# Occupation Dynamics in General Equilibrium

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# Motivation

- What are the effects of new technologies, such as automation, on income distribution and welfare? How do these effects differ in the short vs. long run?
- Effects are shaped by gradual adjustment of labor and capital across occupations
  - Labor supply adjusts slowly due to mobility frictions
  - Labor demand evolves with investment in complementary capital
- We develop a framework that:
  - Allows for two-sided, forward-looking dynamics of labor and capital in GE
  - Is rich and tractable enough to map into detailed data on actual occupations
- Can use this framework both for ex-post analysis of past labor market dynamics (inequality, polarization) and for ex-ante assessment of future shocks (e.g., AI)

# This Paper

1. Develop a quantitative model of occupational dynamics
   - Gradual mobility of workers across occupations
   - Gradual accumulation of occupation-specific capital
2. Show how to invert a dynamic path of model fundamentals to match empirical path of occupation-level employment, wages, capital, and labor shares
   - Allow the economy to be anywhere along a transition
   - Fundamentals: (i) Automation (ii) Non-neutral productivity (iii) Investment efficiency (iv) Mobility frictions across occupations & compensating differentials
3. Estimation with model-based instruments
   - K-L EoS approx. 0.8 within occupations; EoS approx. 1.4 across occupations
4. **Application 1**: ex-post analysis of U.S. employment polarization (1980-2018)
   - Important roles for init. conditions, automation, and non-neutral productivity shocks
5. **Application 2**: ex-ante assessment of "AI shocks"
   - AI shock: project AI exposure onto factual changes in fundamentals (2018-2023)
   - Output ↑; wage inequality ↑ (especially in short run); labor share ↑ and then ↓

# Related Literature

- **Dynamic models of technical change & inequality** Zeira (1998), Krusell et al. (2000), Autor et al. (2003), Acemoglu and Autor (2011), Graetz & Michaels (2018), Acemoglu & Restrepo (2019, 2022), Humlum (2021), Moll et al. (2022), ...
  This paper: design to match detailed occupation data & add labor supply dynamics
- **Dynamic discrete choice models of labor mobility** Artuç et al. (2010), Dix-Carneiro (2014), Caliendo et al. (2019), Traiberman (2019), Kleinman et al. (2023)
  This paper: add demand dynamics with occupation-specific capital accumulation
- **Wedge accounting in macro and trade** Eaton & Kortum (2002), Chari et al. (2007), Costinot & Rodríguez-Clare (2014), Berger et al. (2023)
  This paper: apply to occupation employment and wage dynamics
- **Labor market polarization** Autor et al. (2006), ...
  This paper: decompose using a quantitative dynamic model
- **Labor market effects of AI** Acemoglu et al. (2022), Babina et al. (2022), Acemoglu and Johnson (2023), McElheran et al. (2023), ...
  This paper: dynamic effects using a quantitative model

# Outline

- Theoretical Framework
- Inversion and Estimation
- Data
- Applications
- Conclusions

# Theoretical Framework

# Worker Preferences and Mobility

- Instantaneous utility ($u_{ot}$) for a worker in occupation $o$ at time $t$ with amenities ($b_{ot}$), wage ($w_{ot}$), price index ($p_t$)

$$u_{ot} = \ln b_{ot} + \ln w_{ot} - \ln p_t$$

- Value function ($\mathbb{V}_{ot}$) for a worker in occupation $o$ is:

$$\mathbb{V}_{ot} = u_{ot} + \max_{\{i \in \mathbb{O}\}} \{\beta \mathbb{V}_{it+1} - \ln \kappa_{iot} + \rho \epsilon_{it}\}$$

  - $\kappa_{iot}$: cost of moving from $i$ to $o$. $\epsilon_{it}$: extreme value idiosyncratic shock

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

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

- Worker mobility probabilities across occupations

$$D_{iot} = \frac{\left( \exp \left( \beta v_{ot+1} \right) / \kappa_{oit} \right)^{1/\rho}}{\sum_{m \in \mathbb{O}} \left( \exp \left( \beta v_{mt+1} \right) / \kappa_{mit} \right)^{1/\rho}}$$

# Production Technology

- Single final good produced by performing a set of procedures $o \in \mathbb{O}$
- CES unit cost function for the final good price ($p_t$) depends on the cost of each procedure ($q_{ot}$) and productivity/demand ($z_{ot}$)

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

- Within each procedure, continuum of tasks undertaken by perfectly-substitutable labor (wage, $w_{ot}$) or capital (rental rate, $r_{ot}$)
- Tasks are subject to extreme value shocks, delivering CES cost function:

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

where $\alpha_{ot}$ captures capital-bias of technology ("automation")

# Investment

- Representative capitalist maximizes logarithmic intertemporal utility

$$\max_{\{c_t, a_{t+1}\}} \sum_{s=0}^{\infty} \beta^{t+s} \ln c_{t+s}^k, \quad \text{subject to} \qquad c_t^k + a_{t+1} = R_t a_t$$

  - $R_t$ is return to investment, $a_t$ is stock of wealth

- Wealth is stored in occupation-specific capital $\{k_{ot}\}$, with marginal values $\mathcal{Q}_{ot-1}$

$$a_t = \sum_{o \in \mathbb{O}} \mathcal{Q}_{ot-1} k_{ot}$$

- Representative capitalist can invest $\chi_{ot}$ units of the final good in any occupation subject to adjustment costs (Lucas and Prescott 1971)

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

  - $\delta$ parameterizes the magnitude of adjustment costs
  - $\vartheta_{ot}$ parameterizes the efficiency of the investment technology

# Intra-temporal Equilibrium

- Procedure-specific labor market clearing

$$w_{ot}\ell_{ot} = f_{ot}s_{ot}\sum_{m\in\mathbb{O}}\left(w_{mt}\ell_{mt} + r_{mt}k_{mt}\right), \quad f_{ot} = \frac{\left(1-\alpha_{ot}\right)w_{ot}^{1-\zeta}}{\left(1-\alpha_{ot}\right)w_{ot}^{1-\zeta} + \alpha_{ot}r_{ot}^{1-\zeta}}$$

- Procedure-specific capital market clearing

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

- Procedure expenditure shares ($s_{ot}$) and unit-costs ($q_{ot}$)

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

- 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

- Occupation transitions

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

- Worker value function

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

- Capital dynamics

$$\ln k_{ot+1} = \ln \vartheta_{ot} + (1-\delta) \ln k_{ot} + \delta \ln \left[ \beta\delta \left( \sum_{m \in \mathbb{O}} r_{mt} k_{mt} \right) \left( \sum_{s=1}^{\infty} \left(\beta\left(1-\delta\right)\right)^s \frac{r_{ot+s} k_{ot+s}}{\sum_{m \in \mathbb{O}} r_{mt+s} k_{mt+s}} \right) \right]$$

# 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
    - Compute occupation-level values as weighted averages across industries
- **Transition matrix**
  - CPS ASEC data is sparse
  - Dimension reduction to clean noise using SVD (Tintelnot & Dingel, 2025)
  - Apply Iterative Proportional Fitting (IPF) to ensure row and column sums match employment data

# Inversion and Estimation

# Inverting model fundamentals

**Automation coefficients:** invert from labor shares, conditional on prices

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

**Productivity:** invert from occupational VA shares, conditional on prices

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

**Investment efficiency:** invert from growth rate of capital, conditional on prices

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

# Inverting model fundamentals

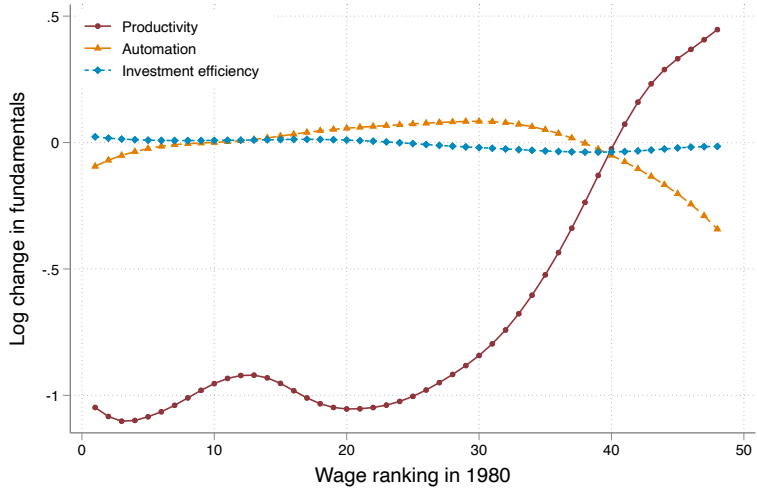
**Mobility frictions:** invert from transition rates, given a guess for value functions

$$D_{oit} = \frac{\widetilde{\kappa}_{oit}^{-\frac{1}{\rho}} \exp\left(\frac{\beta}{\rho}\widetilde{v}_{it+1}\right)}{\sum_{m=1}^{O} \widetilde{\kappa}_{omt}^{-\frac{1}{\rho}} \exp\left(\frac{\beta}{\rho}\widetilde{v}_{mt+1}\right)}, \quad \widetilde{v}_{ot} = \ln w_{ot} - \rho \ln D_{oot} + \beta \widetilde{v}_{ot+1}$$

Note:

- We absorb compensating differentials in mobility frictions (set $b_{ot} = 1$)
- Need to make an assumption on future path of fundamentals (affects $\widetilde{v}_{oT}$)
- Economy can be anywhere along a transition path
- Fully match data on: employment, wages, capital, labor shares, and mobility

# Changes in inverted fundamentals: 1980-2023




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

# Parameterization

- Set three parameters externally:
  - Discount factor: $\beta = 0.95$
  - Dispersion of preference shocks across occupations: $\rho = 1.5$
    - Range of values in the literature, e.g. Burstein et al. (2019), Traiberman (2019)
  - Investment elasticity: $\delta = 0.05$
    - Linearized law of motion consistent with linear depreciation of 5 percent
- Estimate $\zeta$ and $\sigma$

# Estimating EoS across occupations ($\sigma$) and EoS across labor and capital ($\zeta$)

- Identify $\zeta$ by projecting labor shares on exogenous varation in wage-rental ratios
  - IV: counterfactual $\frac{\hat{w}_{ot}}{\hat{r}_{ot}}$ from a dynamic equilibrium without automation shocks

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

- Identify $\sigma$ by projecting procedure shares on exogenous varation in prices
  - IV: counterfactual $\hat{q}_{ot}$ from a dynamic equilibrium without productivity shocks

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

- Moment conditions:

$$\mathbb{E}\left[\tilde{q}_{ot} z_{ot}\right] = 0, \qquad \mathbb{E}\left[\frac{\tilde{w}_{ot}}{\tilde{r}_{ot}} \frac{1-\alpha_{ot}}{\alpha_{ot}}\right] = 0$$

- Joint fixed point of inversion + estimation

# Estimation results

| | $\zeta$ | $\sigma$ |
|---|---|---|
| Counterfactual: no changes in $\alpha$ | 0.819*** | |
| | (0.111) | |
| F-stat | 215.233 | |
| Counterfactual: no changes in $z$ | | 0.920 |
| | | (0.379) |
| F-stat | | 69.927 |
| Counterfactual: no changes in $z$ and $\alpha$ | 0.833*** | 1.452* |
| | (0.118) | (0.860) |
| F-stat | 198.116 | 23.356 |
| Counterfactual: no changes in $z$, agg. shock to $\alpha$ | 0.829*** | 1.453* |
| | (0.118) | (0.861) |
| F-stat | 197.773 | 23.753 |
| Counterfactual: $z$ declines in manufacturing, no changes in $\alpha$ | 0.834*** | |
| | (0.118) | |
| F-stat | 197.342 | |

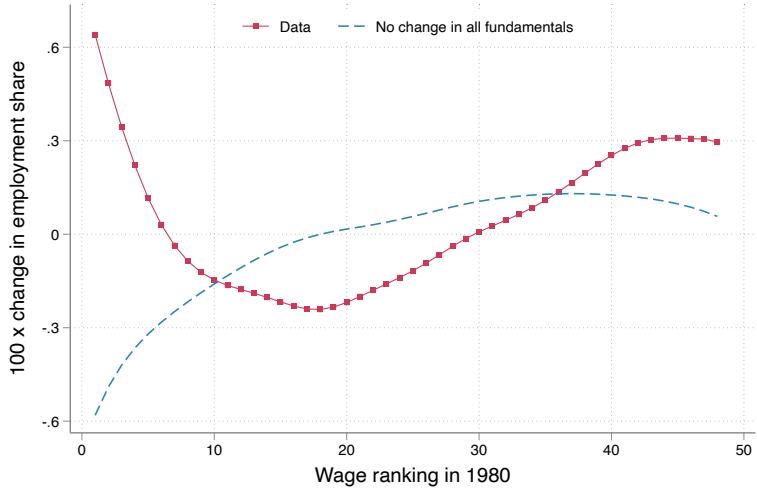
- $\zeta$ tightly estimated around 0.8, in line with key references (Oberfield-Raval)
- $\sigma$ around 1.4, although noisy, in line with SBTC literature

# Application 1: decomposing U.S. polarization

# Decomposing U.S. polarization

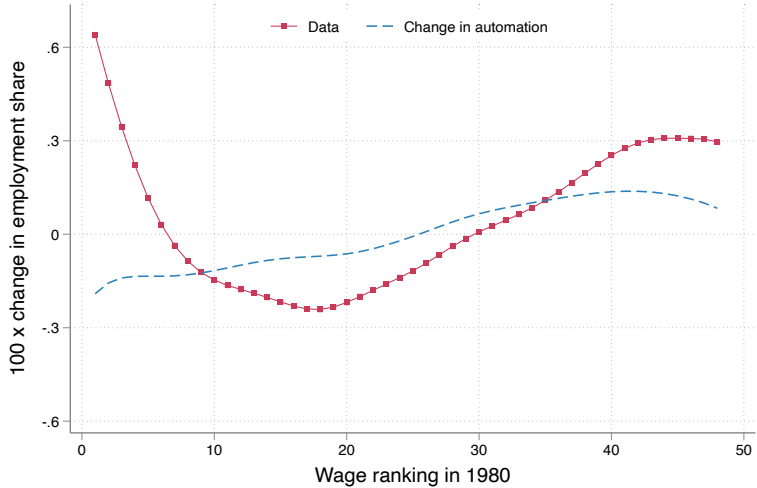
- U.S. labor market polarization: Autor et al. (2006)
- Use our model to decompose key drivers of polarization
- Advantages of our approach:
  - Economy out of steady-state: no need to assume that polarization is driven by post-1980 shocks
  - Allow for both labor supply and demand shocks
  - No assumptions on timing of shocks, and can easily study sub-periods
- Focus on 1980-2018 period, to abstract from Covid shock

# Polarization in employment



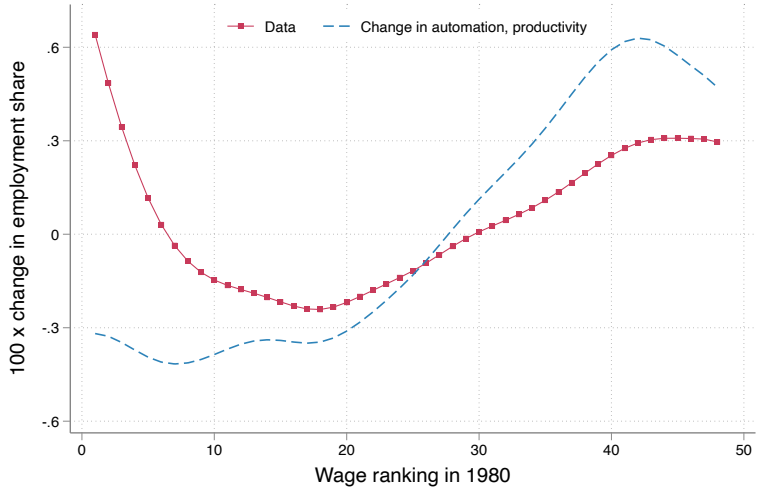

Initial conditions without shocks imply reallocation to high-skill occs., no polarization

# Polarization in employment



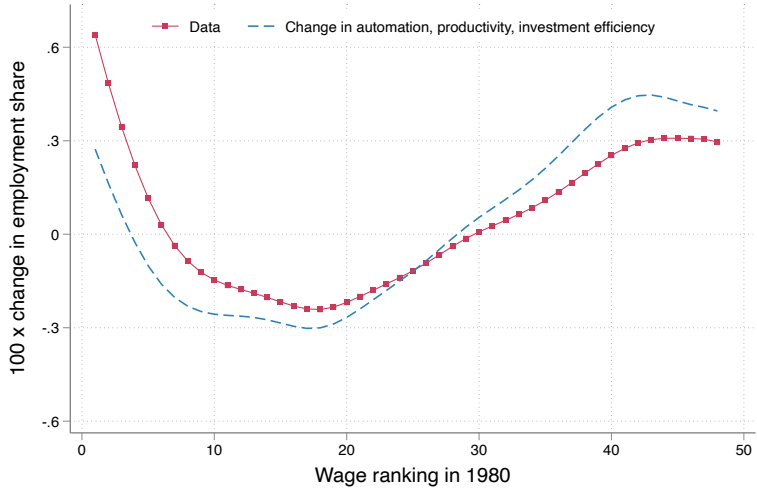

Automation plays a limited role in reallocating to low-skilled occupations

# Polarization in employment



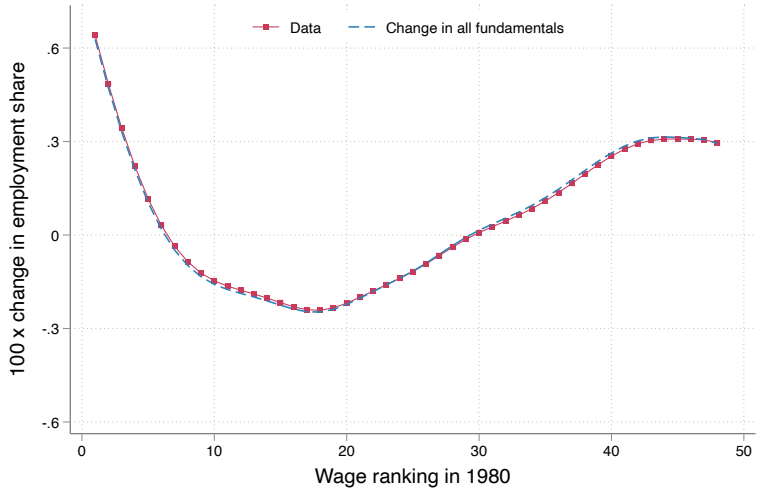

Productivity shocks amplify reallocation to high-skill occupations

# Polarization in employment

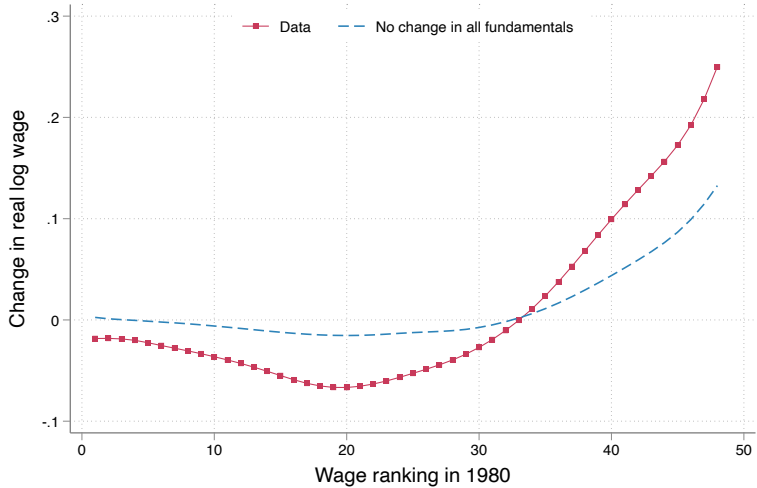



Investment-efficiency shocks play a key role in matching the left-tail

# Polarization in employment

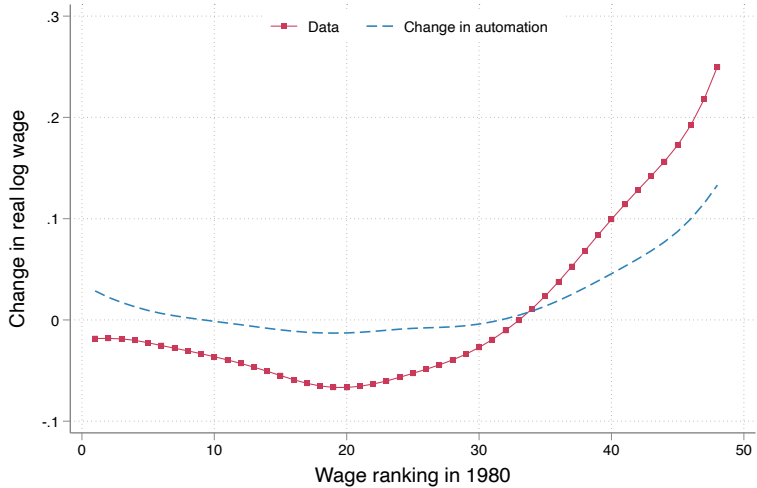


# Polarization in wages



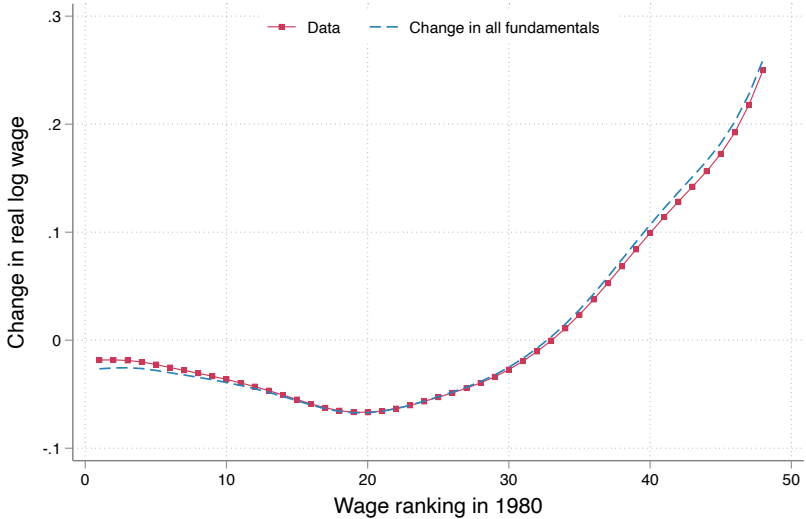

Initial conditions sufficient to get much of the rise in high-skill wages

# Polarization in wages




Relatively minor role for automation in wage polarization

# Polarization in wages



# 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
- **Our approach:**
  - Project changes in inverted fundamentals onto external measures of AI exposure
  - Counterfactual: starting from steady-state, shock the economy only with the predicted changes in fundamentals
- Allows us to study the short- and long-term effects of AI shocks that have already materialized, while abstracting from those that are yet to occur
- 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 2018-2013 changes in inverted fundamentals
  - Captures the fraction of tasks for an occupation where AI is actively used

| | (1) d log $\alpha$ | (2) dlog $z$ | (3) d log $\vartheta$ | (4) d log $\kappa$_in | (5) d log $\kappa$_out |
|---|---|---|---|---|---|
| AI Exposure | 0.026*** | 0.259*** | 0.000 | 0.067 | -0.093 |
| | (0.008) | (0.035) | (0.004) | (0.051) | (0.058) |
| R Squared | 0.02 | 0.15 | 0.00 | 0.02 | 0.02 |
| Obs | 48 | 48 | 48 | 48 | 48 |

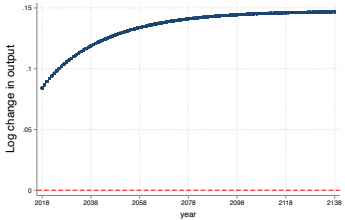
Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

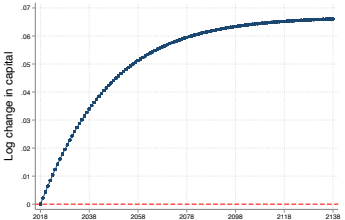
- Through the lens of the model, occupation-level AI exposure reflects a productivity shock and an automation shock

# AI shock to the 2018 steady-state: aggregate implications

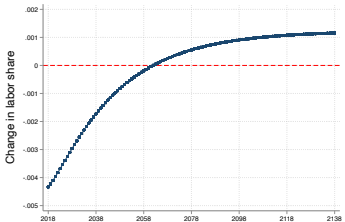
Output



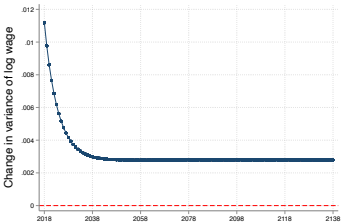

Aggregate capital




Aggregate labor share

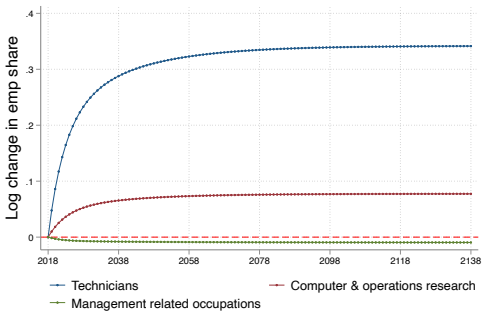



Variance of log wages

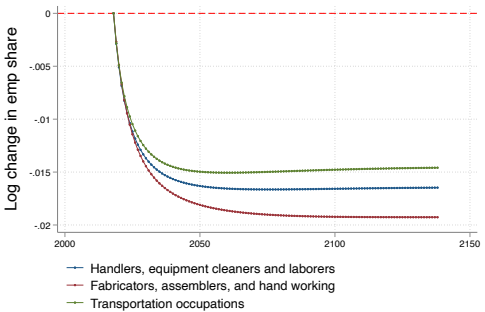


# AI shock: employment dynamics for selected occupations

Top-exposure occupations

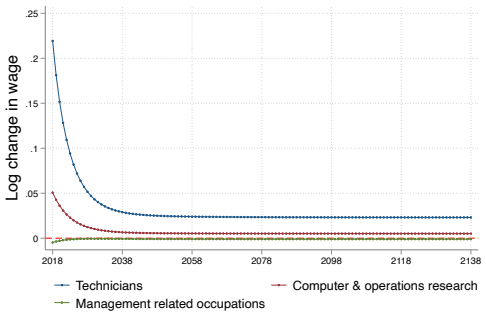



Bottom-exposure occupations

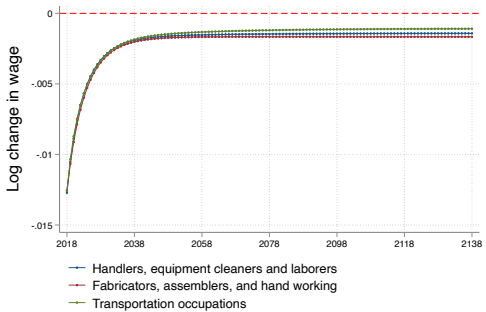


# AI shock: wage dynamics for selected occupations

Top-exposure occupations

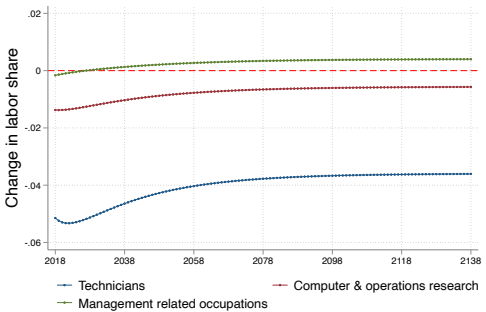



Bottom-exposure occupations

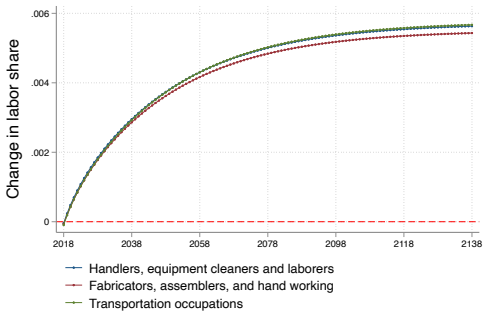


# AI shock: labor share dynamics for selected occupations

Top-exposure occupations




Bottom-exposure occupations



# Conclusion

- What are the effects of new technologies on income distribution and welfare?
- 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