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Demographic Origins of Premature Deindustrialization

Job Market Paper

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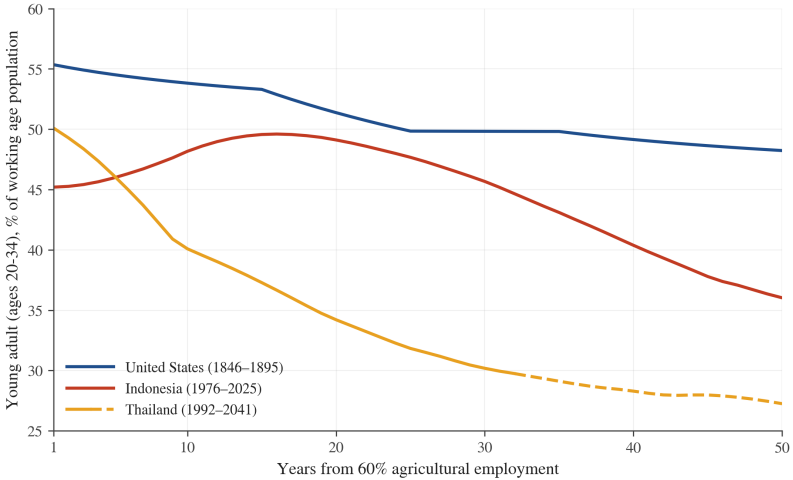
CEMFI

IMF-OECD-PIIE-WB Conference on Labor Markets, AI, and Demography

17th of November 2026

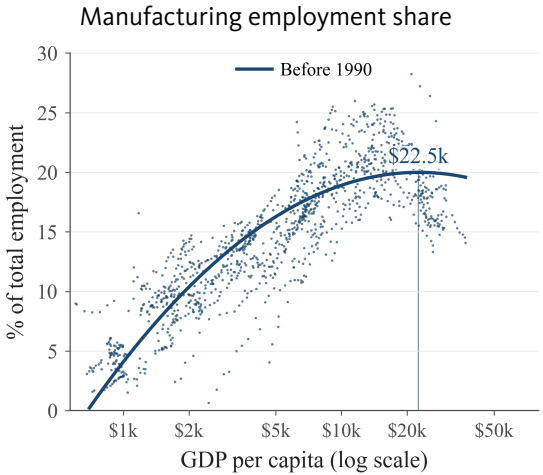
This project received the support of a fellowship from the "la Caixa" Foundation (ID 100010434), fellowship code LCF/BQ/DR23/12000010

Countries Are Industrializing with Older Workforces



Demographic timing

Does workforce aging give rise to premature deindustrialization?



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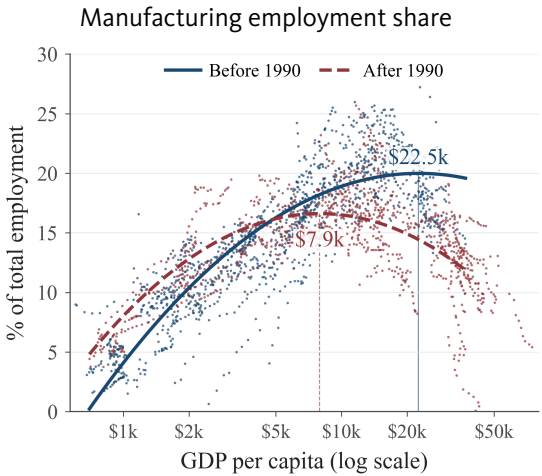

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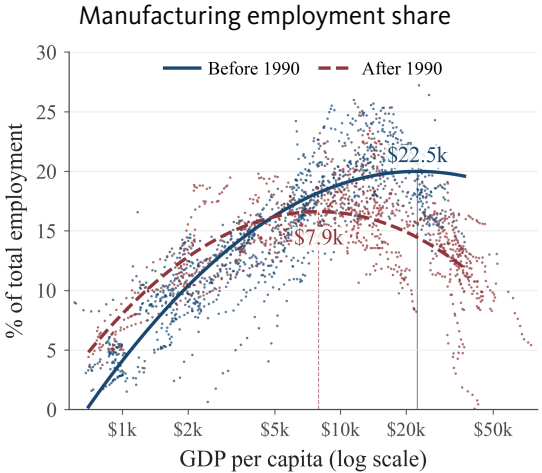

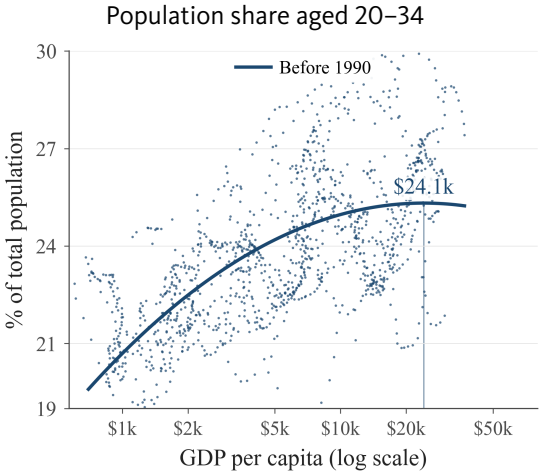

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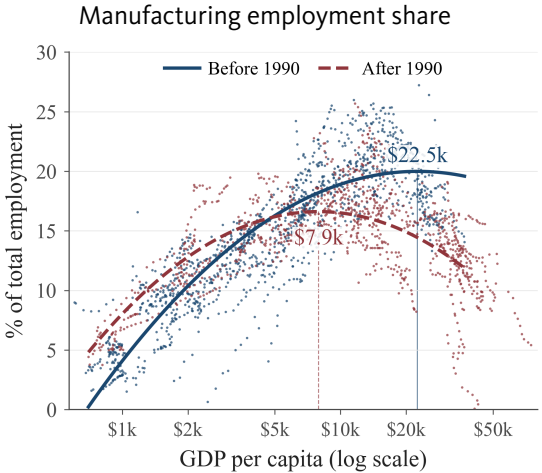
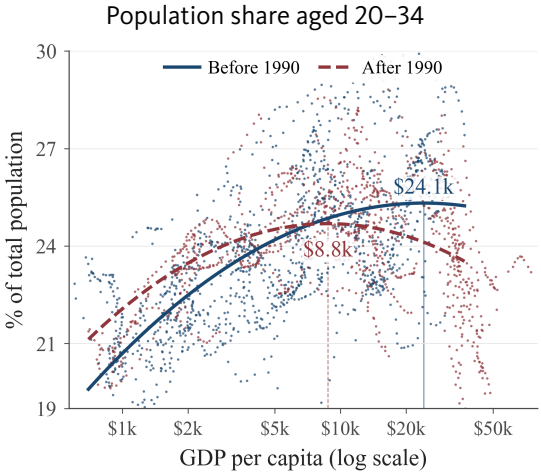
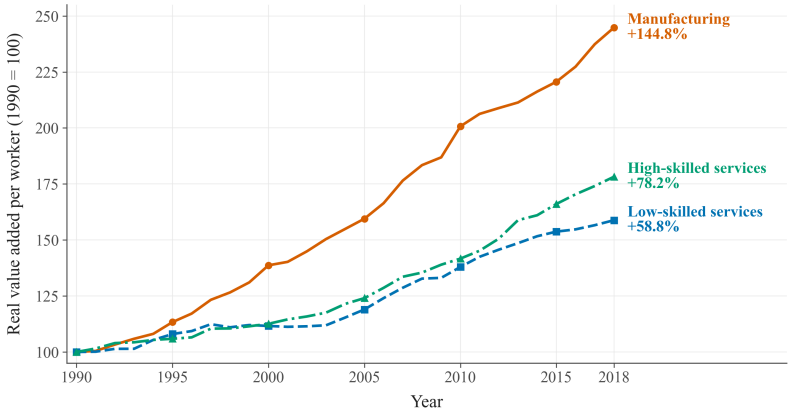




▸ Young adults

Why Muted Industrialization Matters



This paper:

Research question: Does workforce aging give rise to premature deindustrialization?

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- **Empirics**
  - → Both within cohorts & individual careers, probability of working in manufacturing declines sharply with age.
  - → External evidence on physical and cognitive aging, along with sectoral skill requirements, predict the observed life-cycle reallocation from manufacturing to services.

This paper:

Research question: Does workforce aging give rise to premature deindustrialization?

- **Empirics**
  - → Workers shift from manufacturing to services as they age, driven by changing comparative advantage.
- **Theory**
  - → Open-economy model of structural transformation, workers sort across sectors based on their abilities.
  - → Worker abilities depend on age, as well as permanent endowments and schooling.
  - → Sectors differ in how intensively they use each ability.
  - → Permanent components generate sectoral persistence; evolution of abilities with age induces switching.

This paper:

Research question: Does workforce aging give rise to premature deindustrialization?

- **Empirics**
  - → Workers shift from manufacturing to services as they age, driven by changing comparative advantage.
- **Theory**
  - → A theory of life-cycle worker sorting across sectors, based on abilities that evolve with age.
- **Quantification**
  - → Calibrate the model using data from Indonesia over five decades of industrialization (1976-2025).
  - → Period starts with agricultural employment > 60%, ends after manufacturing peak of 21.0% in 2019.
  - → What would Indonesia's industrialization look like under different demographics?
    - → With US demographics, manufacturing's employment peaks at 23.3%, with Thai demographics at 18.4%.
    - → Gap in cumulative growth in real output per worker between the two demographic paths is 20 pp.
    - → Export opportunities directly support industrialization impact of a younger workforce.

Contribution

- **Structural transformation:** sectoral productivity, demand and trade shape industrialization.

  Kongsamut et al. 2001; Caselli–Coleman 2001; Ngai–Pissarides 2007; Acemoglu–Guerrieri 2008; Foellmi–Zweimüller 2008; Matsuyama 2009; Duarte–Restuccia 2010; Buera–Kaboski 2012; Herrendorf et al. 2013; Boppart 2014; Rodrik 2016; Ngai–Petrongolo 2017; Teignier 2018; Cravino–Sotelo 2019; Comin et al. 2021; García-Santana et al. 2021; Fan et al. 2023; Huneeus–Rogerson 2024; Fujiwara–Matsuyama 2024; Sposi et al. 2026.

  → Introduce workforce aging as a novel driver of premature deindustrialization and quantify its importance.

Contribution

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- **Human capital and labor reallocation:** human capital and labor demand shape reallocation.

  Caselli–Coleman 2001; Autor–Dorn 2009; Gathmann–Schönberg 2010; Bustos et al. 2016; Lagakos et al. 2018a,b; Hobijn et al. 2018; Deming–Noray 2020; Dauth et al. 2021; Porzio et al. 2022; Duernecker–Herrendorf 2022; Donovan et al. 2023; Hanushek et al. 2025.

  → Document manufacturing-to-services reallocation over careers and trace this pattern to life-cycle changes in workers' productive abilities.

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  → Document manufacturing-to-services reallocation over careers and trace this pattern to life-cycle changes in workers' productive abilities.

- **Demographics and the macroeconomy:** demographic change affects labor supply and productivity.

  Becker et al. 1990; Bloom–Williamson 1998; Galor–Weil 2000; Bloom et al. 2003; Doepke 2004; Feyrer 2007; Fernández-Villaverde–Krueger 2011; Cai–Stoyanov 2016; Acemoglu–Restrepo 2022; Cravino et al. 2022; Maestas et al. 2023; Delventhal et al. 2024; Acemoglu et al. 2026; Peters–Walsh 2026; Kopecky 2026.

  → How age composition within the workforce shapes its allocation across sectors and output growth.

Contribution

- **Structural transformation:** sectoral productivity, demand and trade shape industrialization.
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- **Human capital and labor reallocation:** human capital and labor demand shape reallocation.
  - → Document manufacturing-to-services reallocation over careers and trace this pattern to life-cycle changes in workers' productive abilities.
- **Demographics and the macroeconomy:** demographic change affects labor supply and productivity.
  - → How age composition within the workforce shapes its allocation across sectors and output growth.
- **Worker sorting and labor-market dynamics:** heterogeneity & frictions shape allocation & earnings.

  Ohnsorge–Trefler 2007; Artuç et al. 2010; Lagakos–Waugh 2013; Lindenlaub 2017; Bárány–Siegel 2018; Caliendo et al. 2019; Lise–Postel-Vinay 2020; Guvenen et al. 2020.
  - → Develop a theory of life-cycle sorting across sectors: permanent relative strengths generate sectoral persistence, aging and wages in GE can induce switching.

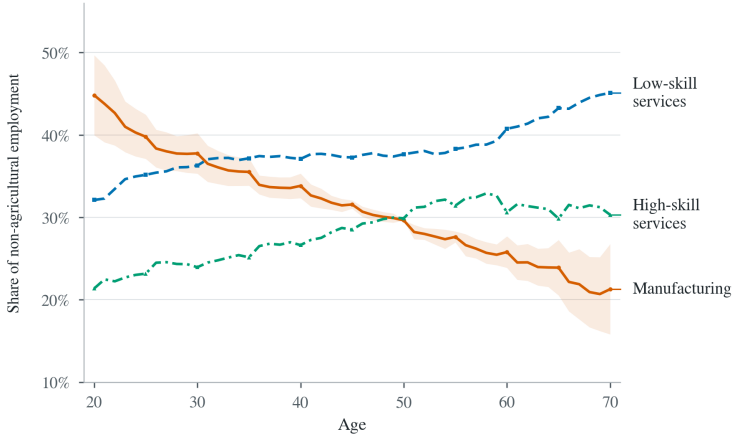
Manufacturing Employment Falls With Age; Services Rise

$$s^j_{c,t,a} = \sum_{a' \neq 50} \delta^j_{a'} \mathbf{1}[a = a'] + X'_{c,t,a}\beta^j + \gamma^j_1 \ln GDP_{ct} + \gamma^j_2 (\ln GDP_{ct})^2 + \mu^j_{c,b(t,a)} + \varepsilon^j_{c,t,a}.$$

- Worker-level data from repeated cross-sections covering 88 countries.
- $s^j_{c,t,a}$: sector j's share of non-agricultural employment at each age.
- Country$\times$five-year birth-cohort fixed effects separate fixed cohort differences.
- GDP per capita quadratic captures period variation along the development path.
- X: sex, urban residence, migration status, and schooling.

▸ Indonesia careers ▸ Total emp. ▸ Within man. ▸ Robustness ▸ Middle income

Manufacturing Employment Falls With Age; Services Rise



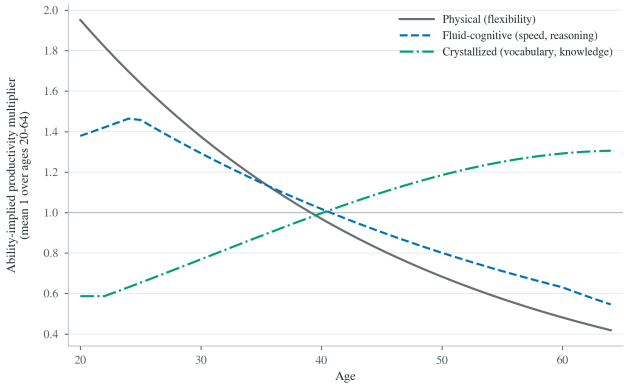
Manufacturing falls 20.9 pp between ages 20 and 64; both service sectors rise.

Here manufacturing includes utilities and construction.

▸ Indonesia careers ▸ Total emp. ▸ Within man. ▸ Robustness ▸ Middle income

External Ability Curves Recover the Shape of Sectoral Sorting

Ability profiles $\rho_k^{pub}(a)$



- Constructed from published evidence on aging.

O*NET sectoral requirements θ_{jk}

	Physical	Fluid	Cryst. & interp.
Manufacturing	.555	.315	.130
Low-skill services	.252	.302	.446
High-skill services	.044	.455	.501

- Constructed from O*NET's U.S. occupational ratings.
- θ_{jk} weights ability k in sector j's ability index; $\sum_k \theta_{jk} = 1$.

▸ Construction ▸ Robustness

External Ability Curves Recover the Shape of Sectoral Sorting

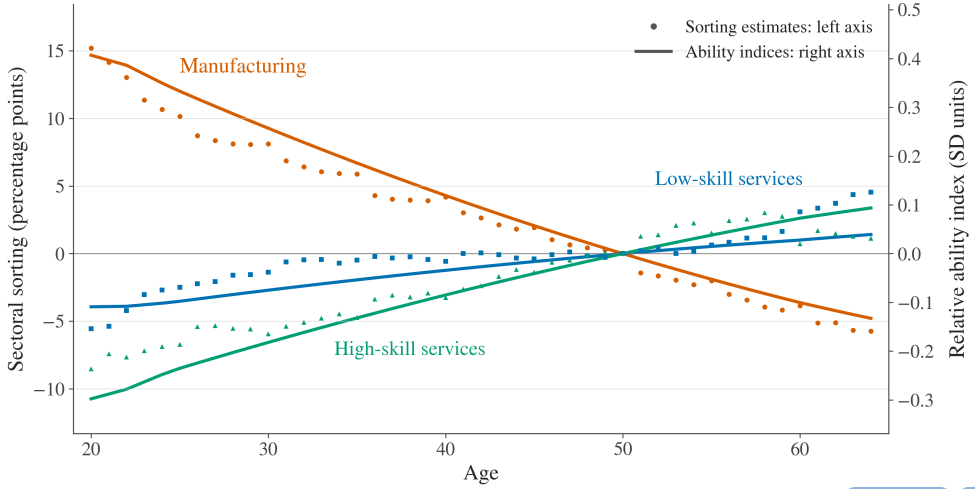
Relative sectoral ability indices, $j \in \{M, L, H\}$

$$\ell_j(a) = \sum_{k \in \{P,F,C\}} \theta_{jk} \rho_k^{\text{pub}}(a), \qquad r_j(a) = \ell_j(a) - \frac{1}{3} \sum_{h \in \{M,L,H\}} \ell_h(a).$$

- $\ell_j(a)$ weights ability profiles by sector requirements; $r_j(a)$ expresses these relative to the three-sector average.
- Compare the direction and shape of $r_j(a)$ with the employment–age effects estimated earlier, $\widehat{\delta}_a^j$.
- Both are relative to age 50: employment in percentage points, ability indices in weighted SD units.

▸ Construction ▸ Robustness

External Ability Curves Recover the Shape of Sectoral Sorting



Ability indices net of the three-sector average.

▸ Construction ▸ Robustness

From Individual Employment Choices to Structural Change

So far:

- Documented a pronounced age pattern in worker's sectoral choices.
- Traced this pattern to the interaction between age-varying abilities and sector-specific requirements.

How do these individual choices affect employment by sector and output in general equilibrium?

- Develop a theory of worker sorting across sectors over the life cycle based on age-varying abilities.
- Embed this in a quantitative model of structural transformation

▸ Aggregate panel ▸ Openness panel ▸ Demand evidence

A Life-Cycle Model of Structural Transformation

- Four sectors: agriculture (A), manufacturing (M), low- and high-skill services (L, H).
- Ages 20–89; individuals work through age 64. The age distribution $\pi_t(a)$ is exogenous.
- The dynasty pools resources and chooses cohort-specific consumption.
- Sectoral productivity, non-homothetic demand, and international trade drive structural change.

$$\sum_{a=20}^{89} \pi_t(a) = 1, \qquad q_t(a) = \frac{\pi_{t+1}(a+1)}{\pi_t(a)}. \qquad L_t = \sum_{a=20}^{64} \pi_t(a),$$

L_t: workers relative to the model population aged 20–89.

Ability Aging and Sectoral Choice

- Worker i has three abilities k: physical (P), fluid-cognitive (F), crystallized-and-interpersonal (C).
- Productivity $z_i(a, j)$ in sector j is a Cobb-Douglas combination of these abilities.

  $\rightarrow$ Same worker abilities mapped into different productivities across sectors with θ_{jk}.

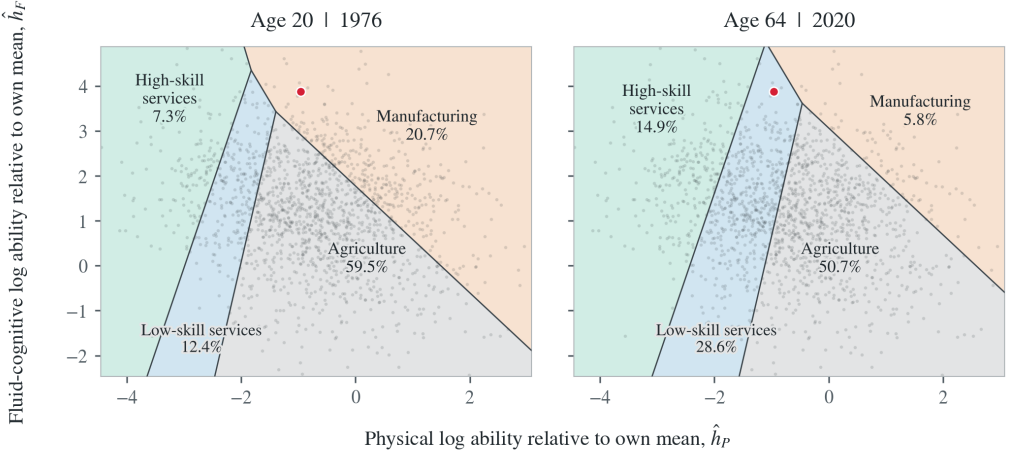
- Each log ability combines a common age profile $f_k(a)$ with a worker-specific permanent intercept $\nu_{ik} + \alpha_k s_i$, where s_i is years of schooling.

$$\log z_i(a, j) = \sum_k \theta_{jk} \left[\underbrace{f_k(a)}_{\substack{\text{common} \\ \text{age profile}}} + \underbrace{\nu_{ik} + \alpha_k s_i}_{\substack{\text{permanent} \\ \text{worker differences}}} \right].$$

- Aging changes a worker's relative productivity across sectors; together with equilibrium wages, this determines the best-paying sector.

▸ Schooling ▸ Comparative advantage

Careers Are Regions in Ability Space



- Same worker: manufacturing at 20, low-skill services at 64

Illustration with costless sectoral switching.

Aggregate Sectoral Employment

Here, $j_i^*(a,t)$ denotes the optimal forward-looking sectoral choice.

$$L_{j,t} = \sum_{a=20}^{64} \pi_t(a)\ \Pr(j_i^*(a,t) = j \mid a,t)\,, \qquad \text{headcount employment,}$$

$$N_{j,t} = \sum_{a=20}^{64} \pi_t(a)\, \mathbb{E}[z_i(a,j)\mathbf{1}\{j_i^*(a,t) = j\} \mid a,t]\,, \qquad \text{effective labor.}$$

- Employment counts workers. Effective labor weights them by productivity in their chosen sector.
- Overall ability cancels from sectoral comparisons but still matters for production.
- The model includes a cost of leaving agriculture $\kappa_A(a)$ proportional to worker earnings.

▸ Worker problem ▸ Sorting with exit costs ▸ Derivation

Preferences, Production, and Trade

- Demand: non-homothetic CES preferences à la Comin et al. (2021):

$$\sum_{j \in \{A,M,L,H\}} \Omega(a,j)^{1/\sigma} \left[\frac{c_{j,t}(a)}{\mathcal{C}_t(a)^{\iota_j}} \right]^{\frac{\sigma-1}{\sigma}} = 1.$$

- ι_j governs income effects; σ governs substitution as relative prices change.
- Age-specific tastes $\Omega(a,j)$ allow spending patterns to differ at given expenditure and prices.
- Production:

$$Y_{j,t} = A_{j,t} N_{j,t}, \qquad w_{j,t} = p^d_{j,t} A_{j,t}$$

- Trade: Households buy domestic and foreign varieties.
- Agriculture and manufacturing export at world prices; downward-sloping foreign demand in services.

▸ Demand details ▸ Durables extension ▸ Trade ▸ Equilibrium

Data and Calibration: Worker Sorting

Indonesia. Calibration period: 1976–2025.

Worker and household microdata

- **Indonesia Family Life Survey (IFLS), 1993–2014:** five panel waves with employment, earnings, schooling and household expenditure (main source of data).
- **IPUMS-I Indonesia 1976–2010:** sectoral employment and cohort schooling (repeated cross-sections).

Population and the aggregate economy

- **UN World Population Prospects:** population by age.
- **GGDC and BPS:** sectoral employment, value added, prices and aggregate expenditure.
- **BACI, NBER–UN, WTO, OECD–WTO BaTIS and OECD ICIO:** sectoral trade flows and input–output tables.

External inputs, held fixed

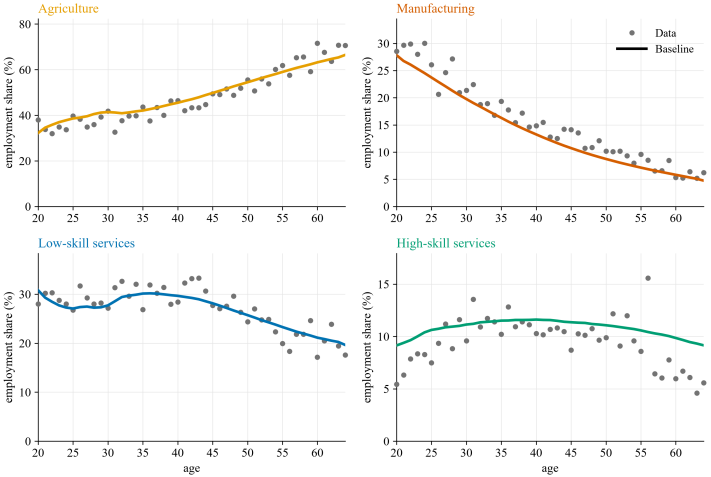
Age–ability profiles $f_k(a)$	Published evidence on ability aging.
Sector ability weights θ_{jk}	O*NET ability requirements.
Cohort schooling distributions	IFLS and IPUMS.

Joint calibration to Indonesian microdata

- Schooling loadings α_k, permanent-ability covariance Σ_0, and agricultural exit costs $\kappa_A(a)$.
- Targets: schooling–earnings relationships, sectoral employment patterns across ages and cohorts.
- $(\alpha_P, \alpha_F, \alpha_C)$ = (0.01,0.30,0.03); $\kappa_A(a) \in$[0.16,1.01] years of earnings, practically monotonic in age.

▸ Calibration details ▸ Demand, productivity and trade

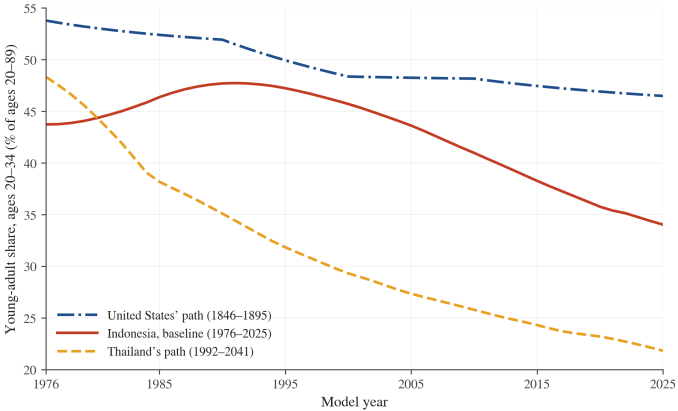
Model Fit: Employment Across Ages



Dots: IFLS, 1993, 1997 and 2000. Lines: baseline, pooled over 1976–2025.

▶ Beyond age profiles

Counterfactuals Isolate Age Structure



- **Three paths:** USA, IDN, THA.
- Last year agriculture accounted for > 60% of employment → 1976
- Replace *only* $\pi_t(a)$; hold all other Indonesian primitives fixed.
- Each economy solved in GE.

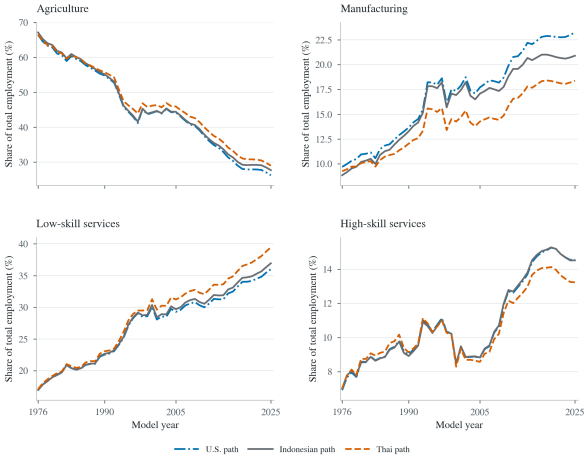
Demographic Timing Shapes Industrialization

Manufacturing share of employment (%)

Path	Peak	Mean
U.S.	23.3	17.1
Indonesia	21.0	16.1
Thailand	18.4	14.2

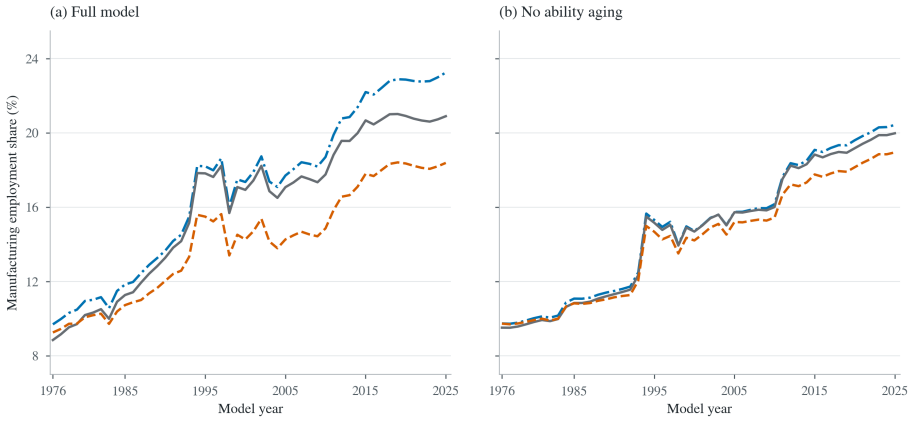
Real output per capita at peak
Indonesia = 100

Path	Peak year	Index
U.S.	2025	121.7
Indonesia	2019	100
Thailand	2019	77.6



Life-Cycle Sorting Drives the Manufacturing Response

- No ability aging: set the age component of productivity to the same constant across ages and sectors.



- The gap between U.S. and Thai manufacturing peaks falls from 4.84 to 1.48 pp.

▸ Channels ▸ Sectoral allocation

Younger Demographics Raise Growth and Living Standards

U.S.–Thailand gap in cumulative real output growth, 1976–2025 (pp)

	Full	No ability aging
Output per worker	19.5	8.6
Output per capita	99.6	93.5

- Removing ability aging more than halves the output-per-worker growth gap.
- Output per capita gap primarily driven by differences in employment per capita.

Living standards:

- 22.1% more spending required each year to give the economy with Thai demographics the living standards achieved under U.S. demographics.

▸ Consumption and welfare

Export Opportunities Support Manufacturing Specialization

- How much do baseline results rely on export opportunities?
- Compare price-taking exports in agriculture and manufacturing (baseline) to downward-sloping demand.
- Moreover, in the baseline, age groups also differ in spending preferences $\Omega(a, j)$.
- No ability aging retains these taste differences. Neither also removes them $\Omega(a, j) = \overline{\Omega}(j)\ \forall a$.

U.S.–Thailand gaps in manufacturing employment shares (pp)

	Export conditions	Full	No ability aging	Neither
Peak	Price-taking goods exports	4.84	1.48	1.32
	Downward-sloping demand	3.11	0.98	0.35
Mean	Price-taking goods exports	2.86	0.68	0.60
	Downward-sloping demand	1.99	0.55	0.27

- Domestic spending matters more when export expansion is constrained.

▸ Manufacturing exports ▸ Durables comparison ▸ Openness empirics

Can Higher Schooling Offset the Effects of Aging?

- Raise mean schooling for Thai-path cohorts entering the workforce after 1976.

Additional schooling (years)	Output per capita in 2025 (U.S. = 100)	Manufacturing employment share at peak		High-skill services employment share at peak	
		Thai (%)	U.S.–Thai gap (pp)	Thai (%)	U.S.–Thai gap (pp)
0	70.0	18.41	4.84	14.12	+1.13
3.2	100.0	19.17	4.08	16.57	-1.32
5.0	123.0	19.59	3.66	18.15	-2.90

- Higher schooling raises productivity and employment in high-skill services.
- Even five extra years close only about one quarter of the manufacturing gap.

▸ Schooling details

Aging Shapes the Path of Industrialization

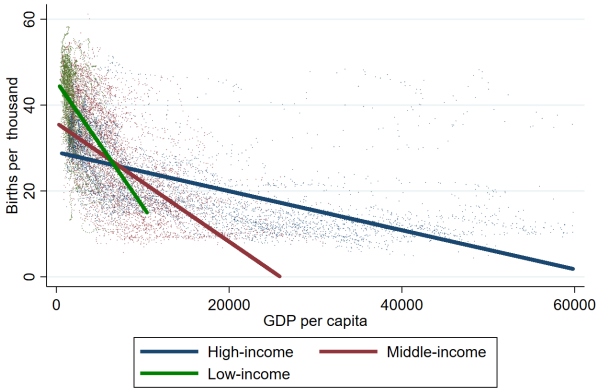
What the paper shows

- Workers move from manufacturing toward services as they age, consistent with shifting comparative advantage.
- Demographics alone make the calibrated Indonesian economy industrialize much further and grow faster.
- Life-cycle worker sorting drives most of this pattern.
- Export opportunities amplify the manufacturing advantage of a younger workforce.
- Workforce aging during structural transformation gives rise to premature deindustrialization.

Thank you for your attention!

Aging Now Arrives Earlier in Development

- Peak young-adult (25–34) share occurs at mean GDP per capita:
  - $30,566 in high-income economies
  - $9,531 in middle-income economies
  - $4,635 in low-income economies
- Economies aging at income levels associated with early manufacturing expansion.

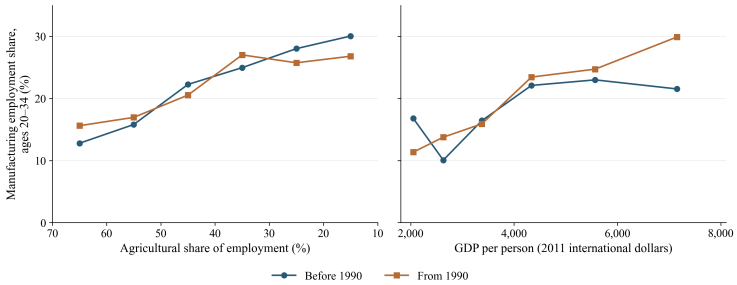


Births per thousand by GDP per capita; income groups based on 2010 GDP per capita.

Back

Young adults' manufacturing employment across periods

Compare manufacturing employment shares among 20–34-year-olds at similar development stages.

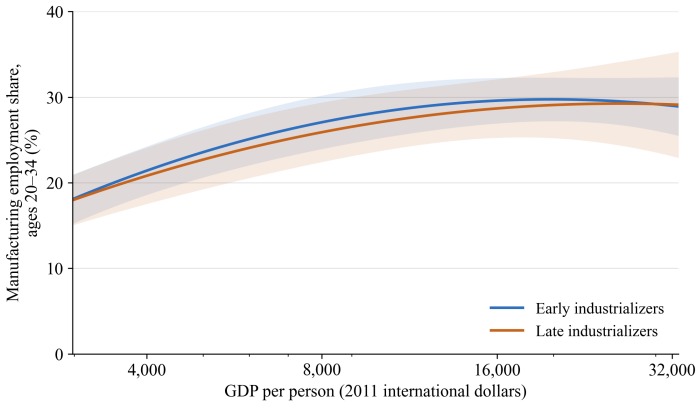


- Following Rodrik (2016), compare before 1990 with from 1990.
- Average manufacturing shares: 22.31% vs. 22.11% at comparable agricultural employment shares; 18.32% vs. 19.85% at comparable incomes.

Low/middle-income sample: 63 countries for agriculture, 49 for income. Within ranges, country means are weighted by young employment in the country's first census. Reported overall shares weight the six common ranges equally. Agriculture shares use ages 20–64; GDP is in 2011 international dollars.

Back

Young adults in early and late industrializers

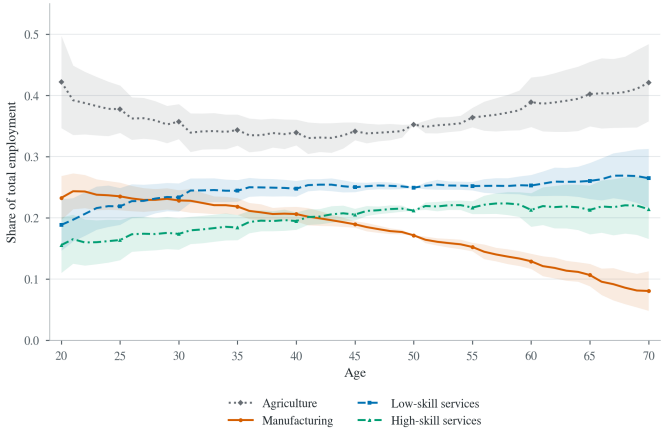


- Classify countries by their manufacturing employment peak.
  - **Early:** peak up to 1990.
  - **Late:** remaining countries.
- Compare shares among 20–34-year-olds at same income.
- Very similar profiles.

268 censuses, 77 countries; recorded national peak at least 10%. Separate quadratics in log GDP per capita, common quadratic in log population, no country FE; equal total weight per country. Population held at its median. Shading: country-clustered 95% intervals. Manufacturing includes utilities/construction; denominator: records with reported industry at ages 20–34. Income axis uses logarithmic spacing.

Back

Within-Cohort Age Profiles: Shares of Total Employment



Manufacturing's share falls 12.1 pp between ages 20 and 64.

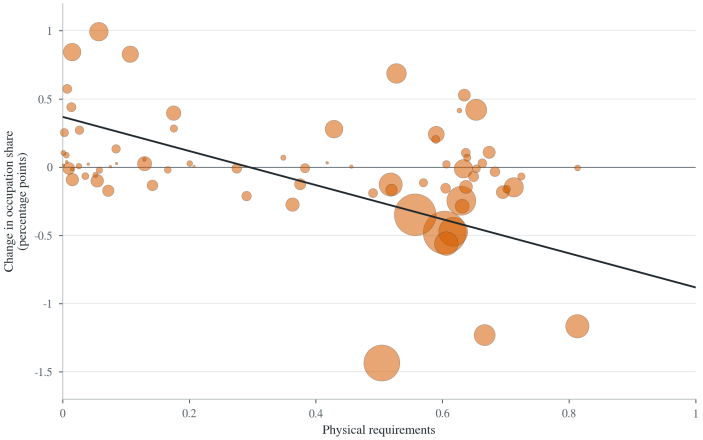
Same specification as the main age profiles; agriculture is included in the employment denominator.

Back

Occupational change within manufacturing

Within manufacturing, more physically demanding occupations tend to lose employment share as cohorts age.

→Follow age groups as they grow older between censuses (4–15 years apart).



- **Textile, fur and leather machine operators**:
  → Share of cohort employment falls 1.17 pp or 36% between censuses.
- **General managers**:
  → Share of cohort employment rises 0.99 pp or 49% between censuses.

Back

Manufacturing's Youth Is Not a Growth Artifact

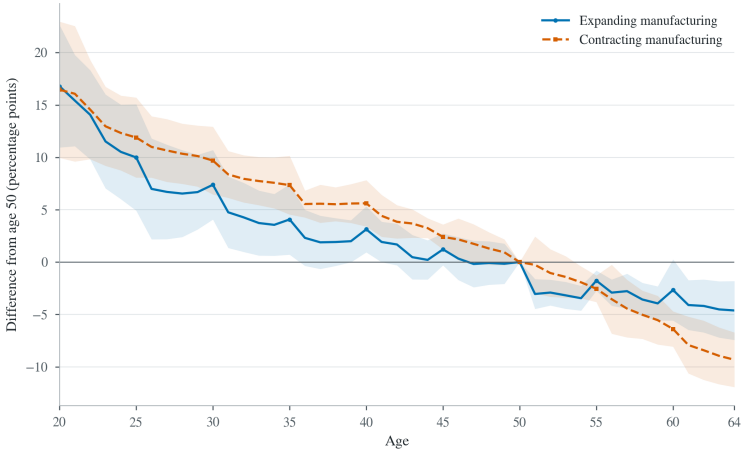
Estimate the main age-profile specification separately in expanding and contracting manufacturing:

$$s^{M}_{c,t,a} = \sum_{a' \neq 50} \delta_{a'} \mathbf{1}[a = a'] + X'_{c,t,a}\beta + \gamma_1 \ln GDP_{ct} + \gamma_2 (\ln GDP_{ct})^2 + \mu_{c,b(t,a)} + \varepsilon_{c,t,a}.$$

- Classify country–census years by the trailing ten-year slope of manufacturing's share of total employment (GGDC): above $+0.5$ pp per decade for expansion, below -0.5 for contraction.
- Same census cells, controls and country $\times$ five-year cohort effects as the main profiles; total-employment weights and country-clustered standard errors.
- Manufacturing's share of non-agricultural employment falls from ages 20 to 64 in both groups: 21.4 pp in expansion and 25.8 pp in contraction.
- Services grow faster but employ older workers: the hiring-growth benchmark predicts the opposite age ordering.

Back

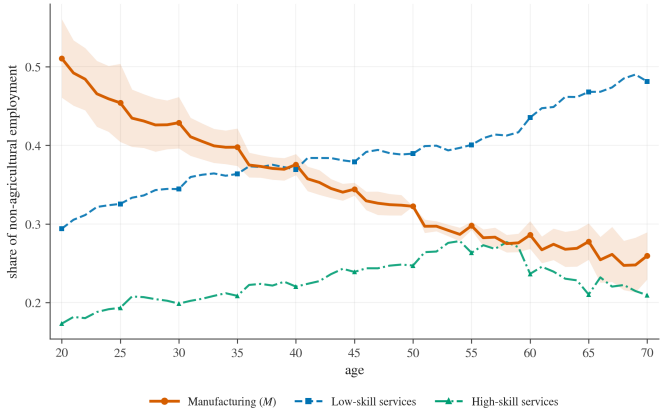
Manufacturing's Youth Is Not a Growth Artifact



Age effects relative to age 50, in percentage points of non-agricultural employment; 95% confidence intervals.

Back

Within-Cohort Age Profiles: Middle-Income Countries



Manufacturing's share of non-agricultural employment falls 24.1 pp between ages 20 and 64.

Same specification as the main profiles; 40 countries with 2010 GDP per capita above 10% and at most 45% of the U.S. level.

Back

Same Reallocation Within Workers' Careers in Indonesia

$$\mathbf{1}\{s_{i,q+1} = k\} = \alpha^{jk} + \sum_{a \neq 25\text{–}34} \beta_a^{jk} D_{ia} + X_i' \gamma^{jk} + \lambda^{jk}_{p(i),q} + \varepsilon_i^{jk}, \quad s_{iq} = j.$$

- Worker panel: same individuals across consecutive Indonesia Family Life Survey (IFLS) waves q and q+1 (1993–2014; interviews 3–7 years apart).
- Province $\times$ wave-pair effects absorb local structural change: compare workers in the same province and interval.
- Controls: sex, education, urban residence. Nonagricultural employment at both interviews.

Same Reallocation Within Workers' Careers in Indonesia

$$\mathbf{1}\{s_{i,q+1} = k\} = \alpha^{jk} + \sum_{a \neq 25\text{–}34} \beta_a^{jk} D_{ia} + X_i' \gamma^{jk} + \lambda^{jk}_{p(i),q} + \varepsilon_i^{jk}, \quad s_{iq} = j.$$

- Worker panel: same individuals across consecutive Indonesia Family Life Survey (IFLS) waves q and q+1 (1993–2014; interviews 3–7 years apart).
- Province × wave-pair effects absorb local structural change: compare workers in the same province and interval.
- Controls: sex, education, urban residence. Nonagricultural employment at both interviews.

Predicted transition probabilities between waves (%)

Origin age	Manufacturing → Services	Services → Manufacturing
20–24	28.7	12.2
25–34	32.3	9.2
35–44	36.0	6.4
45–54	38.9	4.6
55–64	34.4	4.4

▸ L/H split ▸ Retention checks ▸ Wages ▸ Back

Indonesia: Transitions by Service Sector

Predicted transition probabilities between interviews (%)

	Age at origin				
Transition	20–24	25–34	35–44	45–54	55–64
$M \to L$	26.0 (1.6)	29.8 (1.1)	33.4 (1.4)	36.5 (2.1)	30.7 (3.4)
$M \to H$	2.7 (0.6)	2.5 (0.4)	2.6 (0.5)	2.4 (0.6)	3.7 (1.1)
$L \to M$	13.1 (1.0)	10.1 (0.5)	7.6 (0.5)	5.7 (0.6)	5.4 (0.9)
$L \to H$	4.6 (0.7)	4.8 (0.3)	5.5 (0.4)	6.5 (0.6)	5.5 (0.6)
$H \to M$	4.7 (1.6)	3.0 (0.6)	2.1 (0.5)	1.3 (0.6)	2.8 (2.5)
$H \to L$	31.5 (3.2)	21.8 (1.3)	18.3 (1.3)	16.8 (1.8)	36.9 (5.8)
H-origin observations	250	1,021	1,064	546	82

L: low-skill services; H: high-skill services. IFLS 1993–2014; intervals of 3–7 years.
Employed outside agriculture at both interviews; worker-clustered SEs in parentheses.

The rise in manufacturing-to-services transitions through middle age is concentrated in low-skill services.

Back

Indonesia: Manufacturing Retention

$$R_i^M = \alpha + \sum_{a \neq 25\text{-}34} \beta_a^R D_{ia} + X_i' \gamma^R + \delta \Delta M_{p(i),q(i)}^{-i} + \lambda_{q(i)}^R + \varepsilon_i^R.$$

- $R_i^M = 1$ if a manufacturing worker remains there at the next interview.
- Allow any employed destination, including agriculture.
- Control for the province's manufacturing-share change, excluding worker i, and wave-pair effects.

Retention differences relative to ages 25–34 (pp)

Origin age	20–24	35–44	45–54	55–64
Retain manufacturing	2.5	-5.0^{***}	-7.7^{***}	-8.4^{**}
	(2.0)	(1.7)	(2.3)	(3.5)

X_i: sex, education and urban residence. Origin ages 20–64; IFLS 1993–2014, intervals of 3–7 years. Origin-person weights; worker-clustered standard errors in parentheses.

Back

Indonesia: Retention in Manufacturing and Services

$$R_i = \sum_{a \neq 25\text{–}34} \beta_a^{MS}(M_i D_{ia}) + X_i'\gamma^{MS} + \phi_{s(i),p(i),q(i)} + \psi_{a(i),p(i),q(i)} + \varepsilon_i^{MS}.$$

- $R_i = 1$ if the worker stays in the origin sector; $M_i = 1$ for a manufacturing origin.
- ϕ: each sector has its own retention conditions within each province and interval.
- ψ: each age group has its own retention conditions within each province and interval.

Manufacturing-minus-services retention gap, relative to ages 25–34 (pp)

Origin age	20–24	35–44	45–54	55–64
Change in retention gap	5.8^{**}	-5.5^{***}	-8.9^{***}	-2.7
	(2.3)	(1.9)	(2.4)	(3.6)

Manufacturing or services at both interviews; origin ages 20–64. Sex, education and urban controls; origin-person weights; worker-clustered standard errors. IFLS 1993–2014, intervals of 3–7 years.

Back

Indonesia: Within-Worker Wage–Age Profiles

Estimate separately by sector j:

$$\log w_{it} = \sum_{g \neq 20\text{–}24} \beta_g^j \mathbf{1}[a_{it} \in g] + \alpha_i^j + \lambda_t^j + \varepsilon_{it}^j.$$

- Five-year age bands; worker fixed effects α_i^j and sector-specific wave effects λ_t^j.
- IFLS waves: 1993, 1997, 2000, 2007 and 2014; workers aged 20–64.
- Full-time work (≥ 30 hours/week); at least two usable earnings observations in the sector, not necessarily consecutive.
- Real hourly earnings: monthly salary or business earnings, divided by weekly hours $\times 52/12$, in 2010 rupiah.
- Within-wave 1st/99th-percentile trimming among full-time workers, before age and sector restrictions; person weights.
- Plotted index: $\exp(\widehat{\beta}_g^j)$, with ages 20–24 normalized to one.

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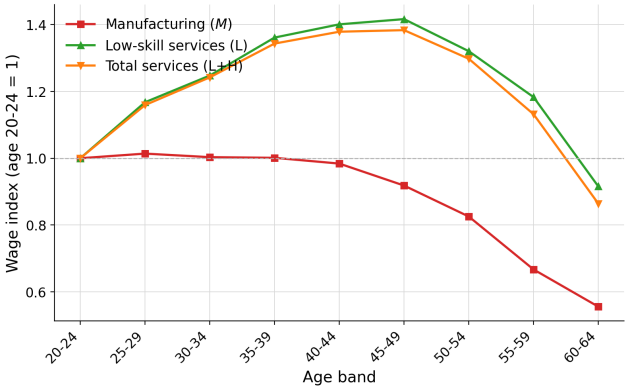
Indonesia: Within-Worker Wage–Age Profiles



Services wages rise through mid-career; manufacturing wages are initially flat, then decline.

Back

Ability Profiles: Sources and Construction

Annual profiles constructed from published evidence, expressed in standard deviations (SD) relative to age 50.

Ability	Construction
Physical	Age decline and conversion into sd units guided by flexibility evidence and grip-strength evidence, 0.035 s.d. decline per year. Medeiros et al. (2013); Dodds et al. (2014).
Fluid-cognitive	Evidence on processing speed, reasoning, spatial visualization and episodic memory: curve peaking at 24.5, falling by 0.85 SD from its peak to age 60, declining faster thereafter. Salthouse (2009).
Crystallized	Vocabulary evidence guides both size of the increase and late peak: a 0.80-SD young–old difference anchors the rise, estimates of peak age around 65. Verhaeghen (2003); Salthouse (2014); Hartshorne and Germine (2015).

Back

Sector Requirements and Robustness

Sector ability weights

- Normalize each occupation's O*NET ability-requirement scores to sum to one across the three abilities.
- Compute sector ability weights by averaging occupation-specific requirements, occupations given equal weight.

Pearson correlations between relative ability indices and estimated employment–age effects:

Manufacturing	Low-skill services	High-skill services
0.997	0.905	0.981

Sensitivity to the constructed ability profiles

- Cognitive profiles: vary peak and plateau ages and magnitudes—81 combinations.
- Physical profile: vary the decline and conversion into SD units—9 combinations.

In every case, relative ability index falls in manufacturing, rises in both service sectors between 20 and 64.

Back

The Manufacturing Age Gap Lies Between Detailed Occupations

Apply the main age-profile specification to workers with valid occupations, first without and then with occupation effects:

$$M_n = \sum_{a' \neq 50} \delta_{a'} \mathbf{1}[a(n) = a'] + Z'_{g(n)}\beta + \mu_{c(n),b(n)} + \varepsilon_n,$$

$$M_n = \sum_{a' \neq 50} \widetilde{\delta}_{a'} \mathbf{1}[a(n) = a'] + Z'_{g(n)}\widetilde{\beta} + \widetilde{\mu}_{c(n),b(n)} + \phi_{o(n)} + \widetilde{\varepsilon}_n.$$

- M_n: manufacturing, utilities or construction rather than other non-agricultural employment; ϕ_o: three-digit occupation effects.
- Z_g: the main demographic and education controls and quadratic log GDP per capita; $\mu_{c,b}$: country $\times$ five-year birth-cohort effects.
- Same workers and weights in both regressions; estimate separately for ISCO-08 and ISCO-88.

Split country–census–age cells by occupation and manufacturing status. Weight each row by $e_n E_g/N_g$, where e_n is its employment and E_g/N_g is total/non-agricultural employment in its cell. All counts require valid occupations.

Back

The Manufacturing Age Gap Lies Between Detailed Occupations

Manufacturing-share gap between ages 20 and 64 (pp)

	ISCO-08	ISCO-88
Without occupation effects	31.2	14.3
	(5.5)	(6.8)
With three-digit occupation effects	4.7	−0.5
	(0.9)	(4.6)

- Differences in detailed occupations account for much of manufacturing's age gradient.
- The gap falls by 85% in ISCO-08; in ISCO-88 it is close to zero but imprecisely estimated.

Country-clustered standard errors in parentheses. ISCO-08: 17 countries, 21 censuses; ISCO-88: 36 countries, 54 censuses. Single ages 20–80 in estimation; age 50 omitted.

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Occupations Requiring Early-Peaking Abilities Have Younger Employment Profiles

Rank occupations by combined physical and fluid-cognitive requirements:

$$\theta_o^{PF} = \theta_o^P + \theta_o^F = 1 - \theta_o^C.$$

- Five approximately employment-balanced groups of matched three-digit occupations; group membership stays fixed across ages.
- $s^q_{c,t,a}$: group q's share of non-agricultural employment among workers with valid occupation codes.

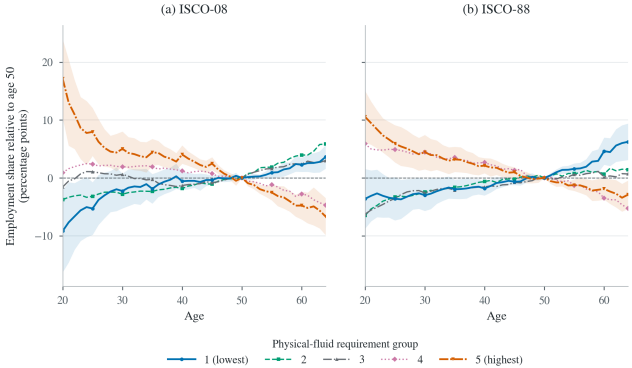
$$s^q_{c,t,a} = \sum_{a' \neq 50} \delta^q_{a'} \mathbf{1}[a = a'] + X'_{c,t,a}\beta^q + \gamma^q_1 \ln GDP_{ct} + \gamma^q_2 (\ln GDP_{ct})^2 + \mu^q_{c,b(t,a)} + \varepsilon^q_{c,t,a}.$$

- Main demographic and education controls, quadratic log GDP per capita and country $\times$ five-year birth-cohort effects.

Single ages 20–80; age 50 omitted. Cells weighted by total employment with valid occupation codes; standard errors clustered by country.

Back

Occupations Requiring Early-Peaking Abilities Have Younger Employment Profiles



Higher combined physical and fluid-cognitive requirements accompany younger profiles.

Percentage-point differences from age 50. Shading: country-clustered 95% confidence intervals for the highest- and lowest-requirement groups.

Back

Young-Adult Cohorts Predict More Industry and Manufacturing Employment

$$\underbrace{s_{ct}}_{\text{sectoral emp. share}} = \beta \underbrace{\text{Young}_{ct}}_{\substack{\text{25–34 pop. share} \\ \textbf{IV}\text{: birth rate 25–34 yrs earlier}}} + \underbrace{X'_{ct}\gamma}_{\text{controls}} + \underbrace{\alpha_c + \delta_t}_{\text{country \& year FE}} + \varepsilon_{ct}$$

Young-Adult Cohorts Predict More Industry and Manufacturing Employment

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Outcome	2SLS coefficient
Industry share, total employment	0.746^{**}
	(0.313)
Services share, total employment	-0.487
	(0.336)
Industry share, non-agriculture	1.027^{***}
	(0.350)
Services share, non-agriculture	-1.027^{***}
	(0.350)

Specification

- Controls: GDPpc quadratic; female labor force participation, schooling, imports, capital–output, investment, TFP; country & year FE;
- IV: mean crude birth rate 25-34 years earlier.

- 1 pp larger young-adult (25-34) share:
  - → 0.75 pp higher industry employment share in total employment;
  - → 1.03 pp within non-agriculture;
  - → 0.93 pp and 1.27 pp for manufacturing employment (GGDC data). Robustness

Back

Young Cohorts Are Linked to Higher Industrial Peaks

$$\underbrace{y_c}_{\substack{\text{peak ind. emp. share} \\ \textit{or} \text{ log GDPpc at peak}}} = \beta \underbrace{\overline{\text{Young}}_c^{10}}_{\substack{\text{pre-peak 25–34 share} \\ \textbf{association}\text{: no IV}}} + \underbrace{Z_c'\gamma}_{\text{controls}} + \underbrace{\eta_{d(c)}}_{\text{peak-decade FE}} + u_c$$

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$$\underbrace{y_c}_{\substack{\text{peak ind. emp. share} \\ \textit{or } \log \text{GDPpc at peak}}} = \beta \underbrace{\overline{\text{Young}}_c^{10}}_{\substack{\text{pre-peak 25–34 share} \\ \textbf{association}\text{: no IV}}} + \underbrace{Z_c'\gamma}_{\text{controls}} + \underbrace{\eta_{d(c)}}_{\text{peak-decade FE}} + u_c$$

	10-year pre-peak
Peak industry share (pp)	$+1.979^{***}$
	(0.577)
log GDP pc at peak	$+0.224^{***}$
	(0.053)
Countries	47

Specification

- Young-adult share (25–34): ten-year average before the peak.
- Controls: peak year, decade FE, pre-peak GDP pc growth and imports/GDP.
- Also: ten-year capital deepening and TFP growth, ending before the peak; mean log GDPpc and its square for peak height.

- A 1 pp larger young-adult (25–34) share before the peak is associated with:
  - → 1.98 pp higher industrial employment peak
  - → 25% higher GDP per capita at peak

▸ Robustness

▸ Back

Alternative Cohort Instruments and Inference

Employment-share pp per 1 pp larger population share aged 25–34

Industry share	Instrument	Coefficient (S.E.)	K–P F	AR p
Total employment	Birth rate	0.746 (0.313)	87.1	0.038
	Child stock	0.730 (0.180)	186.4	< 0.001
	Both	0.730 (0.179)	110.3	0.002
Non-agricultural	Birth rate	1.027 (0.350)	87.1	0.007
	Child stock	0.696 (0.226)	186.4	0.007
	Both	0.694 (0.226)	110.3	0.007

- Birth rate: mean crude birth rate 25–34 years earlier.
- Child stock: ages 5–14 twenty years earlier, aged forward with survival and divided by predicted population aged 20+.

Full WDI controls; country/year effects. 3,650 observations, 147 countries, 1991–2016. Country-clustered S.E. K–P: Kleibergen–Paap rk Wald F. AR: Anderson–Rubin p-value.

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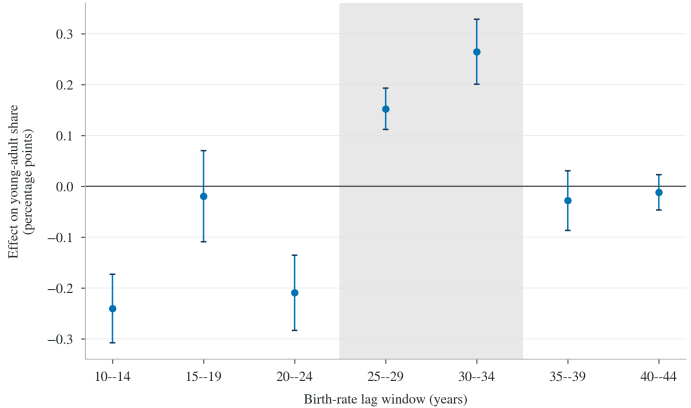
The Birth-Rate First Stage Has the Cohort-Accounting Fingerprint



Seven birth-rate windows enter jointly with full controls and country/year effects.

3,128 country-years, 147 countries. Country-clustered 95% confidence intervals. This checks cohort mapping and relevance, not exclusion.

Back

Panel Estimates Across Controls and Regional Shocks

Birth-rate IV: industry's share of total employment

Specification	Coefficient (S.E.)	Observations
Full baseline	0.746 (0.313)	3,650
No contemporaneous economic controls	0.970 (0.377)	3,650
Baseline + birth-era child/adult mortality	0.856 (0.260)	3,650
Region × year effects	0.820 (0.325)	3,650
Historical-income-sample baseline	0.664 (0.321)	3,353
+ Birth-window income, square and growth	0.681 (0.313)	3,353

Leaving out each country gives coefficients from 0.569 to 0.871.

Employment-share pp per 1 pp larger young-adult share. All rows include country effects and 147 countries. Region–year effects replace common year effects. Country-clustered S.E.

Back

Manufacturing-Specific and Regional Evidence

Employment-share pp per 1 pp larger population share aged 25–34

Outcome	Coefficient (S.E.)
GGDC country panel: birth-rate IV	
Manufacturing / total employment	0.926 (0.331)
Manufacturing / non-agricultural employment	1.266 (0.370)
Subnational regions: OLS association	
Manufacturing / industry-coded employment	0.381 (0.087)
Manufacturing / non-agricultural employment	0.331 (0.113)

- GGDC: 1,364 observations, 56 countries. Country/year effects, economic controls and linear log GDPpc. K–P $F = 45.4$.
- Regions: 8,316 observations, 1,463 regions, 72 countries. Region and country–year effects only.

Country-clustered S.E. GGDC: 1991–2016. Regions: 1960–2020, unweighted.

Back

Pre-Peak Windows and Capital/Productivity Controls

Coefficients per 1 pp larger pre-peak population share aged 25–34

Specification	Peak industry share (pp)	Log GDPpc at peak	Countries
Standard pre-peak controls			
5-year window	1.106 (0.288)	0.177 (0.025)	70
10-year window	1.438 (0.410)	0.220 (0.029)	68
15-year window	1.650 (0.485)	0.261 (0.041)	62
Ten-year window: identical PWT-covered sample			
Standard controls	1.680 (0.456)	0.184 (0.028)	47
+ Capital deepening and TFP growth	1.979 (0.577)	0.224 (0.053)	47

Both associations remain positive after adding capital and TFP controls.

Averages exclude the peak year. Both equations include pre-peak GDP growth, imports/GDP, peak year and peak-decade effects. Peak height adds mean log GDPpc and its square. Capital/TFP changes end before the peak. Equal-country-weight OLS, no constant; robust S.E.

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Young Cohorts and Manufacturing-Specific Peaks

GGDC manufacturing, including the import-exposure control

Pre-peak window	Peak manufacturing share (pp)	Log GDPpc at peak	Countries
5 years	2.639 (0.706)	0.261 (0.133)	38
10 years	3.214 (1.036)	0.271 (0.114)	36
15 years	3.632 (1.296)	0.409 (0.107)	32

- Both peak height and income at the manufacturing peak rise with the pre-peak young-adult share.
- These regressions use standard GDP and timing controls, without capital-deepening or TFP controls.

Coefficients per 1 pp larger population share aged 25–34, averaged strictly before the peak. Manufacturing is a share of total employment. GDP growth, imports/GDP, peak year and peak-decade effects enter both equations. Peak height also includes mean log GDPpc and its square. Robust S.E. in parentheses.

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Peak Results Across Alternative Definitions

Ten-year demographic averages with standard pre-peak controls

Definition	Peak share (pp)	Log GDPpc at peak	Countries
Raw peak, ages 25–34 (baseline)	1.438 (0.410)	0.220 (0.029)	68
Centered five-year-smoothed peak	1.298 (0.368)	0.206 (0.025)	50
Young adults aged 20–34	0.809 (0.293)	0.144 (0.023)	68
Industry / non-agricultural employment	1.393 (0.548)	—	64

Inference for the 68-country raw-peak baseline:

- HC3 standard error: 0.523 $\quad (p = 0.008)$.
- Leave-one-country-out coefficients: 1.215–1.693. Minimum $|t| = 2.96$.

Coefficients per 1 pp larger young-adult share. These checks omit capital/TFP controls. Samples vary with the definition. Robust S.E. in parentheses; the non-agricultural check reports peak height only.

Back

Trade openness and the importance of age structure

Trade allows an economy to specialize in sectors suited to its population's abilities. Does a larger young-adult share matter more in more open economies?

$$s_{it} = \beta Y_{it} + \delta Y_{it} W^c_{it} + \eta W^c_{it} + \mathbf{X}'_{it}\theta + \alpha_i + \gamma_t + \varepsilon_{it}.$$

- s: industry/manufacturing share of employment; Y: population aged 25–34, share of total population.
- $W = (\text{exports} + \text{imports})/\text{GDP}$, with $W^c = W - 0.6774$ (the sample median = 67.74% of GDP).
- **2SLS:** instrument Y and YW^c with birth rate 25–34 years earlier or the predicted surviving child-cohort share.
- Baseline controls: quadratic log GDP per capita, female participation, schooling, imports/GDP, log capital–output ratio, investment share and log TFP. Country and year fixed effects.

Shares enter as fractions. The child-stock instrument ages children aged 5–14 twenty years earlier forward using country survival rates, then divides by the predicted population aged 20+. β is the demographic response at median openness; δ measures how it changes with openness.

Back, model Back, results

Age structure matters more in open economies

	Industry			Manufacturing
Cohort instrument	Birth rate	Child stock	Birth rate	Birth rate
Trade/GDP	Current	Current	Five-year lag	Current
Young share at 67.74% trade/GDP: $\widehat{\beta}$	0.531	0.514***	0.509	0.375
	(0.325)	(0.190)	(0.319)	(0.426)
Young share × openness: $\widehat{\delta}$	2.397***	1.876***	2.193***	1.787***
	(0.644)	(0.385)	(0.673)	(0.489)
Openness at $Y = 0$: $\widehat{\eta}$	−0.367***	−0.289***	−0.329***	−0.218***
	(0.097)	(0.059)	(0.102)	(0.076)
Extra response: $0.20\widehat{\delta}$ (employment pp)	0.479	0.375	0.439	0.357
Observations / countries	3,650 / 147	3,650 / 147	3,474 / 144	1,364 / 56

- First column: a 1pp larger young-adult share predicts 0.53pp more industry employment at 67.74% trade/GDP, versus 1.01pp at 87.74%: an additional 0.48pp.

Back, model Back, results

Young Households Spend More on Manufactured Durables

Cross-country evidence

- Households under 30 devote about 4 pp more of their expenditure to these goods than households aged 60+.
- The difference is also positive in middle-income country–years.

Eurostat/HBS; age of household reference person.

Indonesia: share of household spending

Mean adult age	< 30	30–44	45–59	60+
Share (%)	9.6	9.2	7.7	4.1

IFLS, 1993–2014. Household age is the mean age of members aged 20+.

Both sources include durable and semi-durable goods. IFLS also includes in-kind consumption.

Back

Younger Households Also Spend More in Absolute Terms

Compare household spending on these goods in IFLS: mean adult age under 30 versus 60+, within each wave.

IFLS wave	1993	1997	2000	2007	2014
Young/old spending ratio	5.38	3.45	3.00	3.00	2.56

- Younger households spend 3.5 times as much, averaging the five within-wave ratios.
- The difference remains positive using market purchases only or excluding *other* spending.
- It is also positive when measured per member or grouped by household-head age.

The basket includes furniture/household supplies, clothing, school supplies/uniforms, and other expenditure.

Survey-weighted household means. These comparisons do not hold income or household composition fixed.

Back

Schooling Changes Cohort Ability Distributions

Permanent log ability combines an endowment and schooling:

$$m_{ik} = \nu_{ik} + \alpha_k s_i, \qquad k \in \{P, F, C\}.$$

Within cohort c, the endowment vector $\boldsymbol{\nu}_i$ and schooling s_i are independent and jointly normal.

$$\underbrace{\mu_{c,k} = \mu_{0,k} + \alpha_k \bar{s}_c}_{\text{mean permanent log ability } k}, \qquad \underbrace{\Sigma_{c,kr} = \Sigma_{0,kr} + \alpha_k \alpha_r \sigma^2_{s,c}}_{\text{covariance of log abilities } k \text{ and } r}.$$

- Higher mean schooling $\bar{s}_c$ raises each ability according to its schooling effect α_k.
- Schooling dispersion $\sigma^2_{s,c}$ contributes to ability dispersion and to covariance across abilities.
- Different schooling effects across abilities change comparative advantage as well as overall productivity.
- Endowments and schooling stay fixed over a career. The log ability profiles $f_k(a)$ change.

Back

Age Profiles and Productivity Normalization

Sectoral weights combine the common log ability profiles $f_k(a)$ into a level age component:

$$g_j(a) = \frac{\exp\left[\sum_k \theta_{jk} f_k(a)\right]}{G_j}, \qquad G_j = \frac{1}{45} \sum_{u=20}^{64} \exp\left[\sum_k \theta_{jk} f_k(u)\right].$$

$g_j(a)$ has an unweighted arithmetic mean of one over working ages 20–64.

Worker i's productivity combines this age component with permanent differences:

$$z_i(a, j) = g_j(a) \exp\left[\sum_k \theta_{jk}(\nu_{ik} + \alpha_k s_i)\right].$$

Only the age component is normalized, not full worker productivity.

The main-slide decomposition suppresses the fixed sector normalization constants $-\log G_j$.

Back

Only Comparative Advantage Sorts

- Worker i's permanent log abilities include endowments and schooling:

$$m_{ik} = \nu_{ik} + \alpha_k s_i, \qquad k \in \{P, F, C\}.$$

- Separate overall ability from relative strengths:

$$\underbrace{\bar{m}_i = \frac{m_{iP} + m_{iF} + m_{iC}}{3}}_{\text{worker's mean permanent log ability}}, \qquad \underbrace{\hat{h}_{ik} = m_{ik} - \bar{m}_i}_{\text{deviation from their own mean}} .$$

- Since $\sum_k \theta_{jk} = 1$ in every sector, log earnings are

$$\log\big(w_{j,t} z_i(a,j)\big) = \underbrace{\bar{m}_i}_{\text{same in every sector}} + \log w_{j,t} + \sum_k \theta_{jk}\big[f_k(a) + \hat{h}_{ik}\big].$$

- A worker's overall ability cancels from sectoral comparisons; only their mix of abilities affects sorting.
- $\hat{h}_{iP} + \hat{h}_{iF} + \hat{h}_{iC} = 0$: two coordinates locate each worker on the ability plane.

Derivation Back

Proposition 1: Two Dimensions Determine Sectoral Choice

With costless mobility, sectoral choice depends only on relative abilities.

Write $m_{ik} = \bar{m}_i + \hat{h}_{ik}$, where $\bar{m}_i$ is worker i's mean permanent log ability. Since every sector's weights sum to one,

$$\log\big(w_{j,t} z_i(a,j)\big) - \log\big(w_{\ell,t} z_i(a,\ell)\big) = \log \frac{w_{j,t} g_j(a)}{w_{\ell,t} g_\ell(a)} + \sum_{k \in \{P,F,C\}} (\theta_{jk} - \theta_{\ell k}) \hat{h}_{ik}.$$

Why the result holds

- The common ability level $\bar{m}_i$ cancels from every earnings comparison.
- Two relative abilities determine the third: $\hat{h}_{iC} = -\hat{h}_{iP} - \hat{h}_{iF}$.
- Each comparison defines a straight boundary. A sector's region contains the workers for whom it beats every alternative.
- Fixed sectoral ability weights determine the slopes. Age profiles and wages move the intercepts.

This result does not require normally distributed abilities.

Back

Forward-Looking Exit from Agriculture

Let $\bar{e}_{i,t}(a) = \max_{j \in \{M,L,H\}} w_{j,t} z_i(a,j)$ be worker i's best earnings outside agriculture.

$\Delta_{i,t}(a) = V^O_{i,t}(a) - V^A_{i,t}(a)$ is the value of starting the year with a non-agricultural rather than agricultural employment history.

$$\text{Enter agriculture:} \quad \lambda_t[w_{A,t} z_i(a,A) - \bar{e}_{i,t}(a)] \geq \beta q_t(a) \Delta_{i,t+1}(a+1),$$

$$\text{Stay in agriculture:} \quad \lambda_t[(1+\kappa_A(a)) w_{A,t} z_i(a,A) - \bar{e}_{i,t}(a)] \geq \beta q_t(a) \Delta_{i,t+1}(a+1).$$

- Entering agriculture exposes the worker to future exit costs.
- Staying avoids today's exit cost, which can outweigh higher earnings elsewhere.
- Entrants choose freely using the entry condition, anticipating later exit costs.

λ_t: value of resources. β: discount factor. $q_t(a)$: next year's weight of the same cohort relative to today.

Back

Forward-Looking Exit from Agriculture

Relative abilities still determine careers with proportional exit costs.

Why the result holds

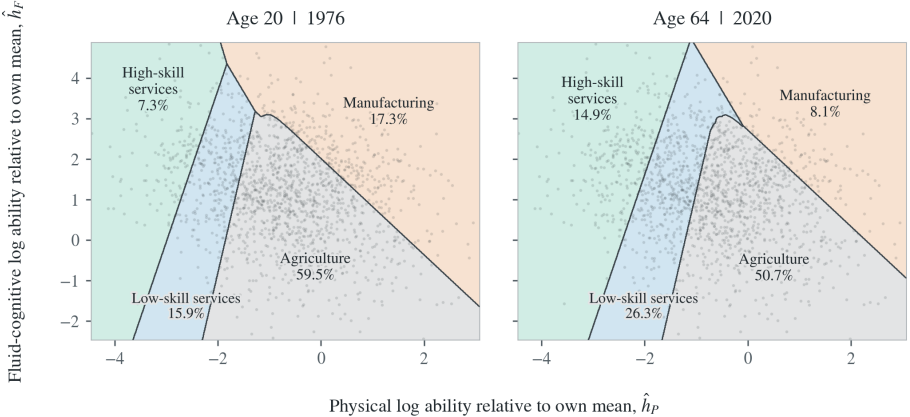
- Adding the same constant d to all permanent log abilities m_{ik} multiplies earnings and the proportional exit cost by e^d.
- Career continuation values are zero after retirement. At given wage and shadow-value paths, backward induction scales every payoff equally, leaving choices unchanged.
- Starting from the common entry rule, the worker's relative abilities therefore determine the entire career.

Agricultural boundaries can depend on past employment and future opportunities, and need not be straight.

The cost is nonmonetary: it changes choices but is not deducted from output or household income.

Back

Worker Sorting with Costly Exit from Agriculture



Same cohort at ages 20 (1976) and 64 (2020), with costly exit from agriculture.

Back

Proposition 2: Employment and Effective Labor

For cohort $c = t - a$, $R_j(a,t)$ contains the relative-ability vectors that lead to sector j at age a and date t.

$$\mathbb{E}[z_i(a,j)\mathbf{1}\{j_i^*(a,t) = j\} \mid c] = \underbrace{g_j(a)J_j(c)}_{\text{mean potential efficiency}} \underbrace{\Pr\left(\widetilde{\mathbf{h}}_i^j \in R_j(a,t) \mid c\right)}_{\text{efficiency-weighted probability}}.$$

$J_j(c) = \mathbb{E}[\exp(\sum_k \theta_{jk} m_{ik}) \mid c]$ averages permanent efficiency over the whole cohort; $j_i^*(a,t)$ is worker i's optimal sector.

Why the result holds

- Weight each worker by $\exp(\sum_k \theta_{jk} m_{ik})$ and divide by its cohort mean.
- With normally distributed permanent log abilities, the weighted distribution shifts mean k by $\sum_r \Sigma_{c,kr}\theta_{jr}$, leaving covariances unchanged.
- Center each draw from this distribution across abilities to obtain $\widetilde{\mathbf{h}}_i^j$, then calculate its probability in the same region $R_j(a,t)$.

Overall ability still matters for production. The calculation also applies to the career regions with costly agricultural exit.

Back

Baseline Consumption: Shares and Allocation

$E_t(a) \equiv \sum_j p^Q_{j,t} c_{j,t}(a)$ is expenditure per person of age a; $p^Q_{j,t}$ is the price paid by households.

Sectoral expenditure shares

$$\zeta_{j,t}(a) \equiv \frac{p^Q_{j,t} c_{j,t}(a)}{E_t(a)} = \frac{\Omega(a,j)(p^Q_{j,t})^{1-\sigma} \mathcal{C}_t(a)^{(1-\sigma)\iota_j}}{\sum_{\ell \in \mathcal{J}} \Omega(a,\ell)(p^Q_{\ell,t})^{1-\sigma} \mathcal{C}_t(a)^{(1-\sigma)\iota_\ell}}.$$

Spending composition responds to prices, consumption and age-specific tastes.

Consumption allocation across cohorts

$$\frac{1}{\mathcal{C}_t(a)} = \lambda_t \frac{\partial E_t(a)}{\partial \mathcal{C}_t(a)} = \lambda_t \frac{E_t(a)}{\mathcal{C}_t(a)} \bar{\iota}_t(a), \qquad \bar{\iota}_t(a) = \sum_j \zeta_{j,t}(a) \iota_j.$$

$$\sum_a \pi_t(a) E_t(a) = \sum_j w_{j,t} N_{j,t} - NX_t, \qquad NX_t : \text{ net exports.}$$

- The common λ_t is the utility gain from an extra unit of spending, equalized across ages.
- Population weights cancel from each cohort's allocation condition, but remain in the pooled budget.

Back

Preferences: Durable Stocks in Non-Homothetic CES

Period utility is $\log \mathcal{C}_t(a)$, with

$$\underbrace{\sum_{j\in\{A,M,L,H\}} \Omega(a,j)^{1/\sigma}\left[\frac{c_{j,t}(a)}{\mathcal{C}_t(a)^{\iota_j}}\right]^{\frac{\sigma-1}{\sigma}}}_{\text{non-durable consumption flows}} + \underbrace{\Omega_D(a)^{1/\sigma}\left[\frac{\bar{d}+D_t(a)}{\mathcal{C}_t(a)^{\iota_D}}\right]^{\frac{\sigma-1}{\sigma}}}_{\text{durable holdings}} = 1.$$

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- Durable are manufacturing goods that provide consumption services over several periods.
- ι_j, ι_D govern income effects; $0 < \sigma < 1$ substitution effects.
- $\Omega(a,j), \Omega_D(a)$ age-specific tastes; $\bar{d} > 0$ permits zero holdings.
- Dynasty jointly chooses consumption index and durable stock
- For a given $D_t(a)$ and $\mathcal{C}_t(a)$, composition of the non-durable bundle retains traditional NHCES form.

Non-durable shares | Derivation | Back

Consumption Index Choice

Given $D_t(a)$, the dynasty chooses $\mathcal{C}_t(a)$ with non-durable expenditure $E_t(a) \equiv \sum_j p^{\mathcal{Q}}_{j,t} c_{j,t}(a)$:

$$\underbrace{\frac{1}{\mathcal{C}_t(a)}}_{\text{marginal utility}} = \underbrace{\lambda_t \frac{\partial E_t(a)}{\partial \mathcal{C}_t(a)}\bigg|_{D,p}}_{\text{valued marginal cost}} = \lambda_t \frac{E_t(a)}{\mathcal{C}_t(a)} \left[\underbrace{\bar{\iota}_t(a)}_{\text{non-durable mix}} + \underbrace{\xi_t(a)\iota_D}_{\text{fixed durable holdings}} \right].$$

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- A 1% higher consumption index requires approximately $(\bar{\iota} + \xi\iota_D)\%$ more non-durable spending.
- λ_t is the shadow value of resource to the dynasty.
- $\bar{\iota}_t(a)$ averages the sectoral income-effect parameters using non-durable spending shares.
- $\xi_t(a)$ measures how strongly additional durables reduce non-durable spending.
- Higher income effect for durables (ι_D) raises cost of increasing consumption for fixed durables.

Sectoral shares | Joint choice | Back

Durable Stock Choice

Entrants have no durable stock, all other cohorts carry forward undepreciated $(1 - \delta_D)$ stock:

$$x_t(a) = D_t(a) - (1 - \delta_D) D_{t-1}(a - 1) \geq 0.$$

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When purchases are positive today and next period, dynasty chooses durables such that:

$$\underbrace{\frac{\partial \log \mathcal{C}_t(a)}{\partial D_t(a)}\bigg|_{\{c_{j,t}(a)\}}}_{\text{current marginal utility}} = \underbrace{\lambda_t E_t(a) \frac{\xi_t(a)}{\bar{d} + D_t(a)}}_{\text{value of spending saved}} = \underbrace{\lambda_t p^Q_{M,t} - \beta q_t(a)(1-\delta_D)\lambda_{t+1} p^Q_{M,t+1}}_{\text{user cost}}.$$

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- Current marginal utility is the non-durable expenditure saved while maintaining a given $\mathcal{C}_t(a)$.
- Adjusted by $\xi_t(a)$, which decreases with the ratio of durable stocks to non-durable consumption.
- User cost is today's purchase cost less the discounted (β) value of purchases saved next period.
- Entrants build stocks; carryover reduces older cohorts' need for new purchases.

Purchase conditions Back

Non-Durable Spending at a Given Consumption Level

For one age and date, write $C = \mathcal{C}_t(a)$ and $p_j = p^{\mathcal{Q}}_{j,t}$. $E = \sum_j p_j c_j$ is non-durable expenditure.

$$T_D = \Omega_D^{1/\sigma} \left(\frac{\bar{d} + D}{C^{\iota_D}} \right)^{(\sigma-1)/\sigma}, \qquad \xi = \frac{T_D}{1 - T_D}.$$

The durable term is T_D; non-durable terms sum to $1 - T_D$. Here $0 < \sigma < 1$ and $T_D < 1$.

$$E = \underbrace{(1+\xi)^{\sigma/(1-\sigma)}}_{\text{adjustment for durable holdings}} \underbrace{\left[\sum_j \Omega_j p_j^{1-\sigma} C^{(1-\sigma)\iota_j} \right]^{1/(1-\sigma)}}_{\text{usual non-homothetic CES expenditure}}.$$

- This is the least expenditure needed for the chosen C and D.
- At fixed C and prices, more durables lower ξ and the non-durable spending required.

Back

How Non-Durable Spending Is Split Across Sectors

For a given consumption index C, durable stock D, and prices:

$$\underbrace{\zeta_j = \frac{p_j c_j}{E}}_{\text{sector } j\text{'s share of non-durable spending}} = \frac{\Omega_j p_j^{1-\sigma} C^{(1-\sigma)\iota_j}}{\sum_\ell \Omega_\ell p_\ell^{1-\sigma} C^{(1-\sigma)\iota_\ell}}.$$

- The durable adjustment is common to all sectors, so it cancels from their shares.
- At fixed C and prices, larger stocks reduce all non-durable quantities in the same proportion.

$$\bar{\iota} = \sum_j \zeta_j \iota_j, \qquad \frac{\partial \log \zeta_j}{\partial \log C} = (1-\sigma)(\iota_j - \bar{\iota}).$$

As C rises at fixed prices, spending shifts toward sectors with $\iota_j > \bar{\iota}$. Durables can affect this composition indirectly by changing the chosen C.

Back

Choosing the Consumption Index

Holding durable stocks and prices fixed, the dynasty balances the utility gain against the expenditure needed:

$$\underbrace{\frac{1}{C}}_{\text{marginal utility}} = \lambda_t \frac{\partial E}{\partial C} = \lambda_t \frac{E}{C} \left[\bar{\iota} + \xi \iota_D \right].$$

- λ_t is the value of an extra unit of resources to the dynasty.
- A 1% higher C requires approximately $(\bar{\iota} + \xi \iota_D)$% more non-durable spending.
- $\bar{\iota} = \sum_j \zeta_j \iota_j$ reflects the spending mix. The extra term $\xi \iota_D$ reflects raising C without increasing durable holdings.

This condition and the durable-stock condition hold jointly: neither choice is made first.

Back

The Consumption Benefit of Additional Durables

An extra unit of durable stock allows the same consumption index with less non-durable spending:

$$-\left.\frac{\partial E}{\partial D}\right|_{C,p} = \frac{E\xi}{\bar{d}+D}, \qquad \xi = -\left.\frac{\partial \log E}{\partial \log(\bar{d}+D)}\right|_{C,p}.$$

- A 1% increase in $\bar{d}+D$ saves approximately ξ% of non-durable expenditure, keeping C fixed.
- At the chosen consumption index, valuing this saving at λ_t gives the marginal utility of additional durables:

$$\left.\frac{\partial \log C}{\partial D}\right|_{\{c_j\}} = \frac{\xi}{(\bar{\iota}+\xi\iota_D)(\bar{d}+D)} = \lambda_t \frac{E\xi}{\bar{d}+D}.$$

One expression holds utility fixed and measures spending saved; the other holds non-durable quantities fixed and measures utility gained.

Back

Durable Purchases and Carryover

$$\underbrace{x_t(a)}_{\text{new purchases}} = \underbrace{D_t(a)}_{\text{holdings}} - \underbrace{(1-\delta_D)D_{t-1}(a-1)}_{\text{stock carried forward}} \geq 0.$$

When the cohort buys both today and next period:

$$\underbrace{\lambda_t \frac{E_t(a)\xi_t(a)}{\bar{d} + D_t(a)}}_{\text{current consumption benefit}} = \underbrace{\lambda_t p^Q_{M,t}}_{\text{purchase cost today}} - \underbrace{\beta q_t(a)(1-\delta_D)\lambda_{t+1}p^Q_{M,t+1}}_{\text{discounted purchases saved next period}}.$$

- One unit bought today leaves $1-\delta_D$ units next period, reducing the purchases needed then.
- $q_t(a) = \pi_{t+1}(a+1)/\pi_t(a)$ adjusts for the cohort's changing population weight.
- At the final age, there is no future saving and no resale value.

Back

Durable Purchases and Carryover

No resale means the dynasty cannot sell inherited holdings. Let $\chi_t(a) \geq 0$ measure the value of relaxing this restriction.

$$\lambda_t \frac{E_t(a)\xi_t(a)}{\bar{d} + D_t(a)} = \lambda_t p^Q_{M,t} - \chi_t(a) - \beta q_t(a)(1-\delta_D)\left[\lambda_{t+1} p^Q_{M,t+1} - \chi_{t+1}(a+1)\right].$$

$$x_t(a) \geq 0, \qquad \chi_t(a) \geq 0, \qquad \chi_t(a) x_t(a) = 0.$$

- Positive purchases imply $\chi_t(a) = 0$. Positive purchases in both periods guarantee the simpler equation.
- If next period's no-resale restriction binds, extra holdings today save less than the full purchase price next period.
- Entrants start with no stock. At the final age, omit the future term.

Back

Age Structure and Manufacturing Demand

The dynasty weights both utility and spending by each age group's population share:

$$\max \sum_t \beta^t \sum_a \pi_t(a) \log \mathcal{C}_t(a), \qquad \sum_a \pi_t(a) \left[E_t(a) + p^Q_{M,t} x_t(a) \right] \leq I_t.$$

I_t is labor income net of the external transfer. Each date has its own budget; there is no borrowing or lending.

$$Q_{M,t} = \sum_a \pi_t(a) \left[\underbrace{c_{M,t}(a)}_{\text{non-durable consumption}} + \underbrace{x_t(a)}_{\text{durable purchases}} \right].$$

$Q_{M,t}$ includes domestic and imported goods, counting new purchases rather than installed stocks.

- Entering cohorts buy any initial holdings; older cohorts carry stock forward.
- Age composition weights these purchases. Stocks and equilibrium prices also adjust.

Back

Trade: Domestic Absorption, Imports, and Exports

Time subscripts are omitted. Q_j combines domestic output sold at home, Y_j^{abs}, and imports, m_j.

Domestic and imported varieties

$$p_j^m = \tau_j^M e p_j^*,$$

$$p_j^Q = \left[\omega_j (p_j^d)^{1-\eta} + (1-\omega_j)(p_j^m)^{1-\eta}\right]^{1/(1-\eta)}.$$

$$Y_j^{\text{abs}}/Q_j = \omega_j (p_j^d/p_j^Q)^{-\eta},$$

$$m_j/Q_j = (1-\omega_j)(p_j^m/p_j^Q)^{-\eta}.$$

$\eta > 1$ governs substitution and ω_j weights the domestic variety.

Export opportunities

Agriculture and manufacturing:

$$p_j^d = e p_j^*/\tau_j^X \quad \text{when } X_j > 0.$$

With no exports, $p_j^d \geq e p_j^*/\tau_j^X$.

Services face foreign demand:

$$X_j = \Xi_j \left(\frac{(p_j^d/e)\tau_j^X}{p_j^*} \right)^{-\varepsilon}, \quad j \in \{L, H\}.$$

While manufacturing exports, $p_M^d = 1$ fixes $e = \tau_M^X/p_M^*$. Otherwise, the exchange rate adjusts with the other equilibrium prices.

Back

Baseline Equilibrium and Resource Accounting

Given demographic, schooling, productivity and trade inputs, equilibrium price paths support optimal household choices and worker careers.

$$Y_{j,t} = A_{j,t} N_{j,t}, \qquad w_{j,t} = p^d_{j,t} A_{j,t}, \qquad Y_{j,t} = Y^{\text{abs}}_{j,t} + X_{j,t}.$$

Domestic absorption equals consumption, $Q_{j,t} = \sum_a \pi_t(a) c_{j,t}(a)$. Household spending equals labor income less net exports:

$$\sum_a \pi_t(a) E_t(a) = \sum_j w_{j,t} N_{j,t} - NX_t, \qquad NX_t = \mathcal{W}_t \sum_j p^d_{j,t} Y_{j,t}.$$

- Workers anticipate wage paths. Firms employ the effective labor supplied by their sectoral choices.
- The dynasty allocates resources across ages. Goods markets and the external-balance condition determine equilibrium prices jointly.
- $\mathcal{W}_t < 0$ permits a net resource inflow. Each year has a separate budget, without financial borrowing or lending.

$E_t(a)$ is baseline consumption expenditure. With market clearing and zero profits, the budget and external balance express the same resource restriction. Agricultural exit costs are nonmonetary.

Back

Calibration: Workers and Agricultural Exit

Schooling and permanent abilities

Parameter	Baseline	Durables
α_P	0.00660	0.01539
α_F	0.30084	0.30938
α_C	0.03375	0.03000
$\mathrm{Var}(\nu_{iP})$	2.30405	2.37019
$\mathrm{Var}(\nu_{iF})$	0.52399	0.50210
$\mathrm{Var}(\nu_{iC})$	3.85952	3.76037
$\mathrm{Cov}(\nu_{iP}, \nu_{iF})$	0.40639	0.34315
$\mathrm{Cov}(\nu_{iP}, \nu_{iC})$	-0.15904	-0.15840
$\mathrm{Cov}(\nu_{iF}, \nu_{iC})$	-0.23152	-0.16162

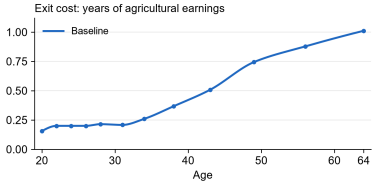
P: physical; F: fluid cognitive; C: crystallized/interpersonal. ν_{ik}: worker i's residual log endowment.

Targets: schooling–earnings relationships; employment by age/cohort.
External inputs: UN demography, IFLS/IPUMS schooling, published age–ability profiles.

Sector ability weights θ_{jk}

Sector	P	F	C
A	0.409	0.217	0.375
M	0.555	0.315	0.130
L	0.252	0.302	0.446
H	0.044	0.455	0.501

Paper's O*NET weights; rounded to three decimals.



Twelve fitted knots, in own potential agricultural earnings; shape-preserving interpolation.

Back

Calibration: Demand, Productivity and Trade

Parameters	Evidence used
Income and substitution effects (ι_j, σ)	Spending-ratio elasticities to total expenditure (IFLS) and relative prices net of income effects: σ=0.72; $(\iota_A, \iota_M, \iota_L, \iota_H)$ = (0.24, 1, 0.93, 1.47).
Age-specific tastes $\Omega(a, j)$	1993 IFLS expenditure patterns by age, aligned with aggregate spending.
Sectoral productivity $A_{j,t}$	Manufacturing: GGDC value added per worker divided by effective labor per worker. Other sectors: annual employment shares.
Trade parameters	Import wedges from sectoral import shares; service export demand from exports/GDP; external balance from net exports/GDP.

Non-demographic inputs remain fixed across the main demographic counterfactuals.

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Calibration: Household Demand

Parameter	Baseline	Durables
σ	0.7208	0.7208
ι_A	0.2364	0.4225
ι_M	1	1
ι_L	0.9331	1.5848
ι_H	1.4673	2.4759
β	0.96	0.96
ι_D	—	2.4901
δ_D	—	0.1680
$\bar{d}$	—	0.02918

$\bar{d}$ is in model units. ι_M=1 in both specifications; β is annual.

Income and price responses

- IFLS Engel slopes; relative-price responses net of income effects.
- ι_j differs by spending basket (durables included or excluded) and slope-to-index conversion.

Age-specific tastes $\Omega(a, j)$ and $\Omega_D(a)$

- Twelve 1993 household-age groups, aligned with aggregate spending.
- Durable targets: 5.208% aggregate purchase share, 0.1% age-group floor.
- Tastes fitted separately; fixed across demographic counterfactuals.

Household age: mean age of adults. δ_D: purchases/holdings proxy; $\bar{d}$: censored holdings regression, converted to model units.

Back

Calibration: Productivity and Trade

Parameter / input	Value, construction and target
Manufacturing productivity $A_{M,t}$	GGDC labor productivity, adjusted for reference effective labor per worker. $A_{M,1993}$=1; common to both models.
Relative paths $A_{j,t}/A_{M,t}$, $j = A, L, H$	Fit annual sectoral employment shares, separately for the baseline and durable extension.
Import elasticity and home bias	η=8; $(\omega_A, \omega_M, \omega_L, \omega_H)$=(0.8505, 0.8704, 0.9400, 0.8863). Home bias uses average gross import penetration.
Annual import wedges $\tau^M_{j,t}$	Invert value-added import shares in domestic absorption at reference prices and exchange rates.
Exports	A and M: price-taking. L and H: downward-sloping demand, $\varepsilon = 8$; $\Xi_{j,t}$ from exports/GDP. $\tau^X_j = 1$.
World-price proxies $p^*_{j,t}$	M: one. A: World Bank commodities relative to a manufacturing benchmark. L/H: GGDC relative deflator proxies. Base year 1993.
External balance $\mathcal{W}_t$	Net value-added exports/GDP, smoothed and joined to the mining/oil-adjusted series outside ICIO coverage.

Trade inversions fit reference, not necessarily final-equilibrium, ratios. Trade and productivity paths stay fixed across demographic counterfactuals.

Back

Model Fit Beyond Age Profiles

	Baseline	Data
Calibration fit		
Annual sectoral employment shares: mean absolute gap (pp)	0.38	—
Peak manufacturing employment share (2019, %)	21.0	21.4
Manufactured spending share: under 30 minus 60+ (1993, pp)	7.3	7.3
Spending shares by sector and age: mean absolute gap to targets (pp)	0.01	—
Moments not directly targeted		
Mean monthly earnings: high-skill services / manufacturing	1.58	1.64
Mean monthly earnings: low-skill services / manufacturing	1.07	1.06
Schooling: agriculture minus the same-age average (years)	-1.86	-1.85
Schooling: low-skill services minus manufacturing (years)	0.4	0.2
Schooling: high-skill services minus manufacturing (years)	3.0	5.5

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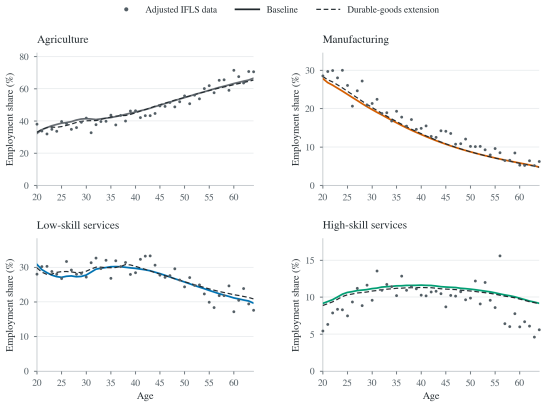
Model Fit: Employment Across Ages



Model: pooled 1976–2025. IFLS: 1993, 1997 and 2000, level-aligned to GGDC and adjusted for retirement. These employment profiles enter calibration.

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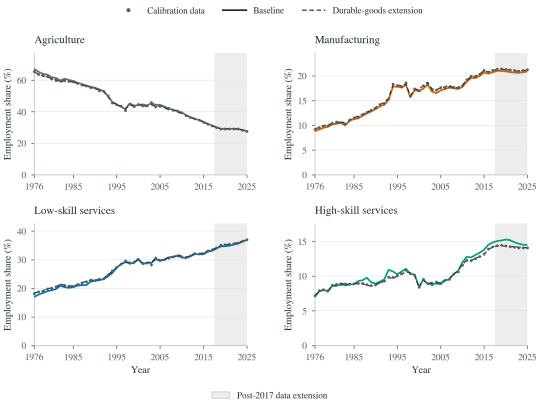
Model Fit: Sectoral Employment Over Time



GGDC through 2017; shaded years use the labor-force-survey/WDI extension, including interpolation and extrapolation. Mean absolute gap: baseline 0.38 pp; durables 0.17 pp.

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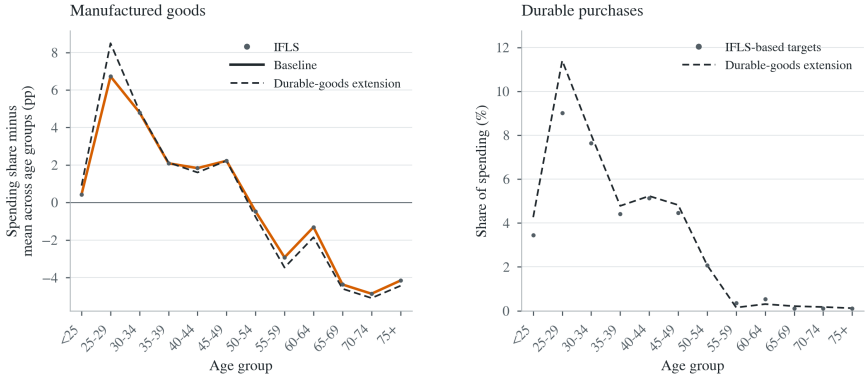
Model Fit: Spending by Age



Left: manufactured spending, pp deviations from each series' mean across age groups. **Right:** durable purchases, percent of total spending; constructed IFLS-based targets.

1993; twelve groups. Mean adult household age in IFLS, individual age in the models.

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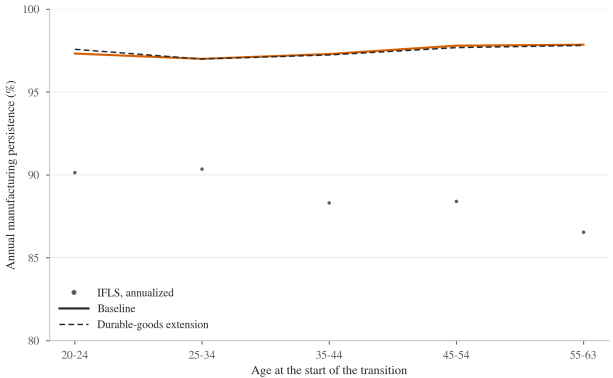
Model Fit: Manufacturing Persistence



Untargeted: both models overpredict persistence in every displayed age group.

Model: one-year transitions, 1976–2024 origins. IFLS: retention between consecutive 1993–2014 waves, annualized as $R^{1/\Delta}$; not directly observed annual transitions.

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Separating the Two Life-Cycle Channels

Economy	Ability aging	Age-dependent demand
Full	On	On
Sorting off	Off	On
Demand off	On	Off
Neither	Off	Off

- Without ability aging, all sectors have the same constant age-efficiency profile.
- Without age-dependent demand, sectoral taste weights no longer vary with age.
- Neither retains: permanent abilities, cohort schooling, agricultural exit costs, workers and retirees.

Back

Where Employment Moves

Sectoral employment in 2025: U.S. minus Thai demographics (pp)

	Agriculture	Manufacturing	Low-skill services	High-skill services
Baseline	-2.75	+4.86	-3.45	+1.33

Accounting for the manufacturing gap

Workforce age composition	Within-age employment shares	Total
4.15 pp	0.72 pp	4.86 pp

- Most of the manufacturing difference reflects the age composition of workers.
- This accounts for equilibrium allocations; it is not the Shapley decomposition or a separate counterfactual.

Baseline model; 2025 levels, not peaks. Components may not sum because of rounding.

Back

Consumption Welfare and Children's Needs

U.S. relative to Thai demographics (%)

	Baseline		Durables	
	2025	1976–2025	2025	1976–2025
Expenditure equivalent	44.4	22.1	43.7	21.4
Output per capita	42.8	22.8	44.1	23.8
Child-adjusted output per person	21.9	5.4	23.0	6.3

- **Expenditure equivalent:** additional spending over the Thai path needed to attain U.S.-path consumption utility at Thai prices and age weights.
- **Child adjustment:** under-20s count as 0.3 adults. Only the output denominator changes, not consumption or welfare.
- Period averages are annual percentage gaps, not cumulative growth or discounted welfare.

Adults: 20–89. Output: each path's 1976 producer prices. No schooling adjustments. Durable spending allows stocks/purchases to adjust jointly over time.

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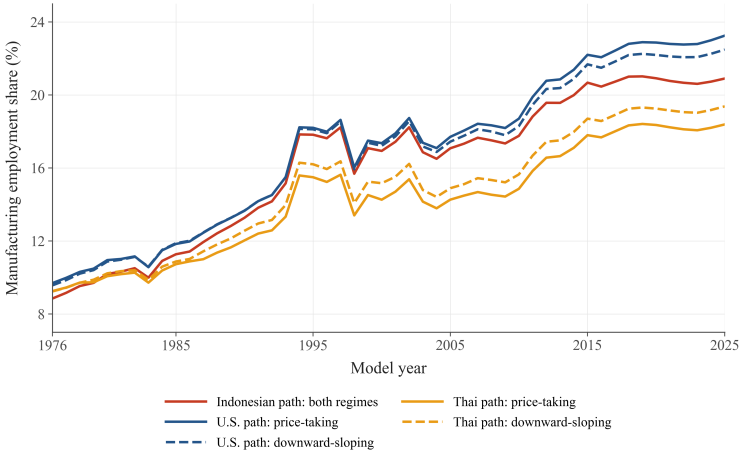
Manufacturing Employment Under Alternative Export Conditions



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Durables and Export Assumptions

U.S.–Thailand gap in peak manufacturing employment (pp)

Model	Export demand	Full	Sorting	Demand	Remaining
Baseline	Price-taking goods	4.84	3.35	0.16	1.32
	Downward-sloping	3.11	2.14	0.62	0.35
Durables	Price-taking goods	4.76	3.27	0.09	1.39
	Downward-sloping	2.97	2.07	0.41	0.49

- Sorting accounts for about 69–70% of the peak gap in all four comparisons.
- With restricted exports, age-dependent demand contributes more.
- Durables is separately calibrated: worker parameters, tastes and relative productivity.

Price-taking applies to A/M; restricted exports impose downward-sloping demand in all sectors. Sorting/demand: Shapley contributions. Remaining: Neither. Sums differ by rounding.

Back

Schooling and Sectoral Reallocation

Family-size adjustment

Adjust each path's cohort schooling using birth-year total fertility f_c relative to Indonesia:

$$\bar{s}_c^{\text{adj}} = \bar{s}_c - 0.107(f_c - f_c^{\text{IDN}}).$$

U.S.–Thailand gaps, baseline model

	Original	Adjusted
Manufacturing peak (pp)	4.84	4.75
2025 output per capita (%)	42.8	36.7

Assumes one unit of fertility equals one additional sibling; applies an estimated sibling effect to cohort schooling.

An additional 3.2 years on the Thai path

Raise schooling for cohorts born from 1957 onward; leave the U.S. path unchanged.

Thai employment change in 2025 (pp)

Sector	Change
Agriculture	-3.92
Manufacturing	+0.79
Low-skill services	+0.03
High-skill services	+3.10

Relative to unchanged Thai schooling. No education-resource or foregone-work costs.

Baseline model. These are separate experiments, not combined schooling adjustments.

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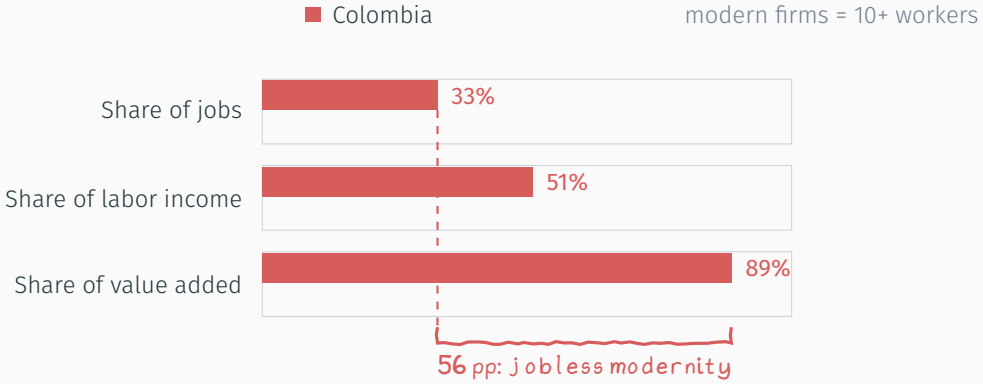
Jobless Modernity

Why modern firms in emerging economies create income but few jobs

Laura Alfaro (HBS) Marcela Eslava (Universidad de los Andes)
Martí Mestieri (IAE-CSIC, CREI, BSE) Luis Felipe Sáenz (University of South Carolina)

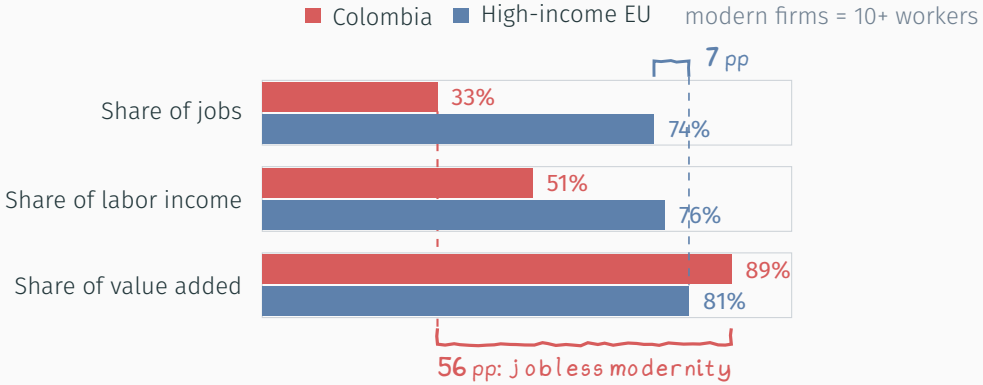
Labor markets and structural transformation in times of change
PIIE, IMF, OECD and World Bank Group · Washington DC, November 17, 2026

Modern firms in emerging economies create income, not jobs



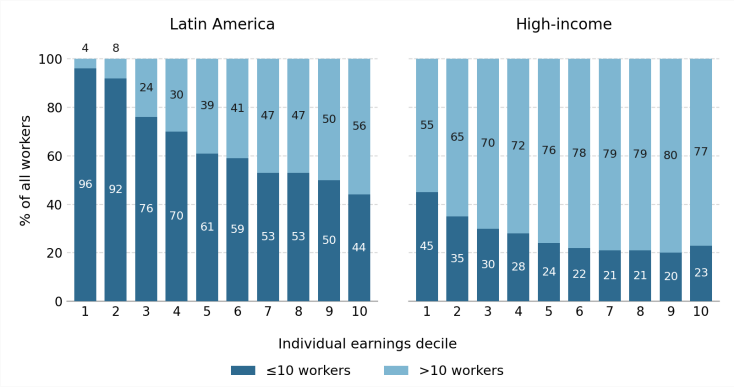
Modern firms employ a third of Colombia's workers and produce nine tenths of its value added.

Modern firms in emerging economies create income, not jobs



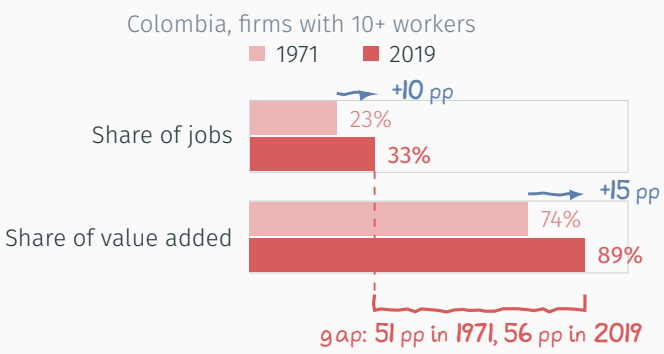
Income shares are close, job shares are not.

Why it matters: a modern job is the ticket to the middle class



- In Latin America, modern jobs sit at the top of the earnings distribution. In high-income economies they span it.
- Modern growth without modern jobs leaves the gains with the few attached to modern firms.

Not modern enough yet? Fifty years of growth did not close the gap

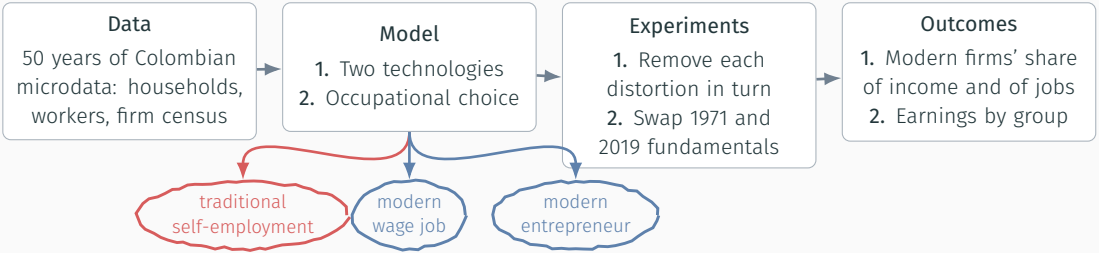


- 1971 to 2019: income per head ×2.7, more schooling, 1990s labor and trade reforms.
- Modern jobs up 10 pp, modern value added up 15 pp. The gap did not close: 51 pp then, 56 pp now.

Transitional: the gap closes as the economy modernizes.

Structural: barriers to jobs that growth does not remove.

What we do: measure the barriers, then remove them one at a time



Distortions, measured directly

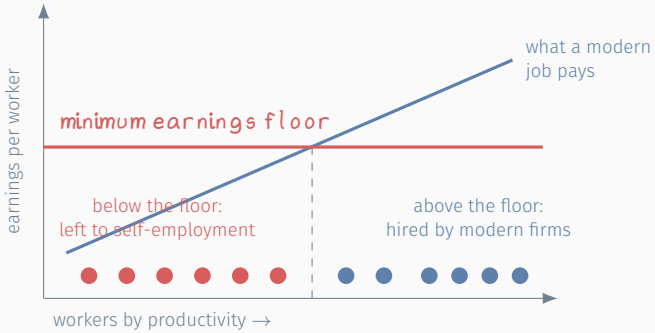
- Non-salary labor costs: 46 cents per peso of wages
- Minimum earnings floor: 46% of workers earn less
- Revenue and capital wedges, estimated firm by firm, correlated with productivity: the best firms face the largest wedges

Fundamentals, estimated

- Technology: labor elasticity fell from 0.37 to 0.26
- Worker and entrepreneur capabilities
- Taste for traditional goods and for self-employment

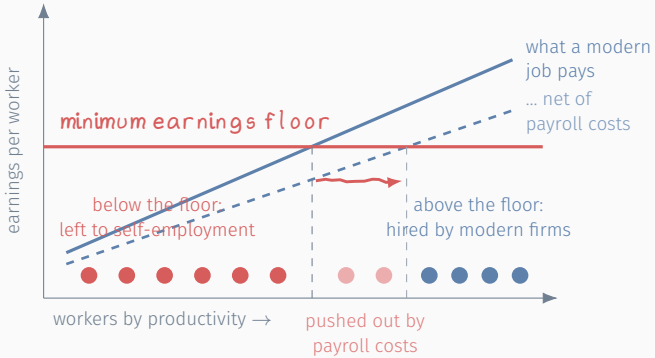
▸ What is new relative to the literature

How labor distortions block jobs: the earnings floor decides who gets in



- **Earnings floor.** A firm hires only if the job pays at least the floor. Workers below it stay self-employed.

How labor distortions block jobs: the earnings floor decides who gets in



- **Earnings floor.** A firm hires only if the job pays at least the floor. Workers below it stay self-employed.
- **Payroll costs.** Firms pass them on: pay per worker falls and the cutoff moves right. Labor also gets dearer than machines.
- **Revenue and capital wedges**, estimated and rising with productivity, shrink the best firms. Income and jobs fall together.

Labor barriers decide *who* gets in, other barriers *how big* firms are.

Result 1: distortions account for 40% of jobless modernity

Colombia 2019	Baseline	No distort.
A. Modern share of income (%)	84.2	90.8
B. Modern share of jobs (%)	33.1	60.0
Jobless modernity (A − B)	**51.1 pp**	**30.9 pp**
Income p.c.	0.77	1.00
Average establishment size	1.45	2.40

- Removing all distortions: modern income $+7\,pp$, modern jobs $+27\,pp$.
- Distortions break the link from modern production to modern jobs.
- The remaining 31 pp is fundamentals. Distortions are not the whole story, but they make it much worse.

Result 2: labor distortions do most of the damage to jobs, and little to income

Colombia 2019	Baseline	Remove revenue & capital wedges	Remove labor floor & payroll costs	Remove all
A. Modern share of income (%)	84.2	89.8	85.9	90.8
B. Modern share of jobs (%)	33.1	45.4	50.6	60.0
Jobless modernity (A − B)	**51.1**	**44.4**	**35.3**	**30.9**

Revenue and capital wedges

Deliver the largest income gains when removed, but close only 7 of the 20 pp that distortions add to the gap.

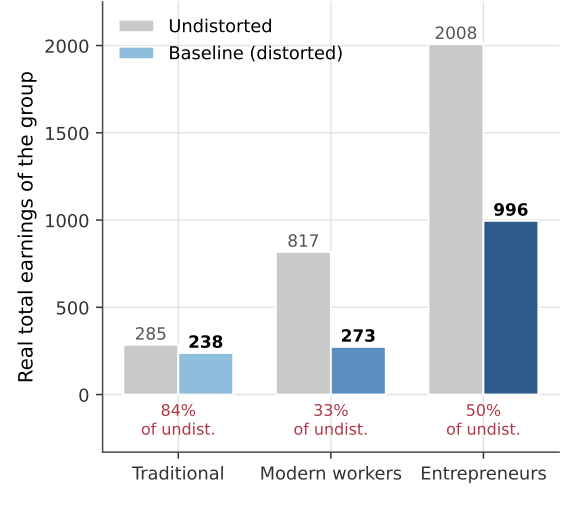
Labor floor and payroll costs

Barely move modern income, but are **70%** of the distortion-induced gap.

In isolation: floor 7.7 pp, payroll costs 5.0 pp.

The distortions that cost the most income are not the ones that cost the most jobs.

Result 3: everyone loses from distortions, and modern workers most of all



- **Everyone loses.** Total real earnings of every group are lower with distortions: the self-employed by 16%, entrepreneurs by half.
- **Modern wage workers lose most.** As a group they keep only a third of what they would earn without distortions, because far fewer people hold a modern job.
- Per person: self-employed 50%, modern workers 63%, entrepreneurs 42% of undistorted income. The middle-class slide in model terms: the losses fall on those kept out.

Result 4: growing like Latin America, 1971–2019: jobless modernity is structural

	1971 baseline	2019 fundamentals 1971 distortions	2019 baseline
A. Modern share of income (%)	69.9	82.7	84.2
B. Modern share of jobs (%)	23.0	31.6	33.1
Jobless modernity (A − B)	**46.9**	**51.1**	**51.1**
Income per capita (1971 = 1)	1.00	2.12	2.72

- Fundamentals deliver most of the growth and of the 10 pp rise in modern jobs, yet widen the gap: income rose faster than jobs.
- Fifty years of distortion changes: income ×1.3, gap unchanged. Lower payroll and firm wedges helped growth, and a more binding earnings floor offset them on jobs.

What this means for policy

1. **Growth alone does not eliminate jobless modernity.** Colombia grew, educated, and reformed for fifty years. The gap did not close.

2. **Growth reforms are not job reforms.** Removing revenue and capital wedges raises income and firm scale but broadens access to modern jobs only modestly.

3. **The design of labor costs is the first-order lever for jobs.** Payroll costs and the earnings floor are 70% of the distortion-induced gap.
   - The model suggests that lowering the non-wage cost of formal hiring, for instance by shifting part of social-protection financing away from the payroll, and anchoring the minimum wage to productivity would open modern jobs at little cost in income.

4. **Opening access to modern jobs is redistribution without transfers.** Most of the gap between modern and traditional workers comes from who gets in, not from what the job pays.
   - Widening access raises real earnings in every occupation and narrows that gap from 2.5 to 2.0.

Looking ahead: AI makes the price of hiring matter more

- Technology already moved against labor in Colombia. The labor elasticity of modern production fell from 0.37 to 0.26, and with 2019 fundamentals the modern sector's income share rose 13 pp while its jobs share rose 9. More of the same is the likely effect of AI.

- In our framework a labor-saving shock widens the gap on its own.

Whether the jobs that remain are reachable depends on the earnings floor and on payroll costs, which is the part that policy controls.

Thank you

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Additional slides

What is new relative to the literature

Literature	What we add
Misallocation and firm size. Why productive firms stay small in poor countries, and the TFP cost. Restuccia–Rogerson 08, Hsieh–Klenow 09, Hopenhayn 14, Bento–Restuccia 17, Eslava–Haltiwanger–Urdaneta 23	The object is the gap between modern firms' income and jobs. Distortions with similar effects on scale have very different effects on hiring.
Wedges inferred from firm size. The residual between observed and optimal size.	Labor distortions measured directly (payroll costs, earnings floor) next to estimated revenue and capital wedges: barriers to jobs separated from barriers to production.
Informality and labor regulation. Formal vs informal firms and workers, enforcement, wages. Ulyssea 18, Dix-Carneiro et al. 21, Meghir–Narita–Robin 15, Haanwinckel–Soares 21	Formal and informal producers in one occupational-choice equilibrium: the traditional sector absorbs those kept out of modern jobs.
Firms and earnings inequality. Employer heterogeneity, sorting, rent sharing. AKM 99, Card–Heining–Kline 13, Song et al. 19, Helpman et al. 17, Autor et al. 20	A new channel, access: who enters modern employment moves earnings by occupation, the modern–traditional gap and the labor share.
Micro to macro development. Aggregate implications of micro heterogeneity. Buera–Kaboski–Townsend 21, Buera–Moll 15, Mestieri–Schauer–Townsend 17	Whole-economy coverage down to one-person producers, at two dates fifty years apart: labor-saving technical change identified alongside capabilities and distortions.

Back to what we do

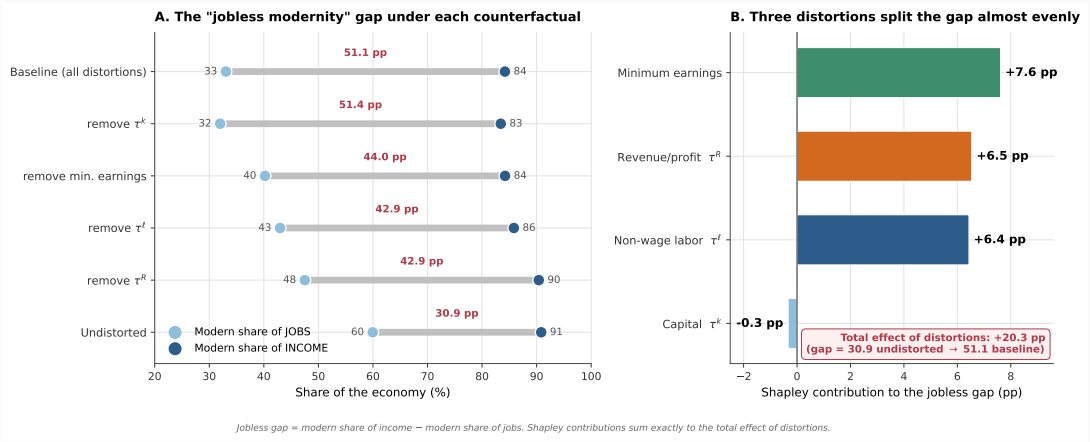
Model: the modern entrepreneur's problem

- Agents endowed with (a_j, d_j): general productivity and entrepreneurial demand draw. They pick the occupation with the highest income.
- Traditional self-employment pays a_j. Modern wage work pays $w\,a_j$ and requires $w\,a_j \geq e_{\min}$.
- Modern entrepreneur j solves

$$\max_{l,k,m} \underbrace{(1-\tau_j^R)}_{\text{revenue wedge}} p_j q_j \; - \; \underbrace{(1+\tau_j^l)}_{\text{payroll costs}} w\,l \; - \; \underbrace{(1+\tau_j^k)}_{\text{capital wedge}} r\,k \; - \; p_M\,m, \qquad q_j = a_j\,l^{\gamma_l} k^{\gamma_k} m^{\gamma_m}.$$

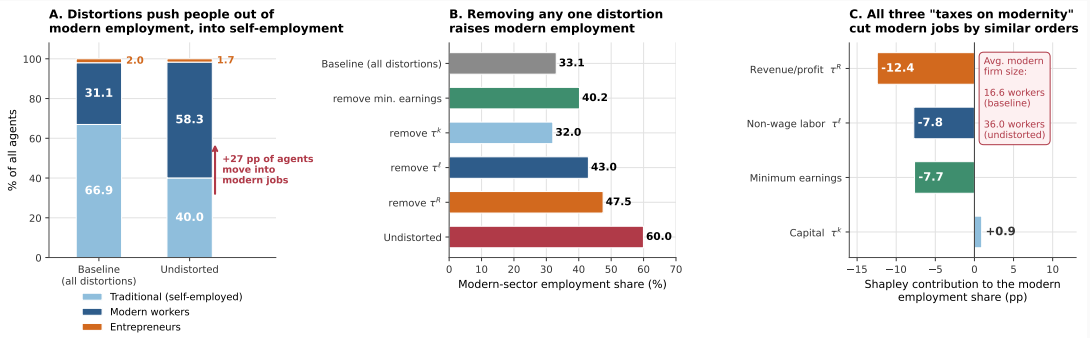
- Demand $p_j \propto d_j^{1/\sigma} q_j^{-1/\sigma}$. Materials are the modern composite itself. Wedge revenue is rebated lump sum.
- Profits are convex in productivity $a_j d_j^{1/(\sigma-1)}$ times the composite wedge $(1-\tau^R)^{\sigma/(\sigma-1)}/[(1+\tau^l)^{\gamma_l}(1+\tau^k)^{\gamma_k}]$.

Which distortion does what: Shapley decomposition of the 2019 gap



Jobless gap = modern share of income − modern share of jobs. Shapley contributions sum exactly to the total effect of distortions.

Distortions push people out of modern employment into self-employment



Entrepreneurs are MORE numerous under distortions (2.0% vs 1.7%) but each runs a far smaller firm: distortions fragment production into many tiny units.

Calibration fit, Colombia 2019

Targeted

Moment	Data	Model
Modern employment share	33.6%	33.1%
$e_{\min}/e_{P50}$	0.90	0.90
Workers below $e_{\min}$	46.0%	46.1%
Modern wage premium	1.80	1.50
e_{P50}/e_{P5}	10.1	10.1
e_{P50}/e_{P10}	3.30	3.30
e_{P75}/e_{P50}	1.30	1.70

Untargeted

Moment	Data	Model
Modern share of labor earnings	51.1%	53.4%
Modern entrepreneurs	1.6%	2.0%
e_{P50}/e_{P25}	1.60	1.80
e_{P90}/e_{P50}	2.00	2.60
Traditional share above e_{P50}	35.0%	36.4%

- Micro-estimated: technology and demand elasticities (GMM on the manufacturing census), capability distributions, wedge schedules. Internally calibrated: $\rho, \phi_M, e_{\min}$ and traditional-job attributes.

Selection versus prices in the earnings effects of distortions

Real earnings, baseline = 1	Baseline	No distortions	Baseline selection, counterfactual w, P	Counterfactual selection, baseline w, P
Traditional self-employed	1.00	2.00	1.66	1.21
Modern wage workers	1.00	1.60	2.15	0.74
Modern entrepreneurs	1.00	2.40	0.53	2.92
Earnings ratio, wage workers / self-employed	2.47	1.97	3.20	1.52
Modern real wage	1.00	2.20	2.20	1.00

- Price effect: distortions depress the real wage. Selection effect: they exclude lower-ability workers from modern jobs, raising average ability inside. Selection dominates for relative earnings.

Which distortions changed, 1971 to 2019

- At 2019 fundamentals, replacing 1971 distortions one group at a time: the gap goes from 51.1 to **54.0** pp with the 2019 minimum earnings floor, to 51.9 with 2019 payroll costs, and to 51.2 with 2019 revenue and capital wedges.
- The 2019 minimum earnings floor is more binding than its 1971 counterpart.
- Non-salary labor costs: same average (0.47 vs 0.46), but in 1971 they fell hardest on the most productive firms (correlation with productivity -0.51). By 2019 that correlation had vanished.
- Revenue and capital wedges became less costly for growth without improving the jobs margin.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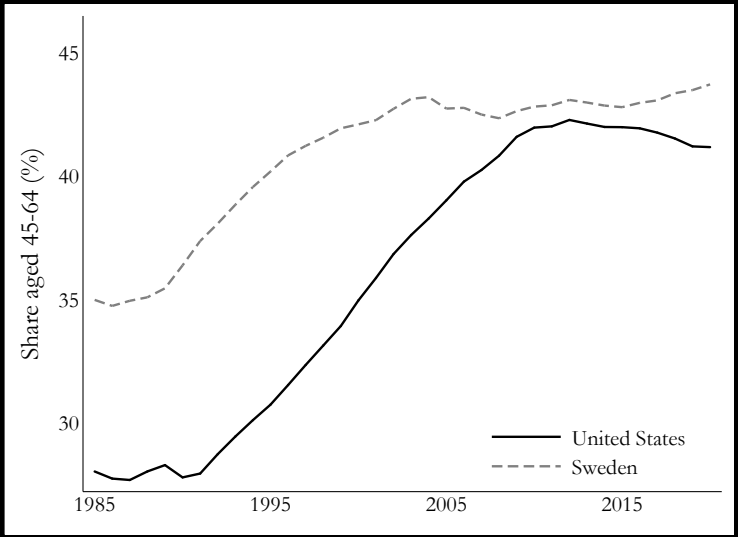
Aging, Labor Market Dynamics, and Growth

Niklas Engbom
New York University

IMF/OECD

November 18, 2026



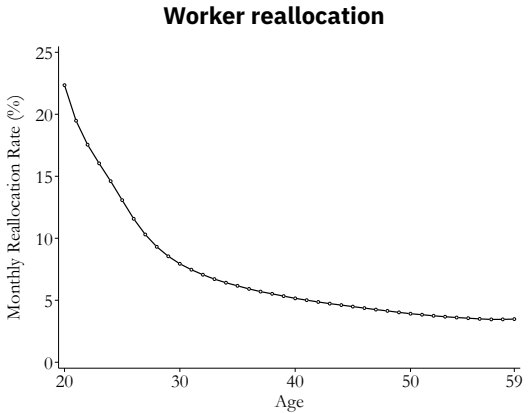
Share among labor-force participants aged 20–64.

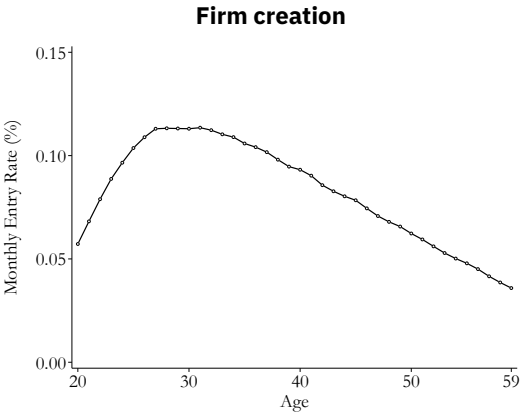
How Does an Aging Workforce Affect Labor Market Dynamics & Growth?

- 2 motivating facts using Swedish administrative data from 1986 to 2018
  1. Older workers are less likely to switch employer and start new firms
  2. Older markets have lower worker mobility and firm creation conditional on age
- Model of embodied technical change with labor market frictions
  - New firms introduce new technologies embodied in firms
  - Workers gradually relocate to become well-matched to incumbent firms
- The impact of aging
  - Aging improves the economy's match with existing technologies
  - Discourages the introduction of new technologies by making it harder for entrants to recruit
  - Boom in growth through early 2000s due to level effect, lower growth for next 30 years

Motivating Facts

Mobility and Entrepreneurial Entry over the Life Cycle





Worker reallocation rate is the probability of switching employment. Firm creation is the probability of starting a new firm.

Lower Mobility and Entry Conditional on Age in Older Labor Markets

$$\log y_{cat} = \beta \log \left(\frac{\text{\# age 20–44}}{\text{\# age 20–64}} \right)_{ct} + \alpha_c + \alpha_t + \alpha_a + \varepsilon_{cat},$$

IV elasticity	**All ages**		**Age group**		
	No age controls	Age controls	20–29	30–44	45–64
Worker reallocation	3.52	3.08	2.07	2.46	3.90
	(0.93)	(0.86)	(0.67)	(0.71)	(1.15)
Founder entry	4.97	4.41	5.44	2.75	4.93
	(1.52)	(1.49)	(1.81)	(1.26)	(1.64)

- 68 Swedish commuting zones, 1986–2018
- Instrument the young share with local births 20–44 years earlier

Model

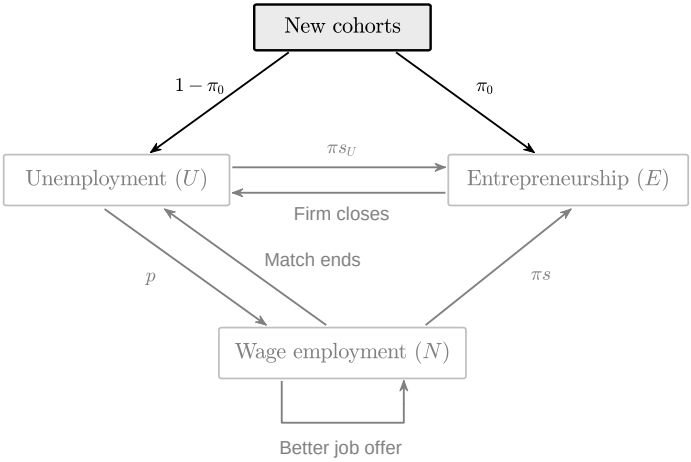
Environment

- Continuous time, risk-neutral individuals, population growth γ
  - Wage employed, nonemployed or self-employed at a point in time
- A firm with blueprint productivity Z_i and n employees produces $e^{Z_i}n$
  - Cost of intermediates $C_I(t)n$
  - Employment-adjustment cost $e^{Z_i}v_i(t)^{1+\eta}/(1+\eta)$ to advertise $v_i(t)$ vacancies
  - Operating cost $C_O(t)$ for a fixed factor in supply $Le^{\gamma t}$
- Standard Cobb-Douglas matching function gives worker and job finding rates

$$q = \chi\left(\frac{V}{U+N}\right)^{\theta-1}, \qquad p = \chi\left(\frac{V}{U+N}\right)^{\theta}.$$

Bargaining over marginal surplus following Bilal, Engbom, Mongey & Violante (2022)

Occupational Choice



Entry costs

Cohort start-up cost $c_0\mathcal{B}(t)$

Idea search costs $\mathcal{B}(t)\frac{s^{1+\omega}}{1+\omega}$

Blueprint draws

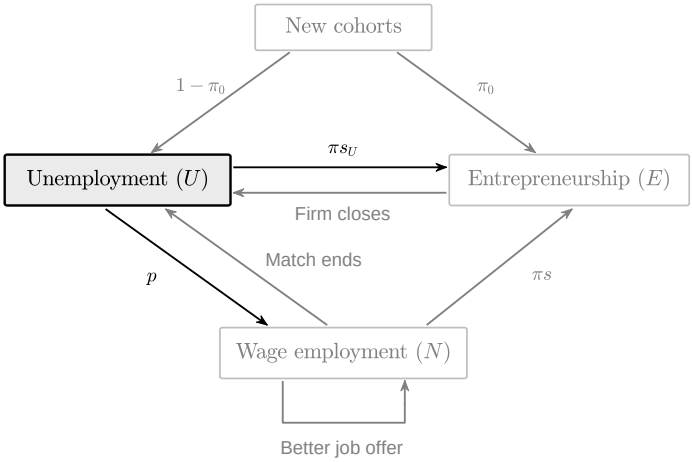
Baseline draw $\widetilde{Z} \sim \mathscr{Z}(\cdot, t)$

From employment

$$\widehat{Z} \quad = \quad \widetilde{Z} + \beta[Z - \underline{Z}(t)].$$

Quit before seeing the draw

Occupational Choice



Entry costs

Cohort start-up cost $c_0\mathcal{B}(t)$

Idea search costs $\mathcal{B}(t)\frac{s^{1+\omega}}{1+\omega}$

Blueprint draws

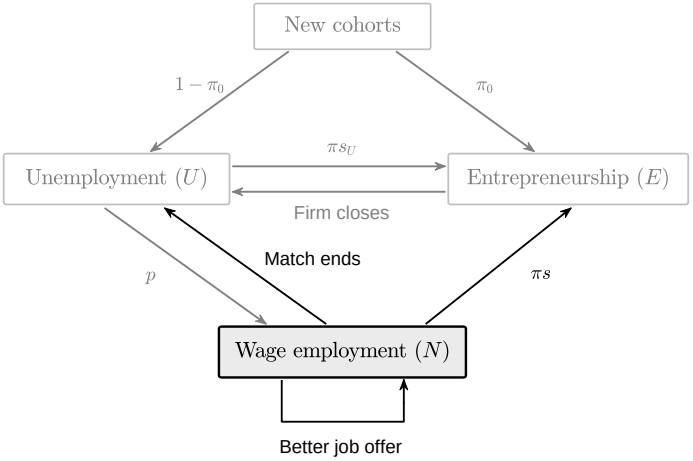
Baseline draw $\widetilde{Z} \sim \mathscr{X}(\cdot, t)$

From employment

$$\widehat{Z} \quad = \quad \widetilde{Z} + \beta[Z - \underline{Z}(t)].$$

Quit before seeing the draw

Occupational Choice



Entry costs

Cohort start-up cost $c_0\mathcal{B}(t)$

Idea search costs $\mathcal{B}(t)\frac{s^{1+\omega}}{1+\omega}$

Blueprint draws

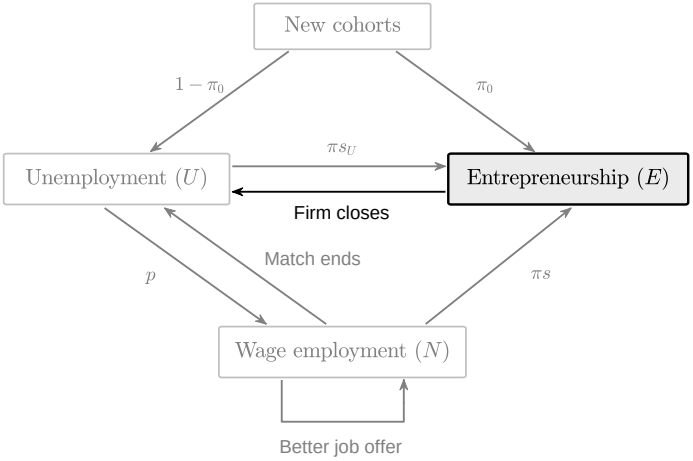
Baseline draw $\widetilde{Z} \sim \mathscr{X}(\cdot, t)$

From employment

$$\widehat{Z} \quad = \quad \widetilde{Z} + \beta[Z - \underline{Z}(t)].$$

Quit before seeing the draw

Occupational Choice



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Blueprint draws

Baseline draw $\widetilde{Z} \sim \mathscr{Z}(\cdot, t)$

From employment

$$\widehat{Z} \quad = \quad \widetilde{Z} + \beta[Z - \underline{Z}(t)].$$

Quit before seeing the draw

The Scaled Joint Value of a Firm

Study an economy scaled in the least productive firm, $z = Z - \underline{Z}(t)$

$$(\rho - m)W(z,n) = \underbrace{(e^z - c_I)n}_{\text{net production}} + \underbrace{k}_{\substack{\text{entrepreneurial}\\ \text{amenity}}} - \underbrace{c_O}_{\text{operating cost}} - \underbrace{mW_z}_{\substack{\text{technological}\\ \text{obsolescence}}} - \underbrace{\delta n[W_n - W_U]}_{\substack{\text{exogenous separation}\\ \text{into unemployment}}}$$

$$+ \max_{v,s\geq 0}\left\{ - \underbrace{e^z \frac{v^{1+\eta}}{1+\eta}}_{\text{recruiting cost}} + \underbrace{\frac{qvU}{U+N}[W_n - W_U]^+}_{\substack{\text{hires from}\\ \text{unemployment}}} + \underbrace{\frac{qvN}{U+N}\int [W_n - W_n(y,h)]^+ \, d\mathcal{G}(y,h)}_{\text{hires from other firms}}\right.$$

$$\left. - \underbrace{nb\frac{s^{1+\omega}}{1+\omega}}_{\text{idea-search cost}} + \underbrace{n\pi s\left[\int W(y,0)\, d\Gamma(y \mid z) - W_n\right]}_{\text{expected net value of a spin-off}}\right\}.$$

Reducing the State Space

- In addition to technical assumptions to ensure bounded values etc, suppose that
  - Leisure, amenities, and input costs scale with $e^{Z(t)}$, with $b > 0$, $c_I \geq 0$, $b + c_I = 1$
  - The amenity value of being one's own boss is sufficiently high, $k > (\rho - m)W_U$

- **Proposition**: The scaled joint surplus of a firm is affine in employment

$$\underbrace{W(z,n) - (n+1)W_U}_{\text{scaled joint surplus of firm}} = n \underbrace{W_N(z)}_{\text{match surplus}} + \underbrace{W_E(z)}_{\text{surplus of an empty firm}}$$

Matches and firms share the cutoff $z = 0$. Recruiting and idea search depend only on z.

A Tractable Growth Equilibrium

- Assumptions
  - All entrepreneurship entry takes place at labor market entry, $\pi = 0$
  - Recruiting is inelastic, with $v(z) = 1$ for $z > 0$ and $v(z) = 0$ otherwise

- **Lemma**: the expected return to entrepreneurship entry is

$$\mathcal{E}(m,\gamma) = \frac{p}{L(\rho+\delta)} \int_0^\infty e^{-(\zeta-1)z} \left(1 - L - \underbrace{N(m,\gamma)(1-G(z,m,\gamma))}_{\text{mismatch effect}}\right) \underbrace{\frac{1-e^{-\frac{(\rho+\delta)z}{m}}}{\rho+(\zeta-1)m}}_{\text{obsolescence effect}} dz$$

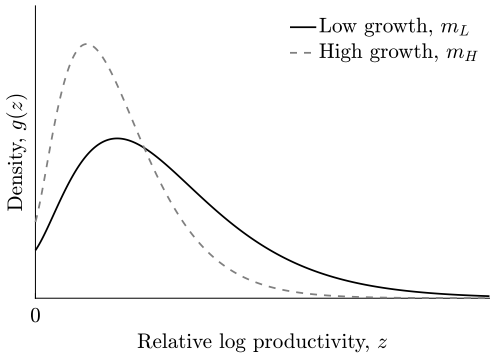
- An interior equilibrium has

$$c_0 b = \mathcal{E}(m,\gamma)$$

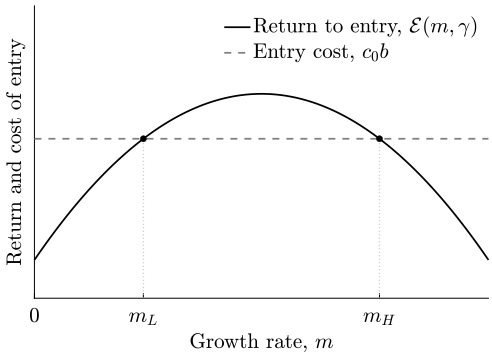
The Impact of Growth on the Return to Entry: Obsolescence & Mismatch

- Obsolescence (Aghion & Howitt, 1994): faster growth shortens firm and match lives
- Mismatch (new): faster growth raises labor market mismatch ⇒ cheaper to recruit

(a) Worker productivity



(b) Multiple growth equilibria



Existence and Uniqueness

With exponential productivity tail parameter ζ, interior growth satisfies $0 < m < M$, where

$$M \quad = \quad \min\left\{\rho, \frac{\gamma(1-L)}{\zeta L}\right\}.$$

- **Existence.** An interior BGP exists if the entry cost lies between the endpoint returns

$$\mathcal{E}(M,\gamma) \quad < \quad c_0 b \quad < \quad \mathcal{E}(0,\gamma).$$

  For sufficiently low χ or ρ, there are entry costs that support an interior BGP

- **Uniqueness.** Obsolescence dominates mismatch throughout $(0, M)$ if

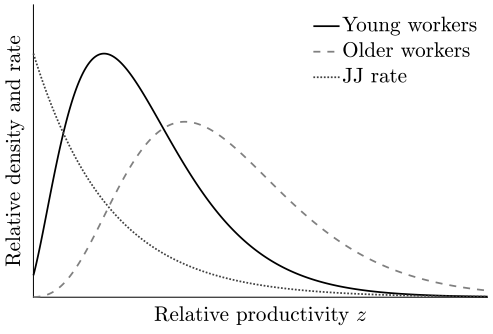
$$\rho + (\zeta - 1)M \quad < \quad \frac{e(\zeta-1)(\gamma+\delta)}{\zeta}.$$

Worker, Firm and Entrepreneurship Life-Cycle Dynamics

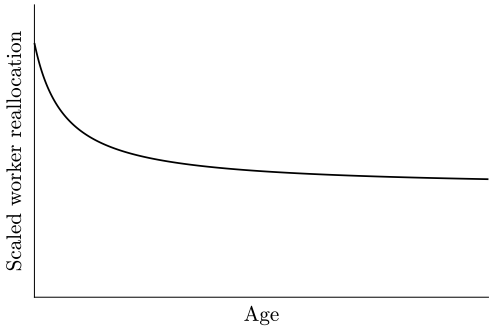
Worker Life-Cycle Dynamics

- Workers climb the job ladder as they accumulate offers
- **Lemma**: Job-to-job mobility and separations into unemployment fall with career age

(a) Productivity and mobility



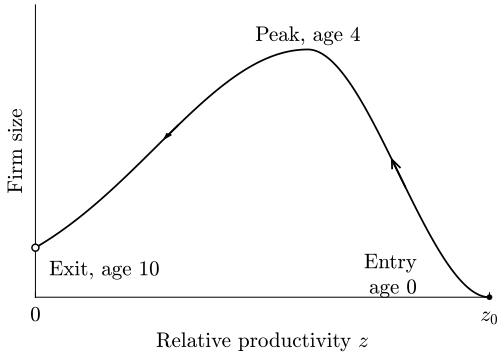
(b) Worker reallocation by age



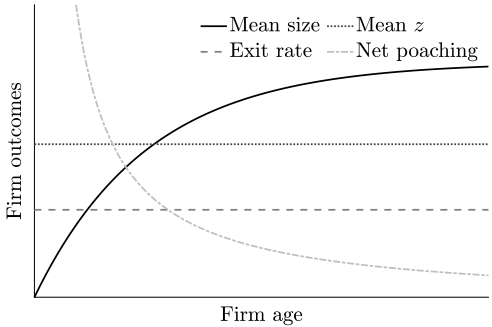
Firm Life-Cycle Dynamics

- An entrant grows and then (potentially) shrinks as its blueprint becomes obsolete
- **Lemma**: Mean size rises with age among survivors, net poaching falls

(a) An entrant firm



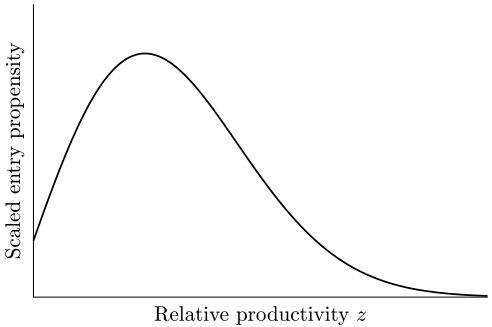
(b) Surviving firms



Entrepreneurship Life-Cycle Dynamics

- Better employers improve ideas and raise the value of staying in the job
- **Lemma**: Spillover values exist such that the entry profile is hump shaped

(a) Entry by employer productivity



(b) Entry by career age



The Impact of Aging

Modeling Workforce Aging

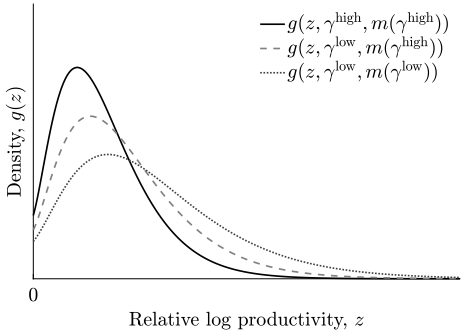
- Career age a is time since labor market entry

$$\underbrace{1 - \Lambda(a)}_{\text{share older than } a} = \frac{e^{\gamma(t-a)}}{e^{\gamma t}} = e^{-\gamma a}, \qquad a \geq 0.$$

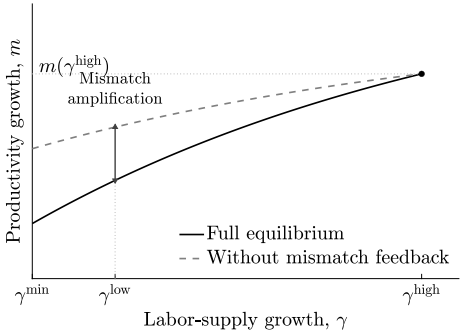
- Aging is a fall in γ, which raises the share older than every $a > 0$
- Compare balanced growth paths with different rates of labor supply growth

Proposition: Aging Raises Productivity Levels and Lowers Growth

Allocation to existing technologies



Equilibrium amplification



$$m'(\gamma) > 0, \qquad \frac{dY}{d\gamma} = Y_m m'(\gamma) + Y_\gamma < 0, \qquad Y = \int e^z \, dG(z).$$

Welfare Effects of Aging

- Compare scaled values across balanced growth paths at a common technology cutoff
- **Proposition**: Aging lowers the value of unemployment and raises the surplus of matches

$$\frac{dW_U}{d(-\gamma)} < 0, \qquad \frac{dW_N(z)}{d(-\gamma)} > 0 \quad (z > 0).$$

- With interior cohort entry, new entrants receive W_U in expectation
- For sufficiently small b at fixed $c_0 b$, marginal joint value $W_U + W_N(z)$
  - Falls at $z < z^\dagger$ and rises at $z > z^\dagger$, for a unique cutoff $z^\dagger > 0$

Proposition: Aging Reduces Worker Mobility and Entry Conditional on Age

Job-to-job mobility



Entrepreneurial entry



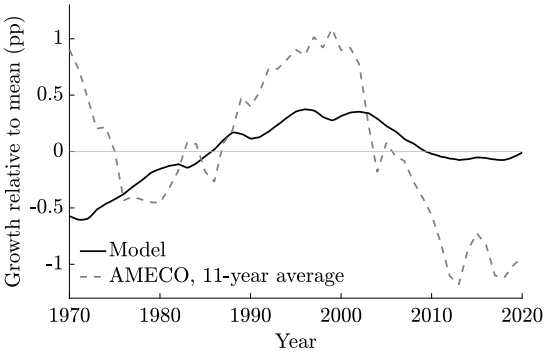
Workers have fewer new technologies to switch to conditional on age; harder recruiting environment discourages entry

Some Numbers

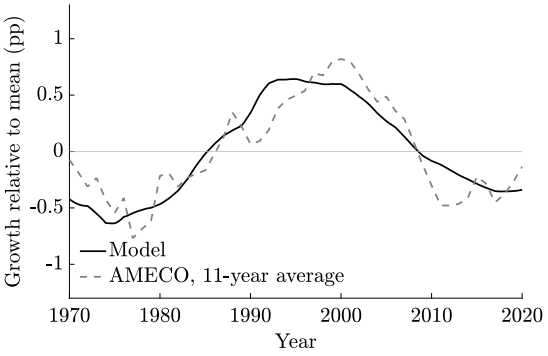
Growth in Output per Worker

- Start each country on its 1900 BGP. Use observed births through 2025, then constant births
- Solve under perfect foresight with common parameters and fixed age schedules

(a) Sweden



(b) United States

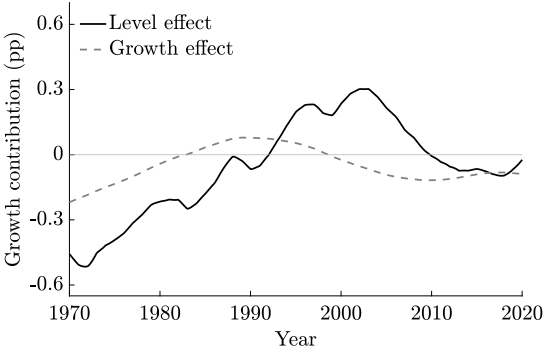


Growth and Level Effects

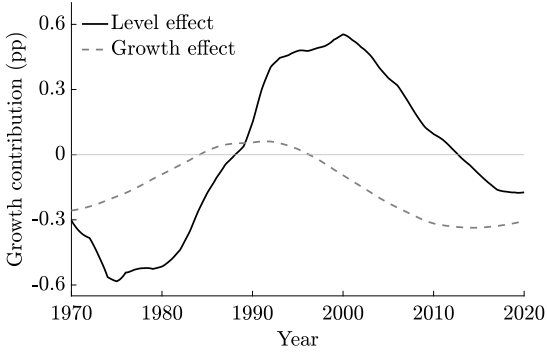
Annual contributions relative to each country's initial balanced growth path

$$\Delta \log\left(\frac{y}{\mathcal{H}}\right) = \underbrace{\Delta \underline{z}}_{\text{growth effect}} + \underbrace{\Delta \log \bar{y}}_{\text{level effect}}.$$

(a) Sweden



(b) United States



Conclusion

Aging, Labor Market Dynamics, and Growth

- Swedish data: workforce aging reduces age-conditional worker mobility and firm creation
- Model of embodied technical change with labor market frictions explains these patterns
  - Older workers are better matched with existing firms since they have had more time to relocate
  - Workforce aging improves economy's match with incumbent technologies
  - Discourages the introduction of new technologies
- Quantitatively, boom in output through early 2000s as level effect outweighs growth effect
  - Better match with incumbent technologies can temporarily sustain output growth even as blueprint growth slows

Aging improves the use of existing technologies while slowing the introduction of new ones

Backup

Reduced Value Functions

$$
\begin{aligned}
(\rho - m) W_U &= b + S_U, \\
(\rho + \delta - m) W_N(z) &= e^z - c_I - b - S_U - m W_N'(z) \\
&\quad + \max_{s \geq 0} \left\{ \pi s [P_N(z) - W_N(z)] - b \frac{s^{1+\omega}}{1+\omega} \right\}, \\
(\rho - m) W_E(z) &= -m W_E'(z) + \max_{v \geq 0} \left\{ v Q(z) - e^z \frac{v^{1+\eta}}{1+\eta} \right\}, \\
c_O &= k - (\rho - m) W_U.
\end{aligned}
$$

S_U is the maximized unemployment search return. $P_N(z) = \int W_E(y)\, d\Gamma(y \mid z)$. Both surpluses vanish at $z = 0$.

The Expected Return to Entry

Back

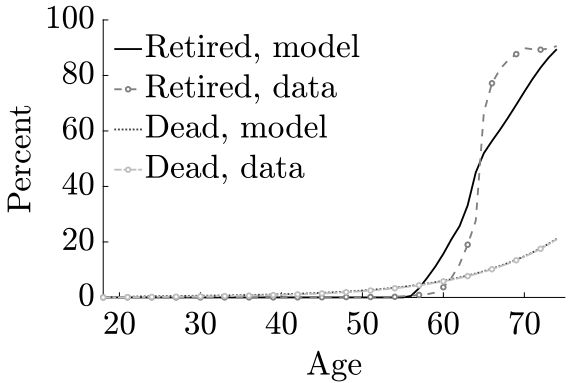
$$\mathcal{E}(m,\gamma) = \frac{p}{L(\rho+\delta)} \int_0^\infty e^{-(\zeta-1)z} \times \underbrace{\left[1 - L - N(m,\gamma)(1 - G(z,m,\gamma))\right]}_{\text{recruiting opportunities}} \times \underbrace{\frac{1 - e^{-\frac{(\rho+\delta)z}{m}}}{\rho + (\zeta-1)m}}_{\text{obsolescence}} dz.$$

$$\mathcal{E}(m,\gamma) = c_0 b, \qquad \gamma\pi_0 = L(\gamma + \zeta m).$$

Benchmark: $\pi = 0$, inelastic recruiting, fixed L, and interior cohort entry.

First-Stage Demographic Fit

Back

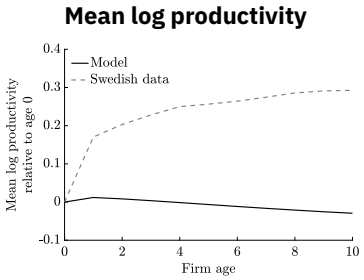


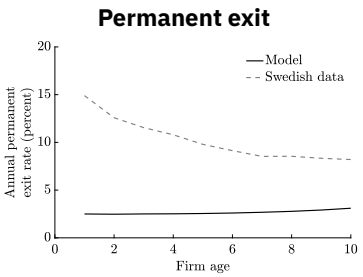
- School completion is taken from the data
- Mortality fits closely
- Career-age retirement smooths the sharp calendar-age retirement pattern

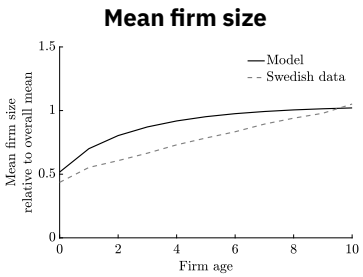
AKU and SCB. Retirement-fit RMSE: 7.79 percentage points. This limitation is retained in the quantitative specification.

Firm Life-Cycle Dynamics

Back







Current human-capital baseline and Swedish data. The entrant–exiter productivity gap and large-firm employment share enter the objective. Other life-cycle features provide validation.

Measuring the Effects of Demographic Change

Back

- Hold school completion, retirement, mortality, search efficiency, and incumbent innovation fixed
- Feed observed birth histories into the age distribution
- Measure both productivity growth and changes in the allocation of workers

$$\log \mathcal{Y}^{\mathrm{pw}}(t) \quad = \quad \underline{Z}(t) + \log \overline{y}(t).$$

Counterfactual design. Relative value added per working person, $\overline{y}(t)$, deducts intermediates and recruiting resources. The denominator includes entrepreneurs. No quantitative aging effect is reported here.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Structural Transformation, Demographics, and Labor Market Frictions

Domínguez-Jiménez · *The Demographic Origins of Premature Deindustrialization*
Alfaro, Eslava, Mestieri & Sáenz · *Jobless Modernity*
Engbom · *Misallocative Growth*

Discussion by Meghana Ayyagari

PIIE · IMF · OECD · World Bank Group Conference • Washington, DC • November 17, 2026

The Development Challenge: Jobs vs. Productivity

YOUNG PEOPLE REACHING WORKING AGE

1.2 billion

Developing economies, next 10–15 years.

Banga, WBG Annual Meetings, Oct 2026

POPULATIONS SHRINKING

28%

of people live in a country whose population has already peaked.

UN World Population Prospects 2024

JOBS PROJECTED ON CURRENT TRENDS

~400 million

World Bank estimate (Banga, Oct 2026)

Three challenges, one question

Young workers are plentiful in some economies, disappearing in others, and too often unable to move into productive employment.

How do economies turn structural transformation into better jobs and sustained growth?

Today's Papers: Three Constraints on Productive Jobs

Domínguez-Jiménez	**Demographic constraint** Who is available to work in manufacturing?
Alfaro, Eslava, Mestieri & Sáenz	**Firm absorption constraint** Why don't productive firms employ more workers?
Engbom	**Dynamic reallocation constraint** Why do workers stop moving toward new technologies?

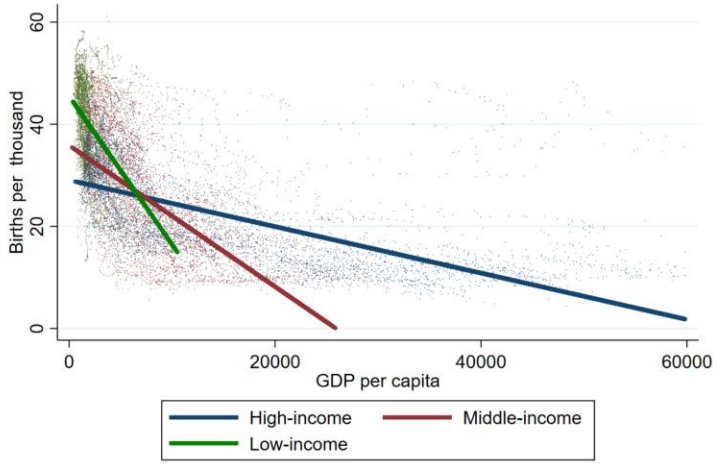
Common thread: what stops demographic and technological change from becoming productive jobs.

Demographic origins of premature deindustrialization

Paper 1 · Domínguez-Jiménez

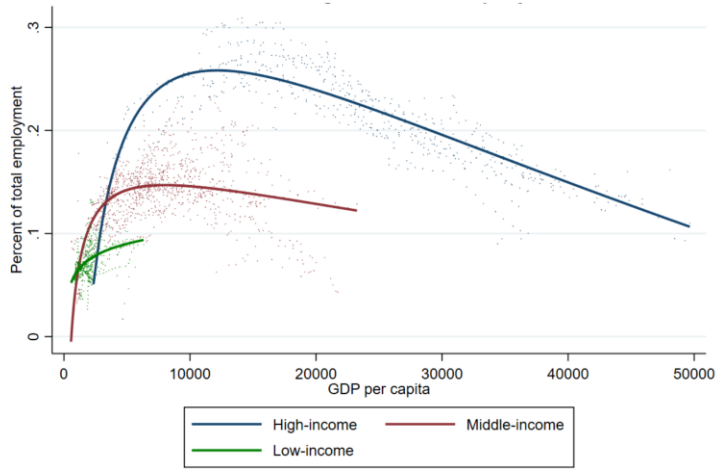
1 Fertility falls at far lower incomes in later developers

Births per 1,000 vs GDP per capita.
Steeper line = fertility falls faster as income rises



2 …and manufacturing peaks lower, at lower income

Manufacturing share of employment vs GDP per capita



Faster demographic transition
fertility falls at lower income

Young-adult cohort shrinks
ages 25–34, while countries are still poor

Less labor for and demand on manufacturing
young adults staff factories (supply) and buy durables (demand)

Manufacturing hump compressed
lower peak, at lower income

Demographic origins of premature deindustrialization

Paper 1 · Domínguez-Jiménez

WHAT I LIKE

- A new, first-order driver of premature deindustrialization: *timing of the demographic transition*
- Macro IV (births 25–34 years earlier as an instrument for today's young share), IPUMS life-cycle facts and an OLG model linking them
- Within non-agriculture, near one-for-one shift from services to industry (**2SLS 0.98**)

- **Timely Question:** China, India, Brazil, Mexico and Vietnam already have below-replacement fertility at middle incomes

TWO BIG QUESTIONS

1. Age, or the whole fertility transition?

- Is the instrument picking up age composition, or the broader transformation that comes with falling fertility?

2. Is earlier deindustrialization a loss?

- That depends on which firms young workers join, and whether services can carry growth

#1. Age, or the whole fertility transition?

Paper 1 · Domínguez-Jiménez

What else do births 25–34 years ago move?

- If schooling, women's work or technology respond to the age shift, they are part of the age effect.
  - Historical fertility also moves *technology*. See Crouzet et al. (2026). A channel to model, or to rule out.
  - Some may be mechanisms, not IV violations.

- **TEST:** How much of the 1-for-1 effect comes from age itself (young people working in factories and buying durables) and how much is left over? A large leftover means the instrument is picking something else

- The real worry: persistent development paths (like institutions or growth trajectories) that drive both past fertility and today's industry
  - Note: Shared with Paper 3 – age instrumented with lagged births so same question there.

#2. Is earlier deindustrialization a loss?

Maybe not

- A bigger manufacturing share isn't automatically good – jobs came back after 2000 in Asia and Africa, but mostly in small informal firms (Kruse et al. 2023)
- Services can carry productivity growth (Nayyar et al. 2021; Fan, Peters & Zilibotti 2023)
- In the paper's own model, most of the output loss (10.5 of 17.1 pp) comes from having fewer workers per person, not from the shift away from manufacturing.

But services aren't automatically an escape

- Younger places adopt new technology faster, so aging may slow services-led growth too (Crouzet et al. 2026)

So: it depends on job quality, not sector shares

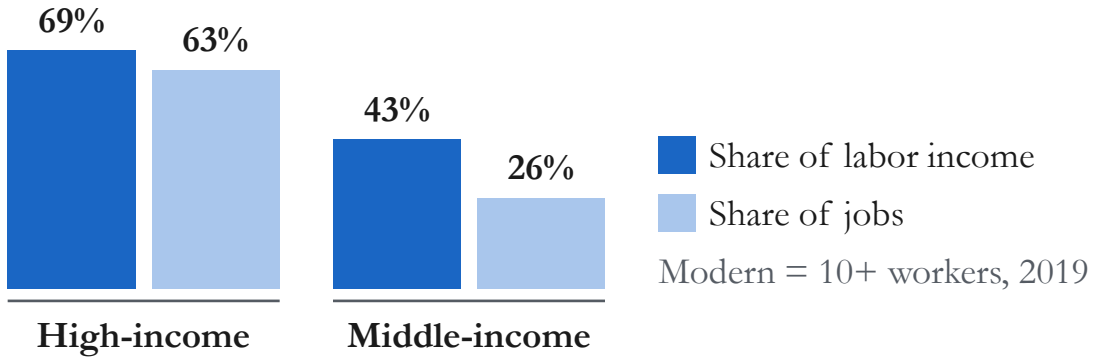
- **TEST:** IPUMS records wage work vs. self-employment. Do large young cohorts raise formal wage jobs and productivity in manufacturing, or only own-account work?
- Most jobs come from small firms that stay small (Ayyagari, Demirgüç-Kunt, and Maksimovic). *Which firms* the young join decides whether it's a loss.

Jobless Modernity

Paper 2 · Alfaro, Eslava, Mestieri & Sáenz

Question

- Why do emerging economies modernize in output but not in jobs?



Setting & Data

- Colombia at its 1970s industrial peak
- Household surveys + manufacturing census
- Model: run a modern firm, work in one, or be self-employed

HEADLINE FINDING

Distortions cut modern jobs from 73% to 24%

and income by 31%

Mechanisms

- **Wage floor:** mainly governs *who* gets a modern job
- **Firm wedges** (payroll, capital, revenue): mainly govern *how big* modern firms get

What I like about this paper

Paper 2 · Alfaro, Eslava, Mestieri & Sáenz

- Puts jobs into the misallocation debate: distortions decide who gets a modern job
- Shows the distortions that hurt jobs are not the ones that hurt output
- Rare data: household and firm records covering informal producers; payroll taxes measured directly

Policy implications

To create modern jobs

- Wage floors in line with low-skill productivity
- Cut payroll taxes
- Skills at the bottom, not the top

To raise output

- Remove the wedges that keep productive firms small

Technology alone

- Raises output, not modern jobs

The floor is not hypothetical: relative to the median wage, Colombia's minimum wage is among the highest in the OECD.

#1. Adding Firm Dynamics

Paper 2 · Alfaro, Eslava, Mestieri & Sáenz

The Question

- The model is static occupational choice: firm entry, growth and collateral constraints are natural next margins
- The calibrated earnings floor explains ~77% of jobless modernity. **Would the ranking survive if entry and finance were in the model?**

What we know from prior work (Ayyagari, Demirgüç-Kunt, and Maksimovic)

- Small firms create most jobs; large firms deliver productivity growth
  - Size at birth predicts the whole life cycle
  - Loan access raises job growth for MSMEs, not large firms
  - Minimum-wage effects differ by employer quality and reduce entry

Suggestion

- Add an entry cost or collateral constraint, recalibrate to firm size at birth and later growth, and check whether the wage floor still dominates

#2. A Natural Test: Colombia's 2012 Reform

Paper 2 · Alfaro, Eslava, Mestieri & Sáenz

The Question

- Can the calibrated wedge predict real-world hiring?

A natural experiment

- Law 1607 (2012) cut payroll taxes by 13.5 pp for workers earning under 10 minimum wages
- Informality fell ~3 pp and formal jobs rose by 200,000+ (Banco de la República review); formal jobs rose for affected groups (Kugler, Kugler & Herrera-Prada 2017)
- The paper's own Table 3: correlation of the payroll wedge with productivity falls from 0.48 (1974–89) to 0.01 (2010–19)

Suggestion

- Calibrate to pre-reform Colombia, model the tax package and phased rollout, and compare formal hiring, wages, size and entry by exposure
  - Model matches → validates the payroll-tax response, not the whole decomposition
- Further test: does the hiring response vary with firms' pre-reform access to finance?

Misallocative Growth

Paper 3 · Engbom

Question

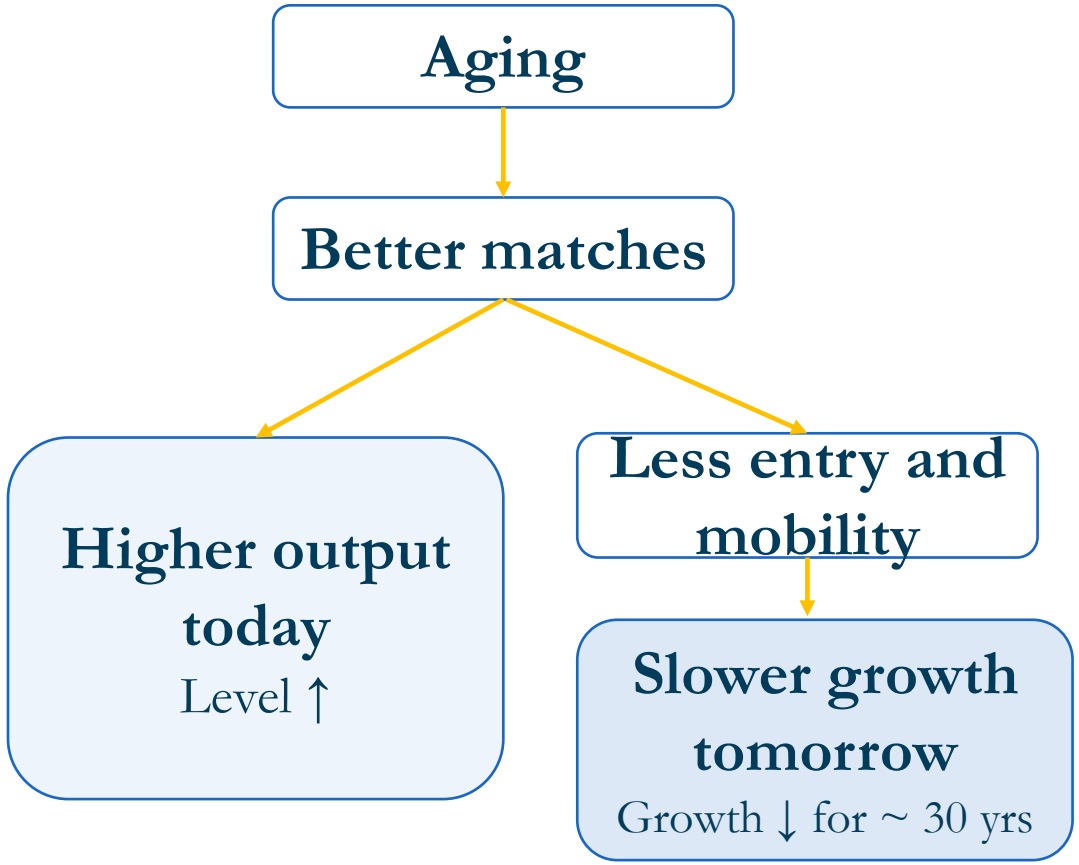
- Does an older workforce slow growth, and why?

Setting & Data

- Sweden 1986–2018: 68 local labor markets
- IV: local births 20-44 years earlier
- Endogenous growth model: firm entry and job ladders

WHAT I LIKE

- Exceptional matched worker–firm–founder data
- Separates aging from labor-supply growth
- Level up, growth down: reconciles US-state and cross-country evidence



Not just composition: people of ***all*** ages in older markets start fewer firms and switch jobs less

#1. Why Does a 30-Year-Old in an Older Market Stay Put?

Better match

Paper's story

Slower renewal gives her more time to find a good match with existing firms.

Test: Are same-age stayers at better firms in older markets? Do the few who move make bigger jumps?

Fewer options

Alternative

Fewer high-growth entrants, weaker local demand, fewer attractive firms nearby.

Test: Do older markets have fewer, lower-quality entrants and vacancies? Do unemployed also find jobs more slowly?

Institutional lock-in

Alternative

Tenure-based protection keeps long-tenured workers in place; when it ends at 67, many of those jobs end
(Saez, Schoefer, Seim, 2026)

Test: 2001 and 2022 reforms – natural experiments –
Did older workers move more at treated firms?

Policy Prescription depends on the Diagnosis

Why people stay put	Is that a problem?	Policy Implication
(1) Good match	Efficient today; Slower growth is a real tradeoff, not a market failure	Don't subsidize job switching. Target entry where it is cheapest: young, not-yet-matched workers; Help incumbents adopt technology. Retire at 67 instead of 65: +8% output per worker, - 0.06pp/yr growth → ~130yrs before slower growth cancels the gain?
(2) Fewer outside options	A shortfall of entry and demand	Lower entry and finance barriers; Raises output and growth together.
(3) Institutional lock-in	Set by the rules, not the matches	Protect the worker not the job: retraining Later retirement alone extends lock-in.

#2. Looking Ahead: Politics and the Direction of Technology

When aging creates winners, who writes the rules?

An older electorate may lock in protection for existing jobs. Akcigit, Baslandze and Lotti show market leaders lobby more and innovate less in Italy

→ Local estimates may be a lower bound.

What kind of technological change does aging encourage?

In this paper: growth comes only from entrants

Acemoglu–Restrepo: aging redirects innovation toward automation by existing firms; no negative growth effect across the OECD.

Who enters matters as much as how many (Ayyagari and Maksimovic)

→ Does aging mainly cut high-skill, high-growth entry, or shift innovation to incumbents?

Three Papers, Three Barriers to Productive Employment

01 WHO IS AVAILABLE?

AGE STRUCTURE

Early demographic change alters the labor supply and demand supporting industrialization.

02 WHO GETS HIRED?

FIRM ABSORPTION

Earnings constraints and firm-level wedges limit modern wage employment.

03 WHO MOVES?

DYNAMIC REALLOCATION

Aging can reduce entrepreneurship, mobility and technological renewal.

Perhaps the missing link between a demographic dividend and a growth dividend is the ability of productive firms to absorb workers and grow.

The key question: Which firms can enter, obtain financing, hire, and scale?