

Occupation Dynamics in General Equilibrium

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Motivation

- ▶ Key questions in macro/labor/trade concern the **dynamics of employment and wages across occupations**
 - Drivers of U.S. labor market polarization and RBTC? (Autor et al., 2006)
 - Exposure to automation and AI shocks? (Hampole et al., 2025)
 - Distributional effects of trade shocks? (Traiberman, 2019)
- ▶ Answers differ in short & long run due to **gradual adjustment of labor and capital**
 - Occupational labor supply adjusts slowly due to mobility frictions
 - Occupational labor demand evolves with investment in specific capital goods

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- ▶ Answers differ in short & long run due to **gradual adjustment of labor and capital**
 - Occupational labor supply adjusts slowly due to mobility frictions
 - Occupational labor demand evolves with investment in specific capital goods
- ▶ We develop a framework that:
 - Features **two-sided, forward-looking dynamics** of K and L in general equilibrium
 - Is rich and tractable enough to map into **detailed occupation-level data**

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 - Fundamentals: (i) Automation (ii) Occupation productivity (iii) Investment efficiency (iv) Mobility frictions across occupations & compensating differentials
 - Allow the economy to be **anywhere along a transition**
3. Estimation with **model-based instruments**
 - EoS across occupations approx. 1.5; EoS across K & L (within occs.) approx. 0.8

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 - Initial conditions matter for observed dynamics; polarization is transitory
5. **Application 2: ex-ante assessment of “AI shocks”**
 - Agnostic approach: project external AI measures onto fundamental dynamics
 - Wage inequality $\uparrow$ (mostly in short run); labor share $\downarrow$ and then $\uparrow$

Related Literature

- ▶ **Dynamic models of technical change & inequality** Zeira (1998), Krusell et al. (2000), Autor et al. (2003), Acemoglu and Autor (2011), Aghion et al. (2017), Acemoglu & Restrepo (2018, ...), Graetz & Michaels (2018), Humlum (2021), Moll et al. (2022), ...
This paper: design to match occupations data + add labor supply dynamics
- ▶ **Dynamic discrete choice models of labor mobility** Lee & Wolpin (2006), Artuç et al. (2010), Kennan & Walker (2011), Dix-Carneiro (2014), Caliendo et al. (2019), Traiberman (2019), Kleinman et al. (2023)
This paper: add task-based demand side and capital accumulation
- ▶ **Wedge accounting in macro & trade** Eaton & Kortum (2002), Chari et al. (2007), ...
This paper: apply to occupation employment and wage dynamics
- ▶ **Labor market polarization & RBTC** Autor et al. (2006), Goos et al. (2014), ...
This paper: highlight key role of *transition dynamics*
- ▶ **Labor market effects of AI** Acemoglu et al. (2022), Babina et al. (2022), Acemoglu and Johnson (2023), McElheran et al. (2023), Hampole et al. (2025), ...
This paper: *dynamic effects* using a quantitative model

Theoretical Framework

Overview

- ▶ Discrete time
- ▶ Output is produced by performing a set of procedures $o \in \mathbb{O}$ (occupations)
 - E.g. providing financial services to a bank's customers
- ▶ Each procedure combines o -specific labor and capital in a task-based framework
 - E.g. dispensing cash can be done by a teller or an ATM
- ▶ Labor is supplied by workers making dynamic discrete choices across occupations
- ▶ Capital is supplied by a rep. capitalist making procedure-specific investments
- ▶ Perfect foresight

Production technology

- The final good is produced by performing a set of procedures $o \in \mathbb{O}$

$$Y_t = \left[\sum_{o \in \mathbb{O}} (z_{ot} y_{ot})^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \quad p_t = \left[\sum_{o \in \mathbb{O}} \left(\frac{q_{ot}}{z_{ot}} \right)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$$

- z_{ot} is the **productivity** augmenting procedure o (or equivalently, demand shifter)
- σ is the **EoS across procedures**

- Each procedure includes a unit measure of imperfectly-substitutable tasks that can be performed by labor (ℓ_{ot}) or capital (k_{ot})

$$y_{ot} = \left[\alpha_{ot}^{\frac{1}{\zeta}} k_{ot}^{\frac{\zeta-1}{\zeta}} + (1 - \alpha_{ot})^{\frac{1}{\zeta}} \ell_{ot}^{\frac{\zeta-1}{\zeta}} \right]^{\frac{\zeta}{\zeta-1}}, \quad q_{ot} = \left[\alpha_{ot} r_{ot}^{1-\zeta} + (1 - \alpha_{ot}) w_{ot}^{1-\zeta} \right]^{\frac{1}{1-\zeta}}$$

- α_{ot} is the **share of automated tasks** in procedure o
- ζ is the **EoS across tasks**

Workers and labor supply: dynamic discrete choice

- Value function for a worker in occupation o in time t is:

$$V_{ot} = \ln \frac{w_{ot}}{p_t} + \ln b_{ot} + \max_{\{i \in \mathbb{O}\}} \{ \beta V_{it+1} - \ln \kappa_{oit} + \rho \epsilon_{it} \}$$

- κ_{oit} : mobility frictions, including cost of acquiring skills and mobility-aversion
- b_{ot} : occupation-specific amenities / compensating differentials
- ρ : governs labor supply elasticity
- ϵ_{it} : extreme value idiosyncratic shock

- Expected value (v_{ot}) for a worker in occupation o :

$$v_{ot} = \ln \frac{w_{ot}}{p_t} + \ln b_{ot} + \rho \ln \left[\sum_{i \in \mathbb{O}} (\exp(\beta v_{it+1}) / \kappa_{oit})^{1/\rho} \right]$$

- Worker mobility probabilities across occupations

$$D_{olt} = \frac{(\exp(\beta v_{it+1}) / \kappa_{oit})^{1/\rho}}{\sum_{m \in \mathbb{O}} (\exp(\beta v_{mt+1}) / \kappa_{omt})^{1/\rho}}$$

Capitalists and investment

- ▶ A **representative capitalist** maximizes logarithmic lifetime utility:

$$\max_{\{c_t, a_{t+1}\}} \sum_{s=0}^{\infty} \beta^{t+s} \ln c_{t+s}^k, \quad \text{subject to} \quad c_t^k + \sum_{o \in \mathbb{O}} \chi_{ot} = \sum_{o \in \mathbb{O}} r_{ot} k_{ot}$$

- ▶ Capital evolves with **investment adjustment costs** (Abel, 2003):

$$k_{ot+1} = \vartheta_{ot} k_{ot}^{1-\delta} \chi_{ot}^{\delta}, \quad 0 < \delta < 1$$

- δ : elasticity of capital w.r.t. investment
 - ϑ_{ot} : investment efficiency in occupation o at time t
- ▶ Investment allocation is a weighted average of income shares and future investment shares:

$$\frac{\chi_{ot}}{\sum_{o'} \chi_{o't}} = (1 - \beta(1 - \delta)) \frac{r_{ot+1} k_{ot+1}}{\sum_{o'} r_{o't+1} k_{o't+1}} + \beta(1 - \delta) \frac{\chi_{ot+1}}{\sum_{o'} \chi_{o't+1}}$$

Intra-temporal equilibrium

- Procedure-specific **labor market clearing**

$$w_{ot}\ell_{ot} = f_{ot}s_{ot} \sum_{m \in \mathbb{O}} (w_{mt}\ell_{mt} + r_{mt}k_{mt})$$

where the **expenditure shares** (s_{ot}) across procedures and within-procedure **labor shares** (f_{ot}) are given by

$$s_{ot} = \frac{(q_{ot}/z_{ot})^{1-\sigma}}{\sum_{m \in \mathbb{O}} (q_{mt}/z_{mt})^{1-\sigma}} \quad , \quad f_{ot} = \frac{(1 - \alpha_{ot}) w_{ot}^{1-\zeta}}{(1 - \alpha_{ot}) w_{ot}^{1-\zeta} + \alpha_{ot} r_{ot}^{1-\zeta}}$$

- Procedure-specific **capital market clearing**

$$r_{ot}k_{ot} = (1 - f_{ot})s_{ot} \sum_{m \in \mathbb{O}} (w_{mt}\ell_{mt} + r_{mt}k_{mt})$$

- Final goods price (numeraire): $p_t = \left[\sum_{o \in \mathbb{O}} \left(\frac{q_{ot}}{z_{ot}} \right)^{1-\sigma} \right] = 1$

Dynamic equilibrium

► Labor dynamics

$$\ell_{ot+1} = \sum_{i \in \mathbb{O}} \frac{(\exp(\beta v_{ot+1}^w) / \kappa_{oit})^{1/\rho}}{\sum_{m \in \mathbb{O}} (\exp(\beta v_{mt+1}^w) / \kappa_{mit})^{1/\rho}} \ell_{it}$$

$$v_{ot}^w = \ln(b_{ot} w_{ot} / p_t) + \rho \ln \sum_{i \in \mathbb{O}} (\exp(\beta v_{it+1}^w) / \kappa_{oit})^{1/\rho}$$

► Capital dynamics

$$\ln k_{ot+1} = \ln \vartheta_{ot} + (1 - \delta) \ln k_{ot} + \delta \ln \chi_{ot}$$

$$\sum_o \chi_{ot} = \frac{\beta \delta}{1 - \beta(1 - \delta)} \sum_o r_{ot+1} k_{ot+1}$$

$$\frac{\chi_{ot}}{\sum_{o'} \chi_{o't}} = (1 - \beta(1 - \delta)) \frac{r_{ot+1} k_{ot+1}}{\sum_{o'} r_{o't+1} k_{o't+1}} + \beta(1 - \delta) \frac{\chi_{ot+1}}{\sum_{o'} \chi_{o't+1}}$$

Data

Data

- ▶ **Occupations:** 48 minor groups based on 1980 SOC
- ▶ **Time span:** 1980–2023
- ▶ **Main sources:**
 - Decennial Census + ACS: employment and wages
 - CPS ASEC: occupational mobility
 - BEA industry data: capital and labor shares
- ▶ **Challenge 1:** occupation-level capital
 - Approach 1: allocate sectoral capital based on occ. employment shares
 - Approach 2 (Caunedo et al. 2023): allocate based on usage of different capital using “Tools and Technology” module of O*NET
- ▶ **Challenge 2:** sparsity of transitions data
 - Regularize the matrix (Tintelnot & Dingel, 2025)
 - Apply Iterative Proportional Fitting (IPF) to match employment data

Inversion and Estimation

Inverting model fundamentals along a transition

Automation: from labor shares

$$\tilde{\alpha}_{ot} = \left[1 + \frac{1 - f_{ot}}{f_{ot}} \left(\frac{w_{ot}}{r_{ot}} \right)^{1-\zeta} \right]^{-1}$$

Productivity: from VA shares

$$\tilde{z}_{ot} = q_{ot} s_{ot}^{\frac{1}{\sigma-1}}, \quad q_{ot} = \left[(1 - \alpha_{ot}) w_{ot}^{1-\zeta} + \alpha_{ot} r_{ot}^{1-\zeta} \right]^{\frac{1}{1-\zeta}}$$

Investment efficiency: from k growth

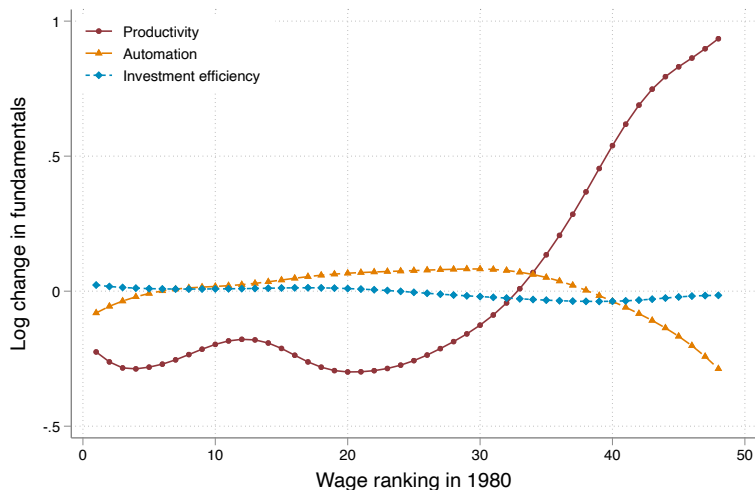
$$\tilde{\vartheta}_{ot} = \left(\frac{\beta \delta}{1 - \beta + \beta \delta} r_{ot} \right)^{-\delta} \frac{k_{ot+1}}{k_{ot}}$$

Mobility frictions: from occupational transition rates

$$D_{oit} = \frac{\tilde{\kappa}_{oit}^{-\frac{1}{\rho}} e^{\frac{\beta}{\rho} \tilde{v}_{it+1}}}{\sum_m \tilde{\kappa}_{omt}^{-\frac{1}{\rho}} e^{\frac{\beta}{\rho} \tilde{v}_{mt+1}}}, \quad \tilde{v}_{ot} = \ln w_{ot} - \rho \ln D_{oot} + \beta \tilde{v}_{ot+1}$$

Note: (a) need assumption on future fundamentals (b) amenities absorbed into mobility costs

Changes in inverted fundamentals: 1980-2023



Automation of middle-skill jobs; relative productivity growth in high-skill jobs

Estimation: model-generated instruments

- ▶ **Externally set parameters:** $\beta = 0.95$, $\rho = 1.5$, $\delta = 0.05$
- ▶ **Estimated parameters:** ζ (EoS labor–capital), σ (EoS across occupations)

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- ▶ **Estimated parameters:** ζ (EoS labor–capital), σ (EoS across occupations)
 - Identify ζ from labor shares vs. wage–rental ratios:

$$\log \frac{f_{ot}}{1 - f_{ot}} = (1 - \zeta) \log \frac{w_{ot}}{r_{ot}} + \epsilon_{ot}, \quad \epsilon_{ot} = \log \frac{1 - \alpha_{ot}}{\alpha_{ot}}$$

IV: $\widehat{\frac{w_{ot}}{r_{ot}}}$ from counterfactual without automation shocks

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- Identify σ from procedure shares vs. prices:

$$\log s_{ot} = (1 - \sigma) \log q_{ot} + \epsilon_{ot}, \quad \epsilon_{ot} = -(1 - \sigma) \log z_{ot}$$

IV: $\hat{q}_{ot}$ from counterfactual without productivity shocks

- ▶ **Moment conditions:** $\mathbb{E}[\tilde{q}_{ot} z_{ot}] = 0$, $\mathbb{E}\left[\frac{\tilde{w}_{ot}}{\tilde{r}_{ot}} \frac{1 - \alpha_{ot}}{\alpha_{ot}}\right] = 0$
- ▶ **Joint fixed point for estimation and inversion**

Estimation results

Specification	Estimate for ζ	Estimate for σ
<i>IV: shut down change in α</i>	0.786 (0.093) F-stat: 189.724	
<i>IV: shut down change in z</i>		1.050 (0.459) F-stat: 47.289
<i>IV: shut down change in $z + \alpha$</i>	0.772 (0.099) F-stat: 136.398	1.577 (0.893) F-stat: 20.147
<i>IV: agg. $\alpha +$ shut down change in z</i>	0.750 (0.097) F-stat: 139.530	1.586 (0.896) F-stat: 20.715
<i>IV: z predicted by manuf. shock + shut down α</i>	0.772 (0.099) F-stat: 136.822	

- ▶ ζ is precisely estimated around 0.8, consistent with Oberfield–Raval
- ▶ σ between 1-2 but noisy, broadly in line with the SBTC literature

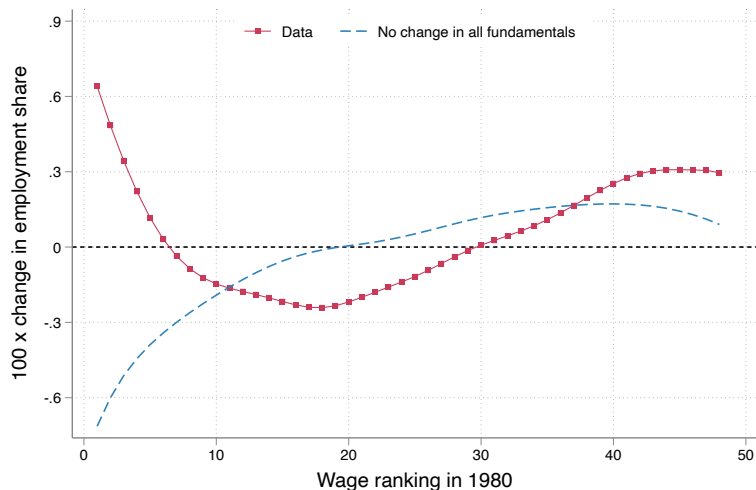
Application 1: decomposing U.S. polarization

Employment polarization (1980-2018)



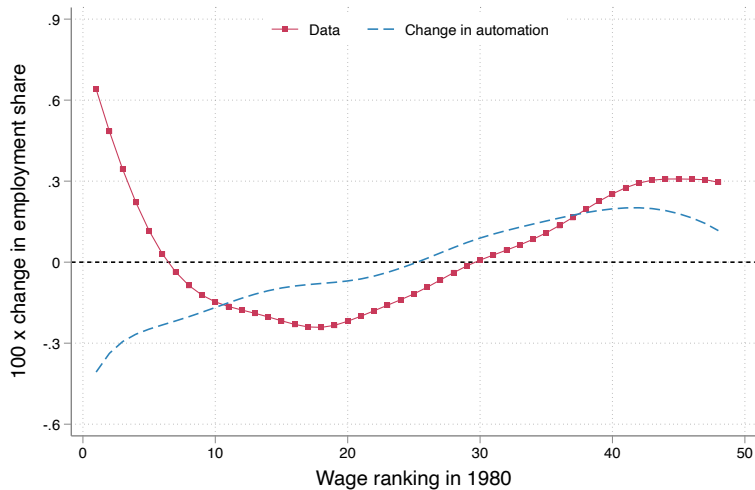
Employment polarization (Autor et al., 2006): relative decline in “middle skill jobs”

Employment polarization (1980-2018)



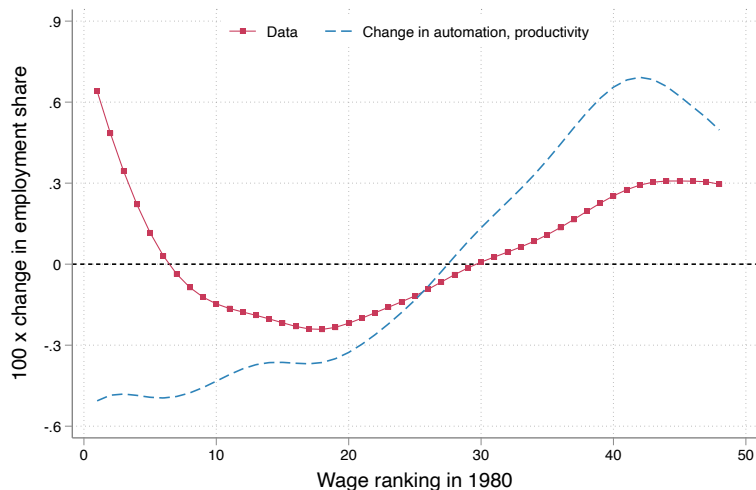
Initial conditions matter: get reallocation to high-skill occs. without shocks

Employment polarization (1980-2018)



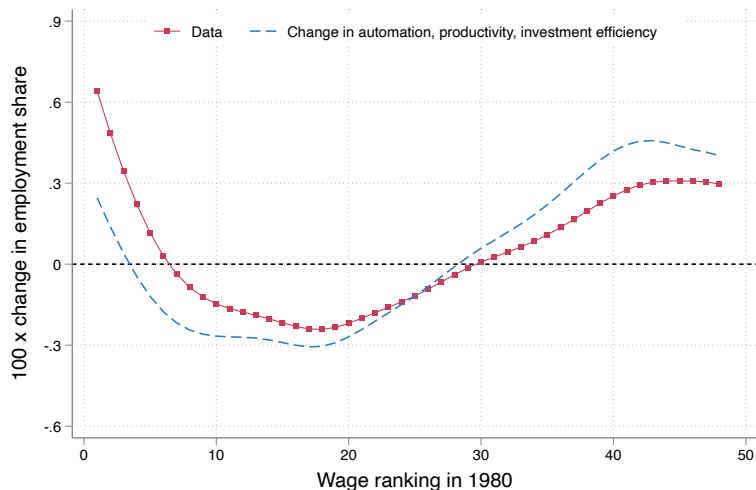
Automation plays a limited role in reallocating to low-skilled occupations

Employment polarization (1980-2018)



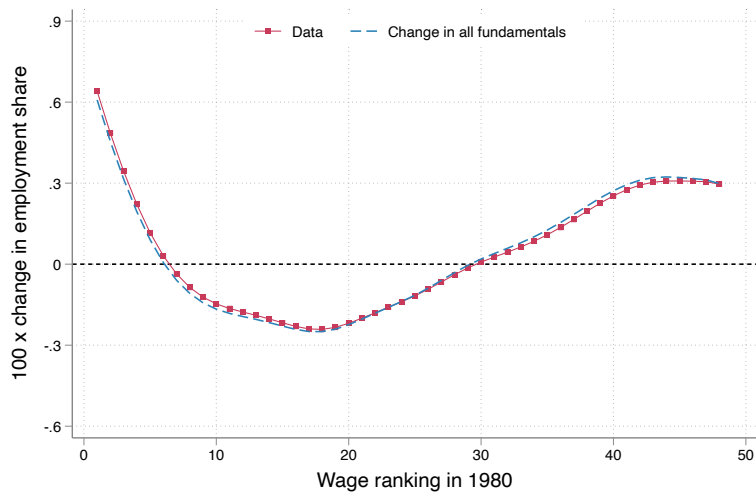
Productivity shocks amplify reallocation to high-skill occupations

Employment polarization (1980-2018)



Investment-efficiency shocks play a key role in matching the left-tail

Employment polarization (1980-2018)



Labor-supply shocks also important in matching the left-tail

Future polarization?

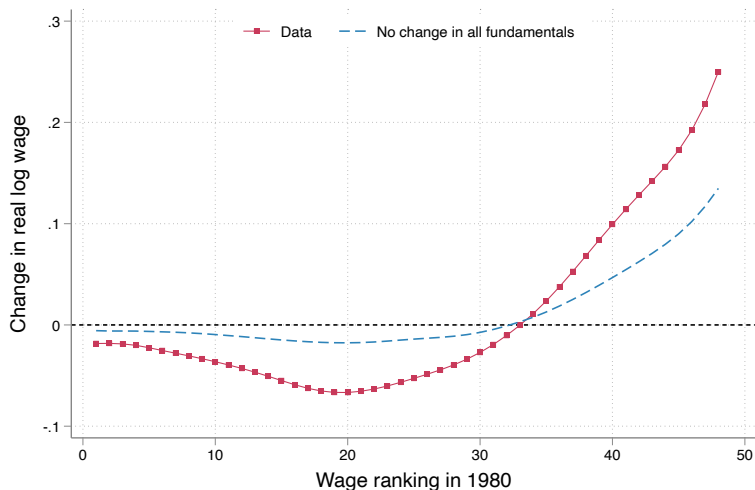


New steady-state (2018 funds.): reallocation to high-skill jobs, no polarization

Wage polarization (1980-2018)

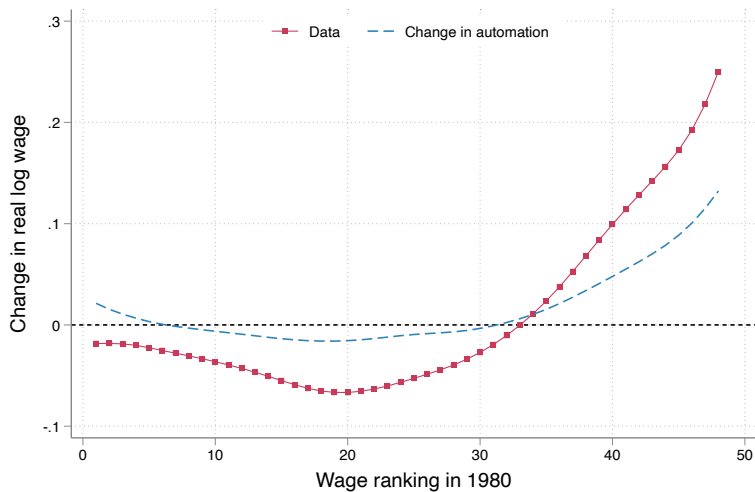


Wage polarization (1980-2018)



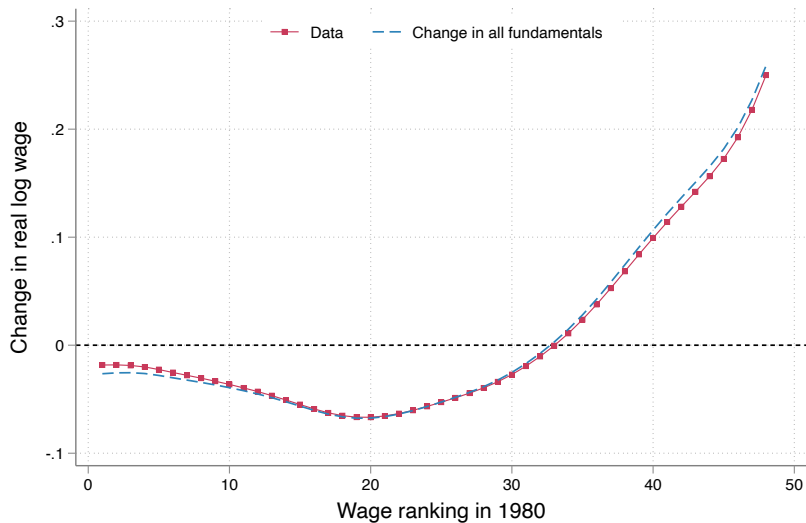
Initial conditions sufficient to get much of the rise in high-skill wages

Wage polarization (1980-2018)

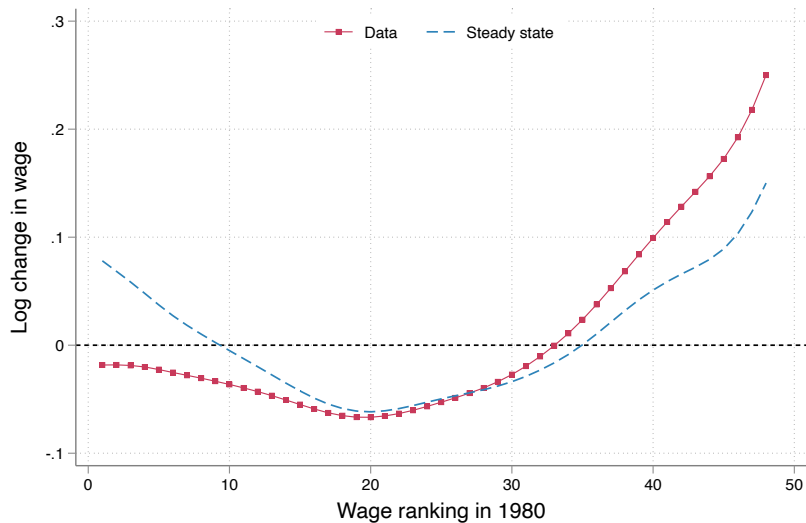


Relatively minor role for automation in wage polarization

Wage polarization (1980-2018)



Wage polarization (1980-2018)



Takeaways: labor market polarization

- ▶ **Initial conditions matter**: much of the shift to high-skill jobs reflects pre-1980 shocks; adjustment is slow
- ▶ High wage inequality in the 2010s is partly **transitory** and might revert
- ▶ **Limited role for automation** in explaining polarization
- ▶ Important role for **investment and labor-supply shocks** in explaining low-skill trends

Application 2: labor market effects of AI

Measuring model-consistent AI shocks

- ▶ **Challenge:** unclear **which model fundamentals are affected** by AI (productivity? automation? investment efficiency?), and in **which occupations**
- ▶ **Agnostic approach:** Project changes in inverted fundamentals onto external measures of AI exposure
- ▶ **Caveat:** may also pick up non-AI shocks correlated with AI exposure
 - Can include controls for such non-AI shocks

Projecting AI-exposure from Anthropic onto model fundamentals

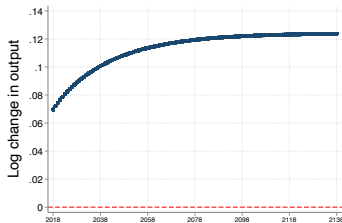
- ▶ Project occupation-level AI exposure from Anthropic (2023) onto 2018-2023 changes in inverted fundamentals
 - Captures the fraction of tasks for an occupation where AI is actively used

	(1)	(2)	(3)	(4)	(5)
	$\Delta \log \alpha$	$\Delta \log z$	$\Delta \log v^{\vartheta}$	$\Delta \log \kappa_{in}$	$\Delta \log \kappa_{out}$
AI Exposure	0.025*** (0.008)	0.197*** (0.025)	0.000 (0.004)	0.067 (0.051)	-0.093 (0.058)

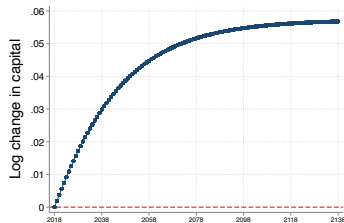
- ▶ Highly exposed jobs see a relative increase in productivity and automation

AI shock to the 2018 steady-state: aggregate implications

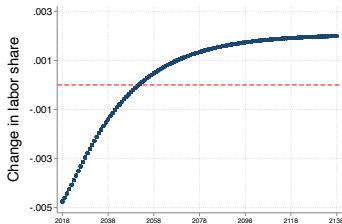
Output



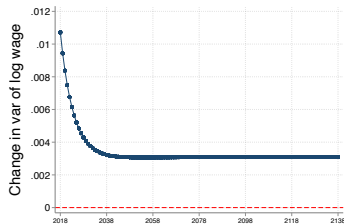
Aggregate capital



Aggregate labor share

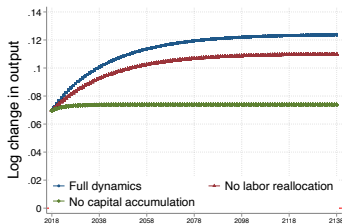


Variance of log wages

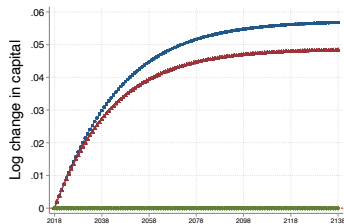


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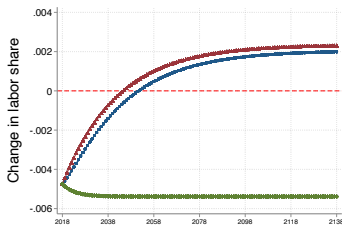
Output



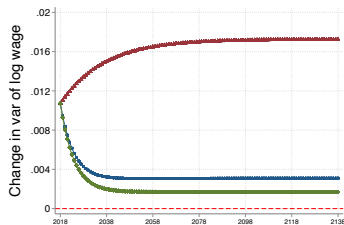
Aggregate capital



Aggregate labor share



Variance of log wages

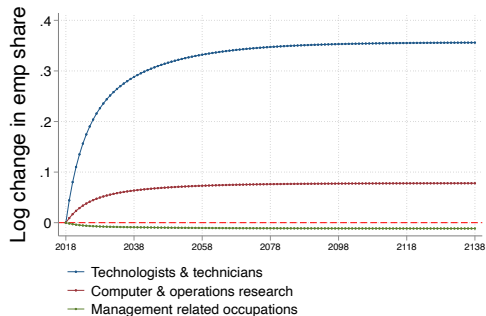


Conclusion

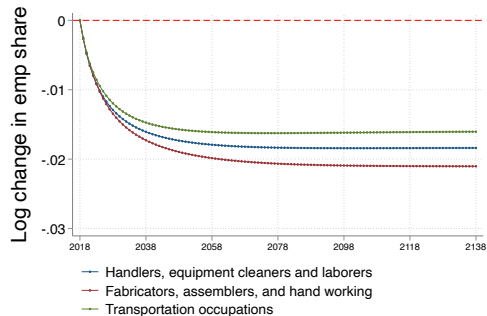
- ▶ How do different occupations respond to new technologies and other shocks?
- ▶ We develop a GE framework that allows for two-sided, forward-looking dynamics of labor and capital with heterogeneous occupations
 - Dynamics for occupation-specific labor demand and supply
 - Allows to study short- and long-run effects
 - Designed to replicate data on and provide predictions for detailed occupations
- ▶ Use it to:
 1. Decompose U.S. wage inequality and polarization 1980-2018
 2. Study long-run effects of recent AI shocks
- ▶ Other potential applications: dynamic effects of trade shocks, effects of working-from-home

AI shock: employment dynamics for selected occupations

Top-exposure occupations

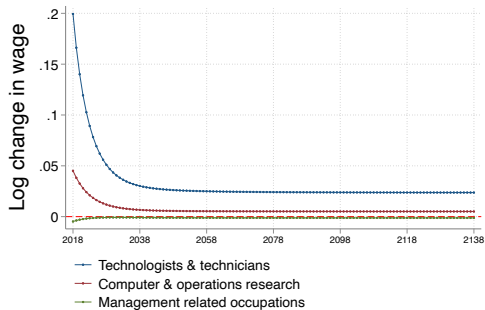


Bottom-exposure occupations

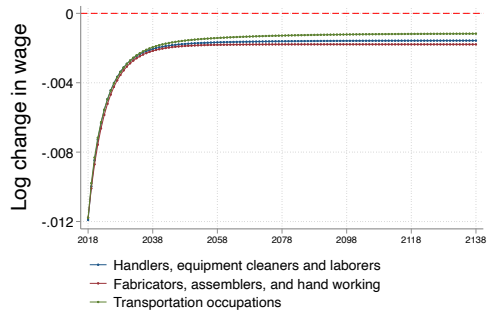


AI shock: wage dynamics for selected occupations

Top-exposure occupations

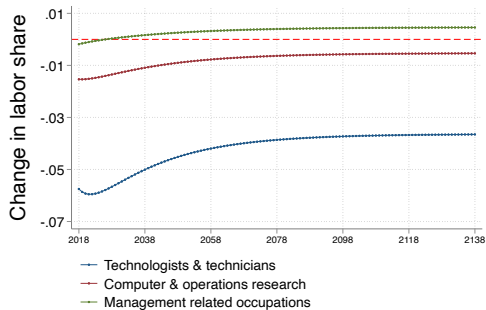


Bottom-exposure occupations



AI shock: labor share dynamics for selected occupations

Top-exposure occupations



Bottom-exposure occupations

