Automation and Comparative Advantage

Shinnosuke Kikuchi
MIT

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Skills, Comparative Advantage, Industrialization

- **"Developing" countries:**
  Low-skill abundant
- Conventional view:
  - **Heckscher–Ohlin**
  - **Comparative advantage**
    in L-intensive sectors
  - "East Asian Miracle"
  - Export-led growth,
    Industrialization, …

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Export Share and Skill Intensity in 1970

Note: Export share is the share of total export in 4-digit SIC code in each country (from Comtrade). Skill intensity is the non-production worker payroll share out of total payroll in the US (from US NBER CES). The lines are Kernel-weighted local polynomial smoothing with bandwidth = 0.2. Regressions are unweighted.

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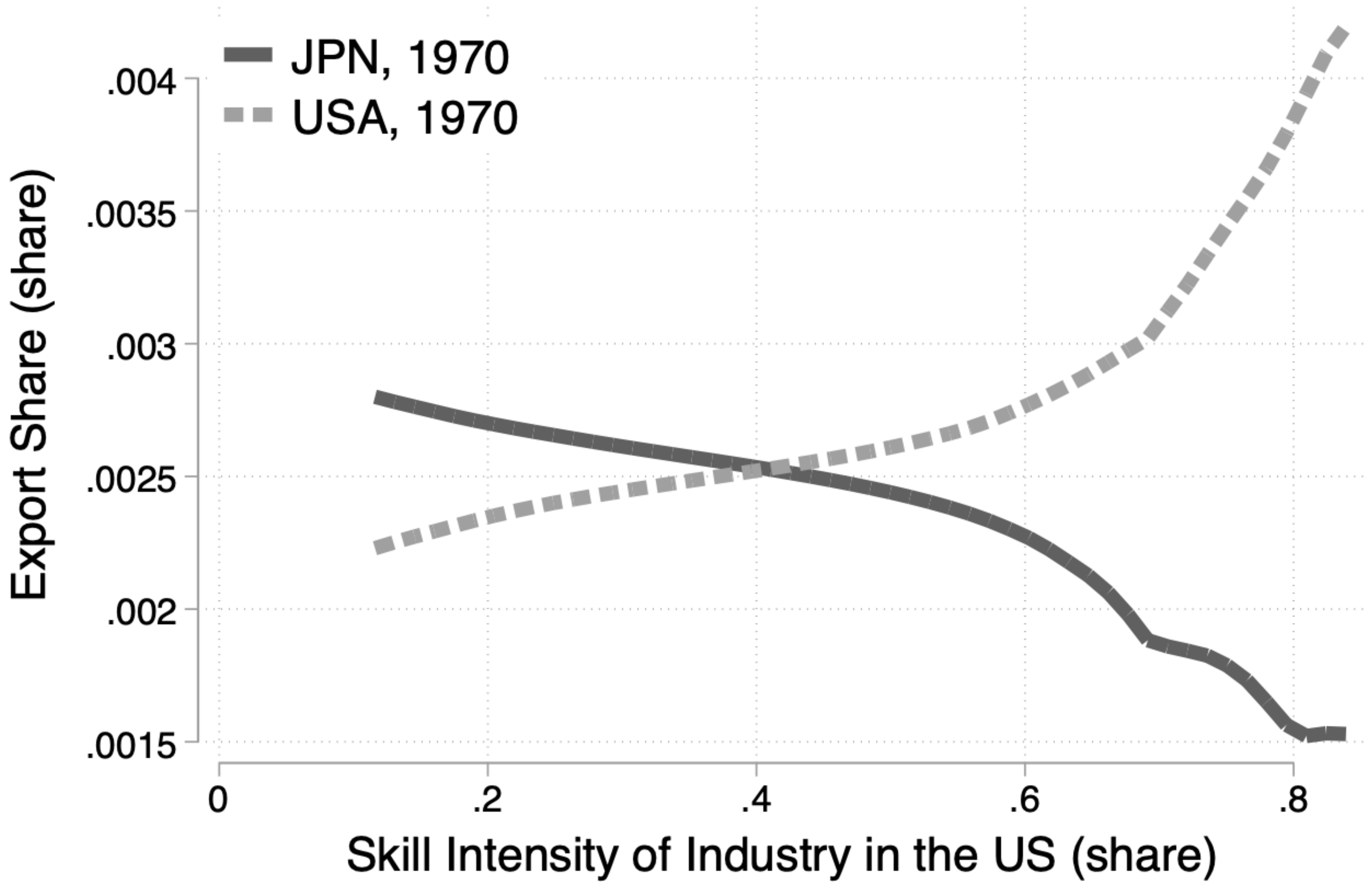

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Automation can Change Comparative Advantage

- **This paper: Automation changes comparative advantage**
  - L-scarcity → (L-replacing) automation — *e.g.* Japan, Germany,…
    - **Endogenous comparative advantage *against* factor-endowment**
    - → Expand (and may even specialize in) L-intensive sectors
  - Can weaken/reverse L-abundant countries' CA in L-intensive sectors
    - Developing countries cannot specialize in L-intensive sectors as much

What I do

- **Reduced-form:** Bilateral HO-gravity guided by Theory
  - **Decoupling/Reversal of Skill and Comparative Advantage**
    - Associate with robot use
- **Theory:** Multi-sector, multi-factor Armington + Task Framework
  - **Automation $\rightarrow$ Comparative Advantage, Structural Change**
- **Quantitative:** Estimate Bilateral HO-gravity in Model and Compare to Data
  - **Without automation, HO would have survived**

Contribution

- New facts on the weakening connection between skill and CA
  - Tests: Davis & Weinstein (2001), Romalis (2004), Nunn (2007), Levchenko (2007) etc
- Simple Framework for Automation in Trade
  - Automation: Zeira (1998), Acemoglu & Restrepo (2018, 2020, 2021, 2022,…) etc
  - Tech. in Trade: Epifani and Gancia (2008) Acemoglu (2003), Acemoglu et al (2015) etc
- North Technology on South Specialization/Structural Change via Trade
  - Structural change with Trade: Matsuyama (2009), Uy et al (2013), Matsuyama (2019) etc
  - Premature deindustrialization: Rodrik(2016), Fujiwara and Matsuyama (2021) etc

Today’s Plan

1. Empirical Evidence
2. Theoretical Framework
3. Two-country Illustration
4. Quantitative Results

Testing Skill Endowment as a Source of CA

- Model-consistent gravity-like regression

$$\ln X_{i,j,s,t} = \beta_t \left[\alpha^L_{s,t} \times \ln \left(\frac{L_{i,t}}{H_{i,t}} \right) \right] + \eta_{i,j,t} + \nu_{j,s,t} + u_{i,j,s,t}$$

  - Units: i-j country pairs (58*58), s sectors (SIC 4-digit, 397 mfg.), year t
  - $\ln X_{i,j,s,t}$: bilateral exports (i, j, s), in log
  - $\alpha^L_{s,t}$: sector-s's production labor share in the US
  - $L_{i,t}/H_{i,t}$: country-i's low-skill endowments
  - PPML for *each year t* ***separately*** (t=1980,…,2015) to estimate β_t

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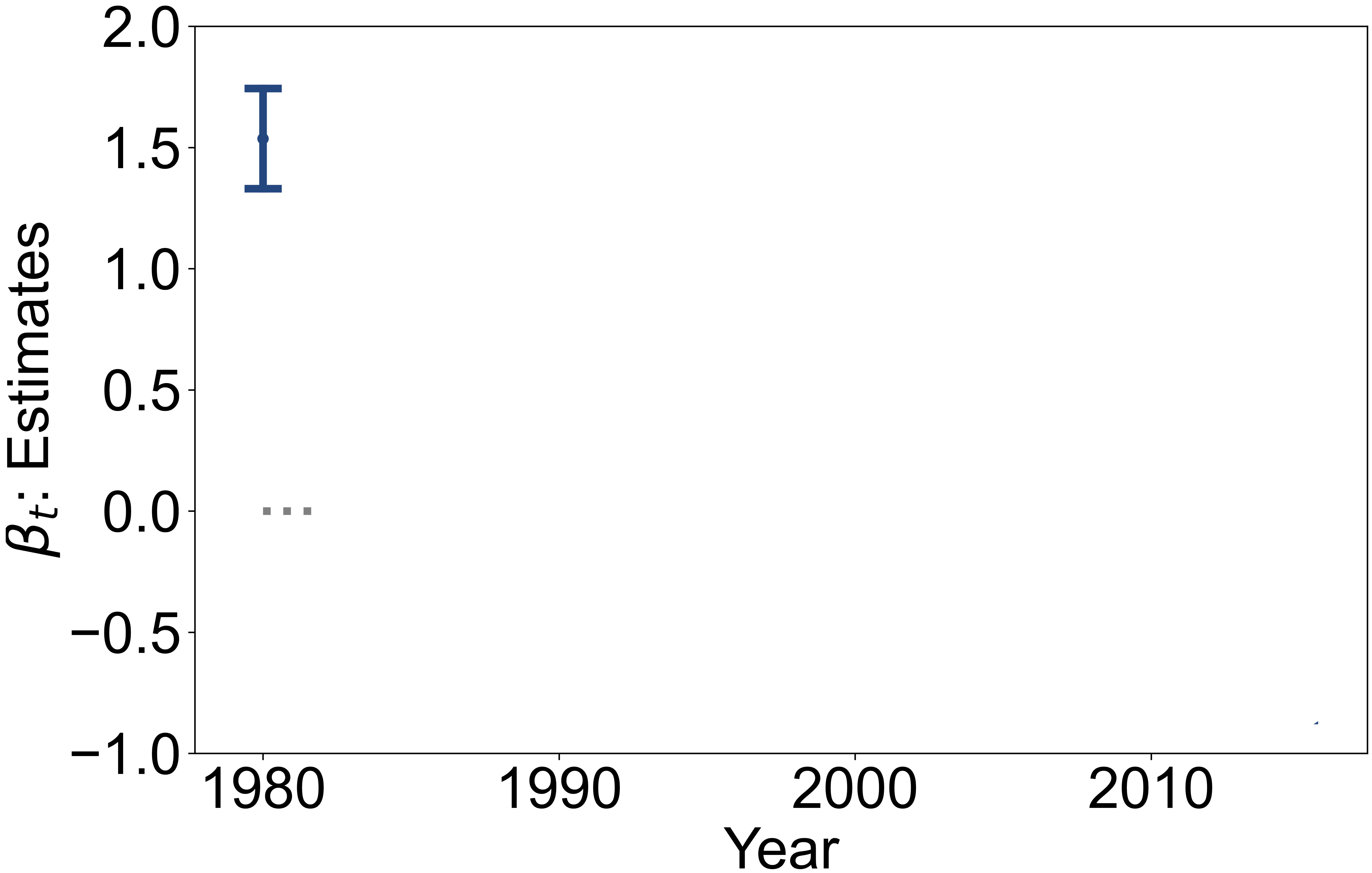
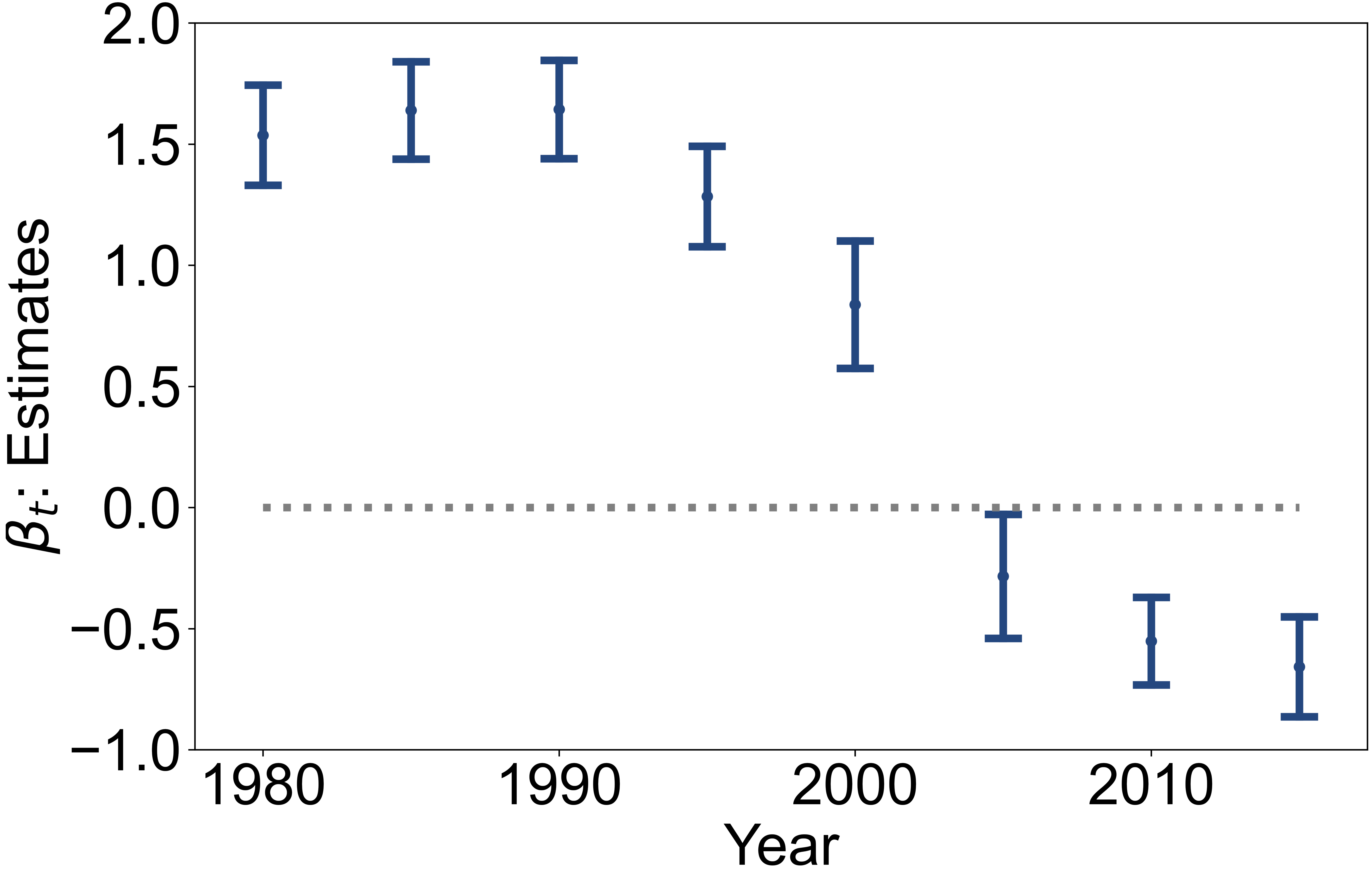
Results:



Results: Skill Endowments Become Less Important



Robustness

- Industry aggregation: 2-digit or 3-digit; instead of 4digit
- Data: World Input Output Table; instead of Comtrade
- Control: K/L intensity and/or institution terms (Nunn, Levchenko)
- More two-way fixed effects: Add TWFE of (2-digit industry) × origin country
- Sample: Dropping China or more strict criteria
- Skill-endowment measure instead of $H_{i,t}/L_{i,t}$
  - $H_{i,1980}/L_{i,1980}$ (fixing rank of skill-abundance)
  - Secondary vs Non-Secondary, High- vs Middle-skill
- More data-driven approach (Country FEs+ML), associating with robot use

Go

Sub-sample Analysis: High robot vs Low robot

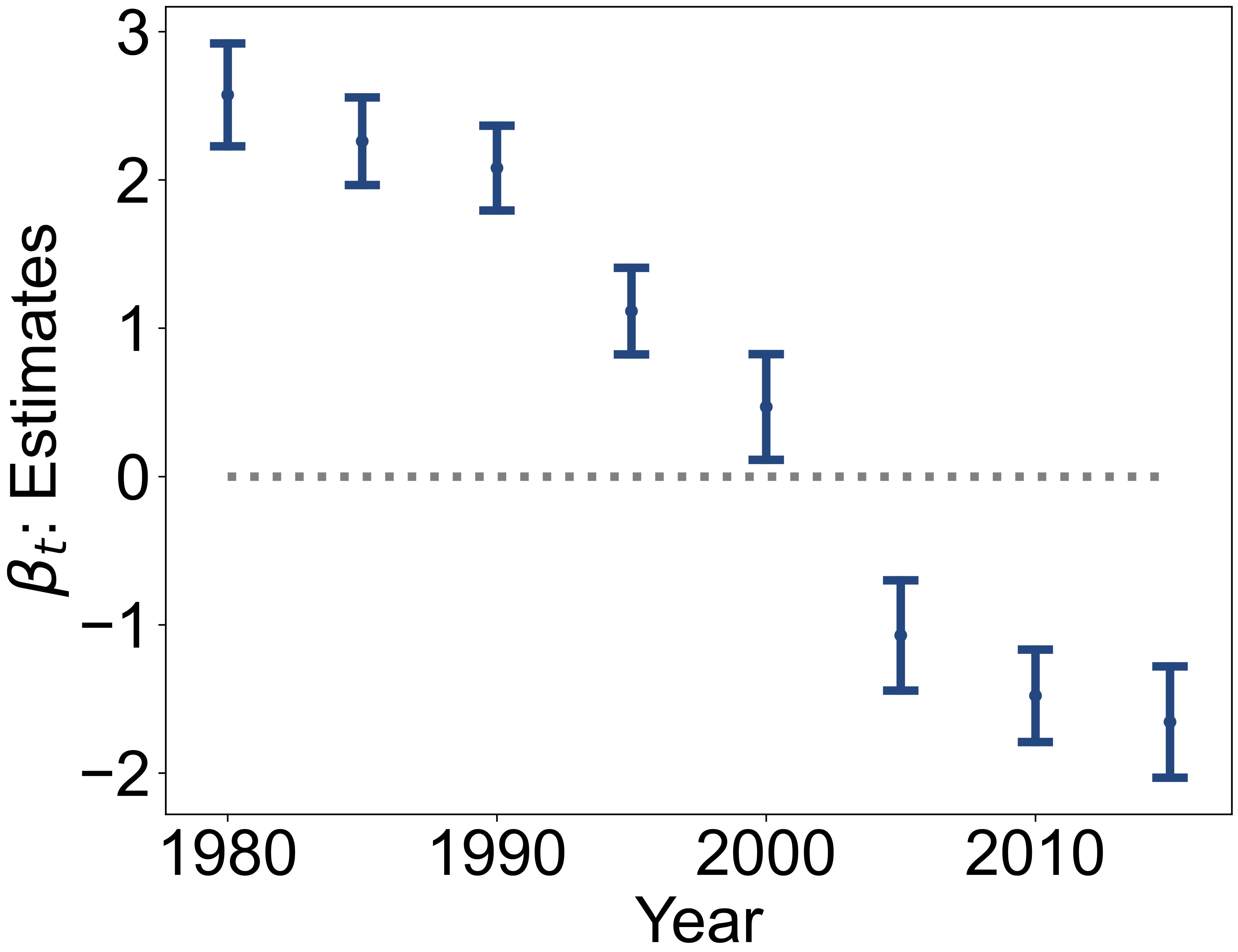
- Re-estimate within each group

	2-digit sector	# of industries	Trade	Robots/1K US emp
High Robot	Automobile + Elec.	56	42%	326
Low Robot	The rest mfg.	341	58%	42

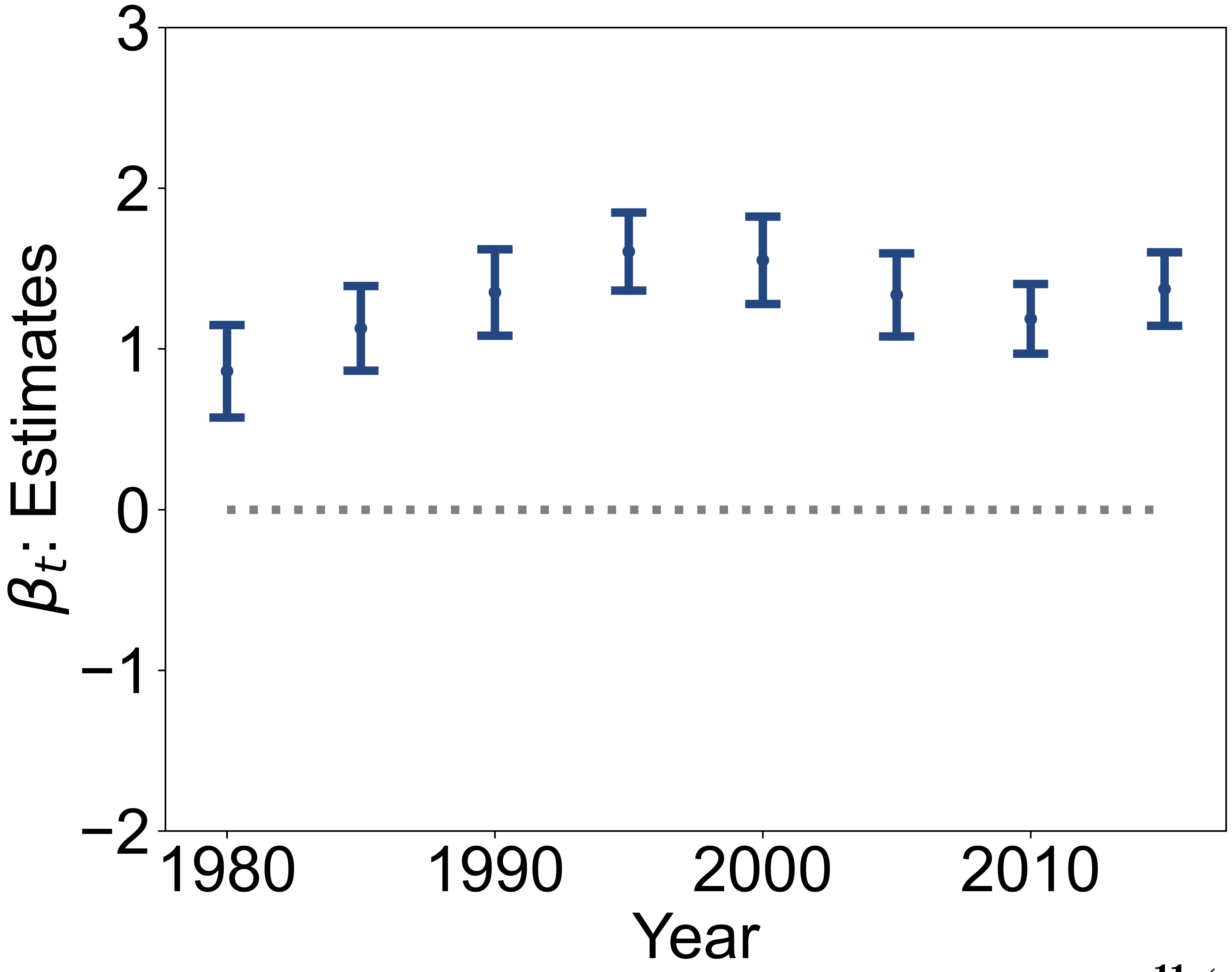
Note: Trade volume is the share of world total export share in 4-digit SIC code in each group of sectors in 1980 (from Comtrade). Robot density is the number of the total number of robot installments over 1995-2015 across the world (from IFR), normalized by the number of production workers in the US.

Subsample: Action Only within High-Robot Sectors

Within High-Robot Sectors

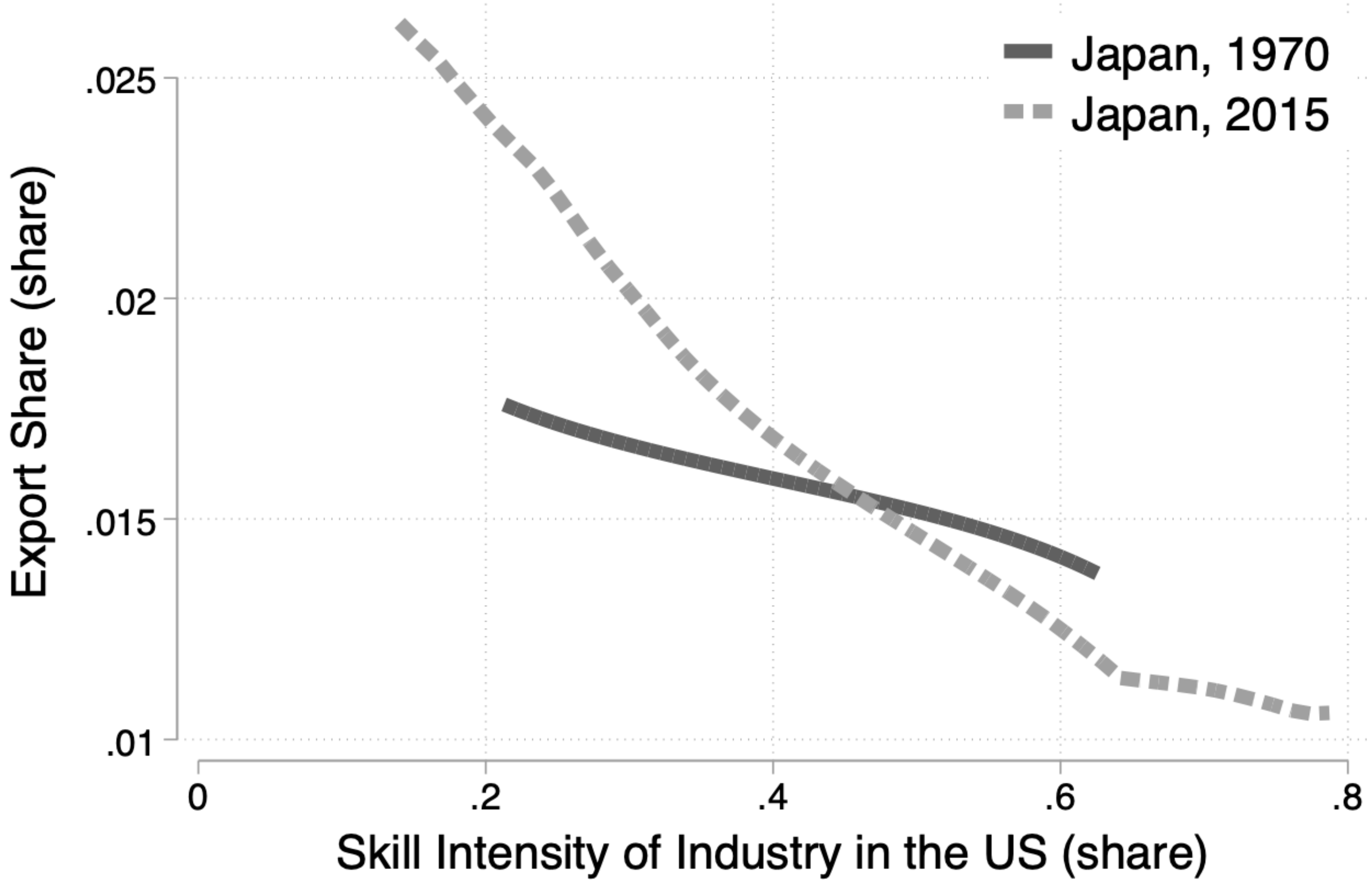


Within Low-Robot Sectors

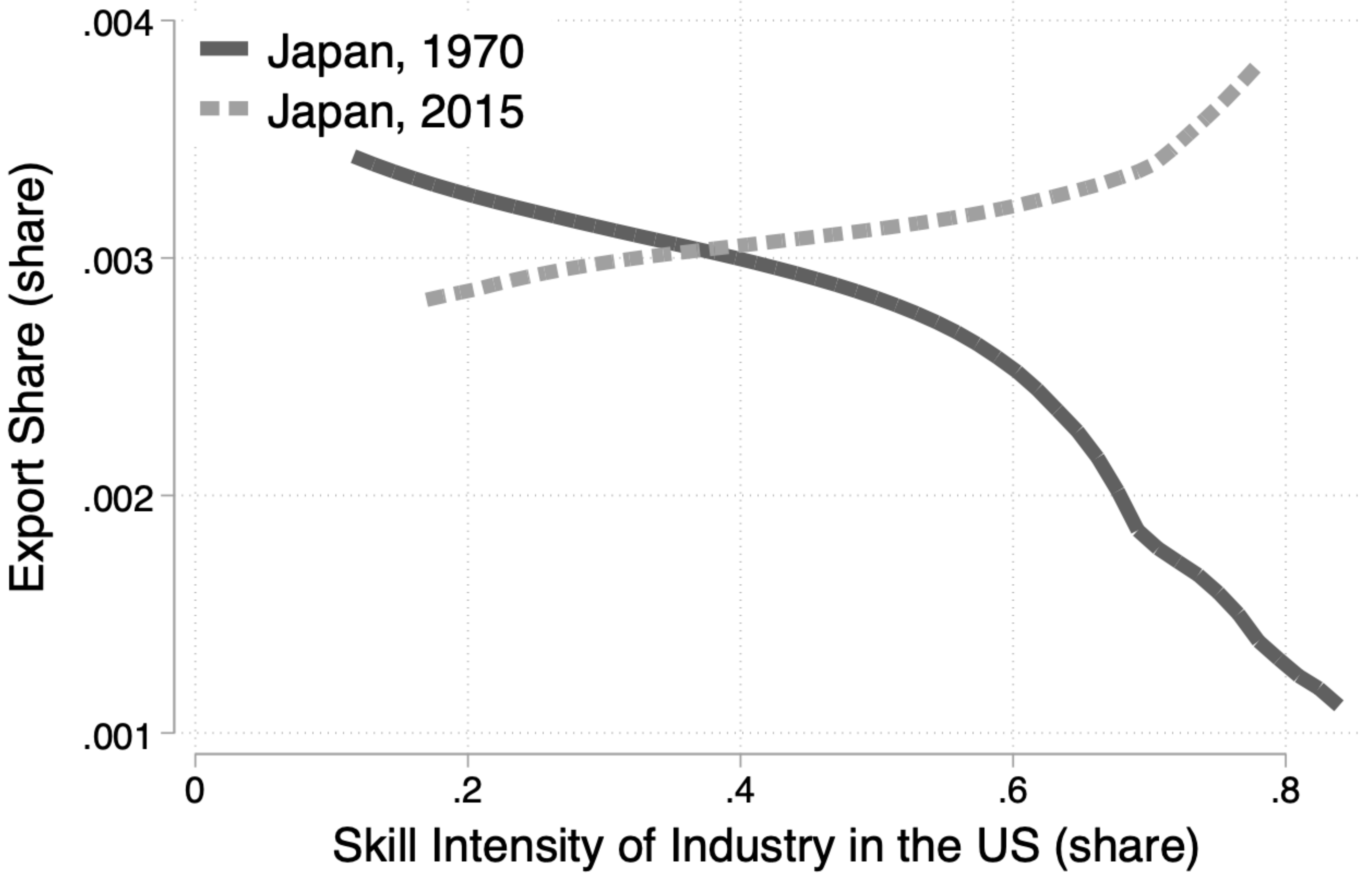


Japan Specializes in L-int. Industries within High Robot Sectors

Within High-Robot Sectors



Within Low-Robot Sectors



Note: Export share is the share of total export in 4-digit SIC code in each country in each year (from Comtrade). Skill intensity is the non-production worker payroll share out of total payroll in the US in each year (from US NBER-CES). The lines are Kernel-weighted local polynomial smoothing with bandwidth = 0.2. Regressions are unweighted. High robot industries (42 SIC 4-digit industries under Electronic and Automobile sectors) share 40% of total exports in 1980.

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Model (1/2): Environment and Preference

Multi-sector, multi-factor Armington

$\mathcal{N}$ country (i, j), $\mathcal{S}$ sector (s)

Factor endowments H_i, L_i

Trade with iceberg trade cost

$$p_{ijs} = c_{is}\tau_{ijs} \qquad \tau_{ijs} \geq 1$$

Preference in country j

$$U_j = \prod_{s \in \mathcal{S}} (q_{j,s})^{\mu_s}$$

$$\text{with } \sum_{s \in \mathcal{S}} \mu_s = 1$$

$$q_{js} = \left(\sum_{i \in \mathcal{N}} (q_{ijs})^{\frac{\sigma - 1}{\sigma}} \right)^{\frac{\sigma}{\sigma - 1}}$$

$$\text{with} \quad \sigma > 1$$

Model (2/2): Production (Task Framework)

Production function

$$Y_{i,s} = \left(\boxed{Y^P_{i,s}}\right)^{\alpha^P_s} \left(H_{i,s}\right)^{1-\alpha^P_s}$$

Intermediates by L or M

$$\boxed{Y^P_{i,s}} = \left(\int_0^1 Y^P_{i,s}(\omega)^{\frac{\varepsilon-1}{\varepsilon}} d\omega\right)^{\frac{\varepsilon}{\varepsilon-1}}$$

Feasible to automate

$$Y^P_{i,s}(\omega) = K_{i,s}(\omega) + L_{i,s}(\omega) \text{ if } \omega \in [0, \boxed{\theta_{i,s}}]$$

$$Y^P_{i,s}(\omega) = L_{i,s}(\omega) \qquad\qquad \text{ if } \omega \in (\theta_{i,s}, 1]$$

Automation and Unit Cost

- Unit cost function: cost of producing one unit of final goods in (i, s))

$$c_{i,s} = \lambda_s \left(\theta_{is}(r)^{1-\varepsilon} + (1-\theta_{is})(w_i^L)^{1-\varepsilon}\right)^{\frac{\alpha_s^P}{1-\varepsilon}} \left(w_i^H\right)^{1-\alpha_s^P}$$

- Assume $\theta_{is} = \theta$ and $r < w_i^L$ (just for expositional simplicity)
- ***Prop. When θ increases, high w_i^L countries decrease log unit cost more in high α_s^P sector***
  - Larger gains in L-intensive sectors more for L-scarce countries

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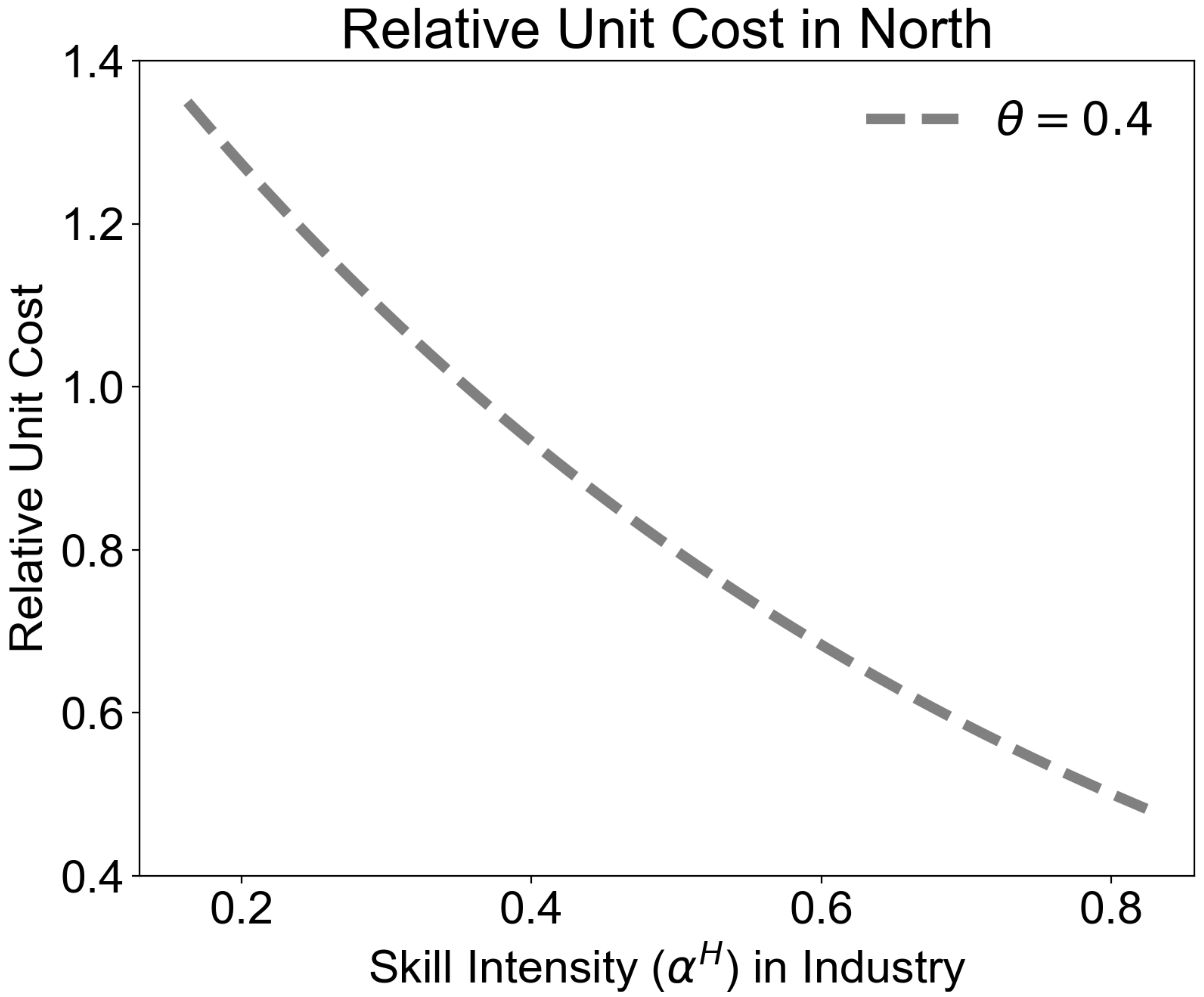
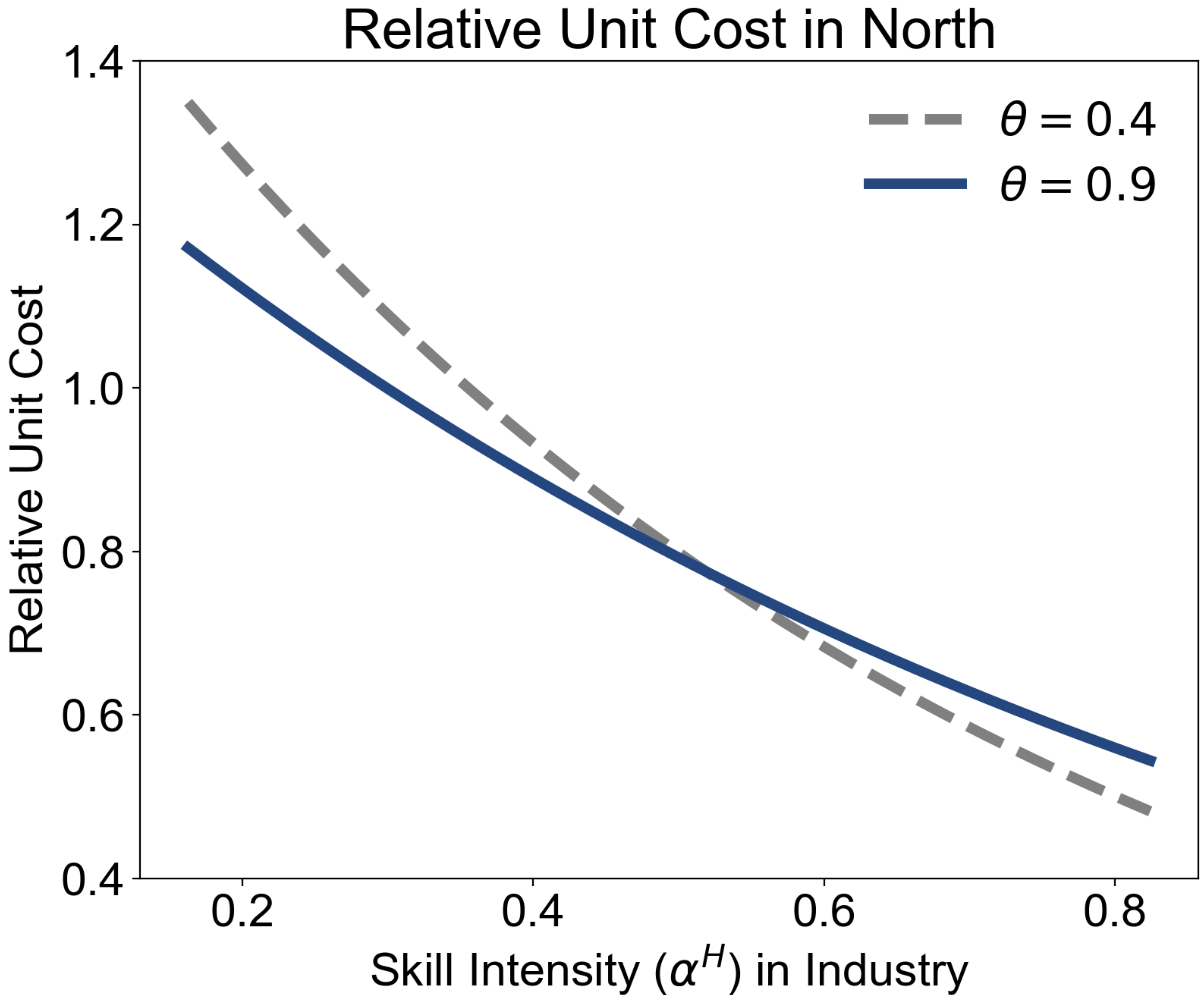
Two-Country Numerical Illustration

- North (H-abundant) and South (L-abundant)
  - Differences (values directly taken from data):
    - Across countries: skill endowment H_i/L_i
    - Across sectors: skill intensity α_s^H and value-added share μ_s
- **Experiments:**
  1. Change θ and see comparative advantage
  2. Change g_θ (growth rate of θ) and see structural change

South's Comparative Advantage in L-intensive Sectors

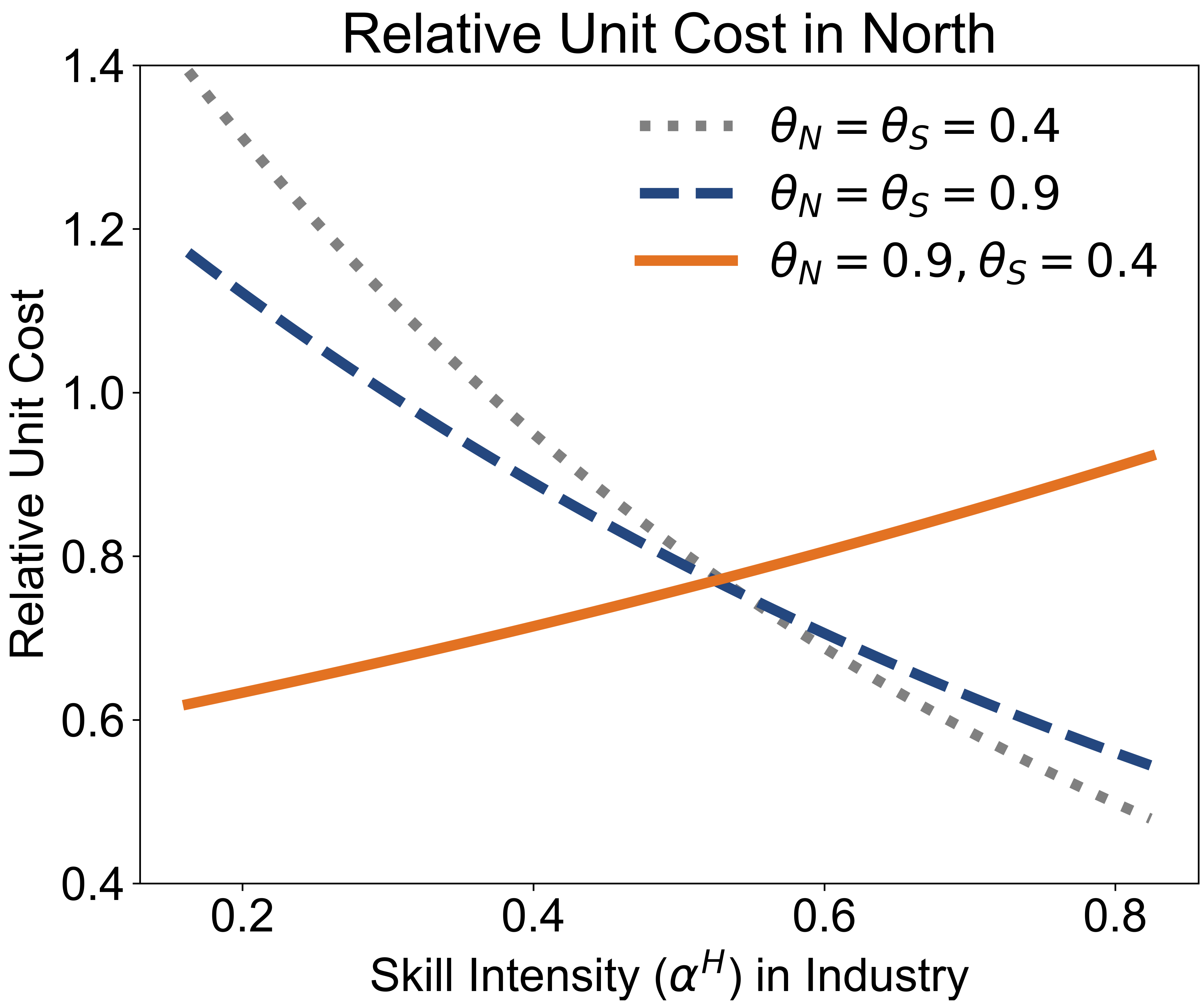


Comparative Advantage is Weakened...



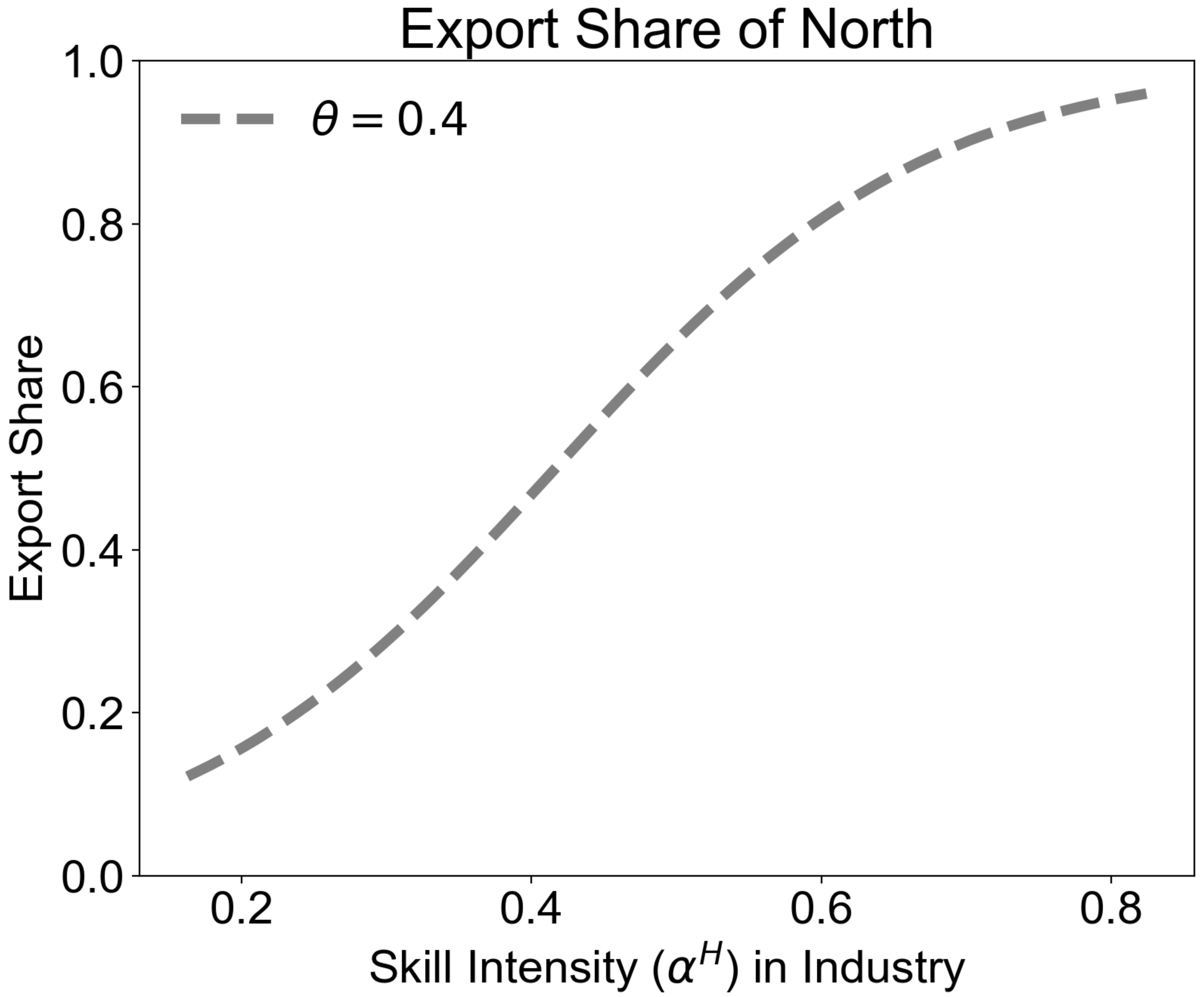
Automation θ is more cost-saving for the L-intensive in N

… or Even be Reversed

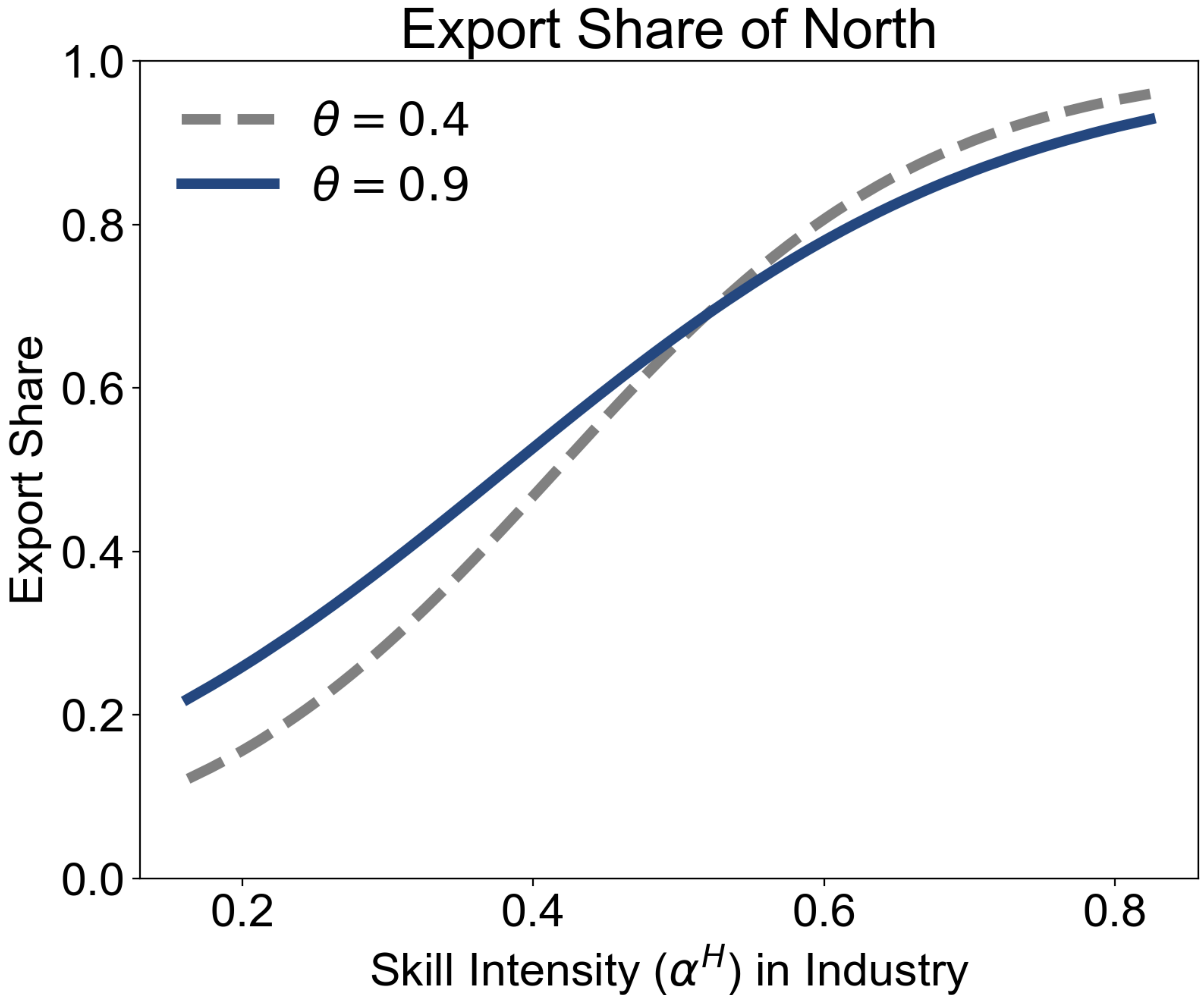


North's relative unit cost is lower in L-intensive sectors

Export share: South's CA in L-intensive Sectors

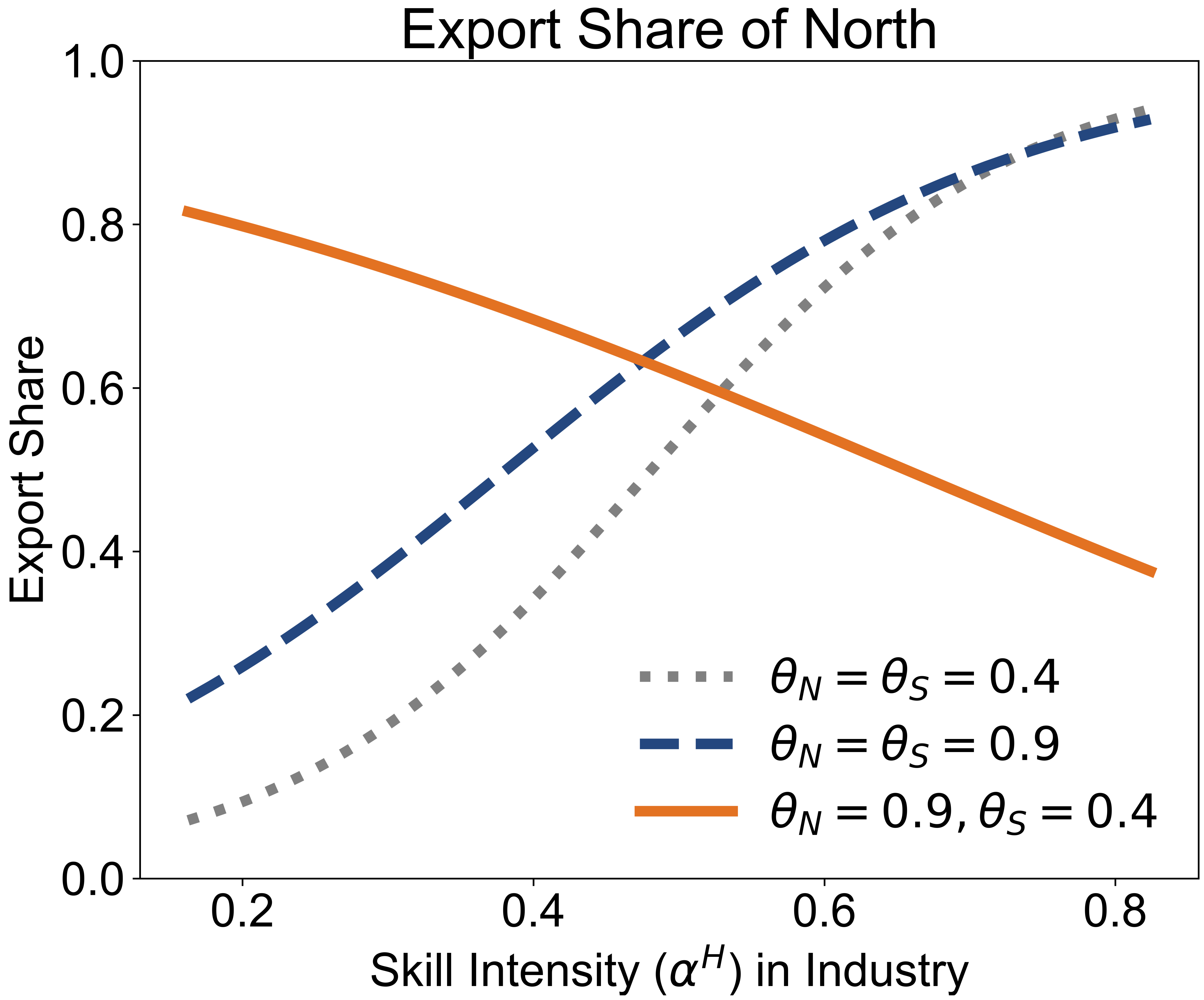


Export share: Comparative Advantage Weakens



Mirror image to cost: N increases L-intensive export

… or Even be Reversed



North now specialize in L-intensive sectors

North Automation to South Structural Change

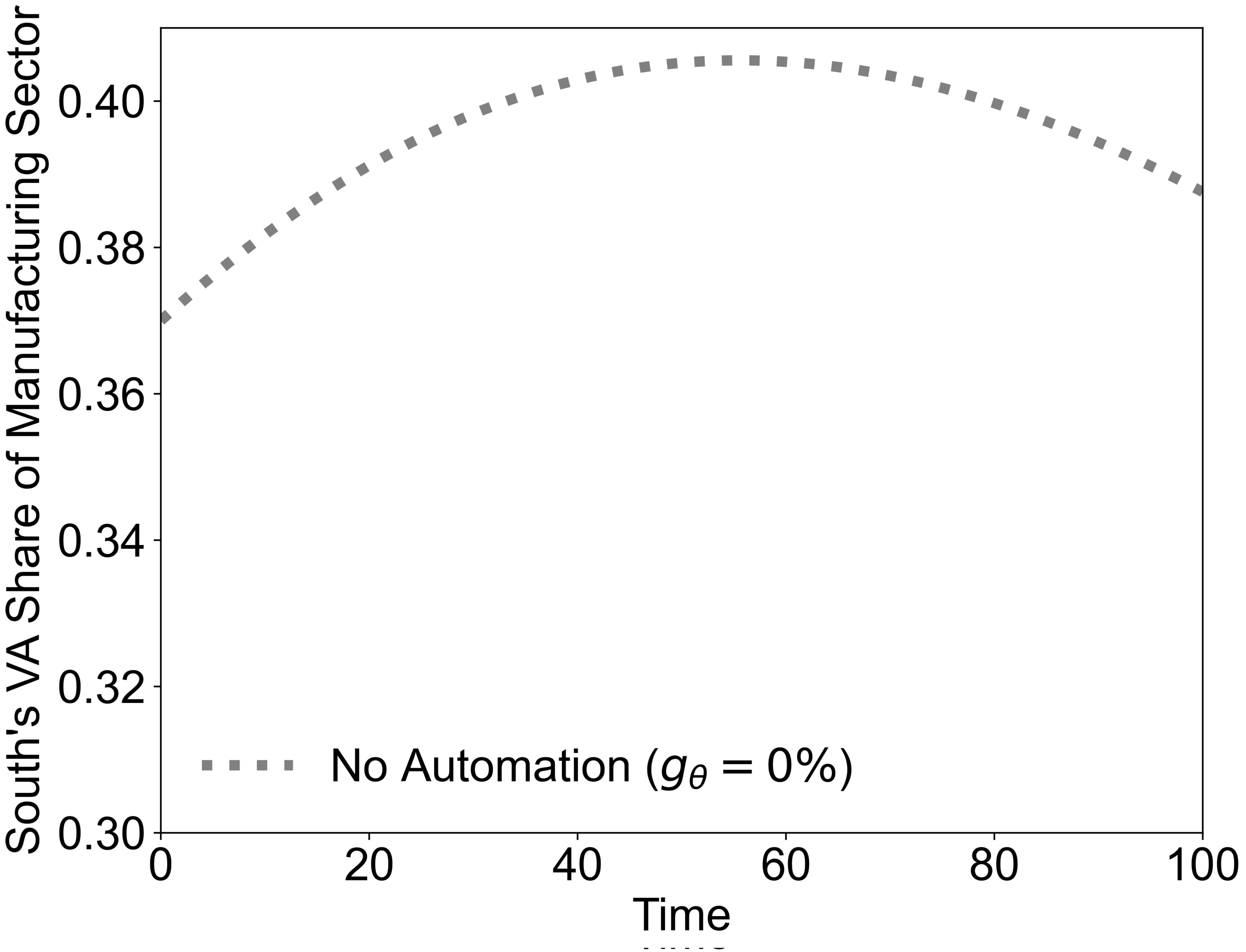
- 3 sectors: $\mathcal{S} = \{A, M, S\}$
- Slight generalization
  - Complement: $\phi < 1$
  - TFP growth $g_A > g_M > g_S > 0$

$$U_j = \left[\sum_{s \in \mathcal{S}} \gamma_j^{\frac{1}{\phi}} (q_{js})^{\frac{\phi - 1}{\phi}}\right]^{\frac{\phi}{\phi - 1}}$$

- South's VA share over time with different growth rate of automation g_θ

Premature Deindustrialization in South

South's Value-Added Share in Manufacturing



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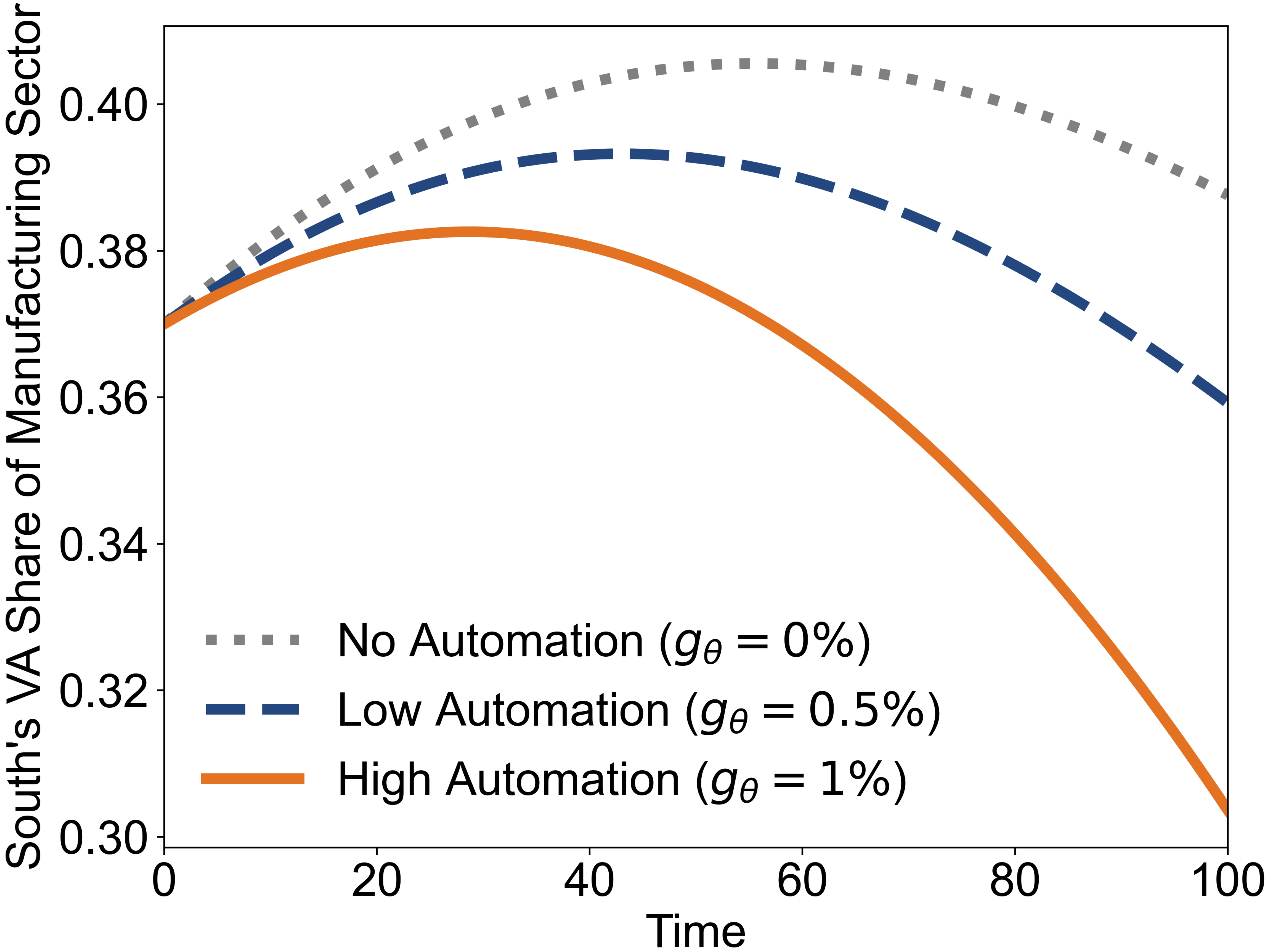

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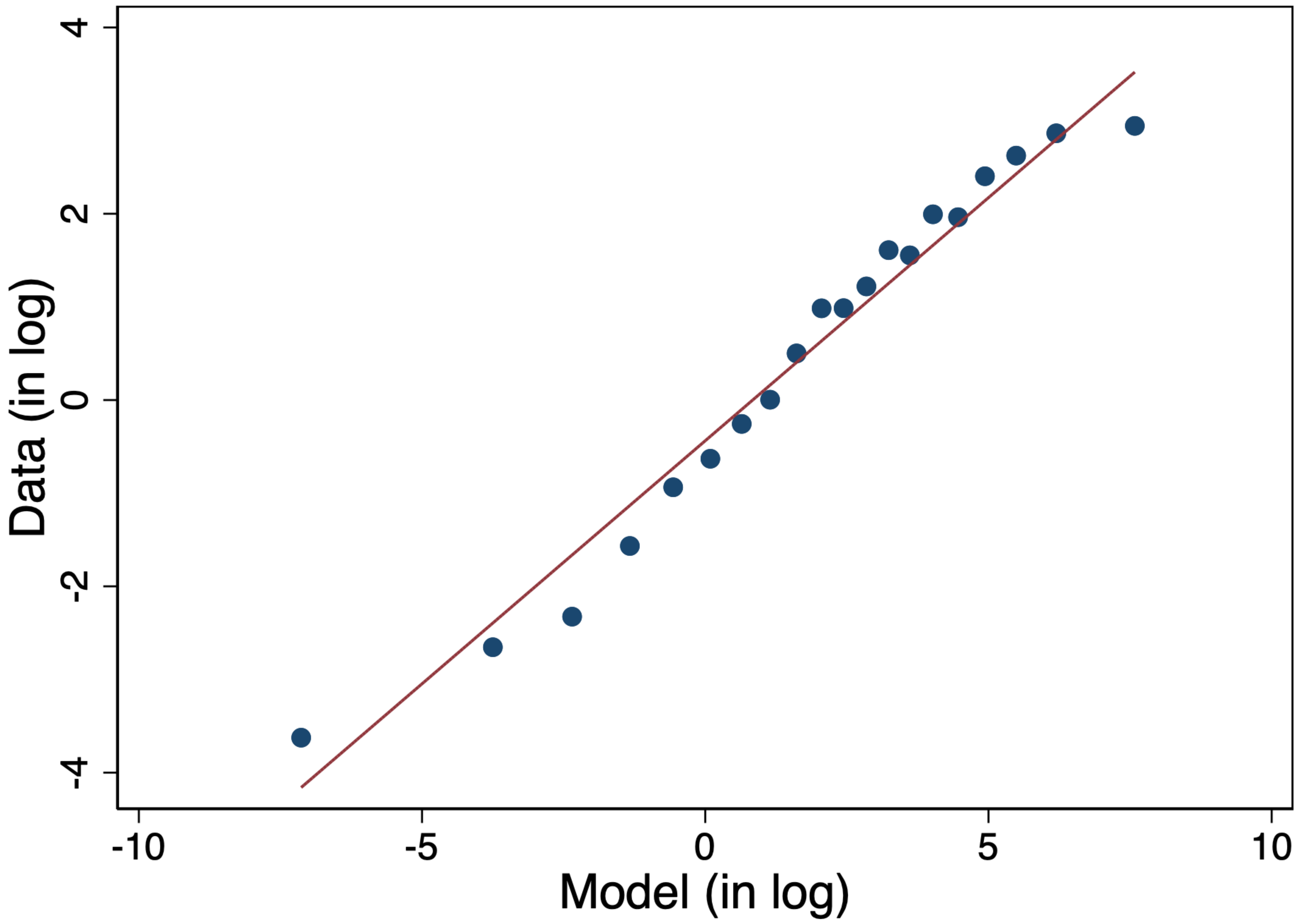
Quantitative Analysis

- **Question:** How much is automation responsible for the decoupling?
- **Calibration:** 38 countries, 18 manufacturing industries (2-digit)
- **Experiment:**
  - Feed θ_{ist}, Match the US labor share to get $\theta_{US,s,2010}$
    - Extrapolate to $\theta_{i,s,t}$ using robot$_{i,s,t}$ (IFR after 1995)
  - Solve the model, and estimate the same gravity equation

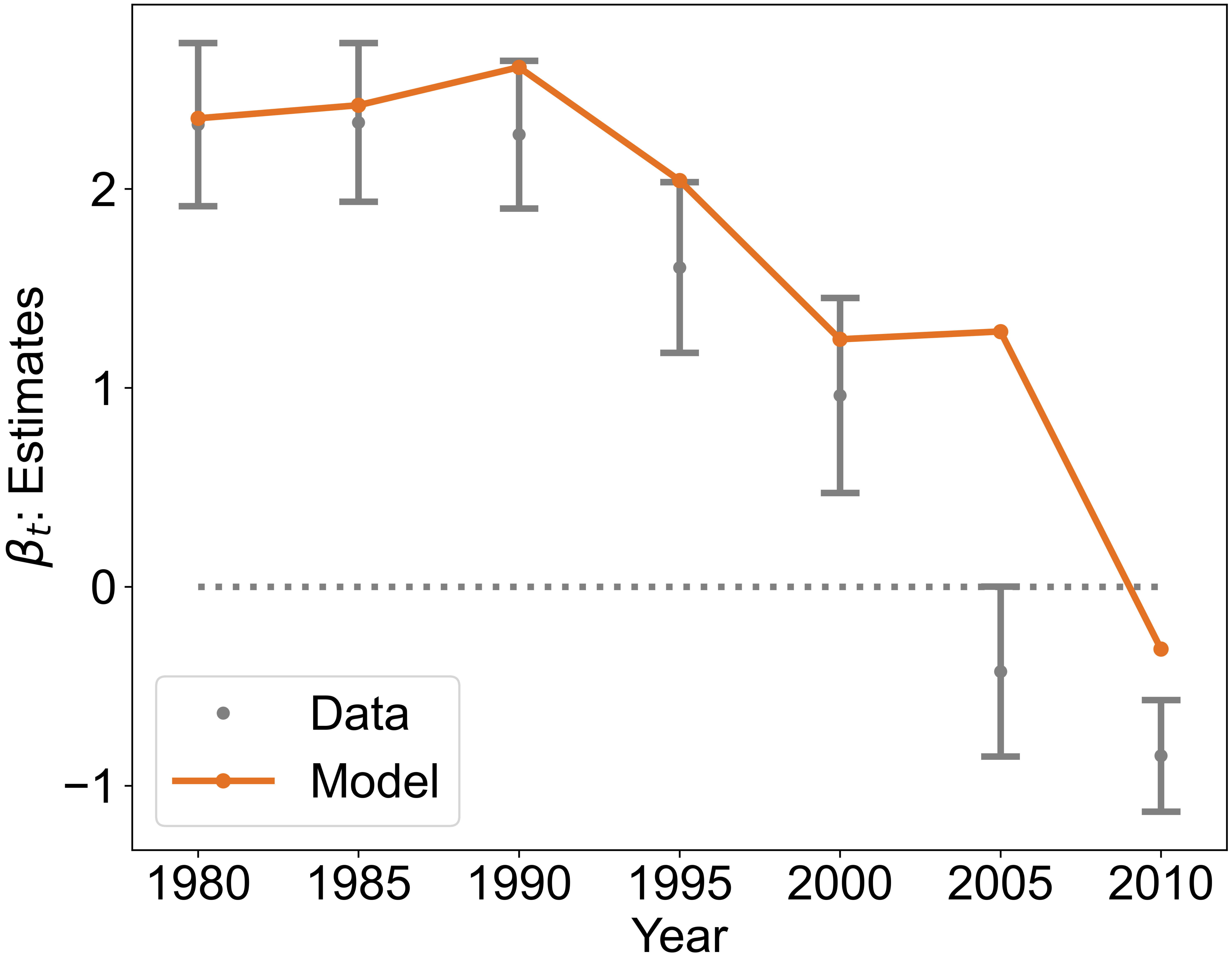
Parameters

	Description	Source, Value, Target
μ_s	Value-added share of sector	World IO Table, 2000
α_s^H	Non-production-labor share	US NBER CES 2000
ε	EoS across Task	0.49 (Humlum, 2021)
r	Capital Price	0.1
σ	Trade Elasticity (+1)	6 (Head & Mayer 2013)
τ_{ijs}	Trade cost	Head and Reis (2001)
$(H/L)_i$	Skill Endowment (college-educated)	Barro-Lee Data set

Model fit: Bilateral Trade Flow $\ln X_{ijs}$ in 2000



Automation and Comparative Advantage

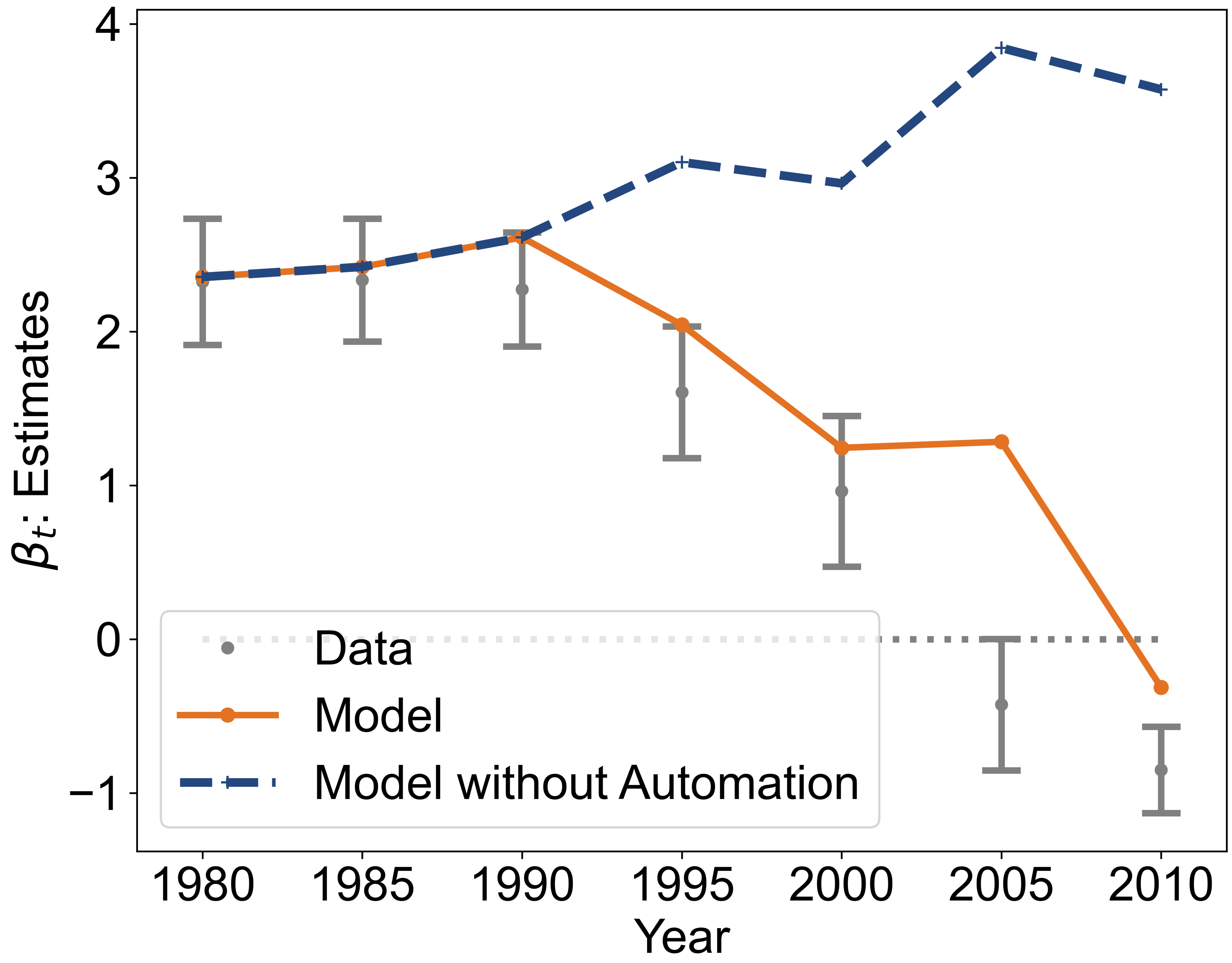


Counterfactual: No Automation

- Previous figure: Feeding $\{\theta_{ist}\}$ can replicate the pattern
  - Matched the US production labor share in 2010
  - Extrapolate using relative robot stock
    - Using IFR (robot) data after 1995

- **Counterfactual:** Fix θ_{ist} to be the 1980-1990 level and redo the analysis

Without Automation, Skills Would Have Still Mattered



Conclusion

- Skill endowments become less important for comparative advantage
- Automation can weaken or reverse the comparative advantage
- Quantitatively, automation can explain the decoupling/reversal well

- **Next Steps:**
  - Quantitative analysis on structural change
  - More counterfactuals: trade cost, China, …

Back-up slides

Data Details

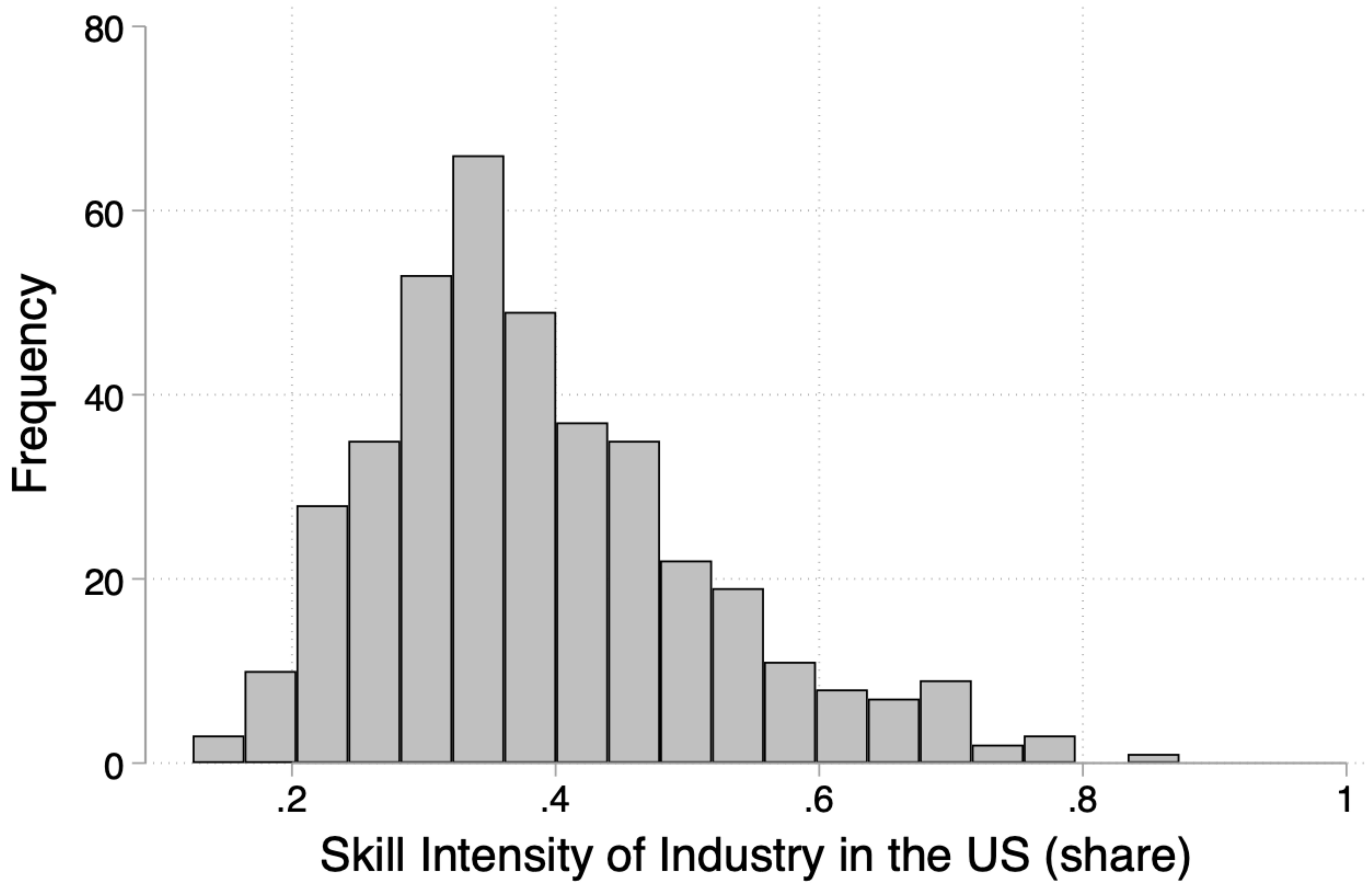
Define Industry-level Skill Factor Share

- Skill share: defined in 397, SIC4-digit manufacturing sector (s)
  - $\alpha_s^H (\equiv 1 - \alpha_s^L)$: Factor payment to H / factor payment to H & L
  - Data: US NBER-CES data in each year

Most skill-intensive sectors	α_s^H
3571: Electronic Computers	0.77
3661: Telephone	0.75
3826: Lab. Ana. Instrument	0.75
3761: Guided Missiles Veh.	0.75

Least skill-intensive sectors	α_s^H
2436: Softwood Veneer	0.13
2281: Yam Spinning Mills	0.15
3221: Glass Containers	0.15
3641: Electric Lamp Bulbs	0.16

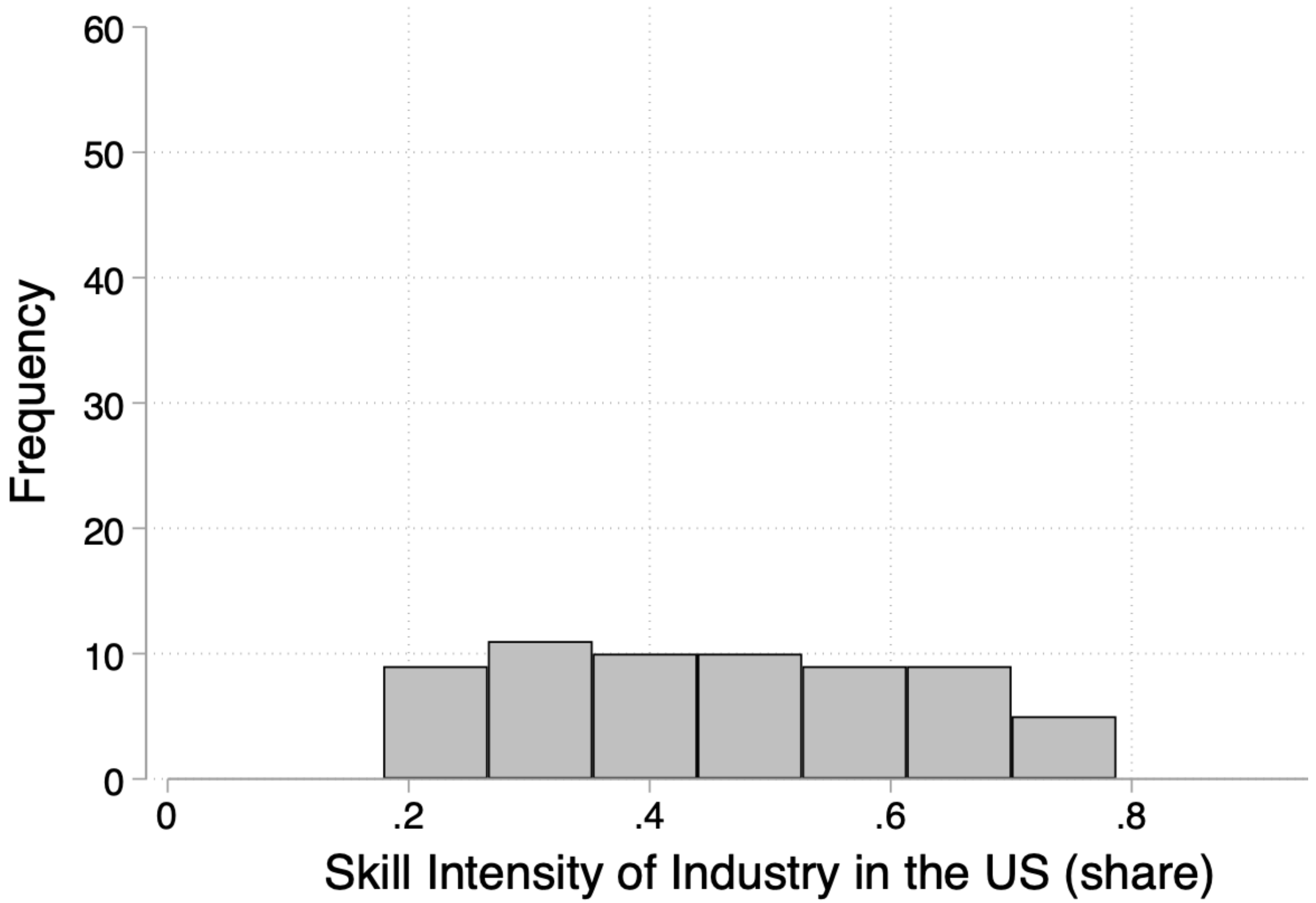
Factor Intensity across Sectors



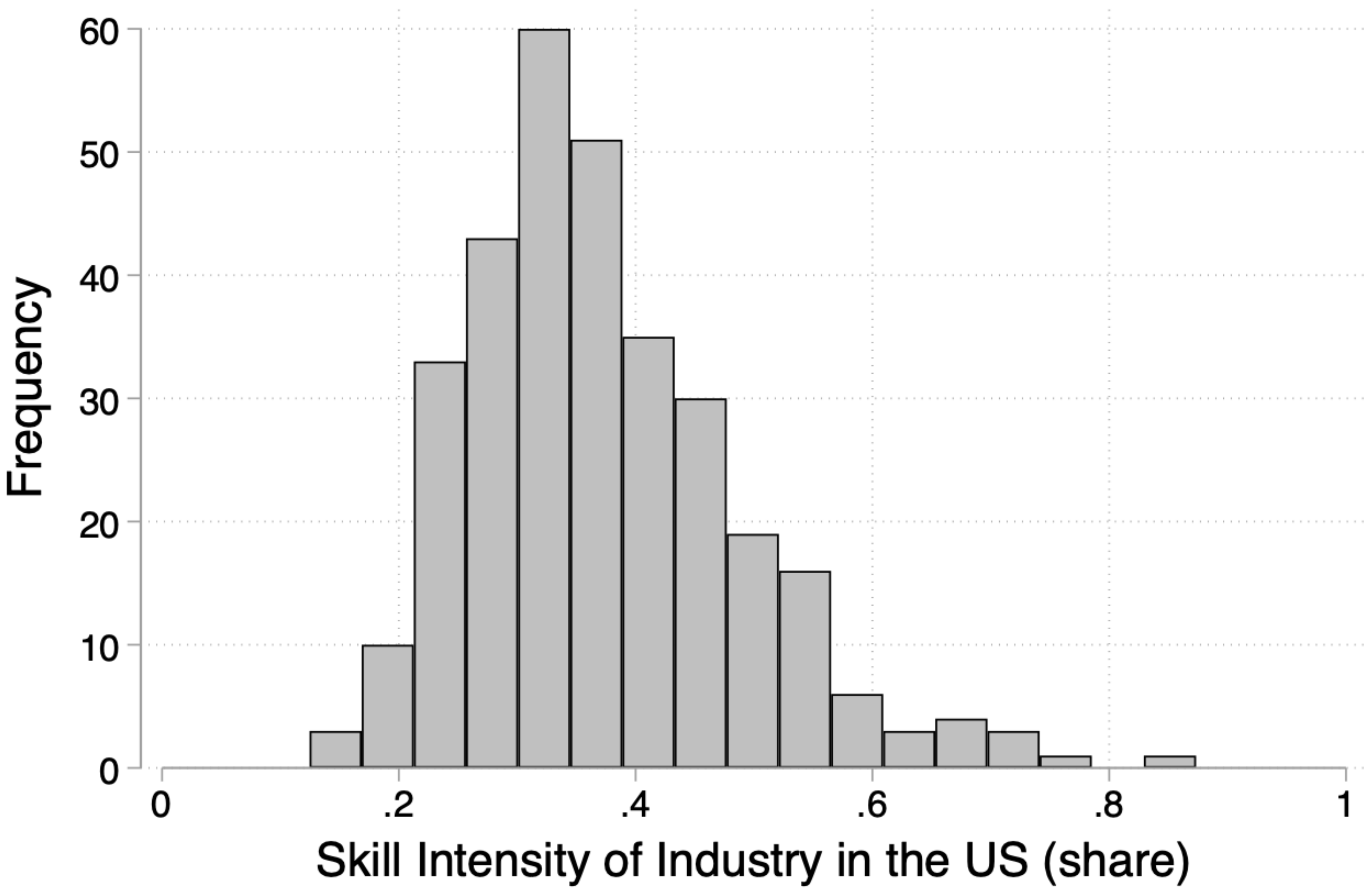
Note: Skill intensity of industry is a non-production worker payroll share out of total payroll in the US in 1980 (from US NBER CES). Units are 397 SIC 4-digit industries

Factor Intensity across Sectors within Groups

Within High-Robot Sectors



Within Low-Robot Sectors

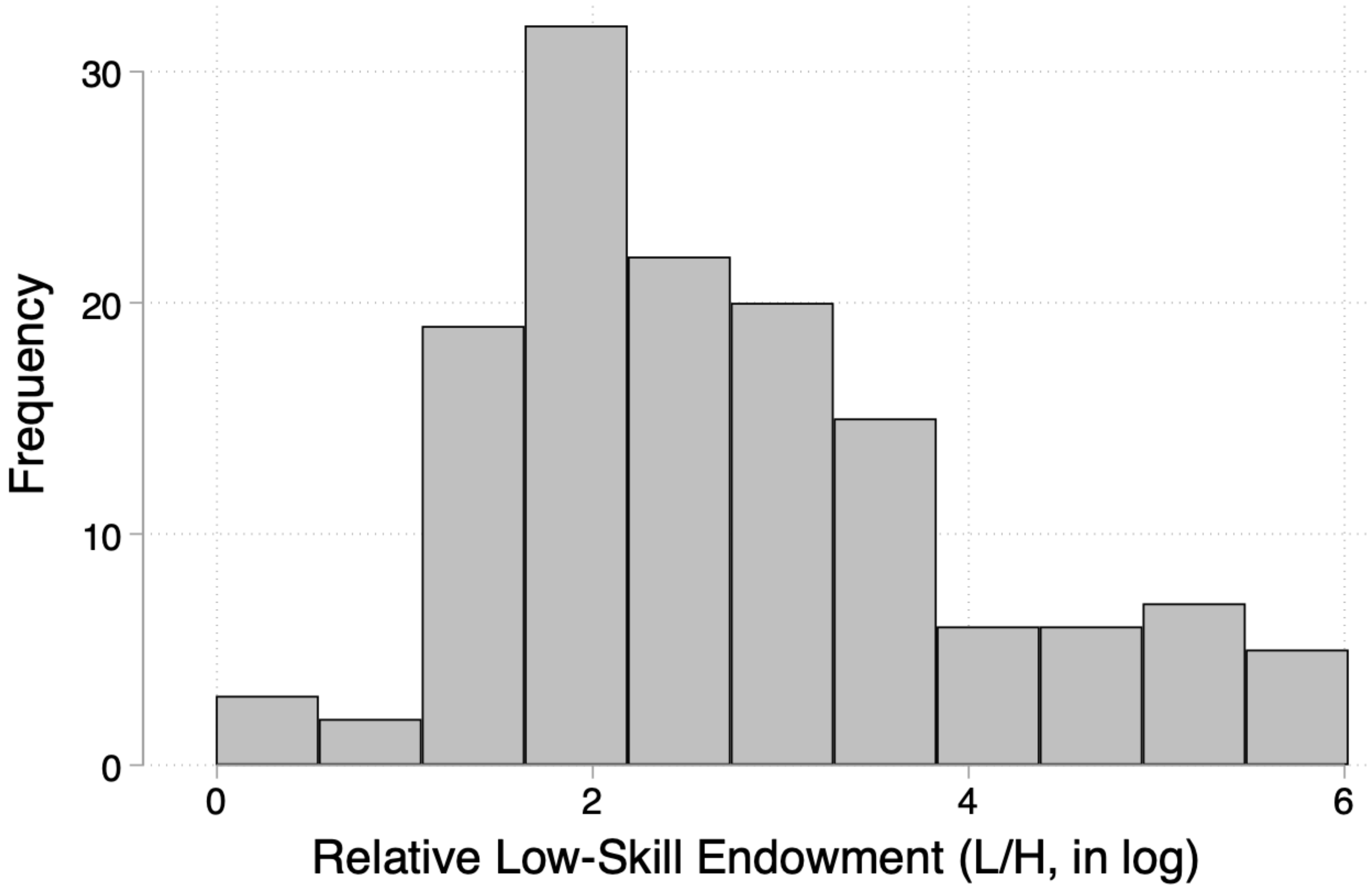


Note: Skill intensity of industry is a non-production worker payroll share out of total payroll in the US in 1980 (from US NBER CES). Units are SIC 4-digit industries. High robot industries share 40% of total exports in 1980.

Define Country-level Skill Endowment

- Country-level skill endowment: $\ln\left(H_{i,t}/L_{i,t}\right)$
  - Baseline: Tertiary vs Non-tertiary for age 25-64
  - Data: Baroo-Lee Data
  - Robustness:
    - Other measures (year of schooling, secondary vs not, aged 15-64)
    - Data-driven using country dummies (later)

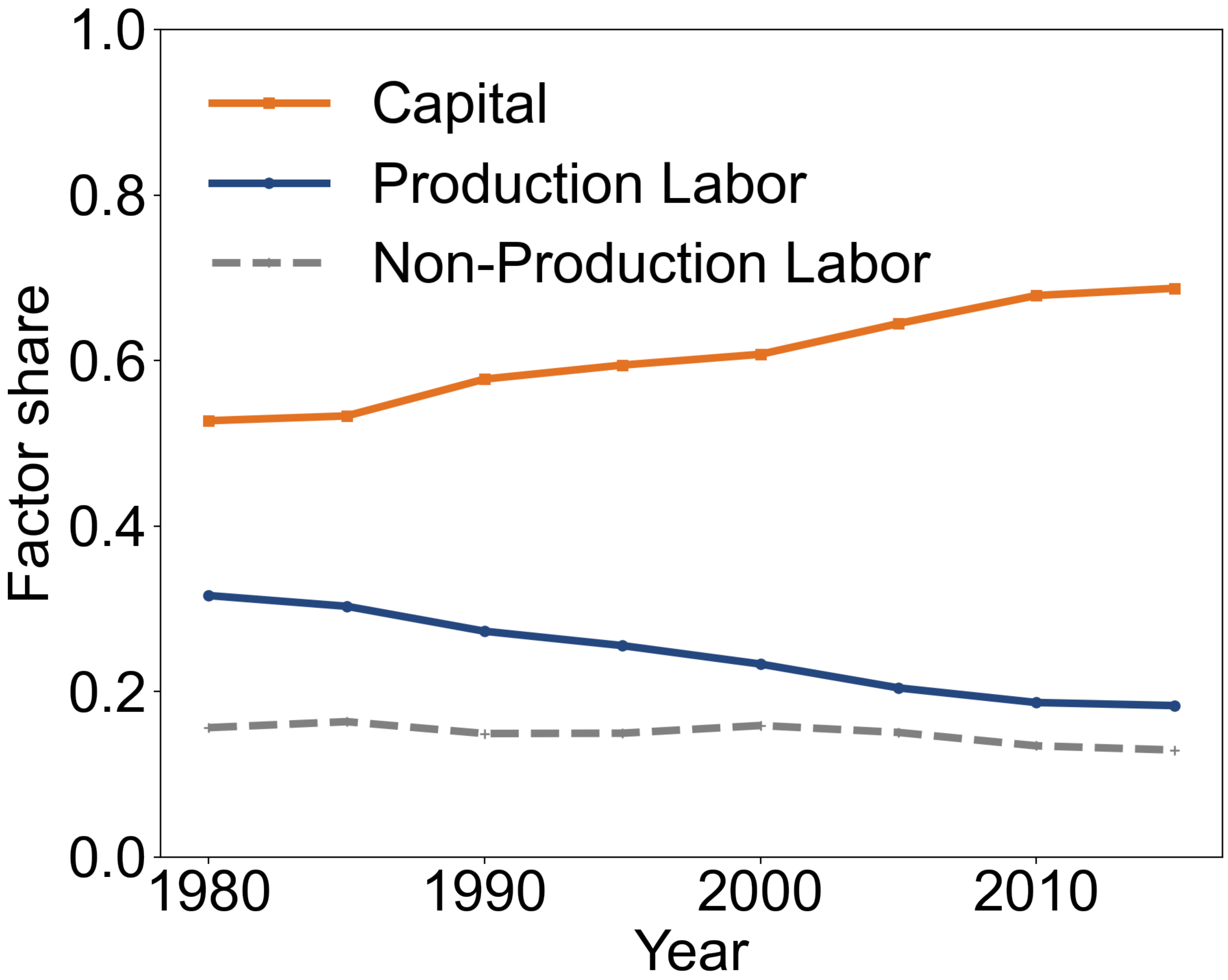
Factor Endowments across Countries



Note: Relative low-skill endowment is the log ratio between the number of non-college workers to the number of college workers in each country in 1990 (from Barro-Lee Data)

US Factor Share in Manufacturing Sector

Back



Another empirical specifications

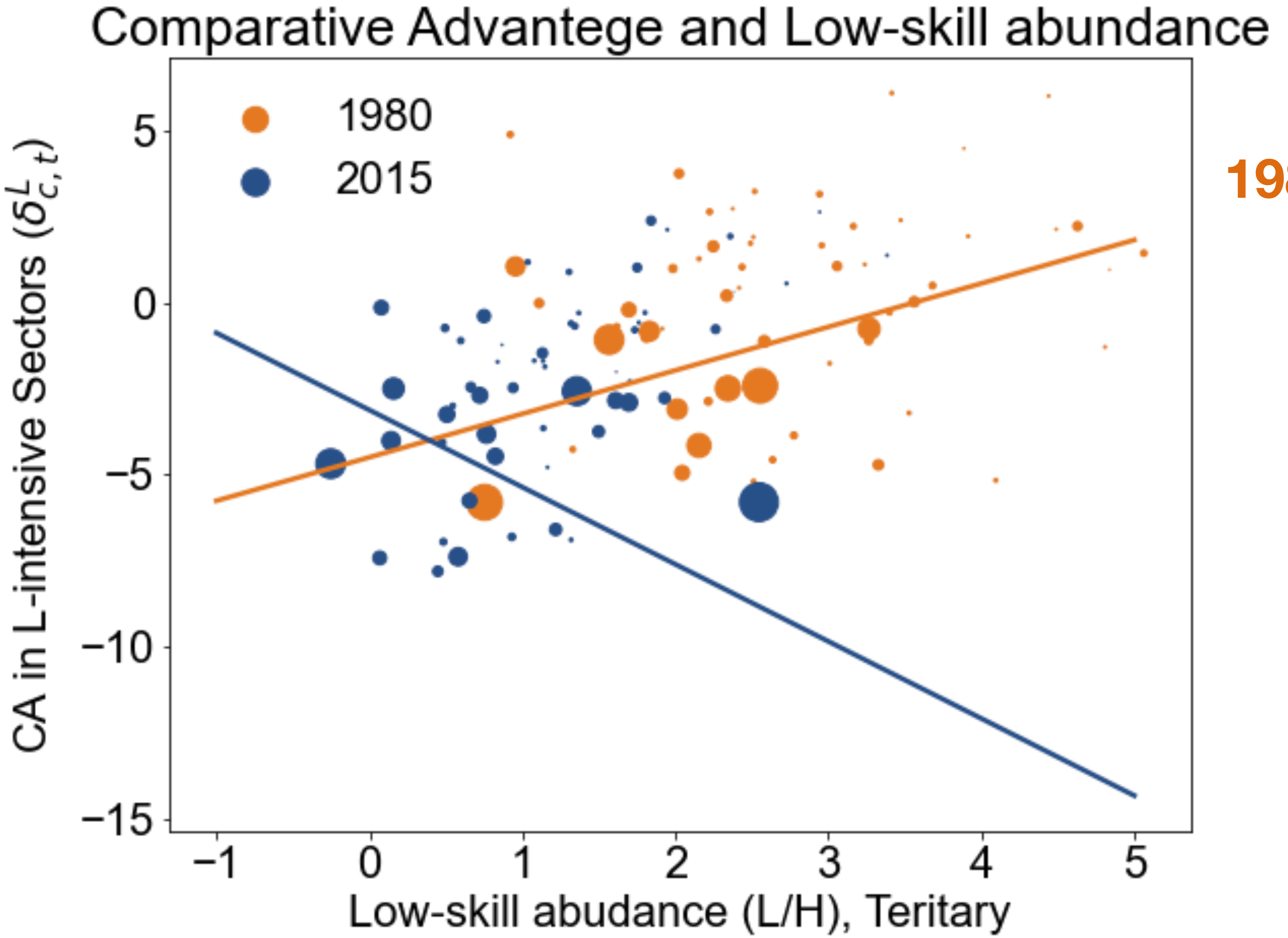
More Data-Driven Approach

- Instead of having country-level skill share, estimate the following

$$\ln X_{i,j,s} = \sum_{c} \delta^L_{c,t} \left[1_{i=c} \times \alpha^L_s \right] + \nu_{i,j} + \eta_{j,s} + u_{i,j,s}$$

  - $1_{c=i}$: dummy for each country c
  - $\delta^L_{c,t}$: “estimated” comparative advantage in L-intensive sectors
- Issue: $\delta^L_{c,t}$ is high-dimensional → need shrinkage
  - Penalized PPML using plug-in lasso (Belloni et al., 2016)
  - Select 44 countries out of 58 countries in 1980 (and fix them)

Factor-Endowment-Based CA is Reversed



1980: L-abundant countries had CA in L-intensive sectors

2015: Reversed.

Changes in CA and Robot Adoption

- Can define "Changes in CA in L-intensive sectors"

$$\Delta\hat{\delta}^L_{c,t,t'} \equiv \hat{\delta}^L_{c,t'} - \hat{\delta}^L_{c,t}$$

- Regress changes in CA on robot adoption at country level

$$\Delta\hat{\delta}^L_{c,t,t'} = \beta\Delta \ln \text{Robot}_{c,t,t'} + \Gamma' X_{c,t,t'} + \mu_t + \varepsilon_{c,t}$$

  - Control: Initial CA, Changes in skill-endowment, demographics
    - Long-difference: 1995-2015
    - 10-year stacked difference: 1995-2005, 2005-2015

Robot Adoption Associates with Changes in CA

	Changes in CA Long-difference		Changes in CA 10 year stacked diff.	
	(1)	(2)	(3)	(4)
Log Robot Adoption	0.32	0.28	0.14	0.17
	(0.10)	(0.10)	(0.02)	(0.03)
CA in 1995		-0.26	-0.11	
		(0.11)	(0.04)	
Num. of Countries	44	44	88	88
Country Covariates		Yes	Yes	
Country Fixed Effects				Yes
Decade Fixed Effects			Yes	Yes

Calibration Details

Challenge: Calibrating Trade Cost

- Factor shares change → cannot use hat algebra
- Too big to invert
- Head and Reis (2001): Assuming free intra-trade and symmetric trade cost:

$$\left(\tau_{ijs}\right)^{1-\sigma} = \sqrt{\frac{X_{ijs}X_{jis}}{X_{iis}X_{jjs}}}$$

  - Data from World Input Output Table in 2000

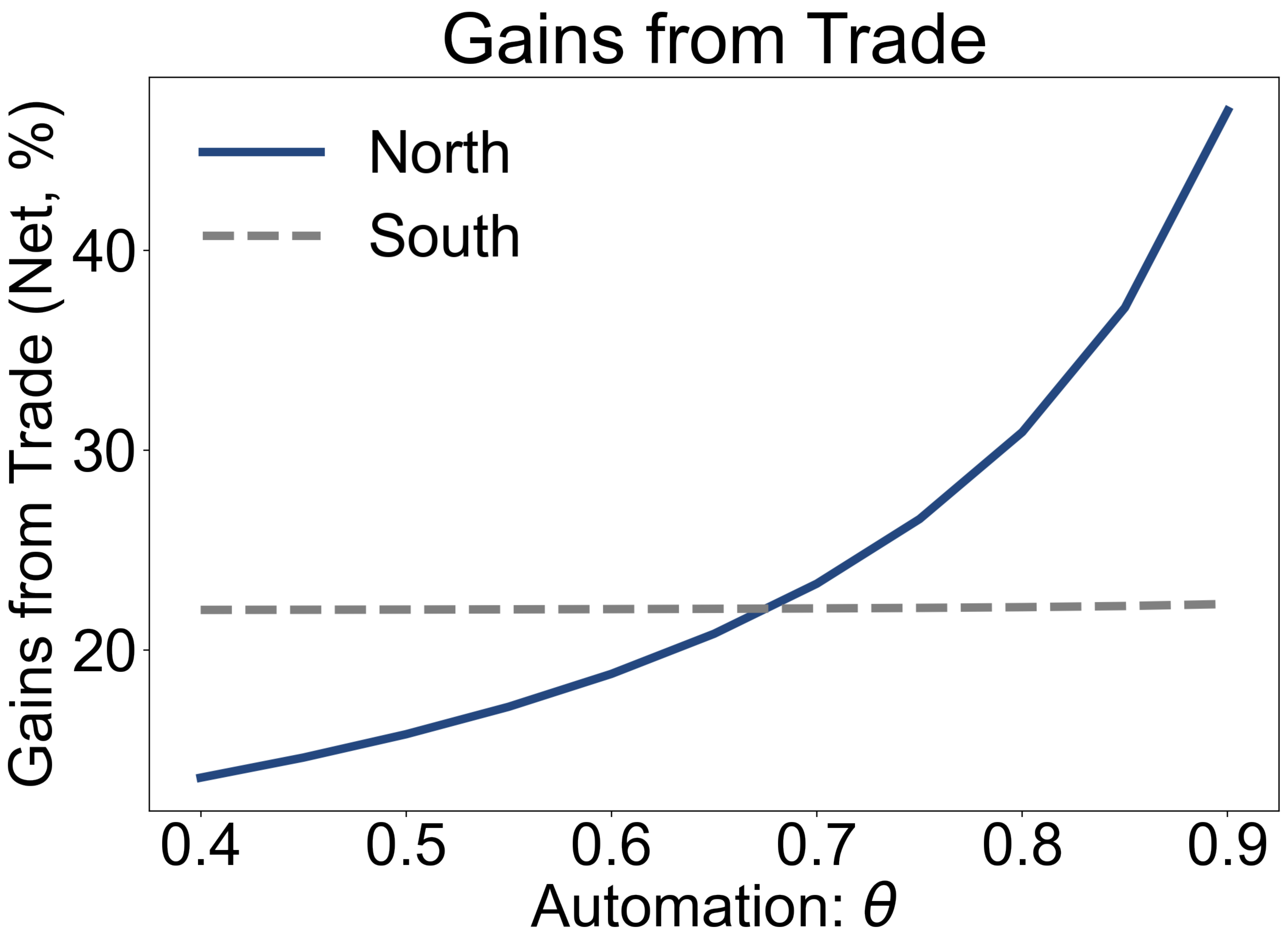
Implications for Growth and Inequality

Automation and Growth/Inequality

- Automation affects comparative advantage…

- This mechanism can also explain…
  - Gain from Trade (Welfare gains relative to autarky)
  - Cross-country Inequality (Income differences)
  - Within-country Inequality (Rise in skill premium)

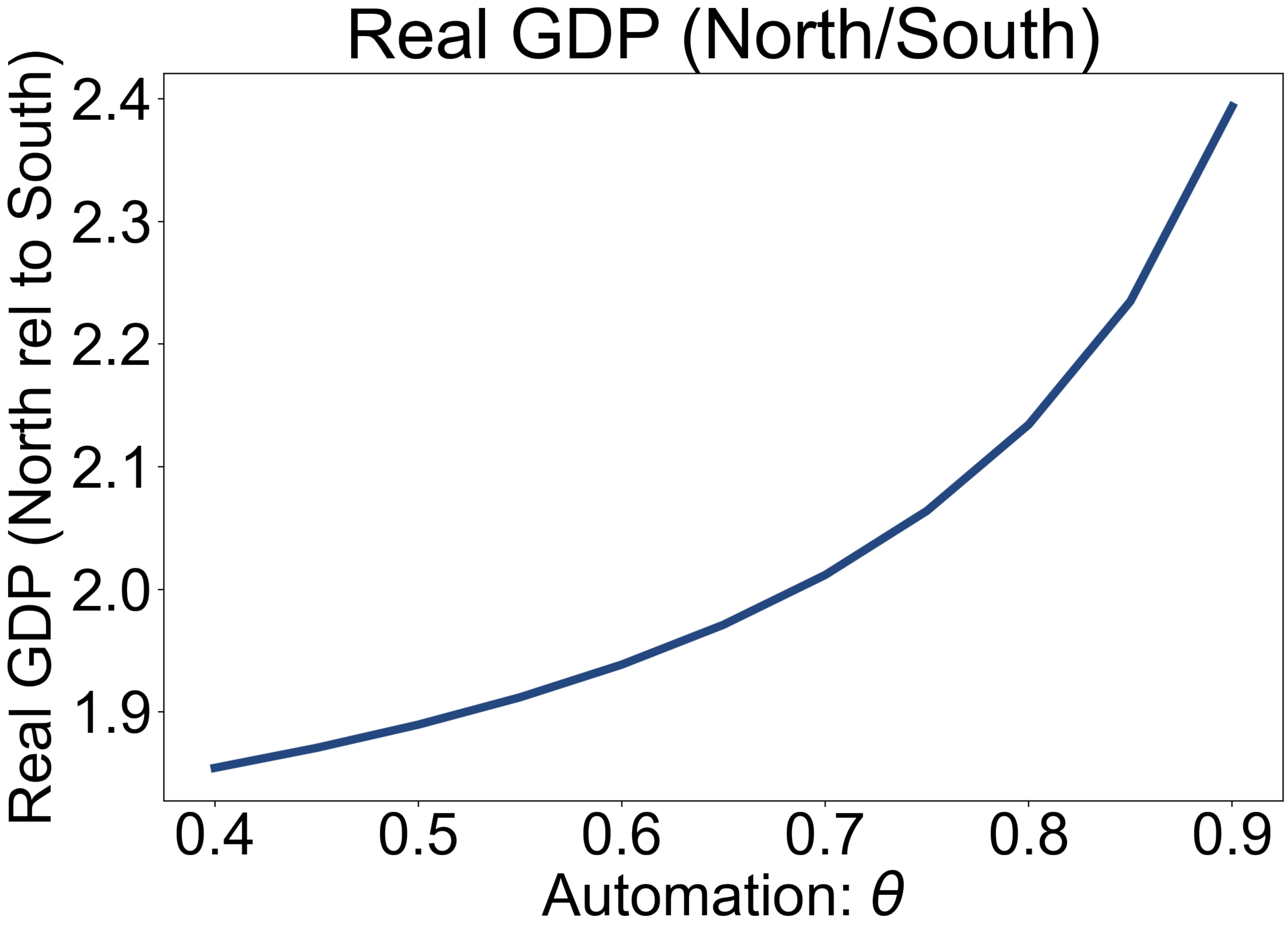
Automation Disproportionally Benefits North



High θ disproportionally increases GT of North

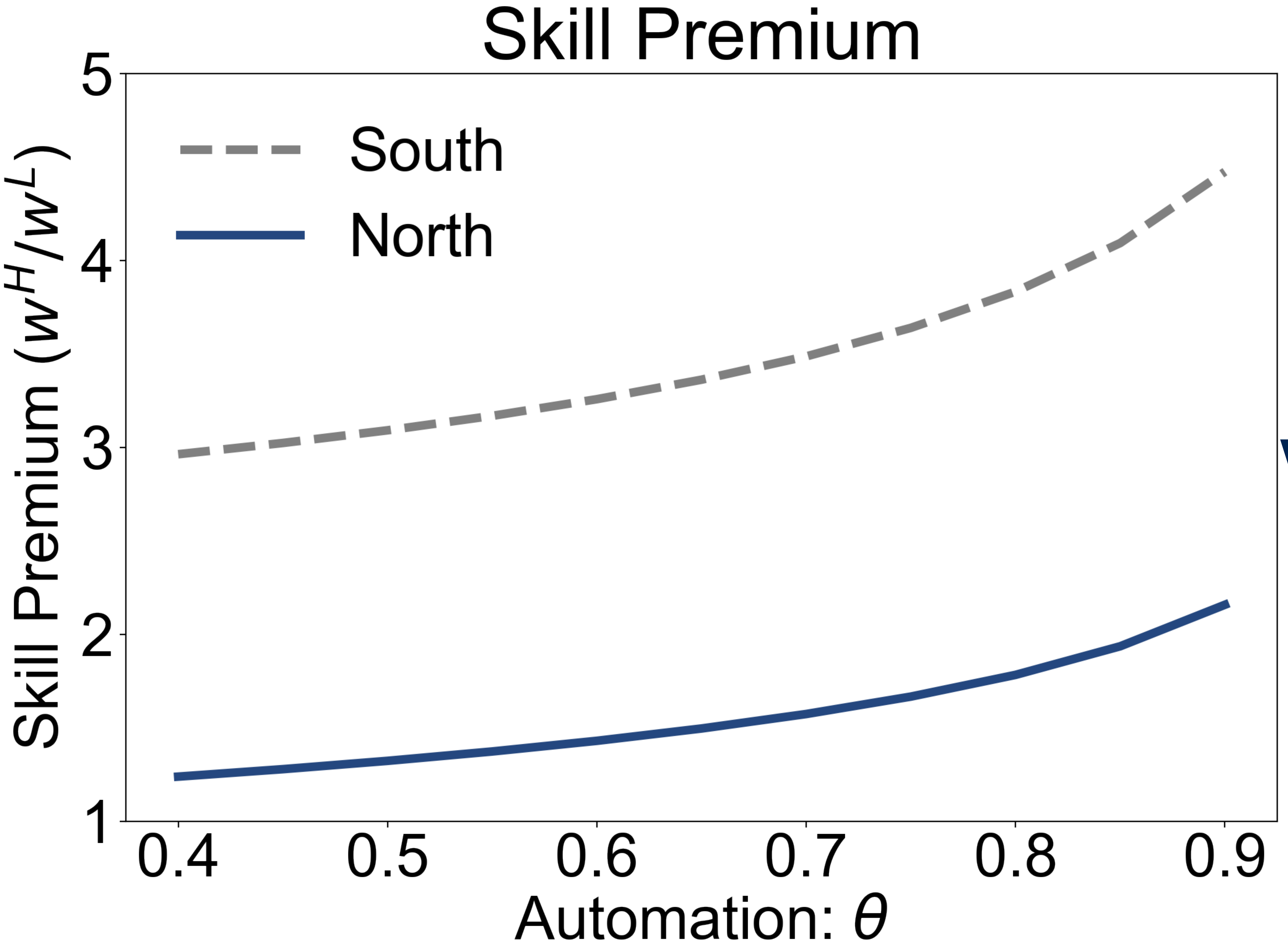
$$\textbf{Gain from trade} \equiv \frac{Welfare_{i,Trade}}{Welfare_{i,Autarky}}$$

Automation Amplifies Cross-Country Inequality



High θ expands across-country inequality

Automation Amplifies Within-Country Inequality



High θ expands within-country inequality

Endogenous Automation

Extension: Endogenous Automation Technology

- **Fact:** Only a few countries develop automation technology
  - Number of granted patents related to automation, 1990-2015, USPTO

Country	Share
USA	49%
Japan	26%
Germany	9%
South Korea	3%
Taiwan	2%

90% from Top 5

- **Theory:** Acemoglu-Restrepo (2022): “L-scarcity leads to automation”

Aggregate Production function

Production function

Intermediates supplied by monopolist, $(1-\eta)$ MC

$$Y_{i,s} = \frac{\eta^{-\eta}}{1-\eta} \left[\left(Y^P_{i,s}\right)^{\alpha^P_s} \left(H_{i,s}\right)^{1-\alpha^P_s} \right]^{\eta} \boxed{V(\theta_{i,s})}^{1-\eta}$$

$$Y^P_{i,s} = \left(\int_0^1 Y^P_{i,s}(\omega)^{\frac{\varepsilon-1}{\varepsilon}} d\omega \right)^{\frac{\varepsilon}{\varepsilon-1}}$$

$$Y^P_{i,s}(\omega) = K_{i,s}(\omega) + L_{i,s}(\omega) \text{ if } \omega \in [0,\theta_{i,s}]$$

$$Y^P_{i,s}(\omega) = L_{i,s}(\omega) \text{ if } \omega \in (\theta_{i,s},1]$$

Technology monopolist

- Let a technology monopolist in each (i, s) develops $\theta_{i,s}$ (no diffusion)
  - Monopoly pricing → Profit of $(1-\eta)/(2-\eta)c_{is}Y_{is}$
  - Assume cost to be proportional to profit (for algebra)
- Net profit

$$\frac{1-\eta}{2-\eta}(c_{is})^{2-\sigma}\big(1-\phi_i(\theta_{is})\big)\sum_j \frac{(\tau_{ijs})^{1-\sigma}}{\sum_l (c_{ls}\tau_{ljs})^{1-\sigma}}\mu_{js}\left(w_j^L L_j + w_j^H H_j + rK_j\right)$$

$\phi_i(\theta_{is})$:Cost function, convex

Comparative Statics: Endogenous Automation

- Profit maximization

Efficiency Gain

$$\max_{\theta_{is}\in[0,1]} \ln \pi^M(i) = \boxed{(2-\sigma)\ln c_{is}(\theta_{is})} + \ln(1-\phi_i(\theta_{is}))$$

- $\rightarrow$ Increasing differences in θ_{is} and w_i^L
  - More automation in L-scarce countries
- $\rightarrow$ Decreasing differences in θ_{is} and α_s^H
  - More automation in L-intensive sectors

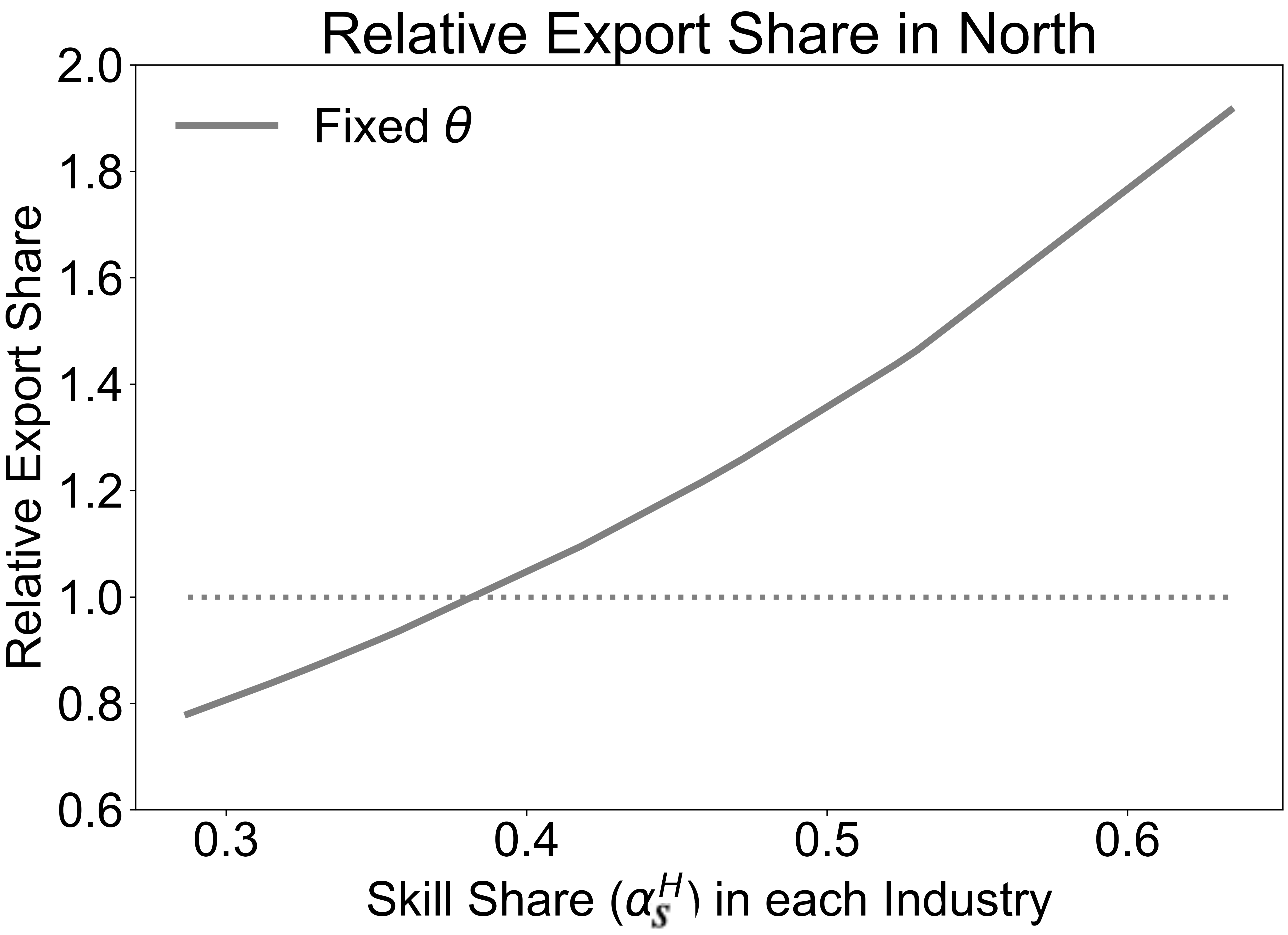
Counteract L-wage increases from L-scarcity

Two-Country Numerical Example

- Parametrize cost of automation to be $\phi_i(\theta) = 1 - (1 - \theta^2)^{\frac{1}{\rho_i}}$
  - Larger ρ_i : Easier to automate in country i (scientists, organizational capital)

- **Experiment: Ex-ante identical** North & South
  - Now, North becomes L-scarce: L-share from 80% to 70%
  - Benchmark: If L gets scarce, L-intensive sector shrinks (**Rybczyński**)
    - but technology was exogenous in these models…

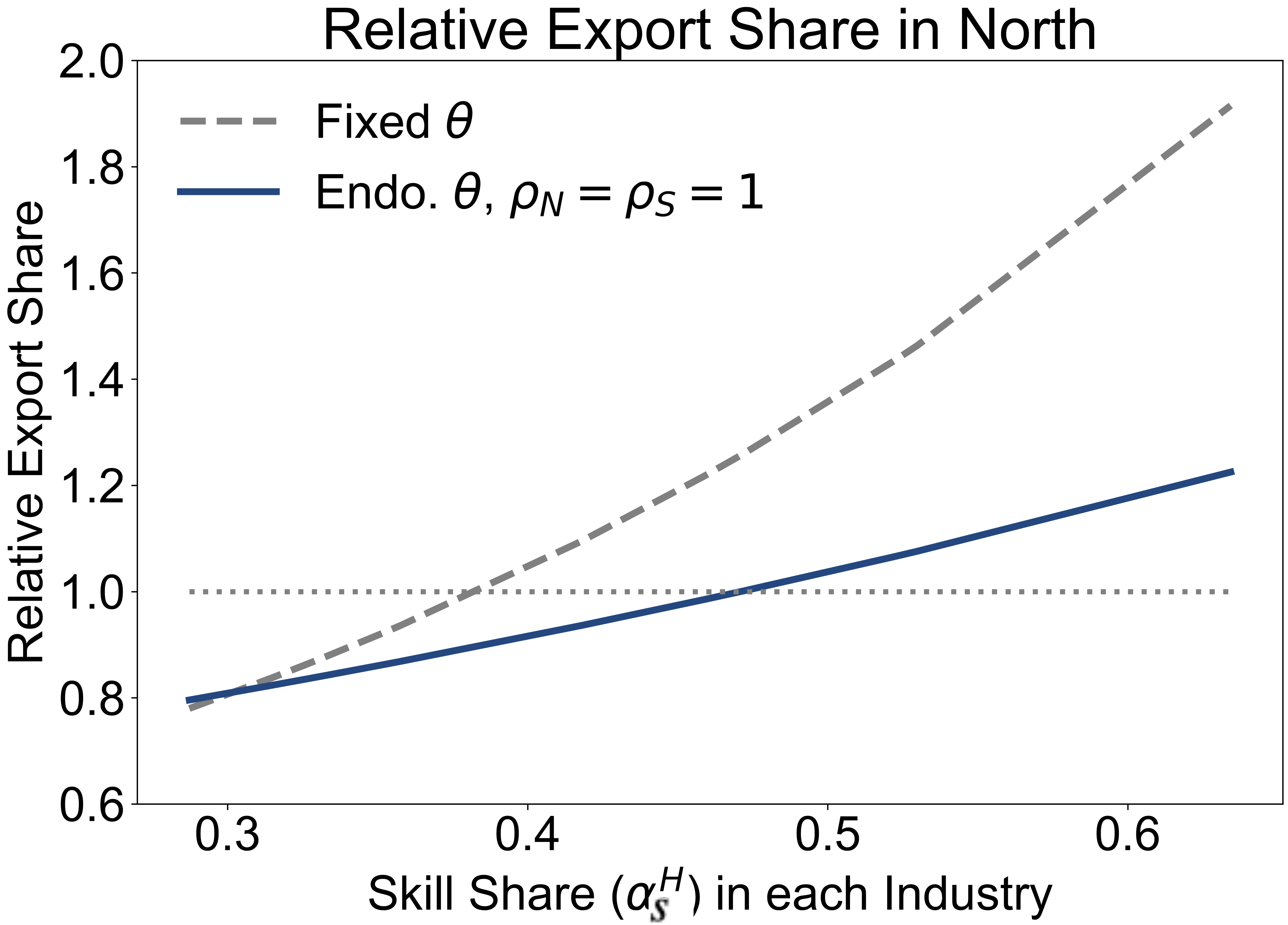
Rybczyński: L gets Scarce, Specialize in H-Intensive



As L gets scarce, North specialize in the H-intensive

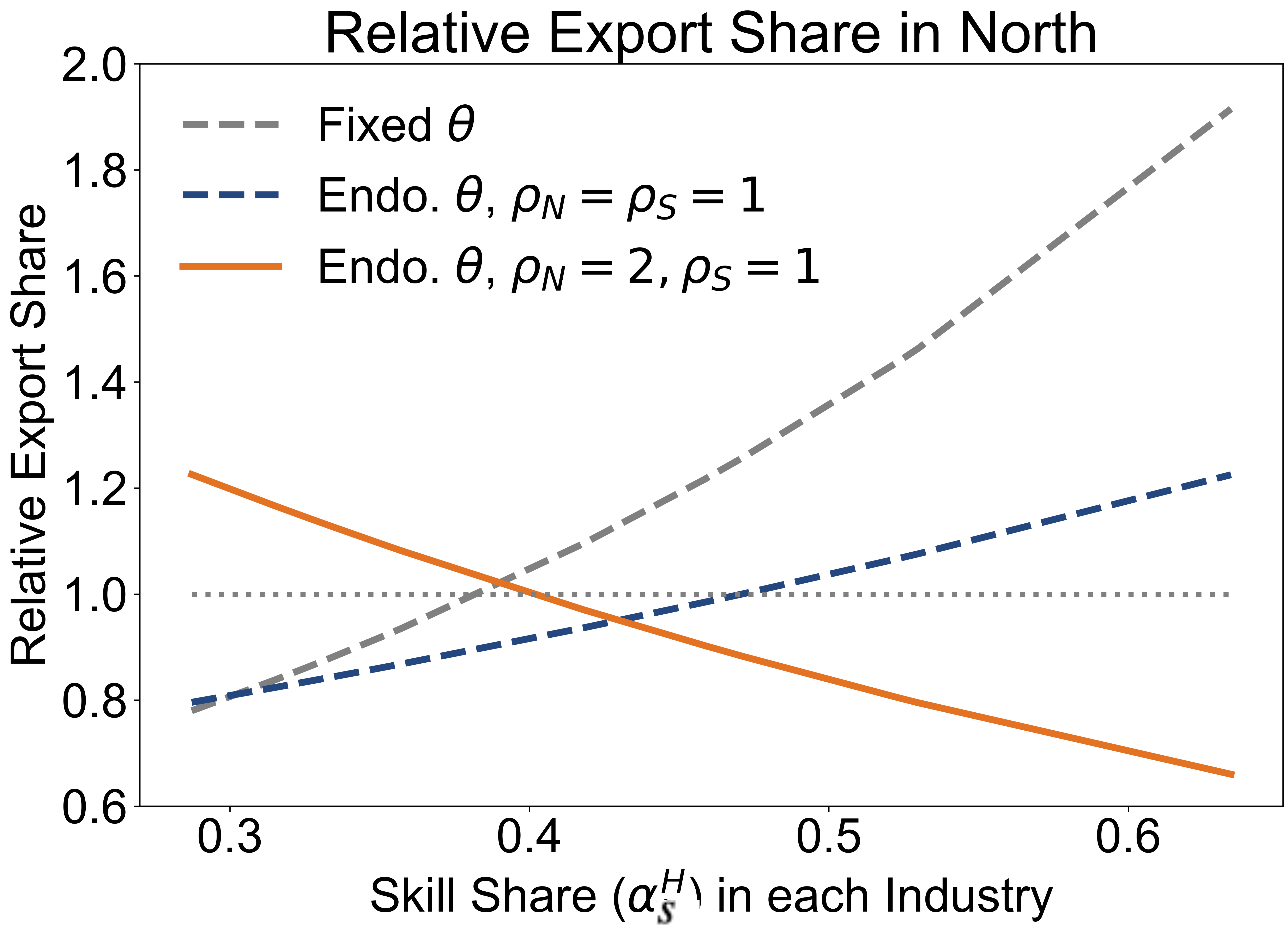
$$\textbf{Relative export share} \equiv \frac{\pi_{N,S,s}}{\pi_{S,N,s}}$$

Endogenous Automation Attenuates Rybczyński



Automation attenuates sectoral shifts

Endogenous Automation can Even Reverse Rybczyński



North gets L-scarce, but expands L-intensive sectors