The Changing Task Content of Production and the Rise of US Wage Inequality

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Rising Wage Inequality Between Groups of Society

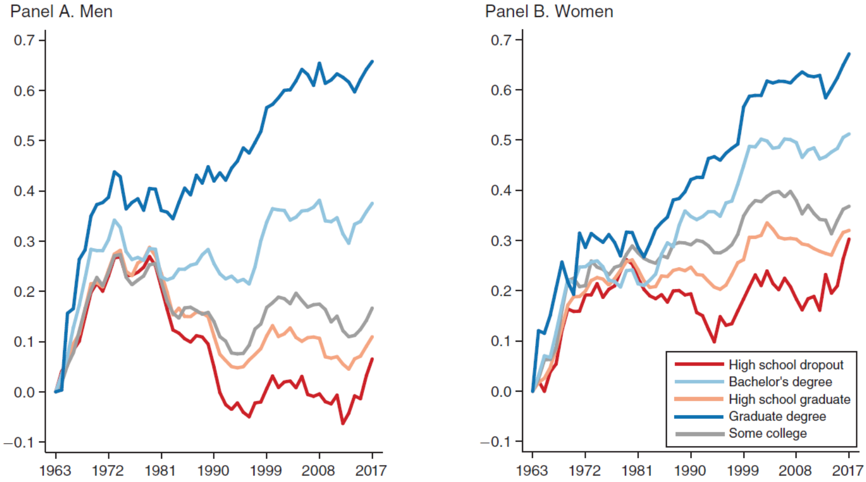

Figure: Cumulative change in real weekly wages, working-age adults (Autor, 2019)

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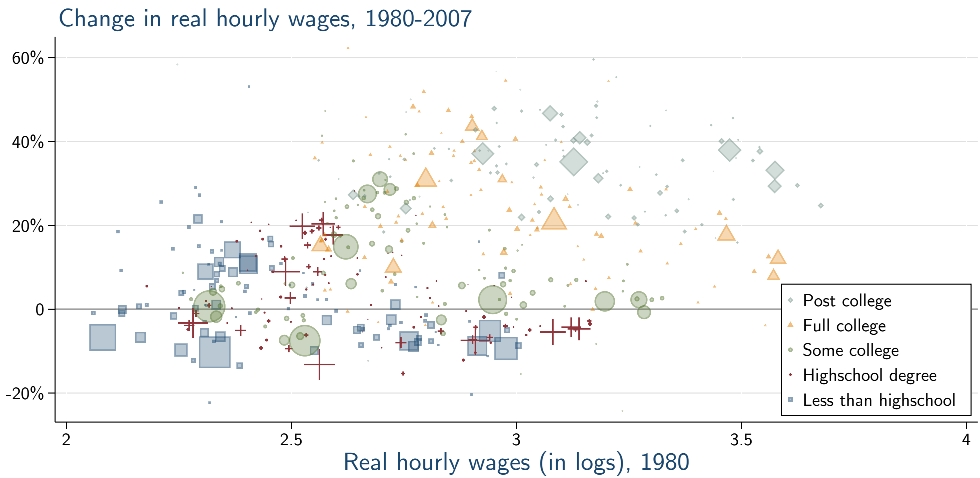

Figure: Change in real hourly wages for 500 education–experience–gender–race–nativity groups

Summary of our Argument

- Our previous work developed a task-based approach to understand changes in productivity and aggregate labor demand (Acemoglu–Restrepo, 2018, 2019).
- **This project:**
  - much of the rise in wage inequality is because of the changing task content of production across sectors and the exposure of workers with different skills to these
  - rather than standard SBTC measures, what is crucial is whether a demographic group is heavily represented in routine occupations in industries experiencing automation or other changes in task structure biased against labor
  - more than 50% of the changes in US wage structure between 1980 and 2016 are due to the exposure of different types of workers to the resulting task displacement
  - changes in task structure appear to be related to automation (not offshoring)

Outline of the Paper

Tractable task framework

- role of task allocation $\ln w_g = a \cdot \ln(y/\ell_g) + b \cdot \ln \text{task share}_g$
- automation and offshoring$\Rightarrow$ change $\ln \text{task share}_g$ and tfp
- large distributional effects and small tfp gains$\Rightarrow$ $d \ln w_g < 0$

Measure task displacement & reduced forms

- $\text{task displacement}_g$ =effect of technology on $\ln \text{task share}_g$
- measure of task displacement captures groups of workers heavily represented in routine tasks in industry with falling labor shares
- extensive reduced-form evidence of a strong relation between task displacement and real wage changes (and declines) across groups

Quantifying effect of task displacement

- use model to compute effects on output and wages
- account for ripple effects, industry shifts and productivity gains
- explain 48% to 57% of wage changes and sizable share of declines

Outline of the Talk

1. Task model with multiple skills
   - effect of technology on wages and tfp
   - model with multiple industries to connect with data

2. Measuring task displacement
   - and reduced-form evidence

3. Quantifying effect of task displacement on wages and tfp

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Model: Environment

Output combines mass M of tasks in $\mathcal{T}$

$$y = \left(\frac{1}{M} \int_{\mathcal{T}} (M \cdot y(x))^{\frac{\lambda-1}{\lambda}} \cdot dx \right)^{\frac{\lambda}{\lambda-1}}, \qquad \lambda = \text{task subs.}$$

Tasks produced by capital or different types of labor g

$$y(x) = A_k \cdot \psi_k(x) \cdot k(x) + \sum_g A_g \cdot \psi_g(x) \cdot \ell_g(x).$$

Factor supply and equilibrium

formal definition

- capital $k(x)$ produced from final good at cost $1/q(x)$
- labor of type g has fixed supply $\ell_g > 0$
- allocation of tasks maximizes $c = y - \int_{\mathcal{T}} (k(x)/q(x)) \cdot dx$

Model: Allocation of Tasks and Task Shares

Task allocation defined by sets $\mathcal{T}_g$ and $\mathcal{T}_k$

$$\mathcal{T}_g := \left\{ x : \frac{1}{\psi_g(x)} \cdot \frac{w_g}{A_g} \leq \frac{1}{\psi_j(x)} \cdot \frac{w_j}{A_j} \quad \forall j, \quad \frac{1}{q(x) \cdot \psi_k(x)} \cdot \frac{1}{A_k} \right\}$$

$$\mathcal{T}_k := \left\{ x : \frac{1}{q(x) \cdot \psi_k(x)} \cdot \frac{1}{A_k} \leq \frac{1}{\psi_j(x)} \cdot \frac{w_j}{A_j} \quad \forall j \right\}$$

Definition of task share of g & task share k

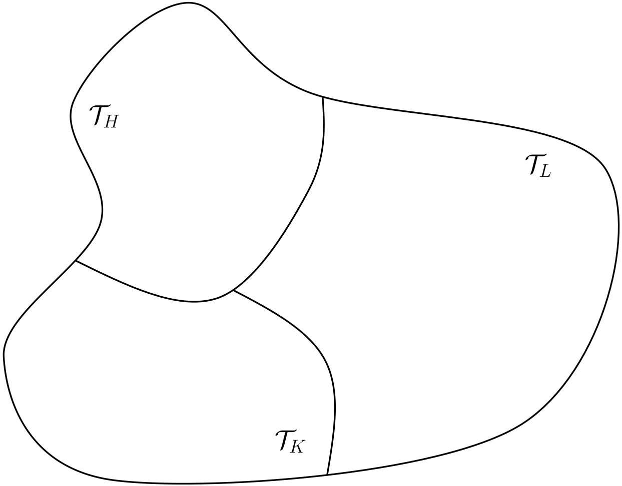
$$\Gamma_g(w^e, \Psi) := \frac{1}{M} \int_{\mathcal{T}_g} \psi_g(x)^{\lambda - 1} \cdot dx$$

$$\Gamma_k(w^e, \Psi) := \frac{1}{M} \int_{\mathcal{T}_k} (q(x) \cdot \psi_k(x))^{\lambda - 1} \cdot dx.$$

Determinants of Γ_g and Γ_k

- wages/rates per efficiency unit $w^e = \{w_1/A_1, \ldots, w_G/A_G\}$.
- task-specific technologies $\Psi \Rightarrow$ also affect boundaries $\mathcal{T}_g, \mathcal{T}_k$!

Model: Allocation of Tasks and Task Shares



Proposition (Equilibrium objects as function of task shares)

Given $\ell = (\ell_1, \ell_2, \ldots, \ell_G)$ *and task shares* $\{\Gamma_1, \ldots, \Gamma_G, \Gamma_k\}$, *output is given by*

$$y = (1 - A_k^{\lambda-1} \cdot \Gamma_k)^{\frac{\lambda}{1-\lambda}} \cdot \left(\sum_g \Gamma_g^{\frac{1}{\lambda}} \cdot (A_g \cdot \ell_g)^{\frac{\lambda-1}{\lambda}} \right)^{\frac{\lambda}{\lambda-1}}, \tag{1}$$

wages are given by

$$w_g = \left(\frac{y}{\ell_g} \right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \Gamma_g^{\frac{1}{\lambda}}. \tag{2}$$

and factor shares are given by

$$s^K = A_k^{\lambda-1} \cdot \Gamma_k, \qquad s^L = 1 - A_k^{\lambda-1} \cdot \Gamma_k. \tag{3}$$

Model: A Rich Menu of Technologies

Besides usual factor augmenting technologies, A_g and A_k, two new technology classes:

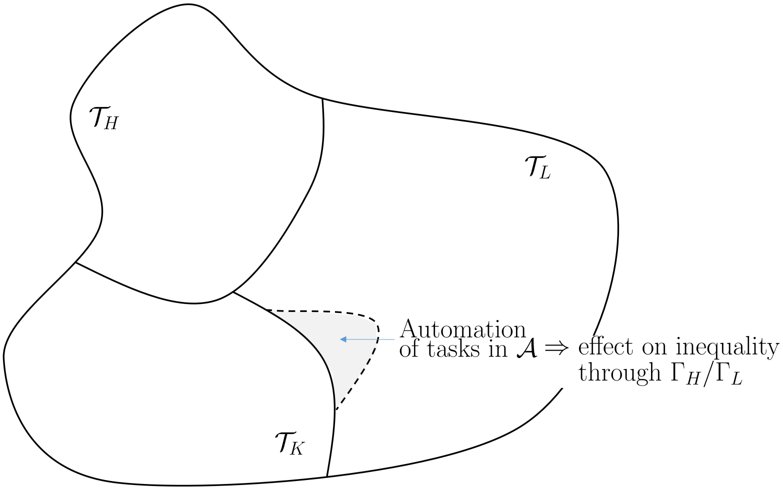
Productivity deepening

- improvements in $\psi_g(x)$ for tasks in $\mathcal{T}_g$
- improvements in $\psi_k(x)/q(x)$ for tasks in $\mathcal{T}_k$
- denote effect on $\frac{1}{\lambda-1} d\ln\Gamma_g$ by $d\ln\Gamma_g^{\mathrm{deep}}$ and $d\ln\Gamma_k^{\mathrm{deep}}$

Task displacement via automation or offshoring

- $\mathcal{T}_g\downarrow$ and $\mathcal{T}_k\uparrow$ due to improvements in $\psi_k(x)/q(x)$ for tasks in $\mathcal{T}_g$
- denote reduction in $d\ln\Gamma_g$ by $d\ln\Gamma_g^{\mathrm{disp}}$
- $\pi_g =$avg cost reduction $\ln\left(\frac{w_g}{A_g\cdot\psi_g(x)}\right)-\ln\left(\frac{1}{A_k\cdot q(x)\cdot\psi_k(x)}\right)>0$

Model: Examples of Different Technologies



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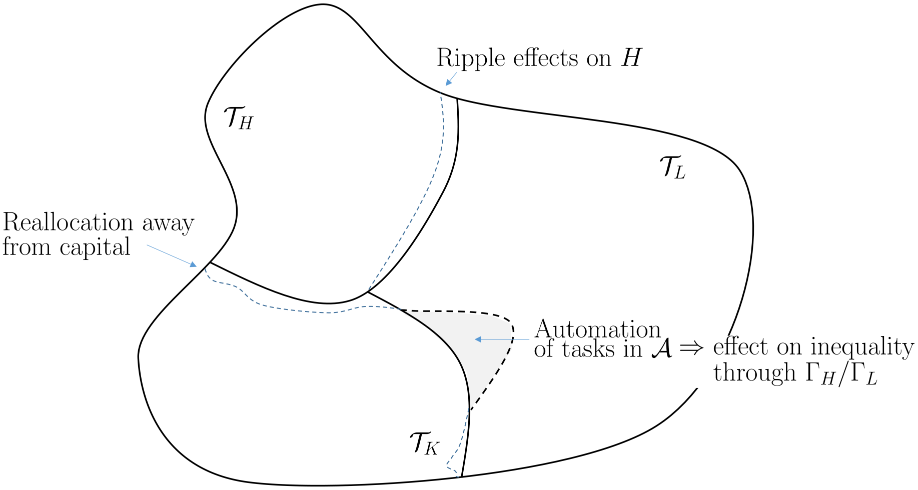

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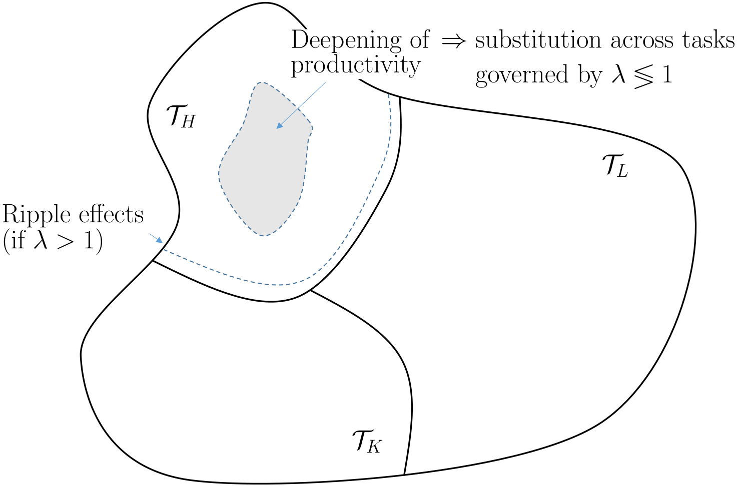

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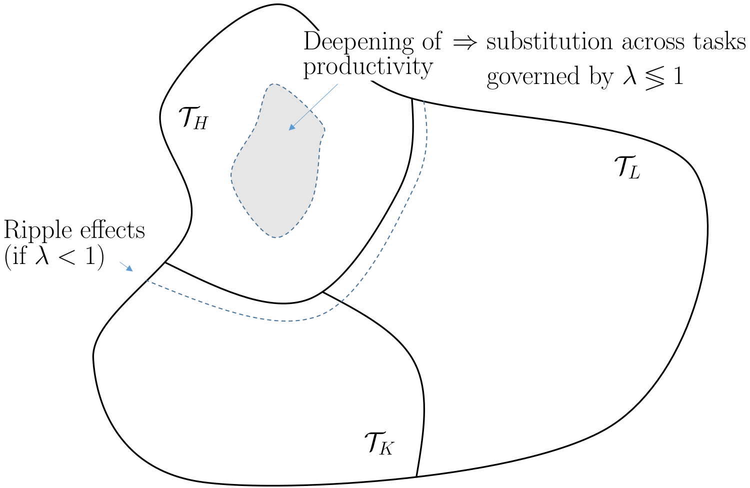
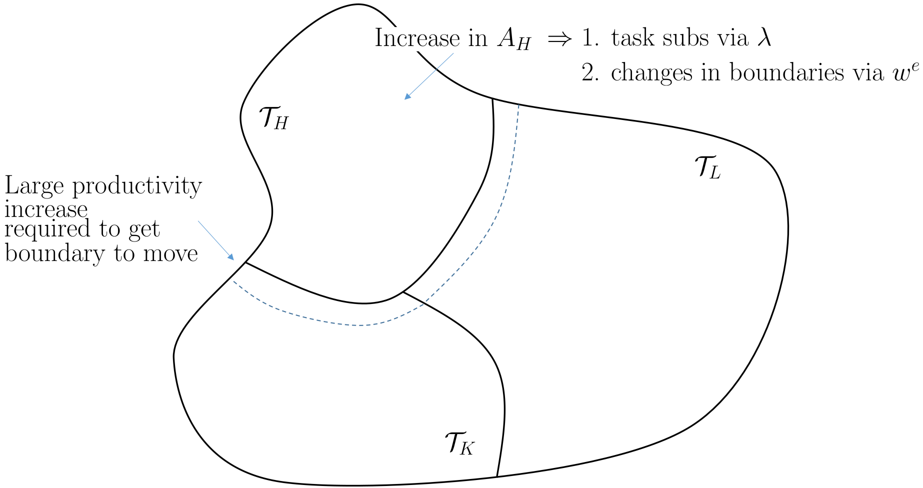


Model: Examples of Different Technologies



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Effects of Technology: No Ripple Effects

No ripple effects: tasks unique to g and capital produces all tasks in which $\psi_k(x) > 0$.

Proposition (Effect of technology on wages and TFP)

The change in wages is given by

$$d\ln w_g = \frac{1}{\lambda} d\ln y + \frac{\lambda-1}{\lambda}\left(d\ln A_g + d\ln \Gamma_g^{deep}\right) - \frac{1}{\lambda} d\ln \Gamma_g^{disp},$$

and the change in aggregate TFP, output and the capital share is given by

$$d\ln tfp = \sum_g s_g^L \cdot \left(d\ln A_g + d\ln \Gamma_g^{deep}\right) + s^K \cdot \left(d\ln A_k + d\ln \Gamma_k^{deep}\right) + \sum_g s_g^L \cdot d\ln \Gamma_g^{disp} \cdot \pi_g$$

$$d\ln s^k = (\lambda-1) \cdot \left(d\ln A_k + d\ln \Gamma_k^{deep}\right) + d\ln \Gamma_k^{disp}$$

$$d\ln y = \frac{1}{1-s^K} \cdot \left(d\ln tfp + s^K \cdot d\ln s^K\right).$$

Effects of Technology: Accounting for Ripple Effects

Propagation of a wage shock

- denote vectors using bold symbols: $\boldsymbol{x} = (x_1, x_2, \ldots, x_G)$
- $d \ln w_g = z_g + \frac{1}{\lambda} \frac{\partial \ln \Gamma_g}{\partial \ln \boldsymbol{w}^e} \cdot \boldsymbol{d \ln w} \Rightarrow \boldsymbol{d \ln w} = \Theta \cdot \boldsymbol{z}$, where

$$\Theta := \left(\mathbb{1} - \frac{1}{\lambda} \frac{\partial \ln \boldsymbol{\Gamma}}{\partial \ln \boldsymbol{w}^e} \right)^{-1} = \mathbb{1} + \frac{1}{\lambda} \frac{\partial \ln \boldsymbol{\Gamma}}{\partial \ln \boldsymbol{w}^e} + \left(\frac{1}{\lambda} \frac{\partial \ln \boldsymbol{\Gamma}}{\partial \ln \boldsymbol{w}^e} \right)^2 + \ldots$$

Properties of propagation matrix Θ

- Θ is a $G \times G$ matrix where ripple effect of j on g is $\theta_{gj} \geq 0$
- row sum $\sum_j \theta_{gj} = \varepsilon_g \in (0, 1) \Rightarrow$ effect of uniform shock on g (lower when g and capital compete for tasks)
- an increase in ℓ_j reduces w_g ($q-$subs) iff $\theta_{gj} > s_j^L \cdot \varepsilon_g$
- ripple effects can dampen or augment inequality

Effects of Technology: Accounting for Ripple Effects

Let us just focus on displacement effects, suppressing the effects of other technologies.

Proposition (Effect of technology on wages and TFP)

The change in wages is given by

$$d \ln w_g = \frac{\varepsilon_g}{\lambda} d \ln y - \frac{1}{\lambda} \Theta_g \cdot \boldsymbol{d \ln \Gamma}^{disp},$$

and the change in aggregate TFP and output is given by

$$d \ln tfp = \sum_g s_g^L \cdot d \ln \Gamma_g^{disp} \cdot \pi_g$$

$$d \ln s^k = d \ln \Gamma_k^{disp}$$

$$d \ln y = \frac{1}{1 - s^K} \cdot \left(d \ln tfp + s^K \cdot d \ln s^K \right).$$

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Model: Multiple Industries

Industry dimension critical

- different demographic groups specialize in different industries
- automation and offshoring not uniform across industries

Industry structure

- demand system with $s_i^Y(p)$:=share industry $i \Rightarrow$ CES $s_i^Y(p) = \alpha_i \cdot p_i^{1-\eta}$
- p =vector of industry prices; final good remains the numeraire

Definition of task share of g & task share k

$$\Gamma_{gi}(w^e, \Psi) := \frac{1}{M_i} \int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1} \cdot dx$$

$$\Gamma_{ki}(w^e, \Psi) := \frac{1}{M_i} \int_{\mathcal{T}_{ki}} (q(x) \cdot \psi_k(x))^{\lambda-1} \cdot dx.$$

Proposition (Equilibrium objects as function of task shares)

Given $\ell = (\ell_1, \ell_2, \ldots, \ell_G)$ and within industry task shares $\{\Gamma_{1i}, \ldots, \Gamma_{Gi}, \Gamma_{ki}\}$ for all i, equilibrium wages, industry prices, and output are the solution to

$$w_g = \left(\frac{y}{\ell_g}\right)^{\frac{1}{\lambda}} \cdot A_g^{\frac{\lambda-1}{\lambda}} \cdot \left(\sum_i s_i^Y(\boldsymbol{p}) \cdot (A_i p_i)^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{\lambda}} \tag{4}$$

$$p_i = \frac{1}{A_i}\left(A_k^{\lambda-1} \cdot \Gamma_{ki} + \sum_g w_g^{1-\lambda} \cdot A_g^{\lambda-1} \cdot \Gamma_{gi}\right)^{\frac{1}{1-\lambda}} \tag{5}$$

$$1 = \sum_i s_i^Y(\boldsymbol{p}). \tag{6}$$

Deriving a Reduced-Form Equation for Wages

Effect of technology on wages abstracting from ripple effects:

$$d\ln w_g = \frac{1}{\lambda} d\ln y + \alpha_g + \frac{1}{\lambda}\sum_i \omega_{gi}\cdot\zeta_i - \frac{1}{\lambda}\sum_i \omega_{gi}\cdot d\ln\Gamma_{gi}^{\mathrm{disp}},$$

where ω_{gi} denotes share of group g wages earned in i.

Real wages depend on:

- common expansion of output, $d\ln y$
- group-specific shifters $\alpha_g = \frac{\lambda-1}{\lambda}\left(d\ln A_g + \sum_i \omega_{gi}\cdot d\ln\Gamma_{gi}^{\mathrm{deep}}\right)$
- industry shifters $\zeta_i = d\ln s_i^Y + (1-\lambda)(d\ln p_i + d\ln A_i)$
- and task displacement affecting g workers $\text{Task displacement}_g := \sum_i \omega_{gi}\cdot d\ln\Gamma_{gi}^{\mathrm{disp}}$

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Measuring Task Displacement: Cobb-Douglas Case

Key idea: displacement takes place in routine tasks at industries undergoing automation

A1. Technology and markups

- no change in markups
- changes in labor share driven by task displacement

A2. Routine tasks in industry i automated at common rate

- $\Gamma_{gi} = \Gamma_{gi}^{N} + \Gamma_{gi}^{R}$
- $d \ln \Gamma_{gi}^{N,\text{disp}} = 0$ and $d \ln \Gamma_{gi}^{R,\text{disp}} = d \ln \Gamma_{i}^{R,\text{disp}}$

A1+A2: recover task displacement from industry data on labor shares

$$d \ln \Gamma_{gi}^{\text{disp}} = -\frac{\omega_{gi}^{R}}{\omega_{i}^{R}} \cdot d \ln s_i^L$$

$\omega_x^R :=$ share wages in routine jobs

$s_L^i :=$ industry labor share

Measuring Task Displacement: CES Case

A1. Set of technologies is restricted

- no change in markups
- changes in labor share driven by task displacement, wages, and price of capital

A2. Routine tasks in industry i automated at common rate

- $\Gamma_{gi} = \Gamma^{N}_{gi} + \Gamma^{R}_{gi}$
- $d\ln\Gamma^{N,\text{disp}}_{gi} = 0$ and $d\ln\Gamma^{R,\text{disp}}_{gi} = d\ln\Gamma^{R,\text{disp}}_{i}$

A1+A2: recover task displacement from industry data on labor shares, s^L_i

$$d\ln\Gamma^{\text{disp}}_{gi} = -\frac{\omega^R_{gi}}{\omega^R_i}\frac{d\ln s^L_i + (1-\sigma_i)\cdot s^K_i\cdot(d\ln q_i - d\ln w_i)}{1+(\lambda-1)\cdot s^L_i\cdot\pi_i}.$$

σ_i =estimate of the K–L elasticity of substitution for industry i ($\sigma_i \geq \lambda$ due to task reallocation)

Data and Measurement

Data for 49 industries from the BLS

- Cobb–Douglas and CES scenarios $\sigma_i = \sigma \in (0.5, 1.2)$, $\lambda = 0.5$
- cost-saving gains from automation $\pi_i = 30\%$
- measure task displacement from 1987-2016

Construct measure of task displacement for 500 skill groups

- Census data for 1980 to measure wage shares
- 500 groups defined by education–experience–gender–race–nativity
- routine jobs defined using ONET as in Acemoglu–Autor 2011

Data and Measurement: Variation Across Industries

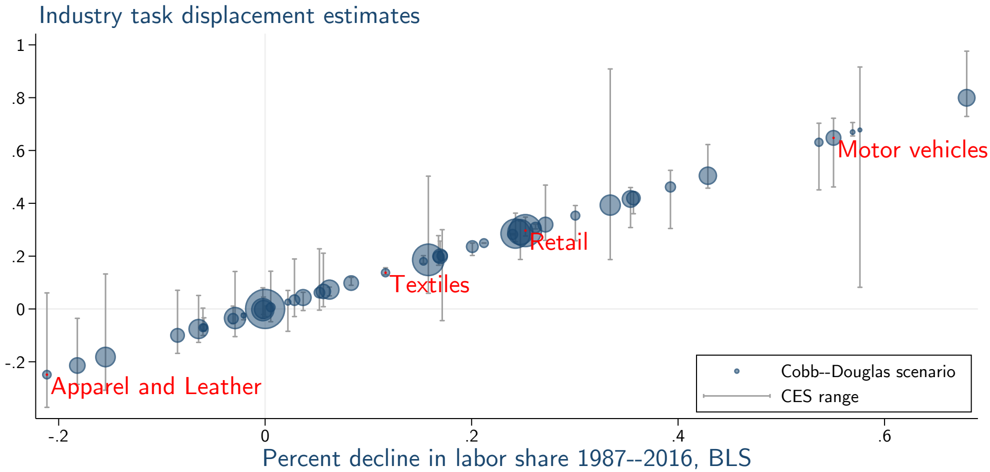

Figure: Estimated task displacement, $d \ln \Gamma_i^{\mathrm{disp}}$, for 49 industries. Marker sizes: value added in 1987.

Data and Measurement: Zeroth Stage Across Industries

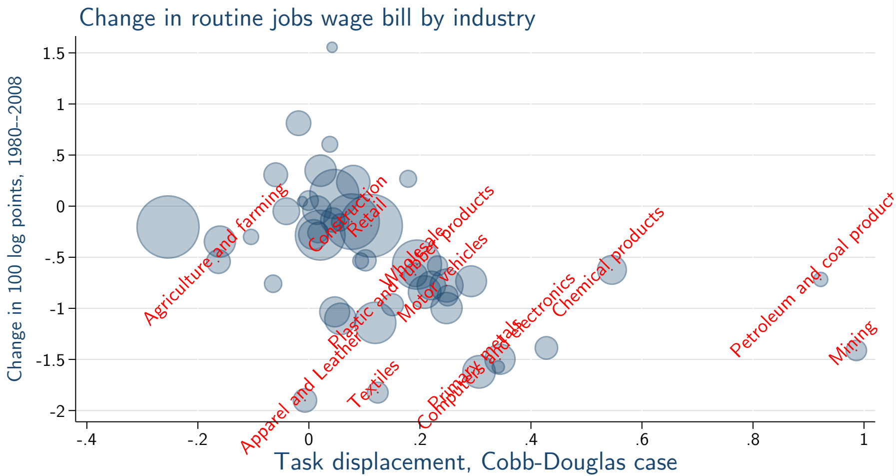

Figure: Estimated task displacement, $d \ln \Gamma_i^{\text{disp}}$, for 49 industries and the decline of routine jobs.

Data and Measurement: Zeroth Stage Across Industries

Zeroth-stage regression at the industry level:

$$\Delta \ln \text{Wage bill routine jobs}_i = \beta \cdot \Delta \ln \Gamma_i^{\text{disp}} + \varepsilon_i$$

Dependent variable:	Wage bill 1980–2007 (1)	Hours 1980–2007 (2)	Employment 1980–2007 (3)
		Panel A: Cobb Douglas	
Task displacement	-1.349 (0.308)	-1.099 (0.301)	-1.066 (0.331)
R-squared	0.22	0.18	0.16
Observations	48	48	48
		Panel B: CES with $\sigma_i = 0.7$	
Task displacement	-1.221 (0.303)	-1.088 (0.324)	-1.062 (0.360)
R-squared	0.20	0.19	0.18
Observations	48	48	48
		Panel C: CES with $\sigma_i = 1.2$	
Task displacement	-1.082 (0.229)	-0.851 (0.219)	-0.824 (0.239)
R-squared	0.21	0.15	0.14
Observations	48	48	48

Data and Measurement: Variation Across Groups

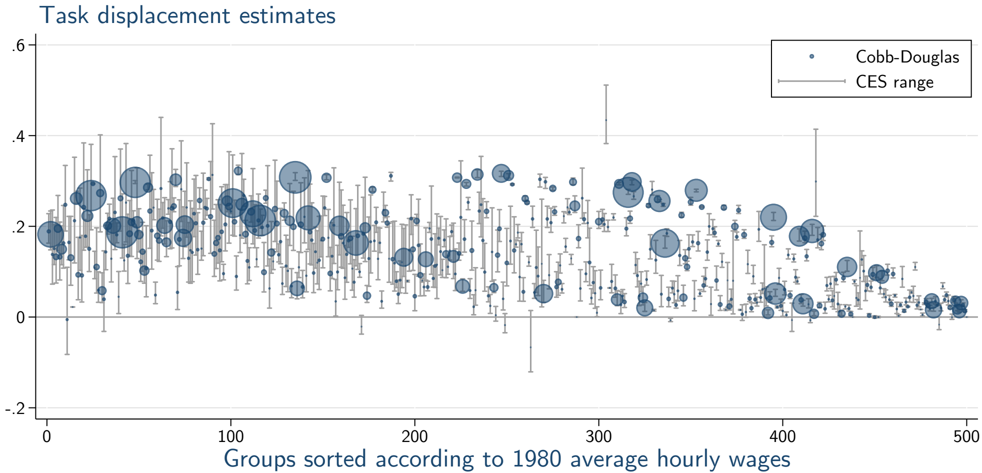

Figure: Estimated task displacement, $d\ln\Gamma_g^{\text{disp}}$, for 500 education–experience–gender–race–nativity groups. Marker sizes: group size in 1987.

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Reduced-form Evidence: Cobb-Douglas

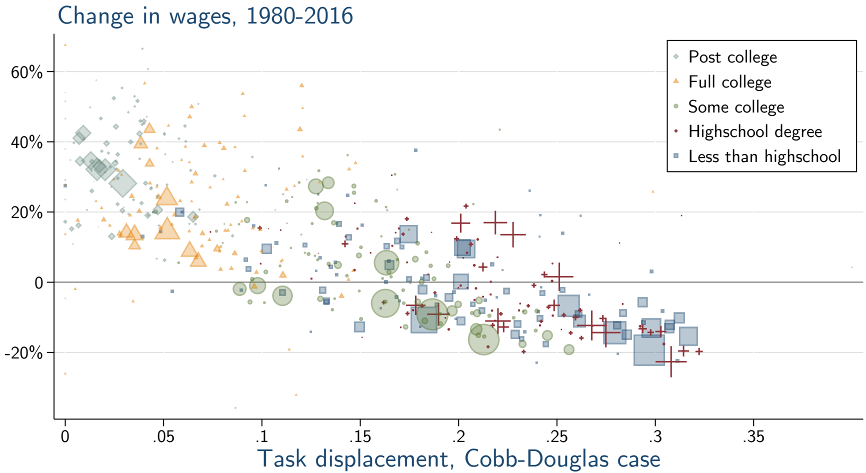
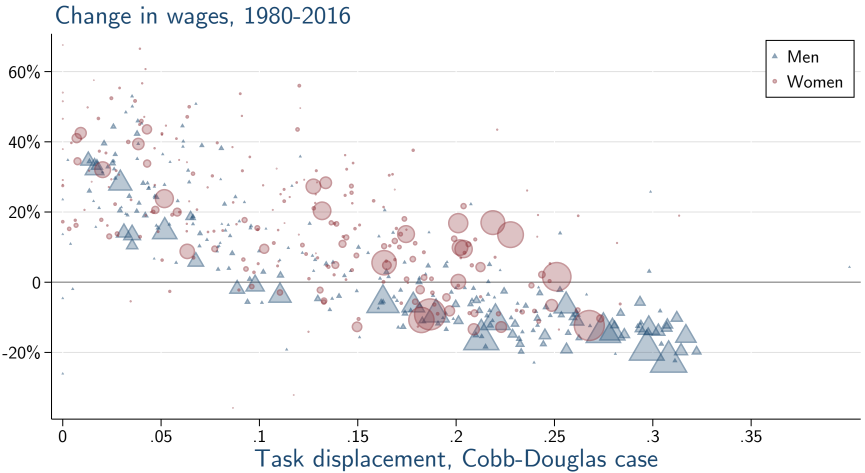


Figure: Relation between task displacement, $d \ln \Gamma_g^{\mathrm{disp}}$, and change in real wages, $d \ln w_g$, 1980–2016.

Reduced-form Evidence: Cobb-Douglas



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Reduced-form Evidence: CES

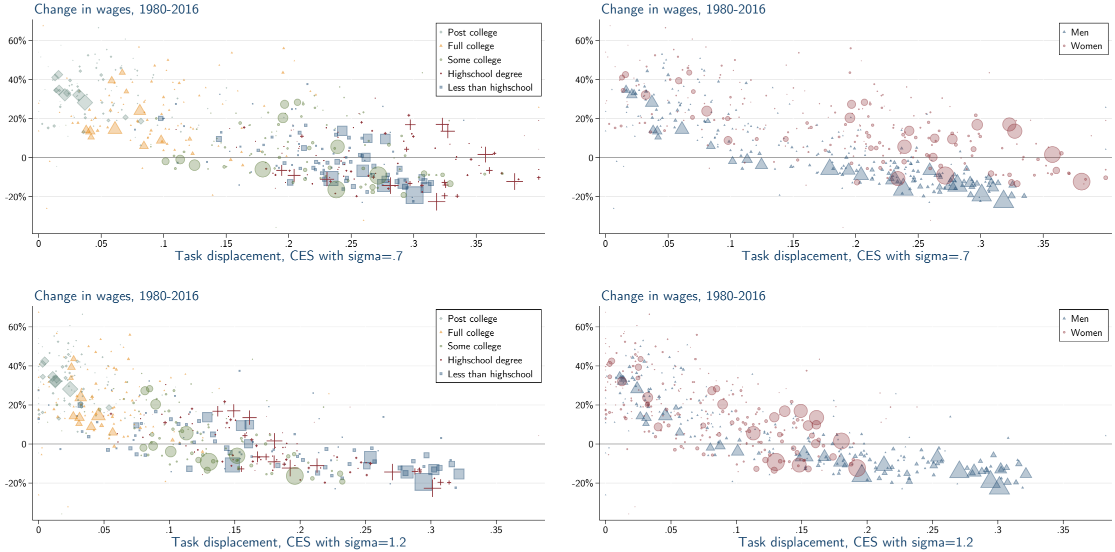

Figure: Relation between task displacement, $d \ln \Gamma_g^{\text{disp}}$, and change in real wages, $d \ln w_g$, 1980–2016.

Reduced-form Evidence: Cobb-Douglas, 1980–2016

Group-level specification derived from the model with no ripple effects:

$$\Delta \ln \text{Real wage per hour}_g = \beta \cdot \Delta \ln \Gamma_g^{\text{disp}} + \gamma \cdot \text{Exposure industry shifs}_g + \alpha_g + \varepsilon_g$$

- to account for changes in factor-augmenting productivity that are common by educational group and gender, we let

$$\alpha_g = \alpha_{\text{gender(g)}} + \alpha_{\text{education}(g)} + \nu_g.$$

- the residual $\nu_g + \varepsilon_g$ is assumed orhtogonal to task displacement
- estimates weighted by baseline wage bill by group
- standard errors robust against heteroskedasticity

Reduced-form Evidence: Cobb-Douglas, 1980–2016

Table: ESTIMATES OF TASK DISPLACEMENT ON THE CHANGE IN HOURLY WAGES, 1980–2016

	DEPENDENT VARIABLE: CHANGE IN REAL HOURLY WAGES 1980–2016						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Task displacement	-1.706 (0.120)	-1.511 (0.140)	-1.396 (0.150)	-1.402 (0.210)	-1.724 (0.156)	-1.652 (0.158)	-1.633 (0.148)
Industry shifters		0.066 (0.040)	-0.143 (0.068)	0.044 (0.045)	-0.028 (0.041)	-0.017 (0.042)	0.219 (0.058)
Exposure to raw labor share changes			-0.963 (0.247)				
Exposure to routine jobs			-0.064 (0.028)				
Share wages earned at routine jobs				-0.103 (0.095)			
R-squared	0.70	0.71	0.76	0.72	0.83	0.85	0.87
Observations	500	500	500	500	500	500	500
Additional covariates:					Common group shifters by gender and education	+ Group regional wage shares	+ Group manufacturing wage share

Reduced-form Evidence: Task Displacement vs SBTC

Table: Educational–specific SBTC vs Task displacement

	Dependent variable: change in hourly wages 1980–2016		
	(1)	(2)	(3)
Education: highschool	0.005	-0.020	0.005
	(0.032)	(0.022)	(0.019)
Education: some college	0.032	-0.116	-0.072
	(0.035)	(0.034)	(0.029)
Education: full college	0.247	-0.012	-0.007
	(0.029)	(0.038)	(0.035)
Education: more than college	0.395	0.100	0.078
	(0.027)	(0.035)	(0.044)
Gender: women	0.144	-0.004	0.023
	(0.026)	(0.024)	(0.019)
Task displacement		-1.722	-1.633
		(0.154)	(0.148)
Industry shifters			0.219
			(0.058)
Partial R-squared task displacement		0.47	0.49
Partial R-squared college and post-college	0.56	0.11	0.06
R-squared	0.68	0.83	0.87
Observations	500	500	500
Additional covariates:			Group wage shares by region and in manufacturing

Reduced-form Evidence: Declining Real Wages

Table: ESTIMATES FOR PROBABILITY OF EXPERIENCING DECLINING REAL WAGES

	Dependent variable: dummy for declining real wages 1980–2016		
	(1)	(2)	(3)
Education: highschool	-0.043	0.016	-0.206
	(0.117)	(0.113)	(0.123)
Education: some college	0.014	0.358	0.055
	(0.129)	(0.158)	(0.169)
Education: full college	-0.726	-0.127	-0.464
	(0.109)	(0.154)	(0.164)
Education: more than college	-0.770	-0.087	-0.565
	(0.103)	(0.168)	(0.205)
Gender: women	-0.503	-0.162	-0.281
	(0.098)	(0.140)	(0.126)
Task displacement		3.987	4.042
		(0.832)	(0.792)
Industry shifters			0.169
			(0.246)
Partial R-squared task displacement		0.20	0.21
Partial R-squared college and post-college	0.34	0.01	0.05
R-squared	0.54	0.63	0.69
Observations	500	500	500
Additional covariates:			Group wage shares by region and in manufacturing

Reduced-form Evidence: Other Labor Market Outcomes

Table: ESTIMATES OF TASK DISPLACEMENT ON EMPLOYMENT, HOURS AND PARTICIPATION

DEPENDENT VARIABLE:	PERCENT CHANGE IN TOTAL HOURS	PERCENT CHANGE IN HOURS PER CAPITA	PERCENT CHANGE IN EMPLOYMENT RATE	PERCENT CHANGE IN NON-PARTICIPATION RATE
	(1)	(2)	(3)	(4)
Task displacement	-4.984 (0.956)	-0.948 (0.268)	-0.138 (0.141)	3.958 (1.418)
R-squared	0.88	0.74	0.53	0.65
Observations	500	500	500	487

Note: Additional covariates not reported include education and gender shifters, industry shifters, and group wage shares by region and in manufacturing.

Reduced-form Evidence: Stacked Differences 1980–2000 and 2000–2016

Table: Stacked-differences estimates of task displacement on the change in hourly wages, 1980–2000 and 2000–2014

	Dependent variable: change in hourly wages						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Task displacement	-1.409 (0.108)	-0.824 (0.127)	-0.876 (0.112)	-0.846 (0.158)	-1.439 (0.155)	-1.343 (0.162)	-1.303 (0.146)
R-squared	0.53	0.68	0.70	0.70	0.80	0.82	0.85
Observations	1000	1000	1000	1000	1000	1000	1000
Additional covariates:		Industry shifters	+ Exposure to raw labor share changes and routine jobs	Industry shifters and group routine jobs wage share	Industry shifters and common group shifters by gender and education	+ Group regional wage shares	+ Group manufacturing wage share

Robustness Checks: Definition of Automatable and Offshorable jobs

Table: Alternative definitions of mediating occupations

	Dependent variable: change in hourly wages 1980–2016				
Mediator:	Routine jobs, ONET		Alt. Def. Routine jobs, ONET	Webb's exposure software automation	Webb's exposure robot automation
	(1)	(2)	(3)	(4)	(5)
Task displacement	-1.633	-1.680	-1.672	-1.723	-1.086
	(0.148)	(0.171)	(0.183)	(0.245)	(0.135)
Task displacement—offshorable jobs		-0.090			
		(0.144)			
R-squared	0.87	0.87	0.86	0.81	0.83
Observations	500	500	500	499	500

Note: Additional covariates not reported include education and gender shifters, industry shifters, and group wage shares by region and in manufacturing.

Robustness Checks: Alternative Measures of the Labor Share

Table: ALTERNATIVE DEFINITIONS OF THE LABOR SHARE

	Dependent variable: change in hourly wages 1980–2016					
	Labor share in value added	Labor share in gross output	Labor share in variable inputs	Only labor share declines	Winsorizing change in labor shares	Exc. commodity sectors
	(1)	(2)	(3)	(4)	(5)	(6)
Task displacement	-1.633	-0.766	-0.789	-0.992	-1.680	-1.876
	(0.148)	(0.054)	(0.062)	(0.253)	(0.305)	(0.152)
R-squared	0.87	0.89	0.88	0.78	0.81	0.88
Observations	500	500	500	500	500	500

Note: Additional covariates not reported include education and gender shifters, industry shifters, and group wage shares by region and in manufacturing.

Reduced-form Evidence: Technology or Markups?

Industry correlates suggest technology important

- task displacement correlates with $\uparrow$tfp, q and $\downarrow p$
- labor share decline more pronounced in manufacturing
- within that sector in industries and firms adopting new automation technologies or that are more capital-intensive
  Acemoglu–Restrepo 20, Acemoglu–Lelarge–Restrepo 20, Hubmer 20

Reduced-form evidence

- as labor share declines, labor demand falls for workers engaged in routine jobs but not uniformly for others

Now

- estimates exploiting component of labor share decline driven by explicit measures of technology and offshoring

Reduced-form Evidence: Explicit Measures of Technology

Table: Component of labor share reduction driven by observed forces

	Dependent variable: change in hourly wages 1980–2016					
	(1)	(2)	(3)	(4)	(5)	(6)
Task displacement due to robot penetration	-0.663				-0.747	
	(0.206)				(0.247)	
Task displacement due to dedicated machinery		-0.898				-1.233
		(0.224)				(0.224)
Task displacement due to software penetration			-0.629		-0.659	-0.992
			(0.269)		(0.281)	(0.281)
Task displacement due to rising intermediate imports				-0.189	0.443	0.625
				(0.249)	(0.282)	(0.241)
R-squared	0.76	0.77	0.76	0.75	0.78	0.80
Observations	500	500	500	500	500	500

Note: Additional covariates not reported include education and gender shifters, industry shifters, and group wage shares by region and in manufacturing.

Reduced-form Evidence: Explicit Measures of Technology, IV

Table: IV estimates exploiting component of labor share reduction driven by robot, machinery, and software penetration

	Dependent variable: change in hourly wages 1980–2016				
Instrument:	Robot APR	Dedicated machinery	Software	All combined	
	(1)	(2)	(3)	(4)	(5)
Task displacement	-0.906 (0.221)	-1.068 (0.200)	-1.691 (0.488)	-1.237 (0.154)	-1.306 (0.156)
Exposure to raw labor share changes					0.184 (0.257)
R-squared	0.85	0.86	0.87	0.87	0.87
Observations	500	500	500	500	500
First-stage F	96.9	104.1	13.0	104.8	69.8

Note: Additional covariates not reported include education and gender shifters, industry shifters, and group wage shares by region and in manufacturing.

Reduced-form Evidence: Exploiting Regional Variation

Reduced-form regression (z indexes 722 commuting zones)

$$\Delta \ln \text{Real wage per hour}_{gz} = \beta \cdot \Delta \ln \Gamma_{gz}^{\text{disp}} + \alpha_g + \varepsilon_{gz}$$

Table: Estimates of task displacement on the change in hourly wages exploiting regional variation across commuting zones and controlling for α_g

	Dependent variable: change in hourly wages						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Task displacement	-0.324 (0.068)	-0.336 (0.061)	-0.367 (0.164)	-0.247 (0.062)	-0.336 (0.061)	-0.208 (0.056)	-0.178 (0.065)
R-squared	0.72	0.72	0.72	0.73	0.72	0.81	0.82
Observations	8664	8664	8664	8664	8664	8664	8664
Additional covariates:		Industry shifters	+ Exposure to raw labor share changes and routine jobs	Industry shifters and group routine jobs wage share	Industry shifters and common group shifters by gender and education	+ Group regional wage shares	+ Group manufacturing wage share

Outline of the Talk

1. Task model with multiple skills
   - effect of technology on wages and tfp
   - model with multiple industries to connect with data

2. Measuring task displacement
   - and reduced-form evidence

3. Quantifying effect of task displacement on wages and tfp

Proposition (Counterfactuals)

The effect of task displacement by automation and offshoring on wages, industry prices and GDP is given by the solution to the following system of linear equations:

$$
\begin{aligned}
d\ln w_g =& \frac{\varepsilon_g}{\lambda} \cdot d\ln y + \frac{1}{\lambda}\Theta_g \cdot \boldsymbol{d\ln \zeta} - \frac{1}{\lambda}\Theta_g \cdot \boldsymbol{d\ln \Gamma}^{disp},\\
d\ln \zeta_g =& \sum_i s^L_{gi} \cdot \left(\frac{\partial \ln s^Y_i(p)}{\partial \ln p} \cdot \boldsymbol{d\ln p} + (\lambda - 1) \cdot d\ln p_i \right),\\
d\ln p_i =& s^L_i \cdot \sum_g s^L_{ig} \cdot \left(d\ln w_g + d\ln \Gamma^{disp}_{gi} \cdot \pi_{gi} \right),\\
d\ln tfp =& \sum_i s^Y_i(p) \cdot \sum_g s^L_{ig} \cdot d\ln \Gamma^{disp}_{gi} \cdot \pi_{gi},\\
d\ln y =& \frac{1}{1 - s^K} \cdot \left(d\ln tfp + s^K \cdot d\ln s^K \right).
\end{aligned}
$$

Key GE Forces Accounted in Counterfactual

Key GE effects explaining why reduced form $\neq$ equilibrium effect:

$$d\ln w_g = \frac{\varepsilon_g}{\lambda} \cdot \underbrace{d\ln y}_{\text{Productivity effect}} + \frac{1}{\lambda}\Theta_g \cdot \underbrace{\boldsymbol{d\ln\zeta}}_{\text{Industry composition}} + \frac{1}{\lambda}\Theta_g \cdot \underbrace{\boldsymbol{d\ln\Gamma}^{\text{disp}}}_{\text{Ripple effects}}$$

We will estimate Θ and make the following assumptions:

- $\varepsilon_g = \varepsilon \Rightarrow$common output elasticity and $\pi = 30\% \Rightarrow$ productivity effect
  (see Dvorkin–Monge-Naranjo 2019 for approach with dif ε_g)
- CES industry structure with sectoral elasticity of subs 0.2 $\Rightarrow$ industry composition
- $\lambda = 0.5$ and σ_i from Oberfield–Raval 20.

Estimating Θ: Parametrization

- $\beta_{gj} = \frac{1}{\lambda} \cdot \theta_{gj}/s_j^L$ is the per unit ripple effect from j to $g \Rightarrow \beta_{gj} = \beta_{jg}$
- Parametric assumption: $\beta_{\text{own}} = \frac{1}{\lambda}\theta_{gg} \geq 0$ and if $g \neq j$

$$\beta_{gj} = \sum_{n=1}^{N} \beta_n \cdot \exp(-d(x_g^n, x_j^n)), \text{ with } \beta_n \geq 0,$$

  where ripple effect depends on distance between group g and j along dif dimensions, x^n:
  - industry and occupational shares in 1980
  - location (state) shares in 1980
  - education and wages in 1980

- Combine labor supply shocks (demographic trends), sectoral shifts (Bartik measure), and task displacement into a single wage shock z_g for 1980–2016.
- Estimate $d\ln \boldsymbol{w} = \frac{1}{\lambda}\Theta \cdot \boldsymbol{z}$ over 1980–2016 imposing parametric restrictions on $\Theta \Rightarrow$ yields estimates for β_n and β_{own}.

Estimating Θ: Results and Parametrization

- evidence of ripple effects among:
  - groups in similar industries
  - groups in similar occupations
  - groups in similar states
  - groups of similar wages and years of education
- reported effects are for the average ripple effect due to proximity along each of these dimensions
- own effects sizable and Θ has dominant diagonal

Estimates of Θ

Effect	Estimate of $\frac{1}{\lambda}\theta$	Significant?
Own effect	0.73	[t=19.27]
Industry	0.09	[t=1.22]
Geography	0.17	[t=2.24]
Occupation	0.05	[t=2.23]
Wages and Education	0.06	[t=3.33]
Implied ε	0.55	

Quantitative Implications: Effects on Wages

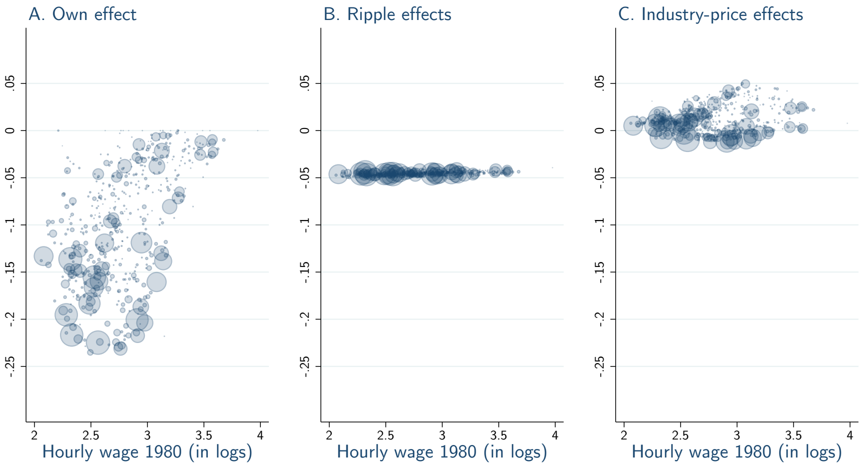

Figure: Effect on wages (not including productivity effects).

Quantitative Implications: Combined Effect on Wages

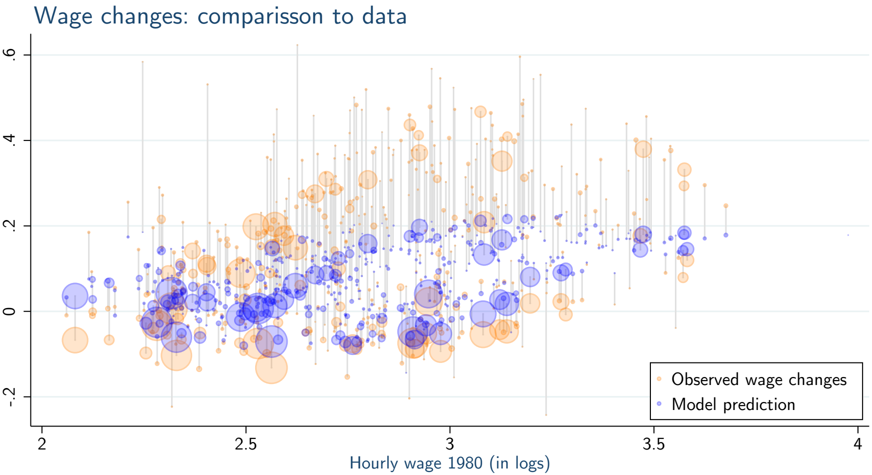

Figure: Combined effect on wages (including productivity effect).

Quantitative Implications: Summary

Implications of measured task displacement via automation and offshoring:

- Increase in GDP of 20% and average wage of 5%
- TFP increase of 3.3%
- Explains 57% of observed wage changes across groups
  (48% ignoring industry price changes)
- Explains a third of wage declines below 5% and half of wage declines below 10%
- Explains a third of the rise in college premium and half of rise in postcollege premium
- Explains 0.6 pp decline in share of manufacturing in GDP (1/10th of decline since 1987)

Concluding Remarks:

- technologies that favor displacement of labor via automation or offshoring can have large distributional consequences and bring small productivity gains
- we made this point theoretically in a task-framework, via reduced-form evidence, and through a quantitative exercise

Work to do:

1. Much more to do regarding estimation of Θ...
2. Repercussions for within-group inequality?