$$w_{i,t} = p_t + h_{i,t}.$$
- Define the average human capital of cohort c at time t
$$h_{c,t} = \mathbb{E}_i \left[h_{i,t} | c(i) = c, t \right].$$
By construction, $\epsilon_{i,t} := h_{i,t} - h_{c,t}$ has a conditional mean of zero.
- Therefore, the wage process can be written as
$$w_{i,t} = p_t + h_{c(i),t} + \epsilon_{i,t},$$
where $\mathbb{E}_i \left[\epsilon_{i,t} | c(i) = c, t \right] = 0, \forall c, t.$

[Discussion]

Framework

- Decompose human capital into two components: $h_{c,t} = s_c + r^c_{t-c}$.
  - $s_c := h_{c,c}$ is the initial human capital of cohort c when entry.
  - $r^c_k := h_{c,c+k} - h_{c,c}$ is the return to k years of experience for cohort c.

- Therefore,

$$w_{i,t} = p_t + s_{c(i)} + r^{c(i)}_{k(i,t)} + \epsilon_{i,t}.$$

  where $k(i,t) = t - c(i)$.

- Common practice $r^c_k \equiv r_k, \forall c$, so

$$w_{i,t} = p_t + s_{c(i)} + r_{k(i,t)} + \epsilon_{i,t}.$$

Cross-Sectional "Golden Ages"

- Cross-sectional profile at some given time t is

$$w(k;t) := \mathbb{E}_i\left[w_{i,t} | c(i) = t-k, t\right] = p(t) + s(t-k) + r(k),$$

with slope

$$\frac{\partial}{\partial k} w(k;t) = \dot{r}(k) - \dot{s}(t-k).$$

Cross-Sectional "Golden Ages"

- Cross-sectional profile at some given time t is

$$w\left(k; t\right) := \mathbb{E}_i\left[w_{i,t} | c\left(i\right) = t - k, t\right] = p(t) + s(t-k) + r(k),$$

  with slope

$$\frac{\partial}{\partial k} w(k; t) = \dot{r}(k) - \dot{s}(t-k).$$

- "Golden age" happens at k^* such that $\dot{r}\left(k^*\right) = \dot{s}\left(t - k^*\right)$.

- Race between returns to experience and inter-cohort human capital growth
  - When $\dot{r}$ is large/$\dot{s}$ is small, the "golden age" tends to be old ($\rightarrow$ US).
  - When $\dot{r}$ is small/$\dot{s}$ is large, the "golden age" tends to be young ($\rightarrow$ China).

Cross-Sectional vs Life-Cycle Profiles

- Cross-sectional profile at some given time t is

$$w\left(k;t\right) := \mathbb{E}_i\left[w_{i,t}|c\left(i\right)=t-k,t\right] = p(t)+s(t-k)+r(k),$$

with slope

$$\frac{\partial}{\partial k}w(k;t)=\dot{r}(k)-\dot{s}(t-k).$$

- Life-cycle profile for some given cohort c is

$$\tilde{w}\left(k;c\right) := \mathbb{E}_i\left[w_{i,t}|c\left(i\right)=c,t=c+k\right] = p\left(c+k\right)+s\left(c\right)+r\left(k\right),$$

with slope

$$\frac{\partial}{\partial k}\tilde{w}\left(k;c\right)=\dot{r}\left(k\right)+\dot{p}\left(c+k\right).$$

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with slope

$$\frac{\partial}{\partial k}\tilde{w}\left(k;c\right) = \dot{r}\left(k\right)+\dot{p}\left(c+k\right).$$

  - When $\dot{s}$ and $\dot{p}$ are small, both profiles are similar to $\dot{r}$ ($\rightarrow$ US).
  - When $\dot{s}$ and $\dot{p}$ are large, the two profiles will differ a lot ($\rightarrow$ China).

Identification

Identification

- Model: $w_{i,t} = p_t + s_{c(i)} + r_{k(i,t)} + \epsilon_{i,t}$, where $\mathbb{E}_i \left[\epsilon_{i,t} | c(i) = c, t \right] = 0, \forall c, t$.
- Data: a repeated cross-sectional dataset of wages $\left\{ w_{i,c,t} \right\}, t = 1, 2, \ldots, T$.
- Non-identification: perfect collinearity among time, cohort, and experience $t = c(i) + k(i,t)$.

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- Data: a repeated cross-sectional dataset of wages $\left\{w_{i,c,t}\right\}, t = 1, 2, \ldots, T$.
- Non-identification: perfect collinearity among time, cohort, and experience $t = c(i) + k(i,t)$.
- Identifying assumption: no experience effects at the end of career
  - Consistent with all prominent models of wage dynamics
    1. human capital investment models (Ben-Porath '67)
    2. search theories with on-the-job search (Burdett and Mortensen '98)
    3. job matching models with learning (Jovanovic '79)
  - Attributed to Heckman, Lochner and Taber ('98)
  - Recent variants in Lagakos, Moll, Porzio, Qian and Schoellman ('18), Bowlus and Robinson ('12), Huggett, Ventura and Yaron ('11)

Identification in a Nutshell

- Assume no experience effect from $R-1$ to R years old

[Algorithm]

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- Assume no experience effect from $R-1$ to R years old
- $(R-1)$-year-old in year $t-1$ v.s. R-year-old in year t

$\Rightarrow$ time effect of year t

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  $\Rightarrow$ experience effect of age a

- $(a-1)$-year-old in year t v.s. a-year-old in year t

  $\Rightarrow$ cohort effect of cohort $c = t - a$

Identification in a Nutshell

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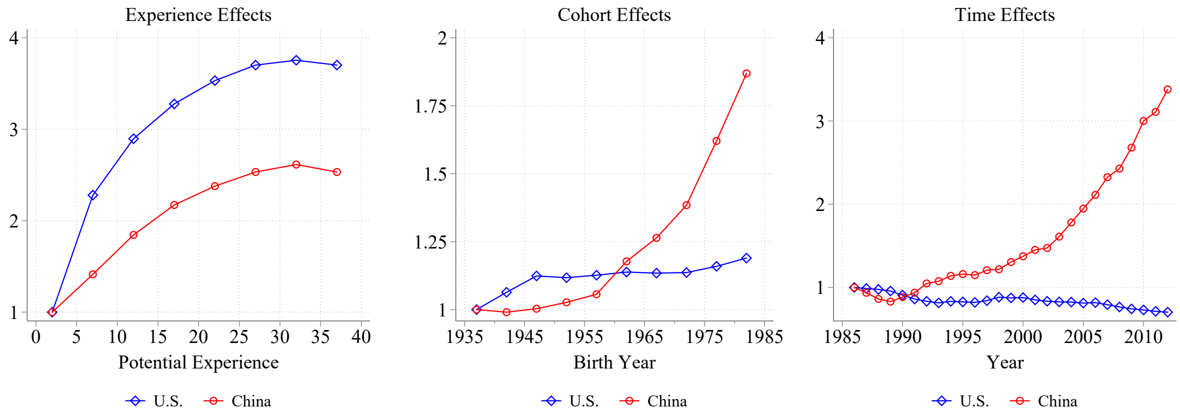
- $(a-1)$-year-old in year $t-1$ v.s. a-year-old in year t

  $\Rightarrow$ experience effect of age a
- $(a-1)$-year-old in year t v.s. a-year-old in year t

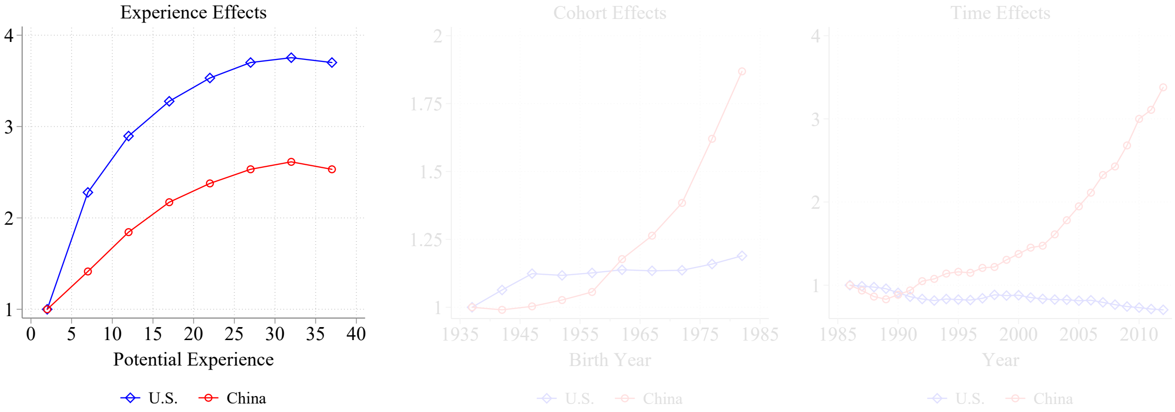
  $\Rightarrow$ cohort effect of cohort $c=t-a$
- In principle, any pre-specified "flat region" would achieve identification
- In practice, we follow LMPQS to set the "flat region" as the last 10 years

[Algorithm]

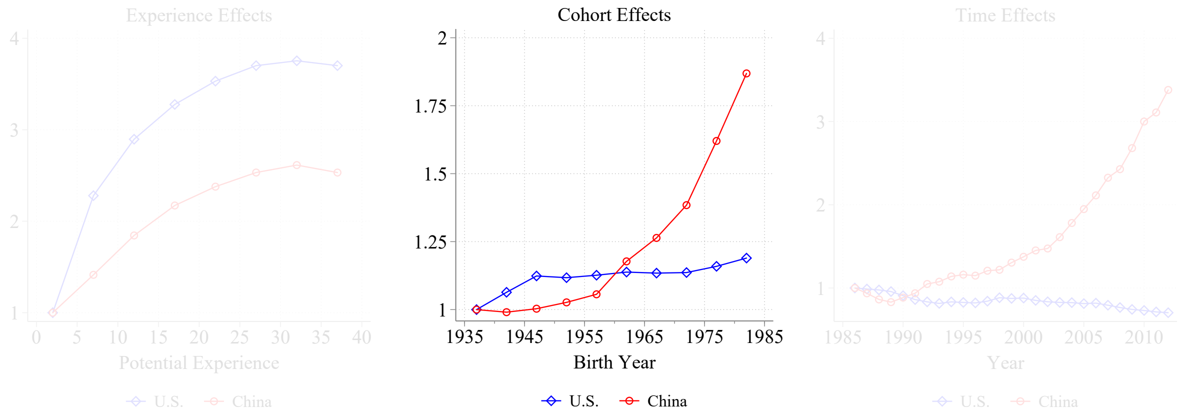
Experience, Cohort, Time Decomposition



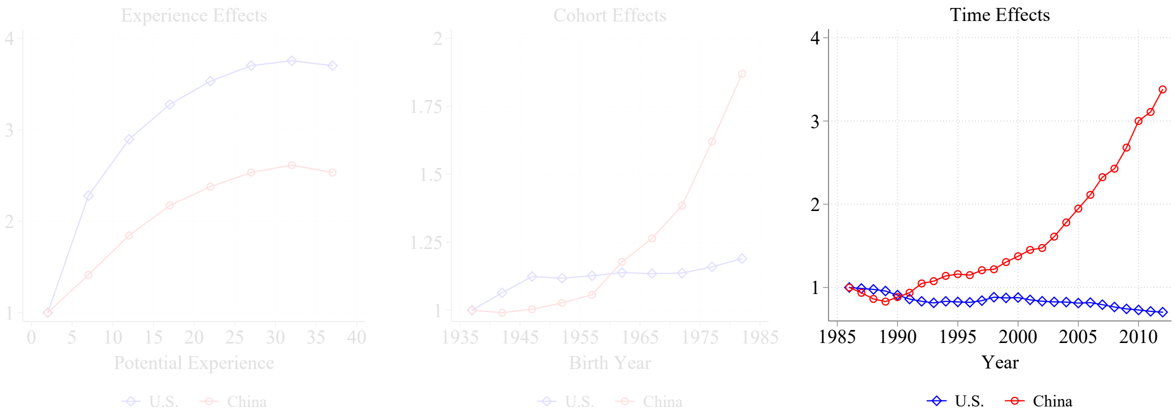
Experience Effect: Life-Cycle Human Capital Accumulation



Cohort Effect: Inter-Cohort Human Capital Growth



Time Effect: Human Capital Rental Price Changes



Robustness

	Experience		Cohort		Time	
	US	China	US	China	US	China
1. Baseline	3.70	2.53	1.19	1.87	0.70	3.38
2. State/province FE	3.71	2.53	1.19	1.78	0.71	2.96
3. Four provinces	/	2.37	/	1.79	/	3.27
4. Experience = Age − 20	3.24	2.55	1.20	1.84	0.85	3.56
5. Years since first job	/	2.31	/	1.71	/	3.92
6. Alternative flat region	4.10	3.18	1.36	2.52	0.65	2.82
7. Depreciation rate	2.87	2.22	0.86	1.57	0.86	3.76
8. 35 years of experience	3.46	2.10	1.03	1.38	0.76	4.15
9. Median regression	3.91	2.11	1.21	1.42	0.60	3.65
10. Controlling education	3.39	2.35	1.04	1.47	0.84	3.64
11. Hourly wage	1.84	/	1.03	/	0.80	/

Applications and Extensions

Growth Accounting

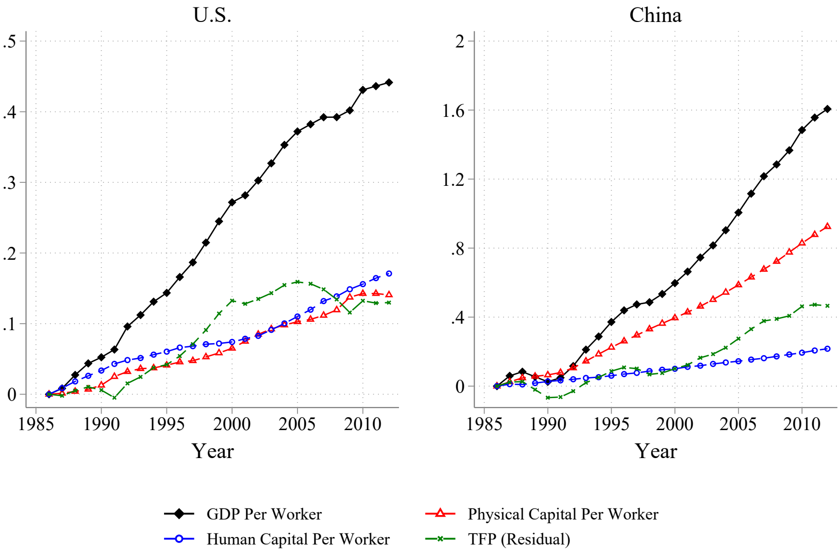
- Suppose the aggregate production function is $Y_t = A_t K_t^{\alpha_t} H_t^{1-\alpha_t}$, then

$$\mathrm{d}\ln y_t = \mathrm{d}\ln A_t + \alpha_t \,\mathrm{d}\ln k_t + (1-\alpha_t)\,\mathrm{d}\ln h_t$$

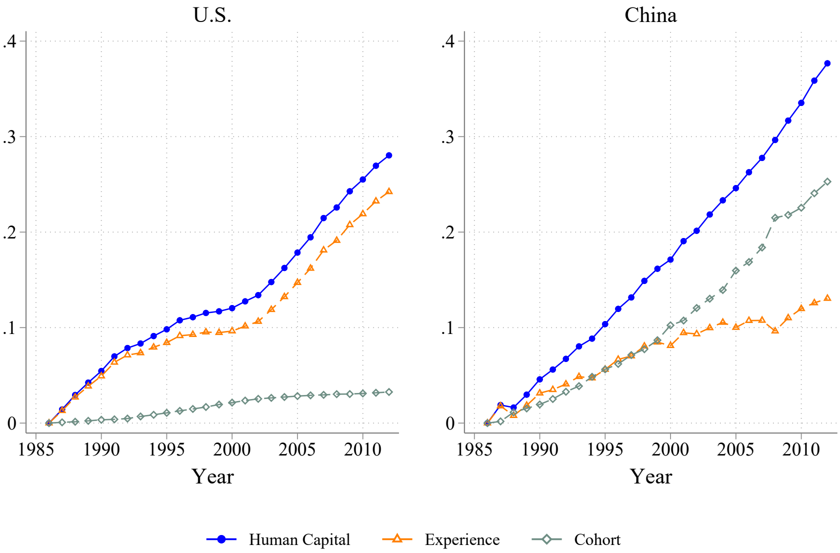
  where lower cases denote per-worker terms: [c.f.]

  - y_t, k_t, α_t from data
  - $\mathrm{d}\ln h_t$ from our decomposition
  - $\mathrm{d}\ln A_t$ as a residual

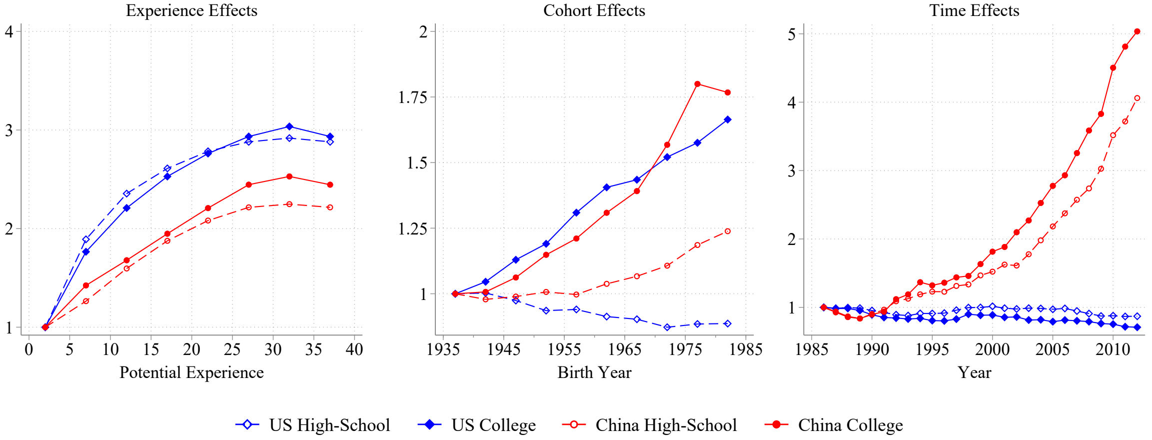
Contributions to Growth in GDP per Worker



Contributions to Growth Human Capital per Worker

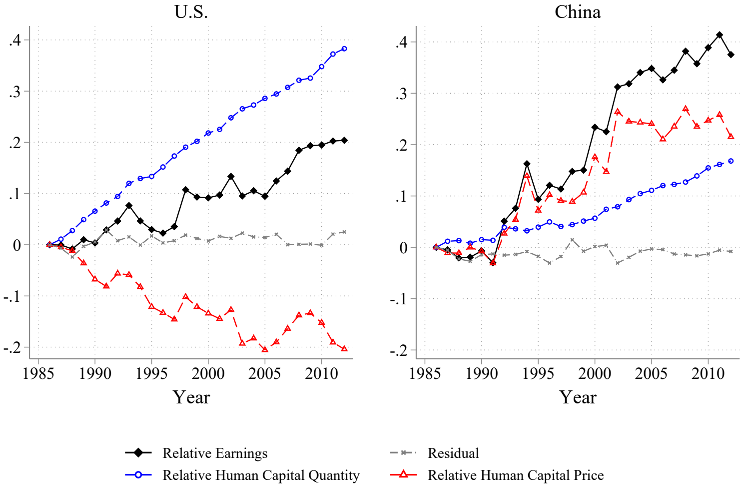


Heterogeneous Human Capital



Decomposing College Premium

- Is rising college premium driven by relative HC quantity or price?



Skill-Biased Technological Change

- Consider a CES aggregator over two types of skills:

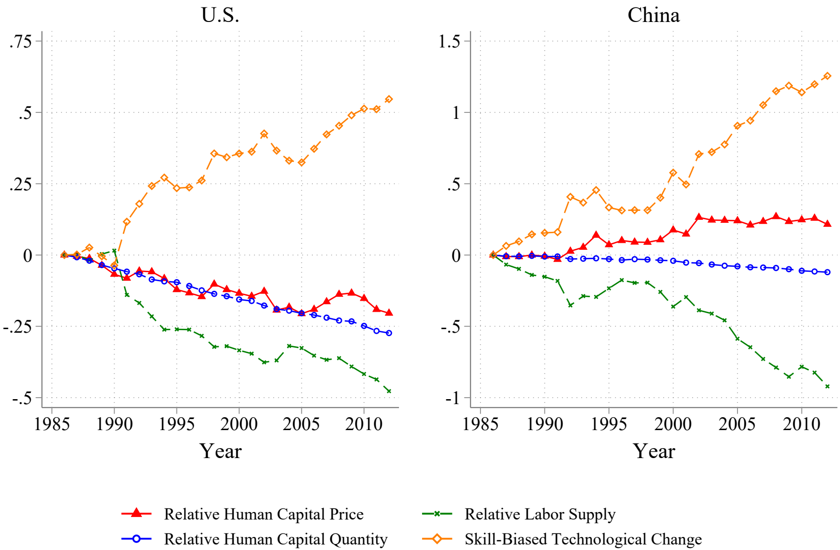
$$Y(t) = \left[\left(A_s(t) H_s(t) \right)^{\frac{\sigma-1}{\sigma}} + \left(A_u(t) H_u(t) \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}$$

- The changes in the relative price of the two types of skills [c.f.]

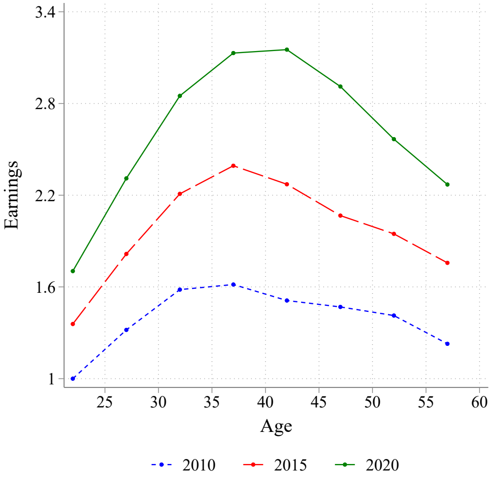
$$\mathrm{d}\ln\left(\frac{p_s}{p_u}\right) = \frac{\sigma-1}{\sigma}\,\mathrm{d}\ln\left(\frac{A_s}{A_u}\right) - \frac{1}{\sigma}\,\mathrm{d}\ln\left(\frac{h_s}{h_u}\right) - \frac{1}{\sigma}\,\mathrm{d}\ln\left(\frac{L_s}{L_u}\right)$$

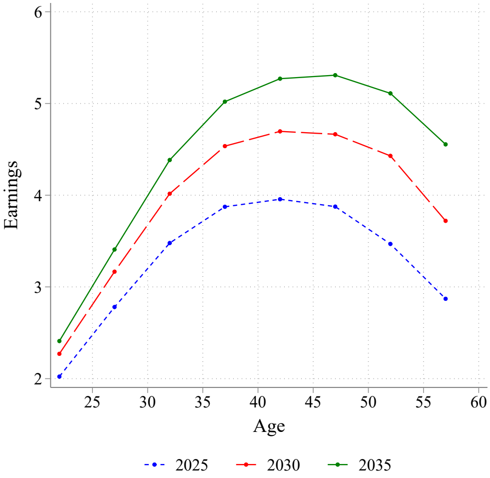
- Katz and Murphy ('92) benchmark: $\sigma = 1.4$

Contributions to Relative Human Capital Price Changes



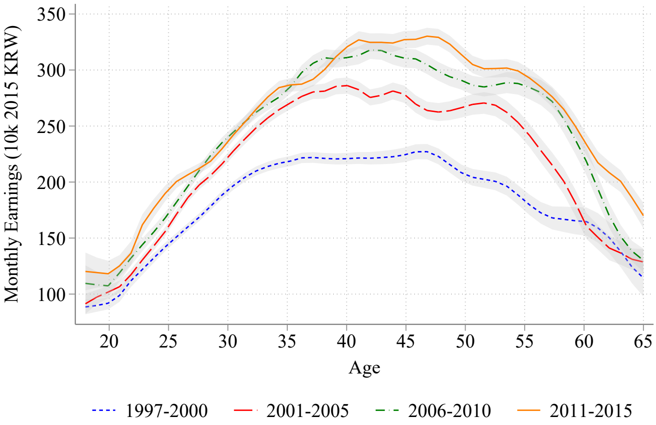
What if the Growth Begins to Slow Down?



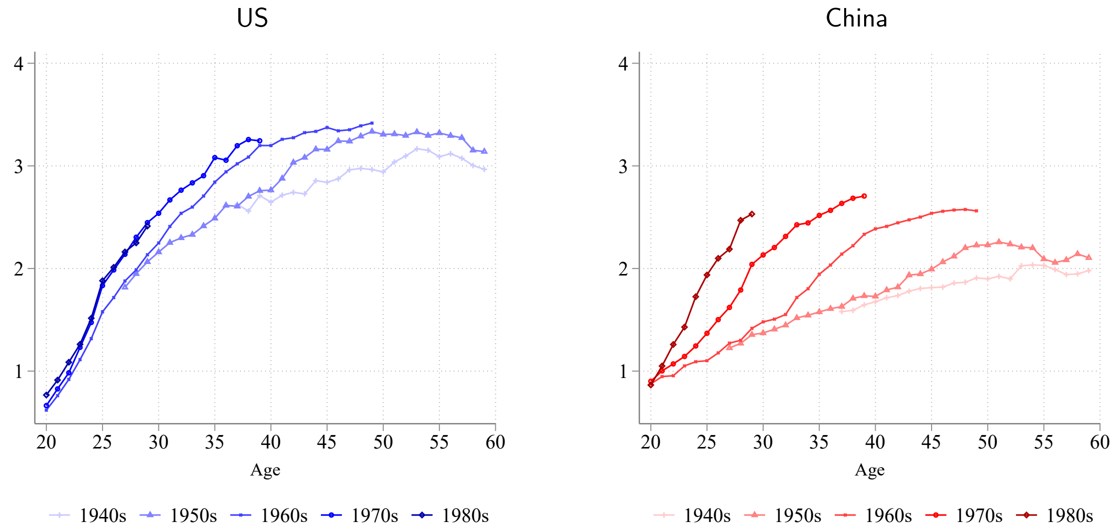


Korea

- This scenario seems to be what happened in Korea during the past 20 years.



Cohort-Specific Experience Profiles



Conclusion

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1. "Golden age" 55 $\rightarrow$ 35 in China but stable at 45 $\sim$ 50 in US
   - The race between returns to experience and inter-cohort HC growth
   - In China, the latter wins
2. Age-specific earnings grow drastically in China but stagnate in US
   - China has higher time effects: increasing human capital returns over time
   - Also higher cohort effects: later cohorts are more productive
3. Cross-sectional & life-cycle profiles differ in China but similar in US
   - Cohort and time effects are almost negligible in US
   - Both cross-sectional & life-cycle profiles are close to experience effects

Conclusion

- Stark differences in age-earnings profiles of US and China
- It is a golden age of inter-cohort productivity growth in China!
- Human capital growth is an important driver of what is typicall labelled as "TFP" growth
- Technological changes are skill-biased in both countries, but even more in China

Future Directions

- "Golden Age" and the "35-year-old phenomenon"?
- Does technological advance favor younger generations?
- What are the roles of specific institutions and reforms?
- Why are returns to experience higher in developed economies?
- Implications on social security system?
- How does it relate to saving motives?
- Many more!

Appendix

Framework: Discussion

- The non-identification issue precludes many papers from fully addressing changes in p_t or changes in $h_{c,t}$

- Interpreting life-cycle wage profiles as human capital accumulation implicitly assumes p_t constant:
$$w_{c,t_1} - w_{c,t_2} = \left(p_{t_1} + h_{c,t_1}\right) - \left(p_{t_2} + h_{c,t_2}\right) = h_{c,t_1} - h_{c,t_2}$$
only if $p_{t_1} = p_{t_2}$.

- Interpreting rising college premium as rising relative price of high skill implicitly assumes constant relative amount of human capital:
$$\frac{d}{dt}\left(w_t^{\text{cl}} - w_t^{\text{hs}}\right) = \frac{d}{dt}\left[\left(p_t^{\text{cl}} + h_t^{\text{cl}}\right) - \left(p_t^{\text{hs}} - h_t^{\text{hs}}\right)\right] = \frac{d}{dt}\left(p_t^{\text{cl}} - p_t^{\text{hs}}\right)$$
only if $\frac{d}{dt}\left(h_t^{\text{cl}} - h_t^{\text{hs}}\right) = 0$ (where $w_t^e = \sum_c \omega_{c,t}^e w_{c,t}^e$ and $h_t^e = \sum_c \omega_{c,t}^e h_{c,t}^e$).

[Back]

Algorithm: Idea

- Variables
  - Impute potential experience as min $\{\text{age} - \text{edu} - 6, \text{age} - 18\}$
  - Consider 40 years of experience
  - Group cohorts and experience into five-year bins
- Assume no HC accumulation in the last two experience bins
- The goal is to estimate

$$w_{i,t} = \text{constant} + s_c + r_k + p_t + \varepsilon_{i,t}$$

  subject to

$$r_{25\sim29} = r_{35\sim39}.$$

- See the next slide for details

Algorithm: Details

Transform the above equation to

$$w_{i,t} = \text{constant} + s_c + r_k + gt + \tilde{p}_t + \varepsilon_{i,t}$$

where $\tilde{p}$ reflect fluctuations orthogonal to a trend ($\sum_t \tilde{p}_t = 0$, $\sum_t t\tilde{p}_t = 0$).

1. Start with a guess for the growth rate g_0 of the linear time trend
2. Deflate wage using the current guess g_m in the m-th iteration

$$\hat{w}_{i,t} = w_{i,t} - g_m t$$

3. Rewrite as Deaton's (1997) problem

$$\hat{w}_{i,t} = \text{constant} + s_c + r_k + \tilde{p}_t + \varepsilon_{i,t}$$

4. Check for convergence (i.e. whether $r_{25\sim29}$ is sufficiently close to $r_{35\sim39}$)
5. If converged, done; If not, update the guess Back

Growth Accounting

- Plain-vanilla growth accounting considers $Y_t = A_t K_t^{\alpha_t} L_t^{1-\alpha_t}$, then

$$\mathrm{d}\ln y_t = \mathrm{d}\ln A_t + \alpha_t \, \mathrm{d}\ln k_t$$

- Attempts in the literature to account for Human Capital
  - Jorgensen estimates and BLS official measures: compositional adjustment
  - Hall and Jones ('99) set $H = \exp\left\{\phi\left(E\right)\right\} L$ with $\phi'(E)$ as the returns to schooling estimated from Mincer regression
  - Bils and Klenow ('00) further introduce interdependence of HC on older cohorts to capture impacts of teachers and extend to include experience
  - Manuelli and Seshadri ('14) calibrate a model of human capital acquisition with early childhood development, schooling, and on-the-job training

[Back]

Skill-Biased Technological Change

- Standard formulation

$$Y(t) = \left[\left(B_s(t) L_s(t) \right)^{\frac{\sigma-1}{\sigma}} + \left(B_u(t) L_u(t) \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

which implies

$$\text{dln}\left(\frac{w_s}{w_u} \right) = \frac{\sigma-1}{\sigma} \text{dln}\left(\frac{B_s}{B_u} \right) - \frac{1}{\sigma} \text{dln}\left(\frac{L_s}{L_u} \right).$$

- Our formulation:

$$Y(t) = \left[\left(\underbrace{A_s(t) h_s(t)}_{B_s(t)} L_s(t) \right)^{\frac{\sigma-1}{\sigma}} + \left(\underbrace{A_u(t) h_u(t)}_{B_u(t)} L_u(t) \right)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}},$$

which implies

$$\text{dln}\left(\frac{w_s}{w_u} \right) = \frac{\sigma-1}{\sigma} \text{dln}\left(\frac{A_s}{A_u} \right) + \frac{\sigma-1}{\sigma} \text{dln}\left(\frac{h_s}{h_u} \right) - \frac{1}{\sigma} \text{dln}\left(\frac{L_s}{L_u} \right).$$

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