

Changes in Relative Employment and Wages in the US, 1980–2019: Skills, Occupations and Sectors

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Empirical Observations

- Employment:
 1. Middle-skill employment has shrunk since the 1980s ([polarization](#))
 2. Rise in high-skill and [manager](#) occupations
 3. Employment shifting from manufacturing to services ([structural change](#))
- Wages:
 1. Rise in high-skill wages, even higher rise in [manager](#) wages
 2. Rise in within-occupation wage dispersion, esp. for managers

What We Do

Analytical and Quantitative

1. Present a tractable model with
 - Managers and workers (span-of-control), **2-dim skill**
 - Workers working in different task/occupations
 - Manufacturing and services sectors
2. Assess candidate channels jointly; different paths alone do not prove distinct causes.
 - **TSTC**: task/occupation-level productivity growth
 - **“Skilling-up”**: changing skill-task complementarity + changing skill supply (distribution) of workforce
3. Model is consistent with
 - Missing rise of low-skill wages
 - Rise in high-skill/manager wages despite negative selection

What We Do

Empirical Results and Counterfactuals

1. Incorporate observed O*NET measures into stylized model
 - Two measures largely capture TSTC and skilling-up
 - Also captures education and robot/software measures
2. TSTC alone can account for employment trends
 - ... but not high-skill and manager wage trends
 - ⇒ Skilling-up essential for wages
3. Counterfactuals
 - Revive manufacturing to bring back middle-skill jobs?
 - Tax robots to protect workers?
 - Longer-run impact of AI? WFH?

What We Do

Empirical Results and Counterfactuals

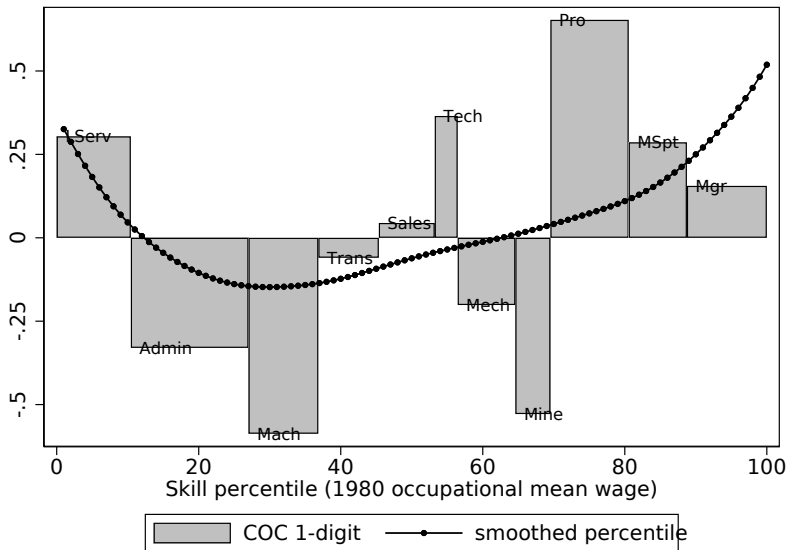
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 - ⇒ Skilling-up essential for wages
3. Counterfactuals
 - Revive manufacturing to bring back middle-skill jobs? **NO**
 - Tax robots to protect workers? **MAYBE...**
 - Longer-run impact of AI? WFH? **possible trend reversals**

Employment Polarization

1980-2019, extends [Autor and Dorn \(2013\)](#)

► by dec.

► RTI

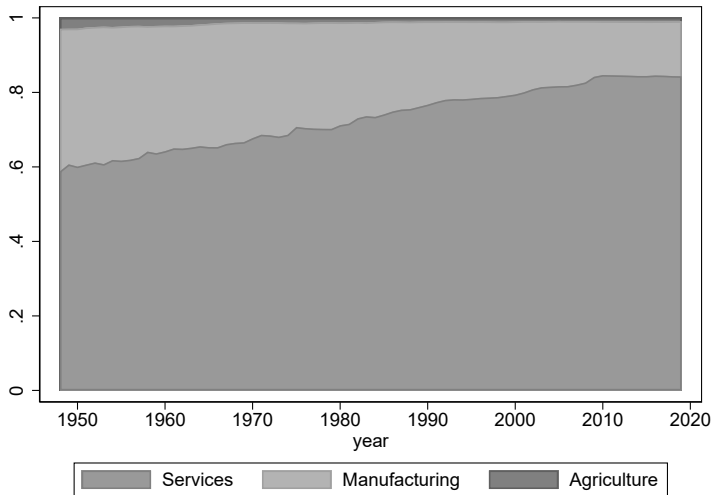


Structural Change: Employment

BEA NIPA Accounts (similar in Census)

► GDP (Nominal)

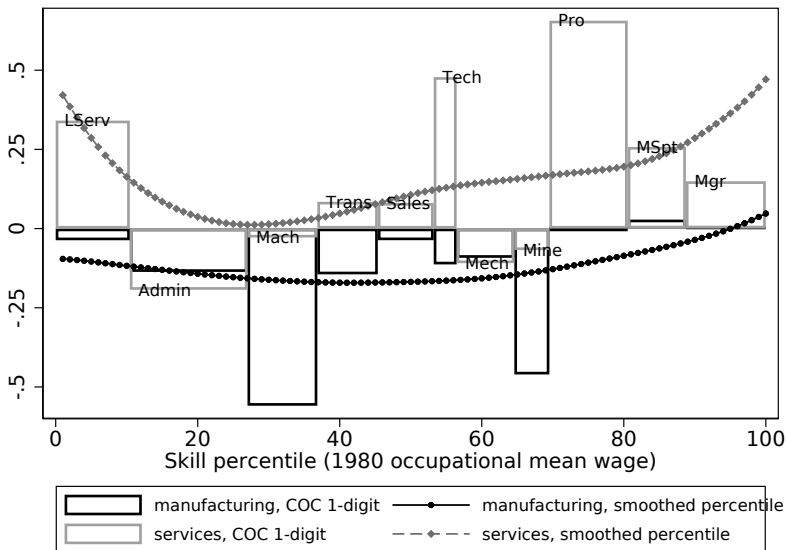
► measured TFP gap



Employment Polarization by Sector

► level by COC

► change by COC



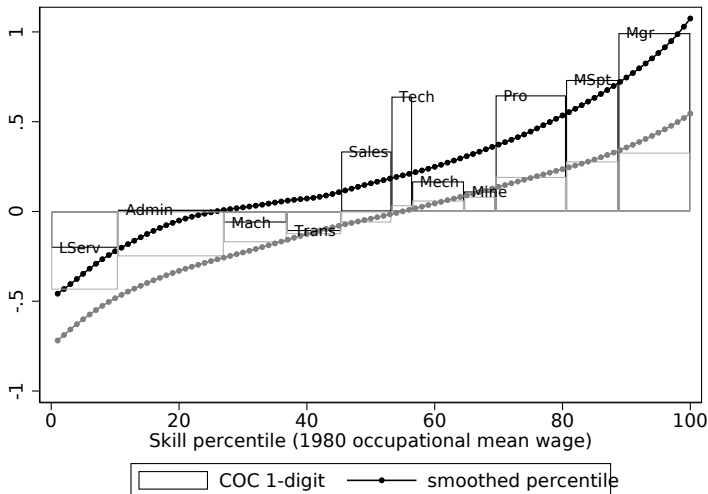
Wage Inequality

1980-2019, extends [Autor and Dorn \(2013\)](#)

► by decade

► change

► change by decade



Managers vs Workers

▸ occupation coding

▸ Emp by Sec

▸ Within Wage Dispersion

▸ firm-individual census

▸ SC by Mgr/Wkr

▸ Wages



What's Behind These Long-Run Trends?

- DOT/O*NET measures?
(Autor et al., 2003; Acemoglu and Autor, 2011)
- Software and robot exposure? (Webb, 2020)
- Rise in college education?
(Katz and Murphy, 1992; Acemoglu and Autor, 2011)

cf. Later years: AI? (Felten et al., 2019; Webb, 2020)

Routinization and Employment Changes

	(1)	(2)	(3)	(4)	(5)	(6)
NR-Cog Anal	0.128 (0.237)					
NR-Cog Pers	0.258 (0.255)					
R-Cognitive	-0.035 (0.128)					
R-Manual	-0.251 (0.134)	-0.601** (0.150)		-0.555** (0.160)		-0.589** (0.119)
NR-Man Phys	-0.204 (0.140)					
Robot (Webb)			-0.487* (0.227)	-0.071 (0.138)		
Software (Webb)			0.087 (0.209)			
Δ College					2.761 (1.982)	0.268 (1.839)
Constant	0.609** (0.128)	0.609** (0.129)	0.609** (0.131)	0.609** (0.129)	0.297 (0.204)	0.579** (0.210)
R^2	0.089	0.067	0.035	0.068	0.015	0.067

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

Skilling-Up and Wage Changes

	(1)	(2)	(3)	(4)	(5)	(6)
NR-Cog Anal	0.087** (0.015)	0.097** (0.013)		0.089** (0.014)		0.073** (0.013)
NR-Cog Pers	0.005 (0.017)					
R-Cognitive	0.019 (0.011)					
R-Manual	-0.036* (0.017)					
NR-Man Phys	-0.039** (0.014)	-0.060** (0.012)		-0.033* (0.016)		
Robot (Webb)			-0.134** (0.016)	-0.044** (0.016)		-0.036** (0.012)
Software (Webb)			0.041* (0.016)			
△College					1.316** (0.117)	0.913** (0.151)
Constant	0.270** (0.011)	0.270** (0.011)	0.270** (0.012)	0.270** (0.011)	0.121** (0.017)	0.167** (0.020)
R^2	0.344	0.333	0.231	0.350	0.336	0.468

Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.

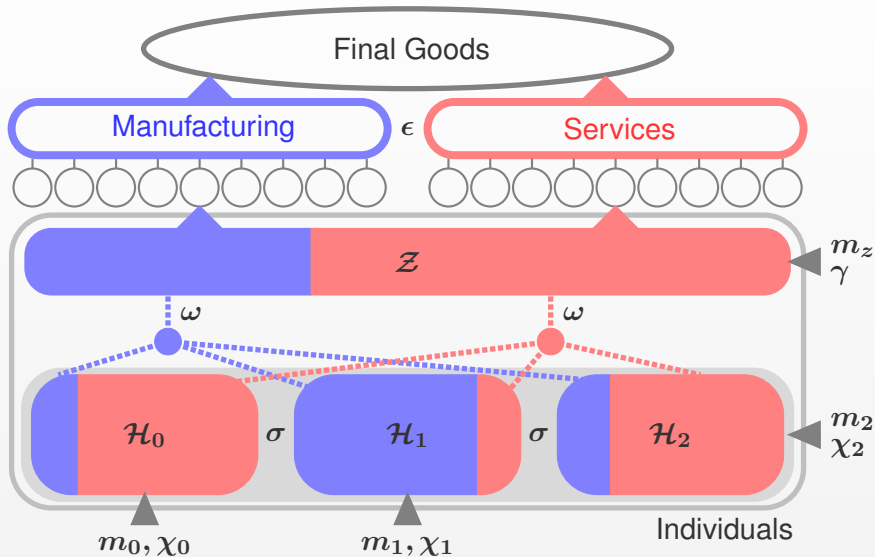
What's Needed in a Model?

- Employment trend correlates with R-man
- Wage trend correlates with NR-cog-anal and college
- Robots seem to matter, but largely explained by O*NET

⇒ Model elements:

- **Routinization** affects employment and wages
- Wages further affected by **skilling-up**

Task-Based Macro Model



Model Elements: Individuals

1. Unit mass of individuals differ in terms of 2 skills

$s = (z, h) \in \mathcal{S} \subset \mathbb{R}_+^2$ with distribution μ

- z : managerial talent
- h : worker skill
- neither sector- nor task-specific

2. Occupation choice: Individuals can work as a span-of-control manager, or as a worker in 1 of 3 tasks:

- Managers organize tasks, using z
- Tasks $j \in \{0, 1, 2\}$ (e.g., manual, routine, abstract) use h

c.f. All results hold for any finite number or continuum of tasks j (in paper)

Task-Specific Technologies

- Production unit: a manager in sector i combines tasks τ_{ij} :

$$y_i(z) = \left[\eta_i^{\frac{1}{\omega}} x_{iz}^{\frac{\omega-1}{\omega}} + (1 - \eta_i)^{\frac{1}{\omega}} x_{ih}^{\frac{\omega-1}{\omega}} \right]^{\frac{\omega}{\omega-1}}$$

$$x_{iz} = M_z k_{iz}^{\alpha} \textcolor{red}{z}_i^{1-\alpha}, \quad x_{ih} = \left(\sum_{j=0}^2 \nu_{ij}^{\frac{1}{\sigma}} \textcolor{red}{\tau}_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

- Simple form of log-supermodularity in skills and tasks:

$$\tau_{i0} = M_0 k_{i0}^{\alpha} \left[\bar{h} \mu_i(h_0) \right]^{1-\alpha}$$

$$\tau_{i1} = M_1 k_{i1}^{\alpha} \left[\int_{h_1} h d\mu_i \right]^{1-\alpha}$$

$$\tau_{i2} = M_2 k_{i2}^{\alpha} \left[\int_{h_2} (h - \chi) d\mu_i \right]^{1-\alpha}$$

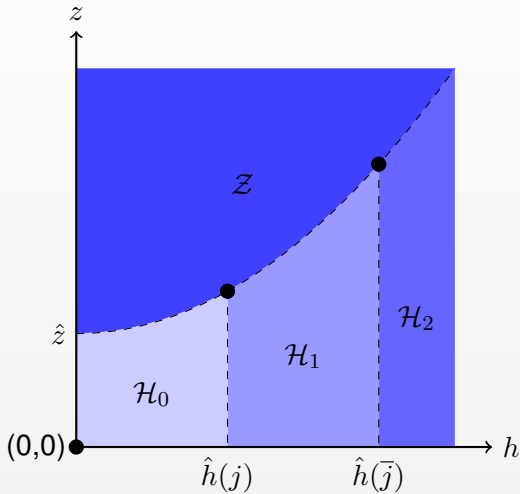
where M_j : task-specific TFP, h_j : set of workers hired

c.f. Discrete analog of general log-supermodular function $b(h, j)$ (in paper)

One Sector Equilibrium

Comparative Advantage and Positive Sorting:

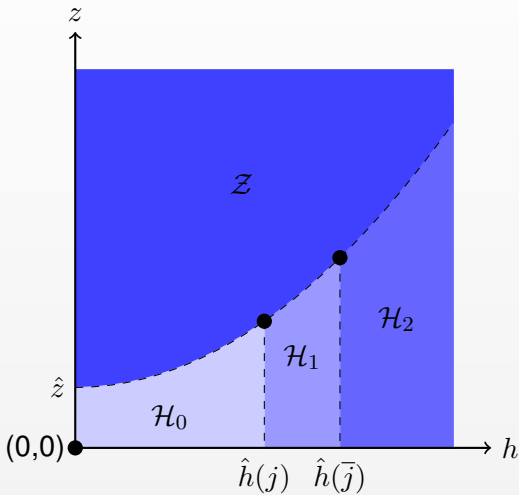
Equal to optimal assignment



Routinization and Job Polarization

Within-Sector: Relative Increase in M_1

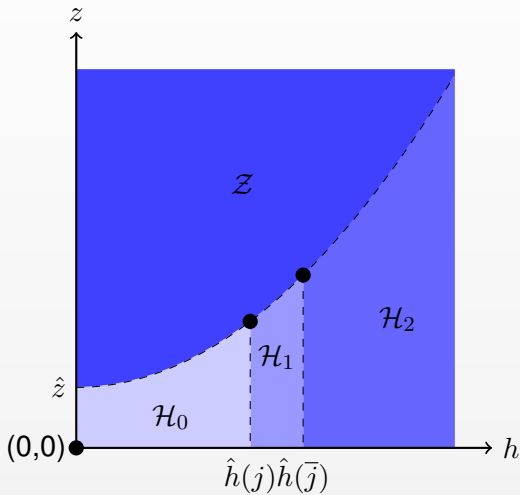
Assume $\omega < \sigma < 1$:



Skilling Up Demand

Within-Sector: Increase in χ

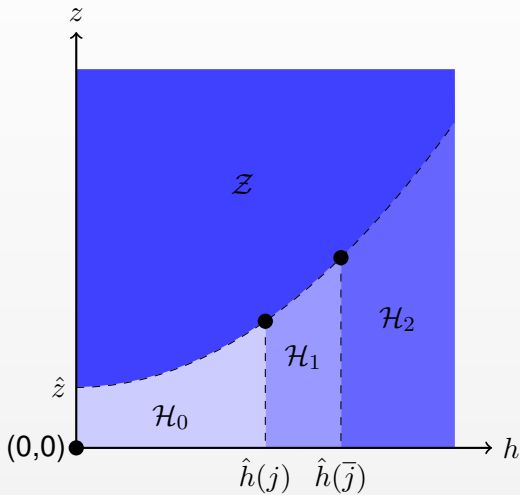
Assume $\omega < \sigma < 1$:



Rise of High-Skill Supply

Within-Sector: Relative Increase in h -skill

Assume $\omega < \sigma < 1$:



Task-Specific Technologies: Sectors

- Production unit: a manager in sector i combines tasks τ_{ij} :

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$$x_{iz} = M_z k_{iz}^{\alpha} z_i^{1-\alpha}, \quad x_{ih} = \left(\sum_{j=0}^2 \nu_{ij}^{\frac{1}{\sigma}} \tau_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

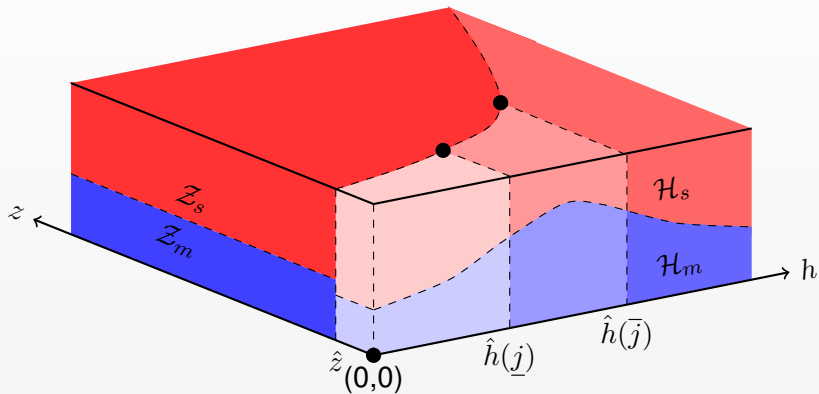
► Manu Shares

- Two types of sectoral output $i \in \{m, s\}$ (e.g., manufacturing and services) form final good:

$$Y = \left[\gamma_m^{\frac{1}{\epsilon}} Y_m^{\frac{\epsilon-1}{\epsilon}} + \gamma_s^{\frac{1}{\epsilon}} Y_s^{\frac{\epsilon-1}{\epsilon}} \right]^{\frac{\epsilon}{\epsilon-1}}.$$

where $\gamma_m + \gamma_s = 1$ and $\epsilon < 1$.

Two Sector Equilibrium



Two Sector Solution

- Sectoral productions can be written as

$$Y_i = \Phi_i K_i^\alpha L_i^{1-\alpha}$$

where Φ_i is endogenous TFP determined by $(\hat{h}_j, \hat{z})$

- So $L_s/L_m = (\gamma_s/\gamma_m) \cdot (\Phi_s/\Phi_m)^{\epsilon-1}$ also function of $(\hat{h}_j, \hat{z})$
- Aggregate employment share of task j :

$$L_j = \sum_{i \in \{m, s\}} (L_{ij}/L_i) \cdot L_i$$

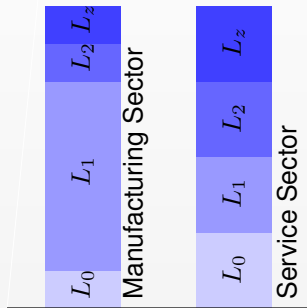
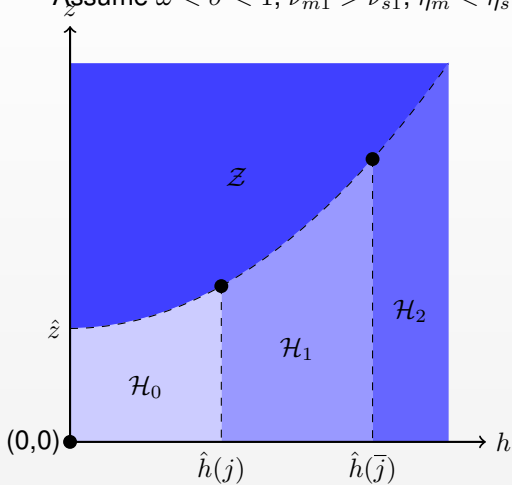
- L_j : aggregate labor supply in task j
- L_{ij}/L_i : within-sector labor demand
- L_i : between-sector labor demand

- * Equilibrium unique under well-behaved μ and small χ

Routinization and Polarization, Two Sectors

Two Sectors: Relative Increase in M_1

Assume $\omega < \sigma < 1$, $\nu_{m1} > \nu_{s1}$, $\eta_m < \eta_s$:

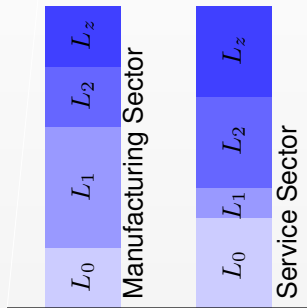
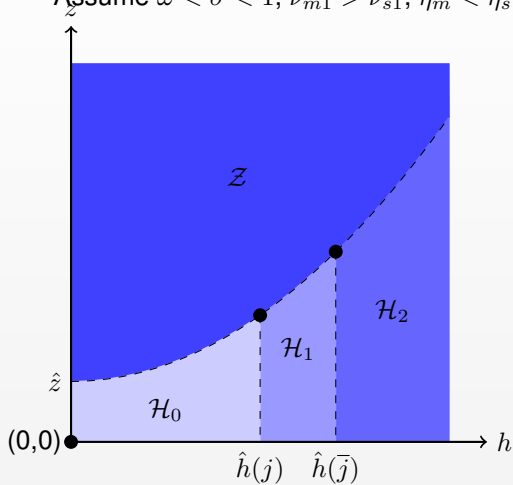


Manufacturing more (less) reliant on routine task (*managers*)

Routinization and Polarization, Two Sectors

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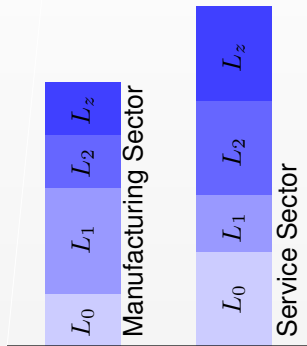
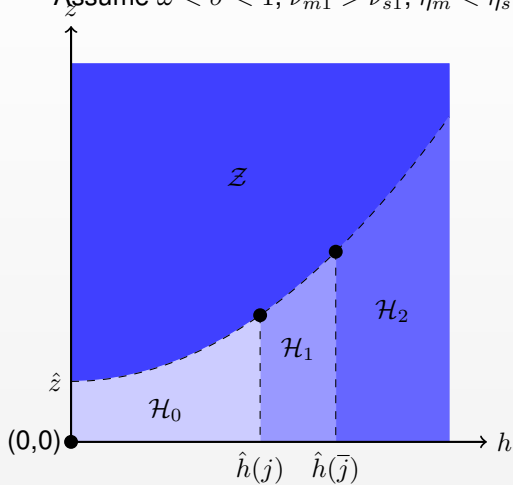


Polarization and rise of managers faster in manufacturing, ignoring sectoral reallocation (structural change)

Routinization and Structural Change

Two Sectors: Relative Increase in M_1

Assume $\omega < \sigma < 1$, $\nu_{m1} > \nu_{s1}$, $\eta_m < \eta_s$:



TFP growth higher in manufacturing
SC toward services if $\epsilon < 1$

Quantitative Analysis

1. Parametrization:

- Divide 1980 COC's into 1+1+7+2 occupations: broadly, management (11%), manual (10%), routine (59%), abstract (19%)
- Bivariate Pareto type IV distribution ([Arnold, 2014](#)):

$$1 - \mu(z, h) = \left[1 + z^{1/\gamma_z} + h^{1/\gamma_h} \right]^{-a}$$

(a, γ_h, γ_z) fit to 1980 and 2019 relative wages

► graph

2. Target 1980 and 2019, interpolate interim decades

- Feed k_t into model for each decade
- **Employment shares: Constant growth rates m_j**
- **Relative wages: $(\chi_{jt}, a_t, \gamma_{ht})$**

* *Exogenous sector-specific productivity growth (a_m, a_s)*

(Implied) Calibration Targets

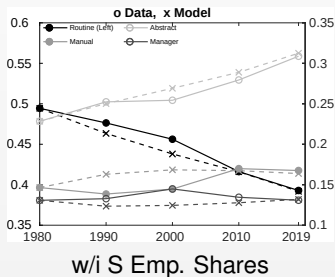
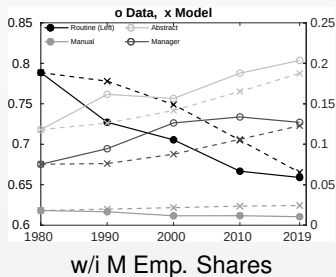
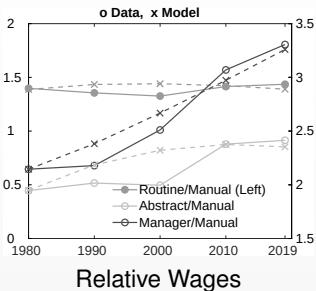
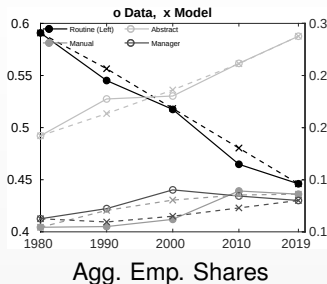
Ranked by mean wage (except management)	SOC Code	Employment Shares			
		1980	2010	Manufacturing	
Low Skill Services	400	10.44	13.92	0.59	0.23
Middle Skill		59.09	46.48	25.86	12.93
Administrative Support	300	16.57	14.13	3.47	1.53
Machine Operators	700	9.81	3.75	8.79	3.02
Transportation	800	8.73	6.64	3.80	2.28
Sales	240	7.87	9.37	0.79	0.62
Technicians	200	3.23	3.86	1.00	0.57
Mechanics & Construction	500	7.91	6.02	4.44	3.19
Miners & Precision Workers	600	4.97	2.71	3.58	1.73
High Skill		19.22	26.16	3.87	3.64
Professionals	40	11.02	16.51	1.73	1.45
Management Support	20	8.20	9.65	2.14	2.20
Management	1	11.26	13.44	2.47	2.59

Calibrated Parameters

Estimated		
α	0.363	BEA NIPA accounts
γ	0.339	Herrendorf et al. (2013)
ϵ	0.002	
Fit to 1980 (solved in close form)		
η_i (2), ν_{ij} (18)		Employment shares by occupation/sector
A_m	1.038	Manufacturing employment share
$M_j \equiv M$	0.974	Output per worker, normalization
a	9.174	
γ_h	0.210	Relative wages by occupation
χ_j (8)		
Fit to 2019 (method of moments)		
σ	0.610	Output per worker growth,
ω	0.250	employment shares by task
m_j (11)		only within sector
a	2.706	
γ_h	0.258	Relative wages by occupation
χ_j (8)		
Fixed		
$\bar{h}$	1.000	Not separately identified from M_0
γ_z	1.000	Monotonic firm-size distribution
A_s	1.000	Normalization

Model Fit: Employment Shares

► more



What is driving TSTC and Skilling-Up?

Correlate (m, χ) with empirical measures of COC task content and college attainment

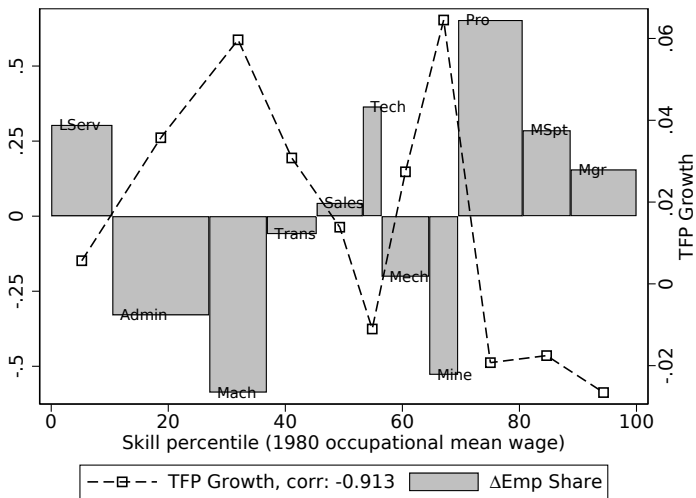
1. TSTC (m):

- Largely determines employment change
- Predominantly ($\sim 80\%$) explained by R-manual

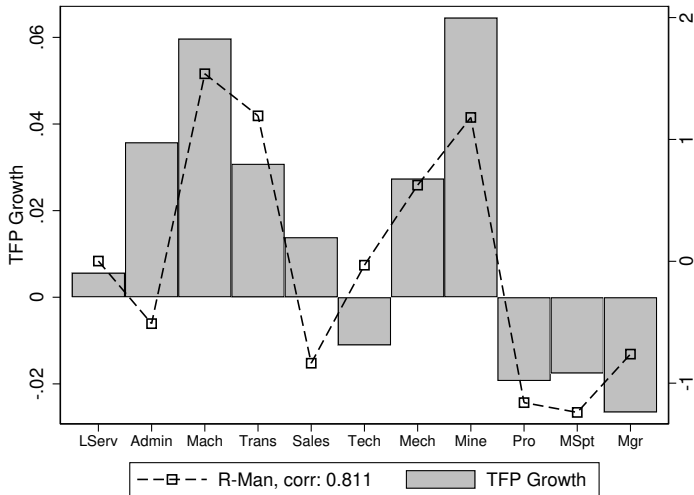
2. Skilling-up (χ)

- Jointly determines wage growth with m
- Predominantly ($\sim 75\%$) explained by NR-cog analytical
- Secondarily rise in share of college workers

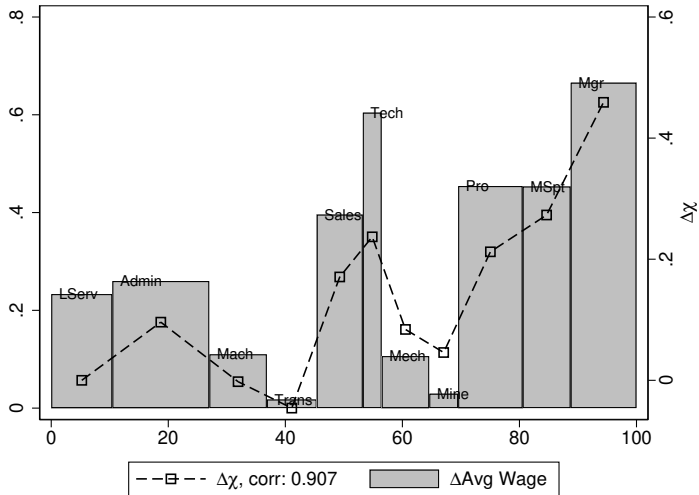
Polarization and TSTC



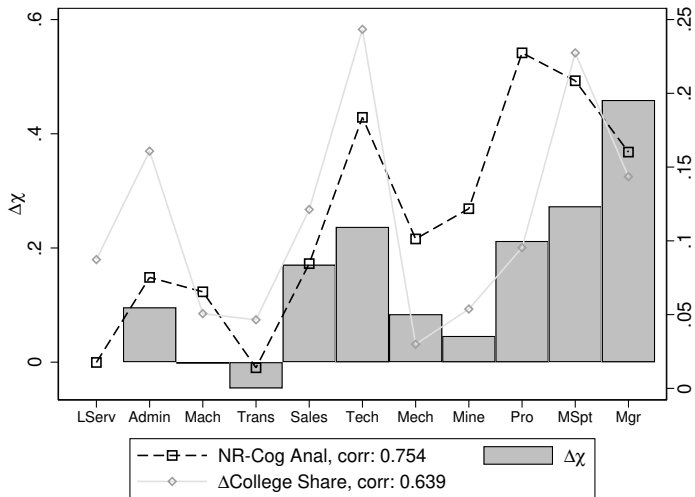
O*NET and TSTC



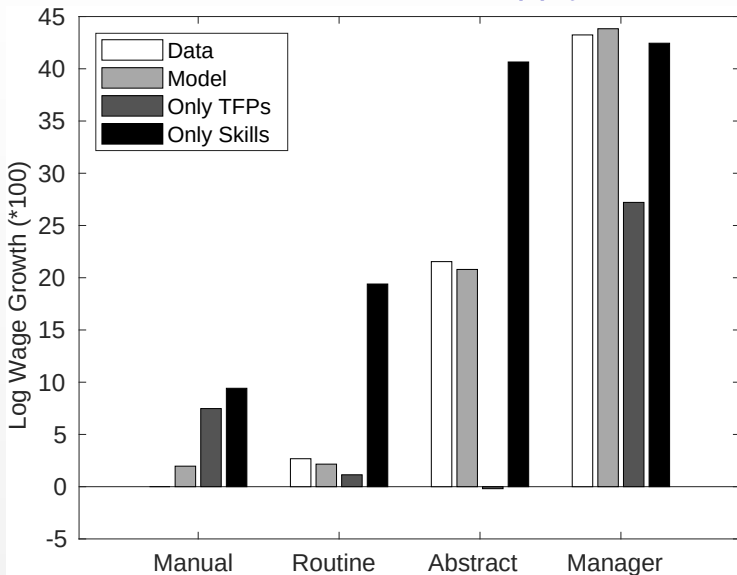
Wage Inequality and Skilling Up



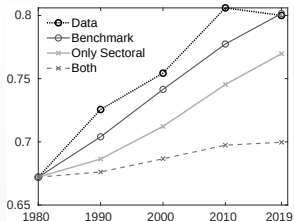
O*NET and Skilling Up



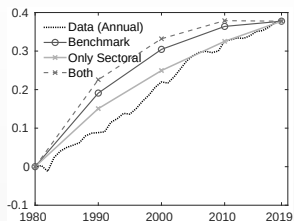
Skill Demand and Supply



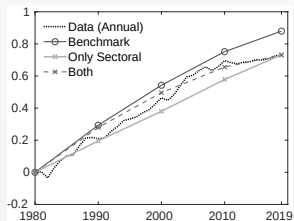
Structural Change and TFP



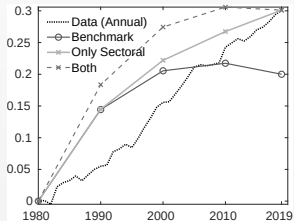
Service Employment Share



Aggregate TFP



Manufacturing TFP



Services TFP

Interim Summary

1. TSTC can explain
 - almost all of employment shifts at the task level
 - more than 100% of structural change
2. Skilling-up important to match asymmetry of high-skill and managers' wage and employment
3. Each closely correspond to empirical objects
 - Are also transparent components in the model
 - Gives structural interpretation to abstract measures

* Results robust to including sector-specific TC

► managers

Policy Implication

A Hypothetical Intervention

- “Dislocation” blamed on trade
 - But services also polarized
 - And manufacturing polarized faster
 - Production complementarity between M and S

⇒ Subsidize manufacturing to bring jobs back?:

... 1 p.p. increase in manufacturing employment share ⇒
0.25 p.p. increase in middle-skill/routine job share

Bringing Back Manufacturing Jobs

Tax Services to Subsidize Manufacturing

L_m (ppt)		τ_s (%)		L_R (%)	
1980	2019	1980	2019	1980	2019
32.79	19.86	-	-	59.08	44.61
+5		60.76	33.09	60.60	45.83
+10		74.81	42.58	62.11	47.06

- Due to low $\epsilon \approx 0$, reviving manufacturing is costly
 - R -worker share affected by routinization in both M and S
- ⇒ Rise in middle-skill jobs is muted

Taxing Robots?

- Guerreiro et al. (2022):
 1. Tax robots till all routine workers retire
 2. Long-run optimal tax is zero *...but no selection*
- We don't model dynamic optimization, but
 1. Workers choose occupations based on skill
 2. All occ's are essential *...but no endogenous labor supply*

⇒ Taxing robots a losing game due to high m

... Marginally more justified now than before due to skilling-up

Robot Tax

Tax on Occupation-Specific Capital

τ_K (%)	Y Loss (%)	T/Y (%)	K_R/K (%)	L_R (%)
1980				
0	-	-	53.25	59.08
10	2.86	1.72	51.46	59.44
20	5.43	3.11	49.82	59.75
30	7.75	4.24	48.32	60.04
40	9.87	5.17	46.93	60.31
50	11.82	5.94	45.64	60.56
2019				
0	-	-	33.58	44.61
10	1.82	1.10	31.90	44.96
20	3.47	2.01	30.41	45.29
30	4.98	2.77	29.08	45.59
40	6.37	3.41	27.88	45.86
50	7.65	3.96	26.79	46.12

- K and L imperfect substitutes
- L_R rise comes with skills affected by χ

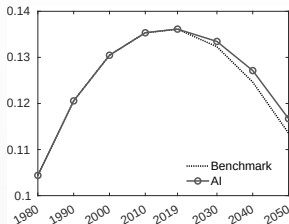
Advent of AI

- Will AI exacerbate, or transform existing trends?
- Recent measures of AI exposure only for the last decade:

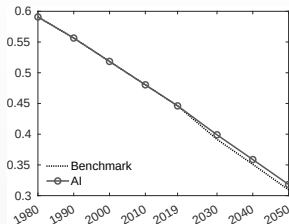
	(1)	(2)	(3)	(4)
NR-Cog Anal	0.015 (0.008)	0.015 (0.008)	0.008 (0.008)	
AI (Webb)		0.000 (0.006)		
AIOW (Felten et al.)			0.015** (0.006)	0.018** (0.006)
$\Delta 2010$ Wage	-0.201* (0.086)	-0.201* (0.087)	-0.233* (0.090)	-0.208* (0.082)
Constant	0.048** (0.008)	0.049** (0.008)	0.051** (0.008)	0.049** (0.008)
R^2	0.030	0.030	0.042	0.039
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.				

- Consistent with [Felten et al. \(2019\)](#); [Acemoglu et al. \(2022\)](#), only + association with wages

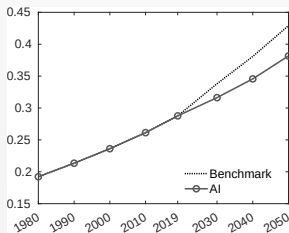
Polarization in an AI World?



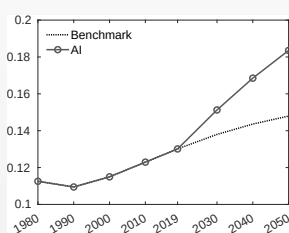
Manual Share



Routine Share

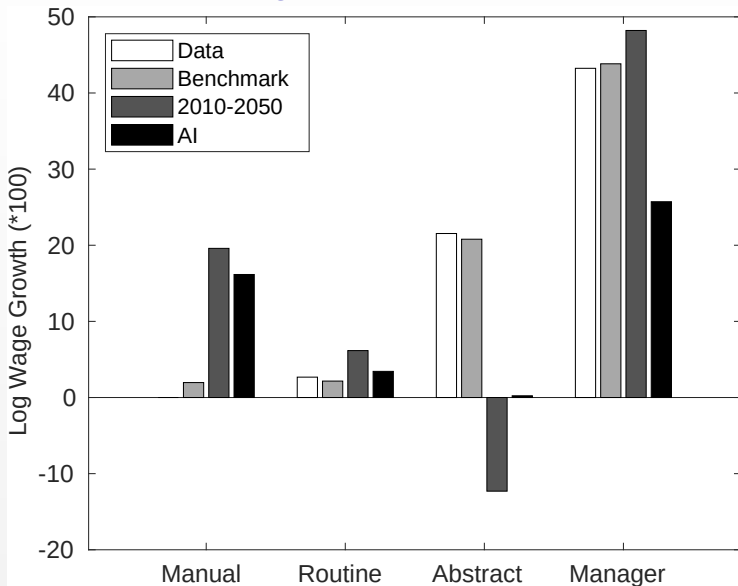


Abstract Share



Manager Share

Wage Losses to AI



Conclusion

- Tractable task-based macro model of skill, occupations, and sectors
 1. TSTC accounts for almost all of employment trend
 2. Skilling up additionally explains wage trend
 3. TSTC understood as R-man and skilling-up as NR-cog analytical
- Applications
 1. Manufacturing revival won't bring back middle-skill jobs
 2. Robot taxes more effective in skilled-up world
 3. AI predicted to reduce high-skill share but raise their wages

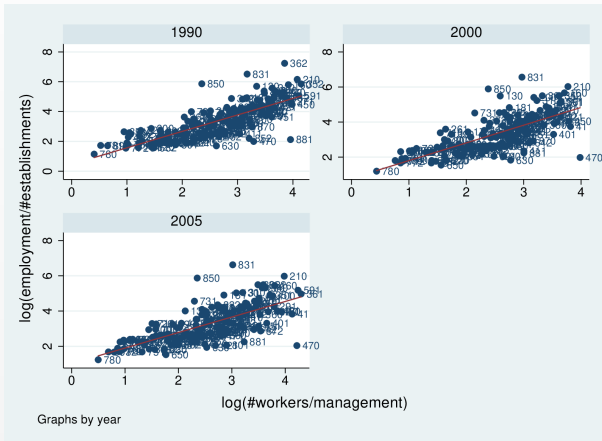
cf. WFH predicted to reduce manual employment

► WFH

Establishment Size and Span of Control

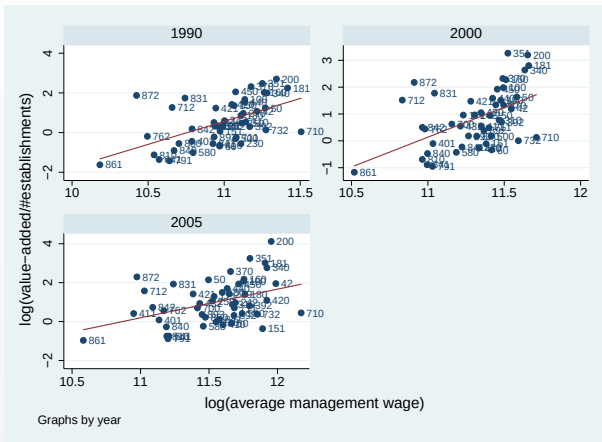
► [back to data](#)

▶ back to model



x -axis: Census, y -axis: SUSB, 170 industries.

Establishment Output and Manager Compensation

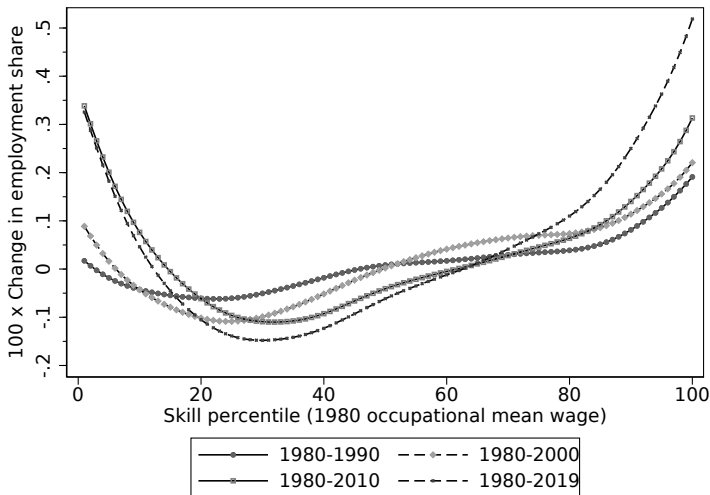


x-axis: Census, *y*-axis: BEA, 48 industries.

Employment Polarization

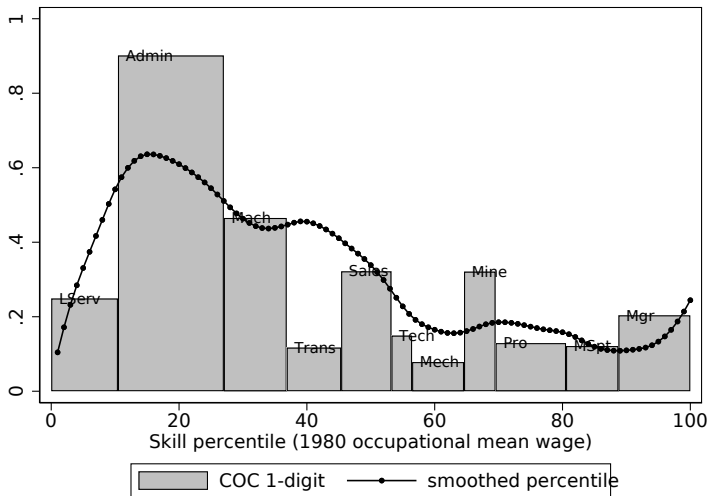
1980-2010, replicated following [Autor and Dorn \(2013\)](#)

▶ back



Routinization Hypothesis

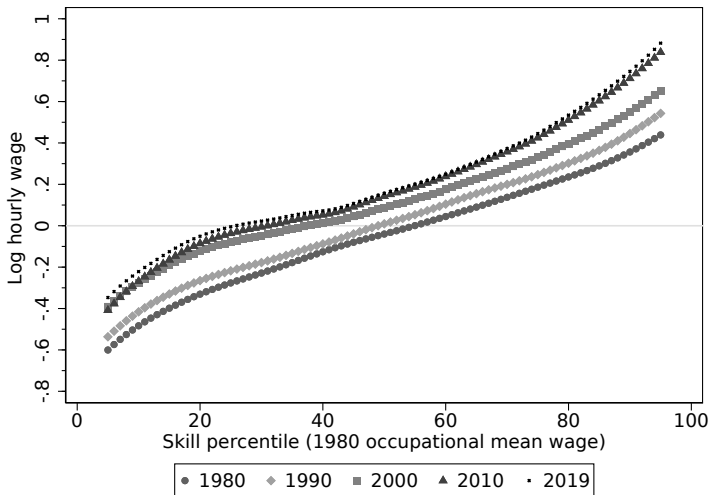
► back



Wage Inequality

1980-2019, extends Autor and Dorn (2013)

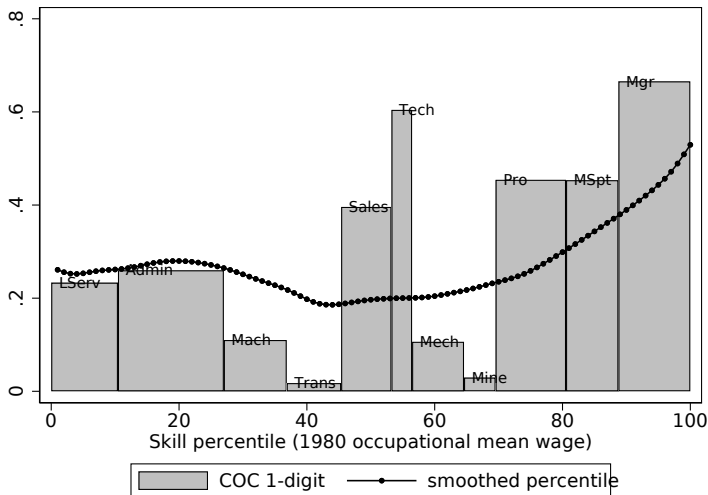
▶ back



Wage Polarization?

1980-2019, extends [Autor and Dorn \(2013\)](#)

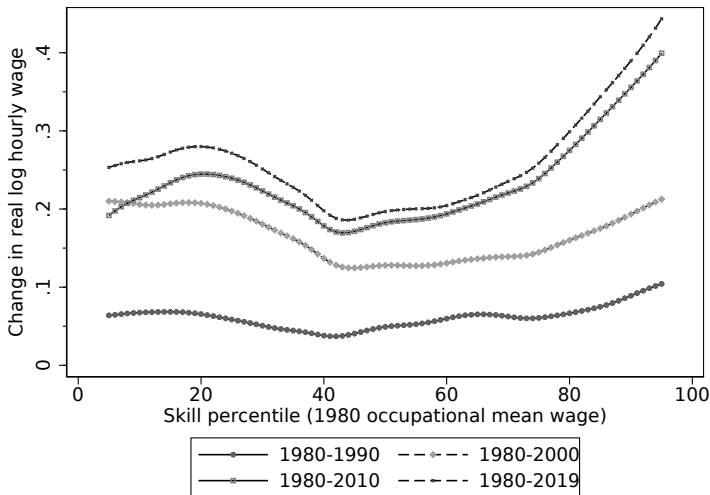
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Wage Polarization?

1980-2019, extends [Autor and Dorn \(2013\)](#)

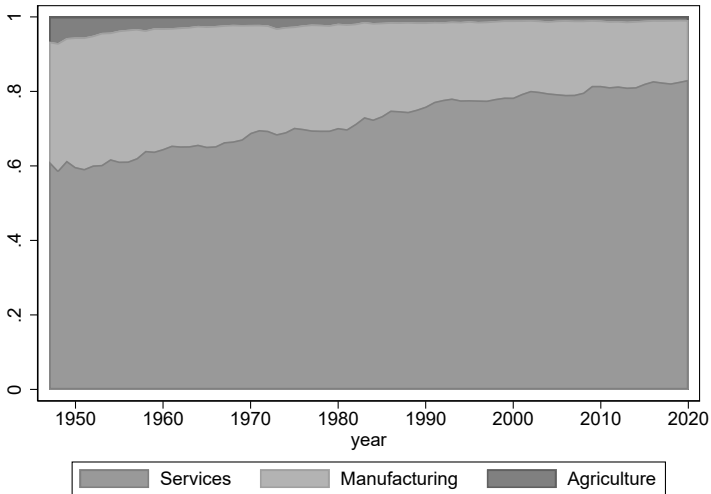
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Structural Change: GDP (Nominal)

BEA NIPA Accounts

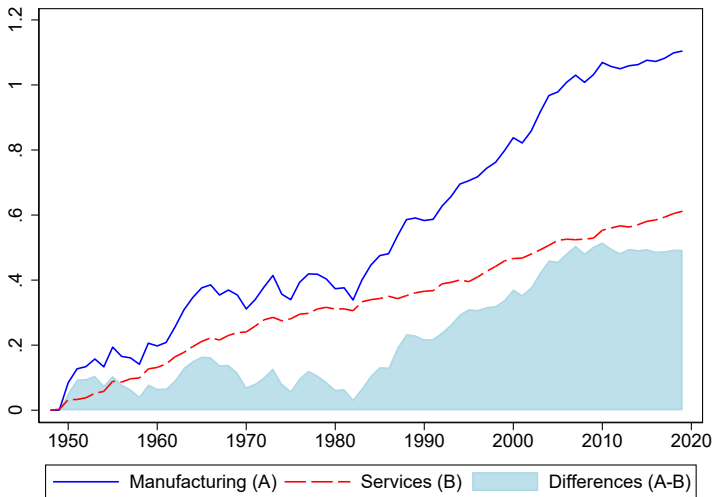
[▶ back](#)



Sectoral TFP's: Since 1947

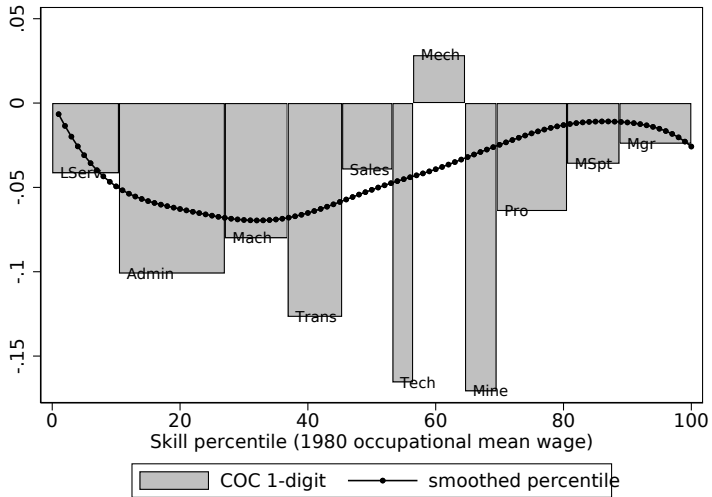
BEA NIPA Accounts

[▶ back](#)



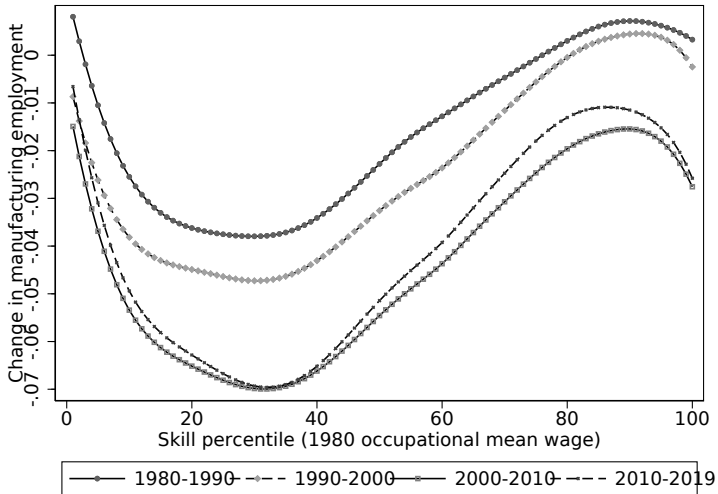
Change in Manufacturing Employment

► back



Change in Manufacturing Employment

► back

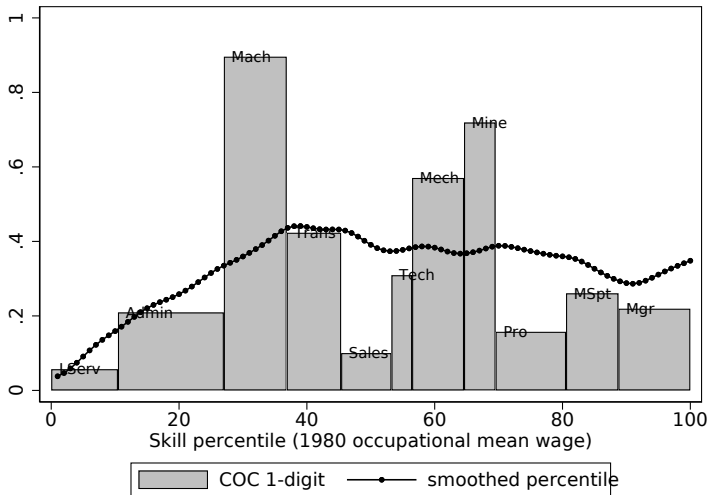


Manufacturing Employment Shares

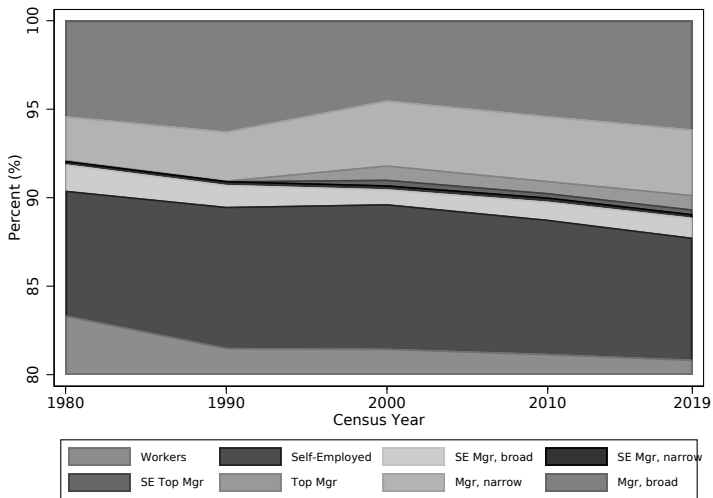
$$\eta_m < \eta_s, \quad \nu_{m1} > \nu_{s1}$$

► data

► model

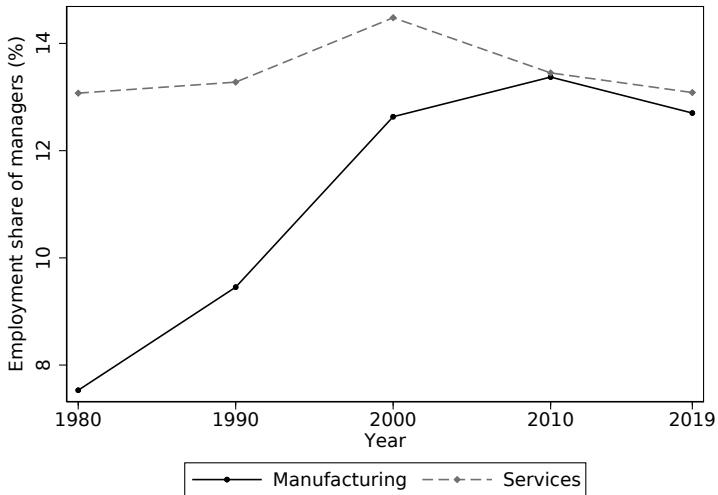


Manager COC and Self-employment

[▶ intro](#)[▶ model](#)

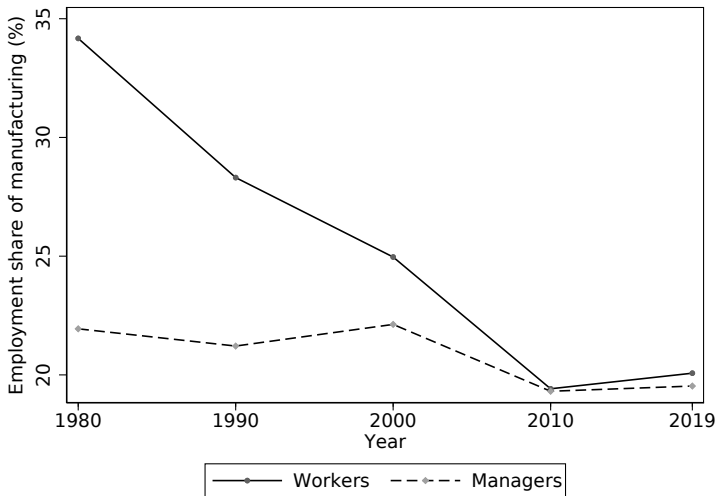
Manager Employment by Sector

► back



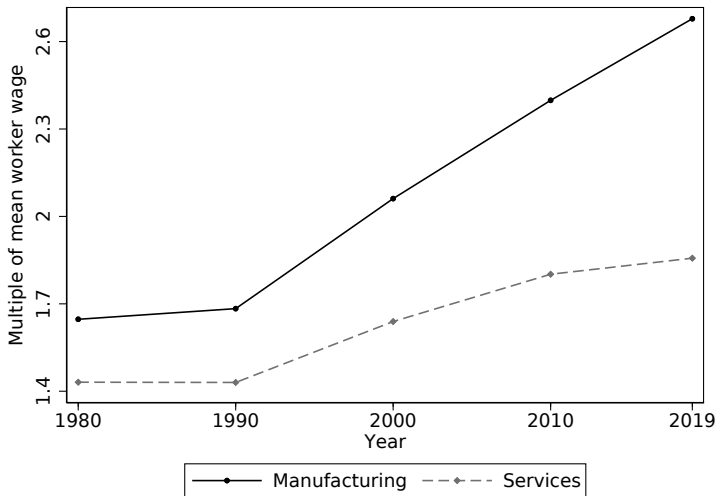
Sectoral Employment Shares by Occupation

► back

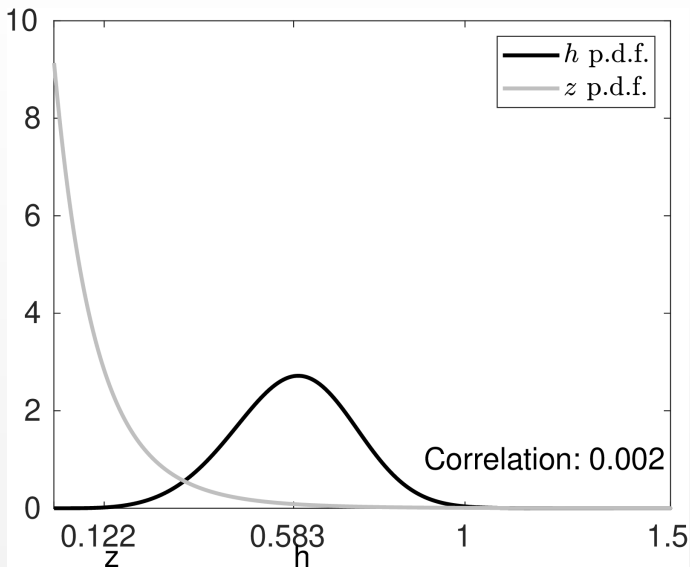


Manager Wages by Sector

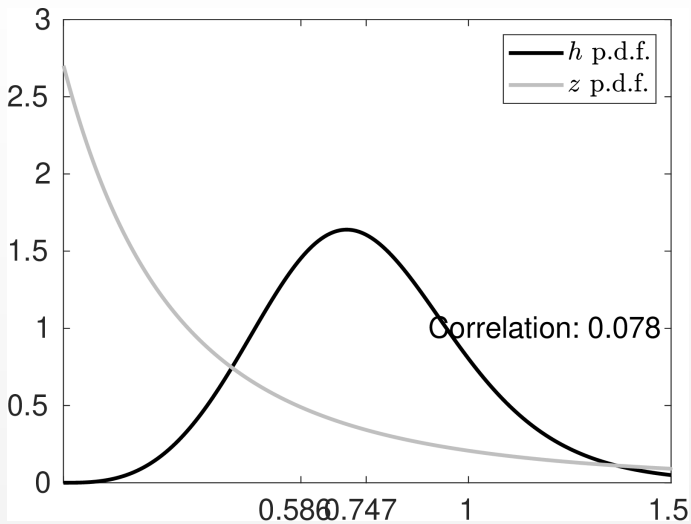
▶ back



Bivariate Pareto Skill Distribution, 1980



Bivariate Pareto Skill Distribution, 2019



Wage Calibration Targets

Ranked by mean wage (except management)	SOC Code	Relative Wages 1980	2019
Low Skill Services	400	0.65	0.53
Middle Skill		0.90	0.76
Administrative Support	300	0.78	0.65
Machine Operators	700	0.84	0.61
Transportation	800	0.88	0.58
Sales	240	0.94	0.90
Technicians	200	1.04	1.22
Mechanics & Construction	500	1.06	0.76
Miners & Precision Workers	600	1.09	0.72
High Skill		1.26	1.27
Professionals	40	1.21	1.23
Management Support	20	1.32	1.34
Management	1	1.39	1.74

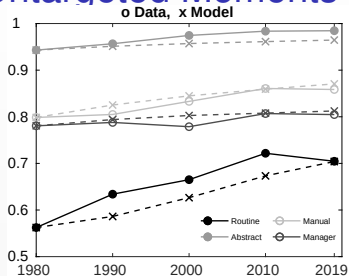
(average wage in each year normalized to 1)

Parameters by Occ.

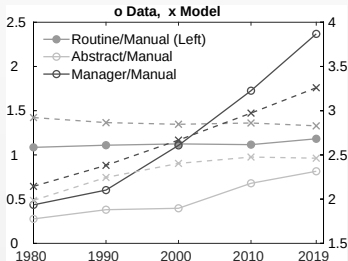
Ranked by mean wage (except management)	Emp Wgts (ν_{ij}, η_i)		m_j (%)	χ_j	
	Manu.	Serv.		1980	2019
Low Skill Services	0.017	0.143	0.566	-	-
Middle Skill	0.816	0.520			
Administrative Support	0.089	0.174	3.573	0.000	0.069
Machine Operators	0.258	0.016	5.968	0.010	0.012
Transportation	0.112	0.080	3.078	0.026	0.000
Sales	0.026	0.121	1.386	0.047	0.168
Technicians	0.034	0.040	-1.104	0.047	0.205
Mechanics & Construction	0.165	0.065	2.740	0.047	0.116
Miners & Precision Workers	0.132	0.027	6.452	0.055	0.101
High Skill	0.167	0.337			
Professionals	0.069	0.193	-1.926	0.059	0.205
Management Support	0.098	0.144	-1.754	0.090	0.267
Management	0.077	0.131	-2.658	-	-

Model Fit: Untargeted Moments

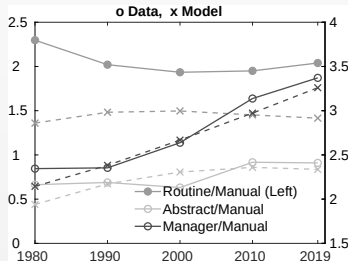
► Emp. shares



Service Share by Task



w/i M Wages



w/i S Wages

TFP Growth and Employment Shares

Δ Emp Share	(1)	(2)	(3)
TFP Growth	-11.316** (1.900)		-15.209** (1.777)
$\Delta\chi$		3.284 (1.598)	-1.225* (0.450)
Constant	0.177* (0.074)	-0.256 (0.202)	0.377** (0.050)
R^2	0.834	0.332	0.947

TFP Growth	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RTI (DOT)	0.019 (0.009)							
R-Manual		0.026** (0.005)				0.028 (0.016)	0.022* (0.009)	0.022* (0.007)
NR-Man Pers			-0.023** (0.004)			0.003 (0.015)		
NR-Cog Anal				-0.019* (0.006)			-0.006 (0.009)	
Δ Col Share					-0.271** (0.076)			-0.069 (0.096)
Constant	0.015 (0.008)	0.015* (0.006)	0.015 (0.007)	0.015 (0.008)	0.046** (0.013)	0.015* (0.006)	0.015* (0.006)	0.023 (0.011)
R^2	0.352	0.658	0.525	0.374	0.388	0.660	0.683	0.673

Standard errors in parentheses

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

Wage Growth and Complementarity

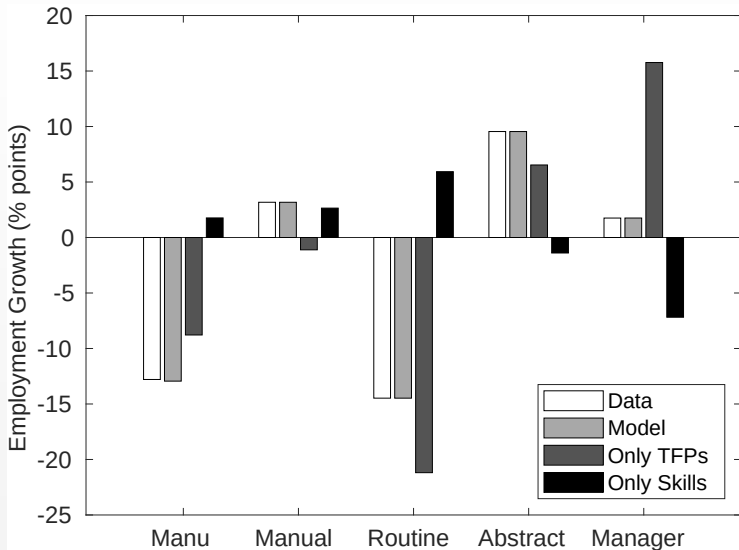
Δ Avg Wage	(1)	(2)	(3)
TFP Growth	-6.240** (0.946)		-3.049* (1.030)
$\Delta\chi$		2.434** (0.433)	1.530* (0.444)
Constant	0.395** (0.038)	0.081 (0.051)	0.208** (0.047)
R^2	0.756	0.746	0.847

$\Delta\chi$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
RTI (DOT)	-0.009 (0.018)							
R-Manual		-0.055** (0.009)				-0.029* (0.009)		-0.021 (0.012)
NR-Man Pers			0.044** (0.012)					
NR-Cog Anal				0.062** (0.008)		0.045** (0.012)	0.048** (0.006)	0.041** (0.010)
Δ Col Share					0.706** (0.151)		0.347* (0.103)	0.211 (0.131)
Constant	0.077* (0.025)	0.080** (0.015)	0.080** (0.019)	0.080** (0.011)	-0.003 (0.029)	0.081** (0.009)	0.040* (0.015)	0.057* (0.020)
R^2	0.016	0.617	0.388	0.787	0.556	0.900	0.880	0.927

Standard errors in parentheses

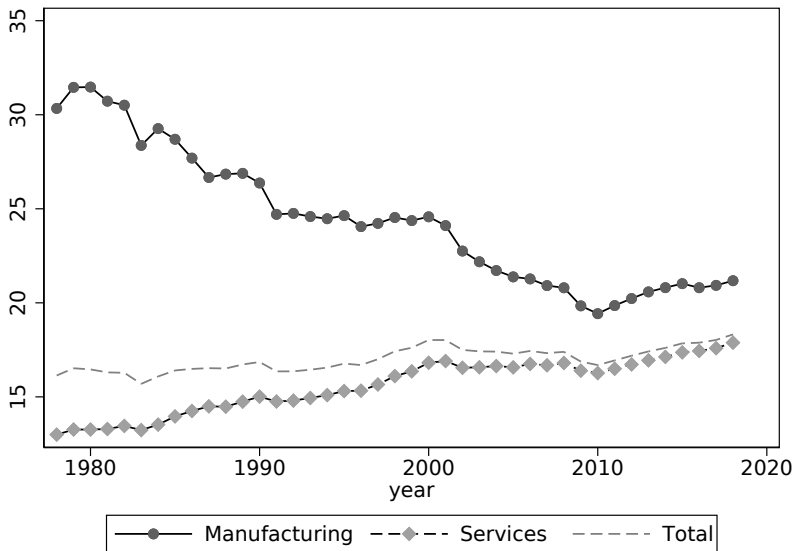
* $p < 0.05$, ** $p < 0.01$

Skilling Up Employment



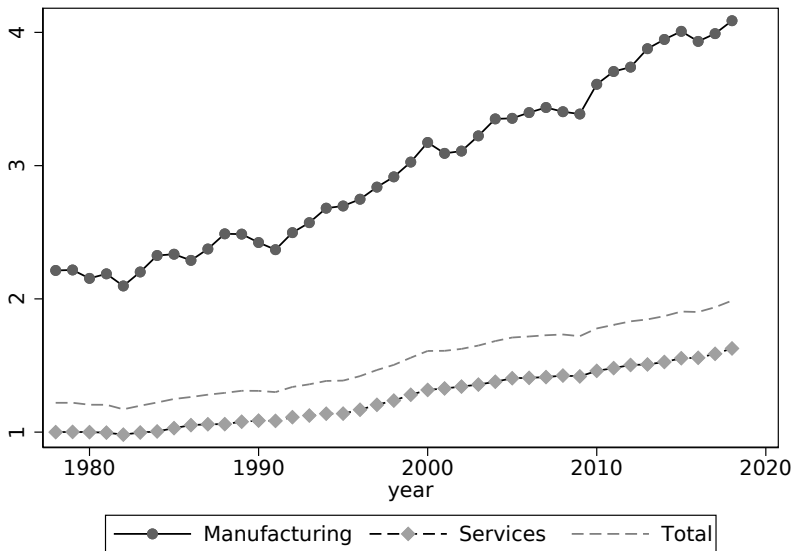
Employment by Establishment

[▶ back](#)



VA Output by Establishment

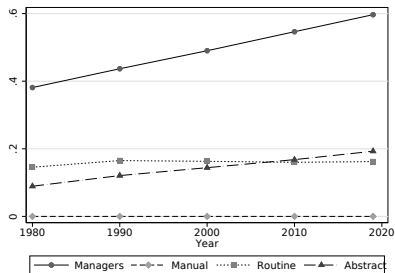
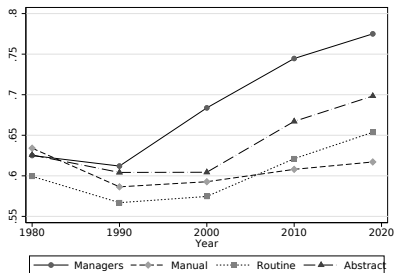
[▶ back](#)



More Implications

- More managers in manufacturing, employment decline but output increase by establishment ▶ Emp/estab ▶ VA/estab
 - But total managers have increased, while average establishment sizes have not shrunk
 - Rise of mid-level managers, which in our model comes from individuals with lower z 's ▶ within mgr shares
 - Larger rise in inequality among managers, also in the data ▶ wage inequality
- ⇒ Consistent with the narrowing gap between manufacturing and service establishment size ▶ back

Witin-Occ Wage Inequality



Log Wage SD, Data vs. Model

► intro

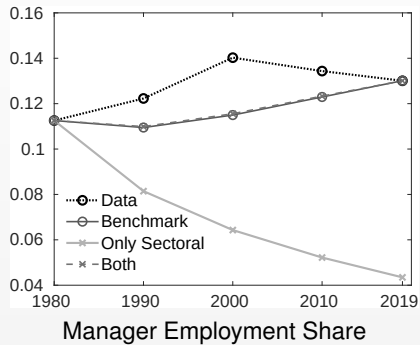
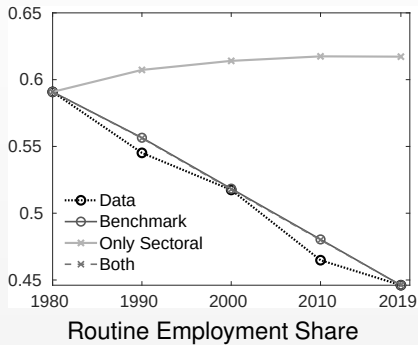
► model

AI and Employment

[▶ back](#)

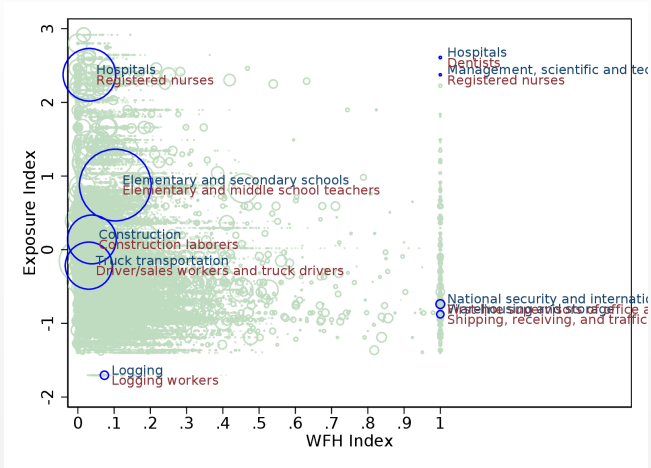
	(1)	(2)	(3)	(4)
R-Manual	-0.019 (0.023)	-0.023 (0.023)	-0.028 (0.030)	
AI (Webb)		0.083** (0.027)		
AI/OI (Felten et al.)			-0.013 (0.045)	0.004 (0.034)
$\Delta 2010$ Share	0.204* (0.079)	0.226** (0.084)	0.198* (0.084)	0.223** (0.081)
Constant	0.030 (0.023)	0.030 (0.023)	0.030 (0.023)	0.030 (0.023)
R^2	0.035	0.077	0.035	0.033
Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$.				

Polarization



Impact of Covid-19

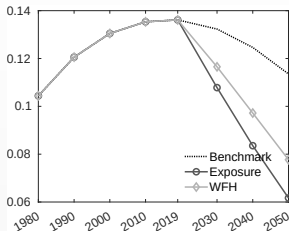
- Shift of TSTC post-pandemic?



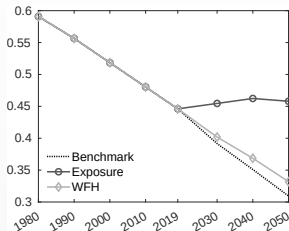
Long-run Impact of Covid-19?

- Technological improvements in
 1. low WFH occupations?
 2. high exposure occupations?
- Start counterfactual from 2019
 1. Extrapolate changes in skill distribution and χ_j 's
 2. Shift TSTC (m_j 's) to (low) WFH/(high) exposure measures
 3. Assume same 2030 GDP

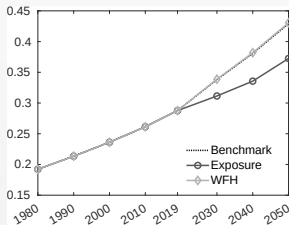
Polarization after Covid?



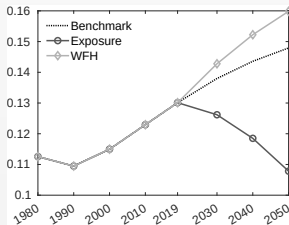
Manual Share



Routine Share

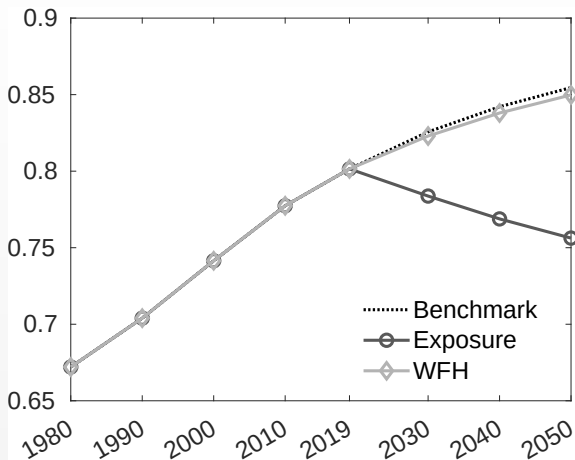


Analytical Share



Manager Share

Structural Change after Covid?



Service Employment Share

Acemoglu, Daron and David Autor, “Skills, Tasks and Technologies: Implications for Employment and Earnings,” in David Card and Orley Ashenfelter, eds., *Handbook of Labor Economics*, Vol. 4, Part B, Elsevier, 2011, pp. 1043 – 1171.

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Autor, David H. and David Dorn, “The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market,” *American Economic Review*, 2013, 103 (5), 1553–97.

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Seamans, “The Occupational Impact of Artificial Intelligence: Labor, Skills and Polarization,” Working Paper, NYU Stern School of Business September 2019.

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