Task Displacement and Wage Inequality

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DC, March 5th, 2020

Rising Wage Inequality Between Groups of Society

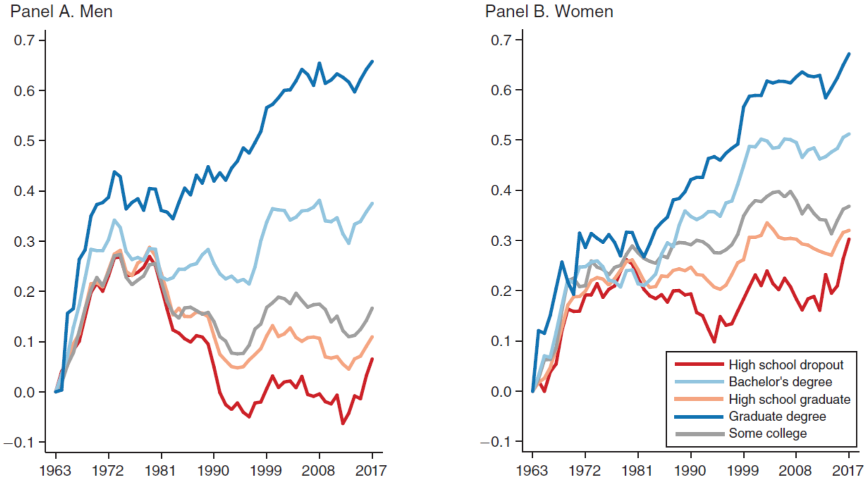

Figure: Cumulative change in real weekly wages, working-age adults (Autor, 2019)

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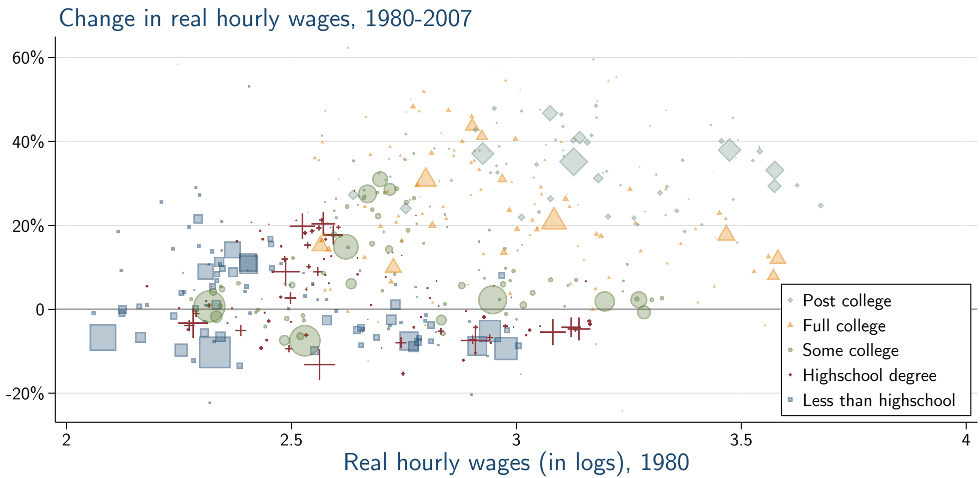

Figure: Change in real hourly wages for 500 education–experience–gender–race–nativity groups

Rising Wage Inequality Between Groups of Society

Task-displacing technologies $\Rightarrow$ wage inequality across groups?

$\Rightarrow$ stagnant or declining wages?

This paper

- Task framework: wages depend on allocation of tasks to workers
  (Grossman–Rossi-Hansberg 2008; Acemoglu–Autor 2011; Acemoglu–Restrepo 2018)
- automation and offshoring change boundaries of allocation
- quantify role of task-displacement via automation and offshoring

Existing literature

- SBTC (Katz–Murphy 92; Krusell–et.al 00; Card–Lemieux 01)
- industry shifts and demand for skills (Buera–et.al 15; Bárány–Siegel 18)
- occupational shifts (Lee–Shin 18; Jaimovich–et.al 20)

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 $\ln \text{task share}_g$ - g displaced from routine tasks in industry with falling labor share - correlates with wage changes 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 rate $r \cdot q(x)$
- labor of type g has fixed supply $\ell_g > 0$
- allocation of tasks to factors maximizes $y - r \cdot \int_{\mathcal{T}} k(x) \cdot q(x) \cdot dx$

Model: Allocation of Tasks and Task Shares

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

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

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

Definition of task share of g & task share k

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

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

Determinants of Γ_g and Γ_k

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

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

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

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

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

Model: A Wide Menu of Technologies

Conditional on w^e, two main technology classes changing Γ_g and Γ_k:

Productivity deepening

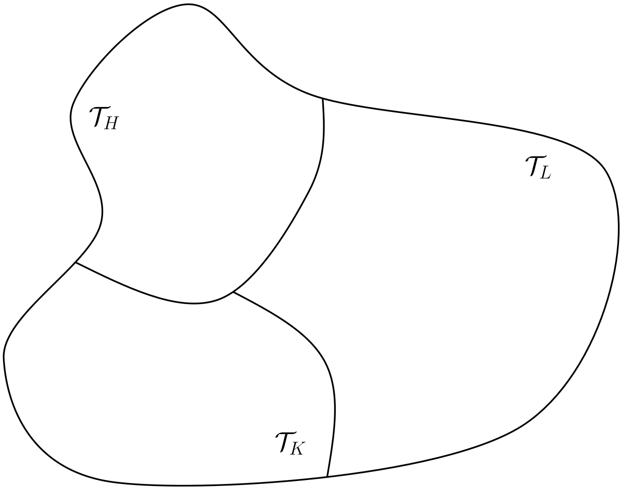
- improvements in $\psi_g(x)$ or $\psi_k(x)/q(x)$ for tasks in $\mathcal{T}_g$ or $\mathcal{T}_k$
- denote effect on $\frac{1}{1-\lambda} d\ln\Gamma_g$ by $d\ln\Gamma_g^{\text{deep}}$ or $d\ln\Gamma_k^{\text{deep}}$

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 effect on $d\ln\Gamma_g$ by $d\ln\Gamma_g^{\text{disp}}$
- $\pi_g =$avg cost reduction in such tasks $\ln w_g/\psi_g(x) - \ln\psi_k(x)/q(x)$

Besides: usual factor augmenting technologies, A_g and A_k, affect task shares through w^e.

Model: Examples of Different Technologies



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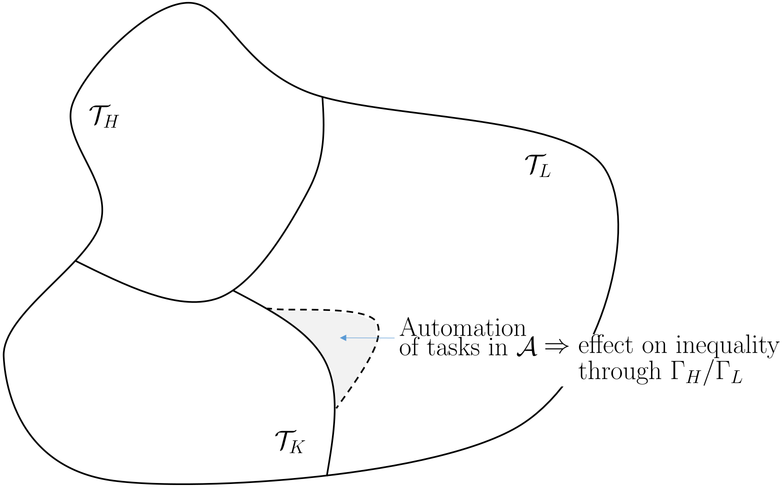

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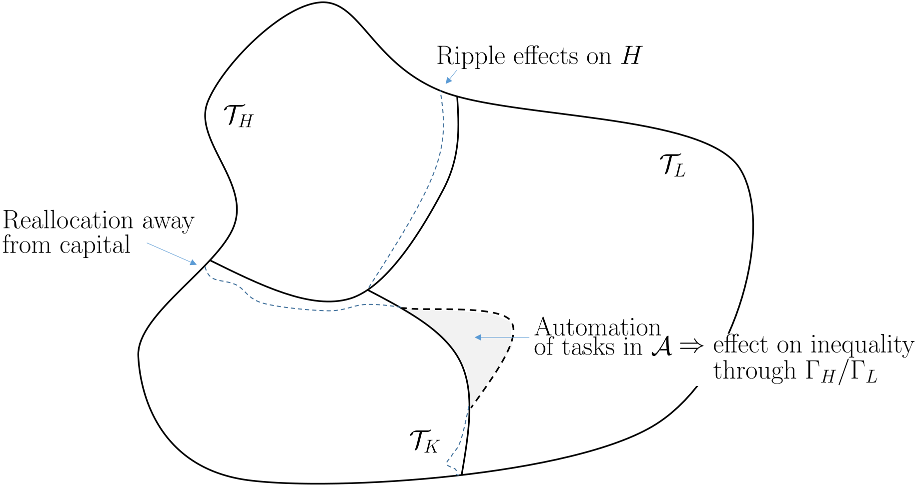

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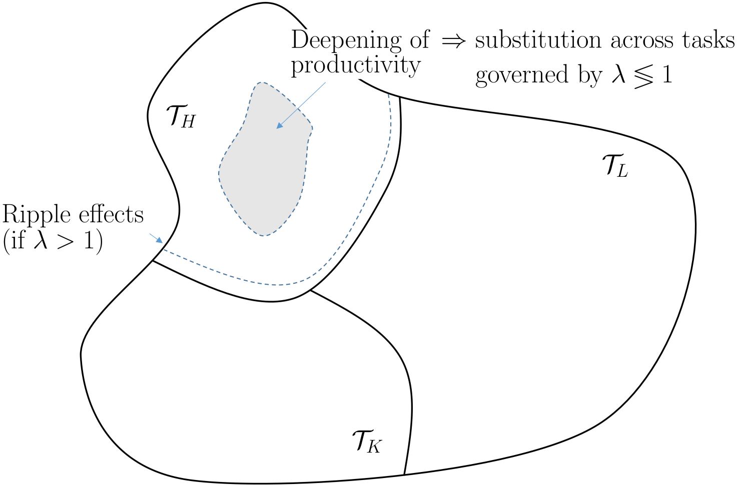

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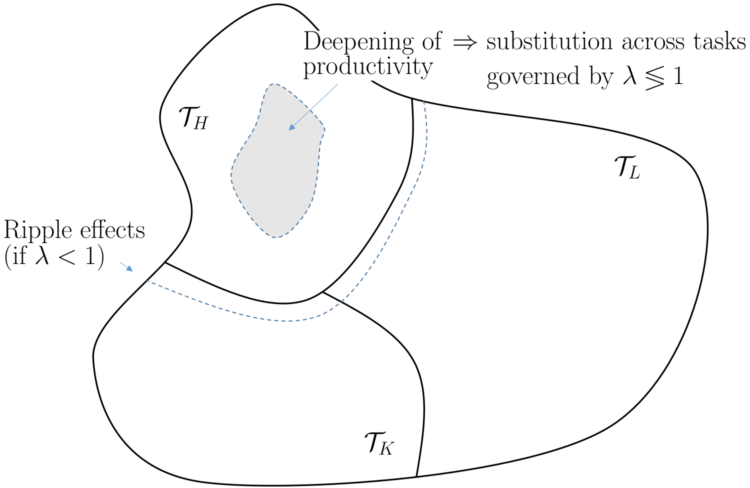

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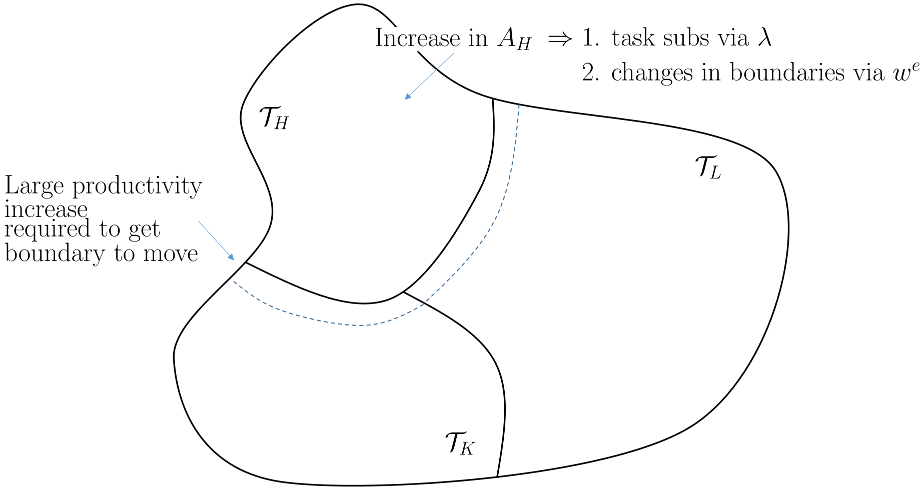

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Effects of Technology: Shock and Propagation

Propagation of a wage shock

- $d \ln w_g = a_g + \frac{1}{\lambda} \frac{\partial \ln \Gamma_g}{\partial \ln w^e} \cdot d \ln w \Rightarrow d \ln w = \Theta \cdot a_L$, where

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

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 equals $\frac{\lambda}{\lambda + \varrho_g} \Rightarrow$ elast. of subs with capital $\lambda + \varrho_g$
- if $\varrho_g = \varrho$, matrix has symmetry property $s_g^L \cdot \theta_{gj} = s_j^L \cdot \theta_{jg}$
- also, g and j are $q-$substitutes iff $\theta_{gj} > s_j^L \cdot \lambda / (\lambda + \varrho)$
- ripple effects can dampen or augment inequality

Proposition (Effect of technology on wages and TFP)

The change in wages is given by

$$d\ln w_g = \frac{1}{\lambda + \varrho_g} d\ln y + d\ln A_g - \frac{1}{\lambda}\Theta_g \cdot d\ln A_L + \frac{\lambda - 1}{\lambda}\Theta_g \cdot d\ln \Gamma_L^{deep} + \frac{1}{\lambda}\Theta_g \cdot d\ln \Gamma_L^{disp},$$

and the change in aggregate TFP and output is given by

$$d\ln tfp = \sum_g s_g^L \cdot d\ln A_g + s^K \cdot d\ln \Gamma_k^{deep} + \sum_g s_g^L \cdot d\ln \Gamma_g^{deep} - \sum_g s_g^L \cdot d\ln \Gamma_g^{disp} \cdot \pi_g$$

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

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Model: Multiple Industries

Industry structure

- y =GDP and p =vector of industry prices
- $s_i^Y(p,y)$:=share industry i in value added $\Rightarrow$ CES $s_i^Y(p,y) = \alpha_i \cdot p_i^{1-\eta}$

Industry i combines M_i tasks in $\mathcal{T}_i$

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

Task shares now given by

$$\Gamma_g(\zeta, w^e, \Psi) := \sum_i \underbrace{s_i^Y(p,y) \cdot (A_i \cdot p_i)^{\lambda-1}}_{:=\zeta_i} \cdot \underbrace{\frac{1}{M_i} \int_{\mathcal{T}_{gi}} \psi_g(x)^{\lambda-1} dx}_{:=\Gamma_{gi}}$$

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

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

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

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

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Measuring Task Displacement: Cobb-Douglas case $\lambda = 1$ and $\varrho_i = 0$

A1. Technology and markups

- changes in $\psi_k(x)/q(x)$ leading to task displacement, $d\ln\Gamma_L^{\text{disp}}$
- no change in markups

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, s_i^L

$$d\ln\Gamma_i^{R,\text{disp}} = \frac{1}{s_i^R}\cdot d\ln s_i^L \qquad d\ln\Gamma_g^{\text{disp}} = \sum_i \frac{s_{gi}^R}{s_i^R}\cdot d\ln s_i^L$$

Measuring Task Displacement: CES case

A1. Set of technologies is restricted

- sectoral productivity shocks: A_i
- capital deepening: uniform decline in $q(x)$ of $d\ln q_i$
- changes in $\psi_k(x)/q(x)$ leading to task displacement, $d\ln\Gamma_L^{\mathrm{disp}}$
- no change in markups

A2. Routine tasks in industry i automated at common rate

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

A1+A2: recover task displacement from industry data on labor shares, s_i^L

$$d\ln\Gamma_i^{R,\mathrm{disp}} = \frac{1}{s_i^R}\,\frac{d\ln s_i^L + (1-\sigma_i)\cdot s_i^K\cdot(d\ln q_i - d\ln w_i)}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}$$

$$d\ln\Gamma_g^{\mathrm{disp}} = \sum_i \frac{s_{gi}^R}{s_i^R}\cdot\frac{d\ln s_i^L + (1-\sigma_i)\cdot s_i^K\cdot(d\ln q_i - d\ln w_i)}{1+(\lambda-1)\cdot s_i^L\cdot\pi_i}$$

Data and Measurement

Data for 49 industries from BEA, BLS, and KLEMS

- for reduced form: $\sigma_i = \sigma \in (0.5, 1.2)$, $\lambda = 0.5$, $\pi_i = 30\%$
- measure task displacement from 1987-2016
- across industries, $d \ln \Gamma_i^{\mathrm{disp}}$ correlates with:
  - ✓ rising tfp and quantities; falling prices
  - ✓ higher demand for skilled workers
  - ✓ proxies of automation and offshoring

Construct measure of task displacement for 500 skill groups

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

Data and Measurement

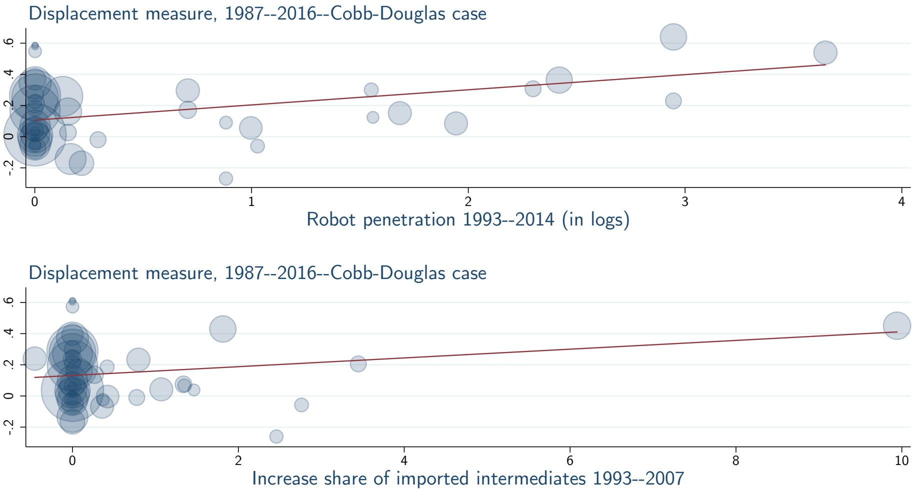

Figure: Industry correlations between proxies of automation and offshoring and task displacement

Data and Measurement

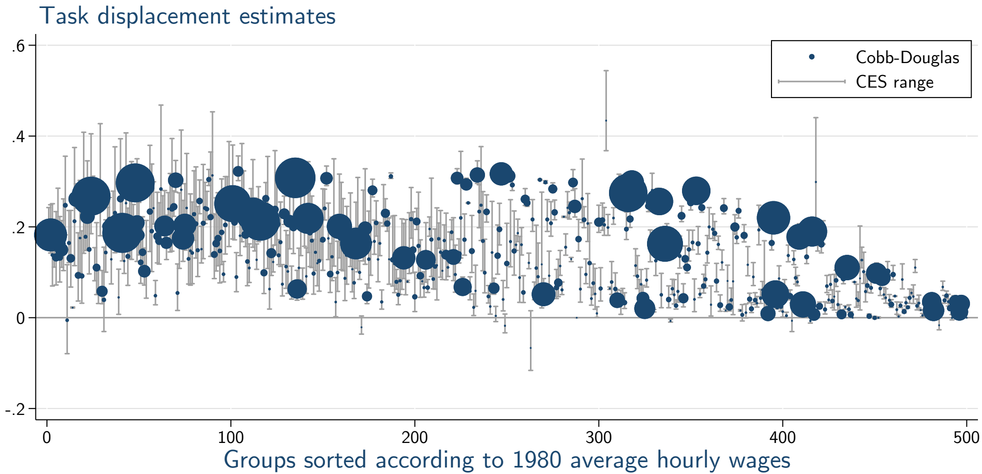

Figure: Estimated task displacement for 500 education–experience–gender–race–nativity groups

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Reduced-form evidence: Cobb-Douglas

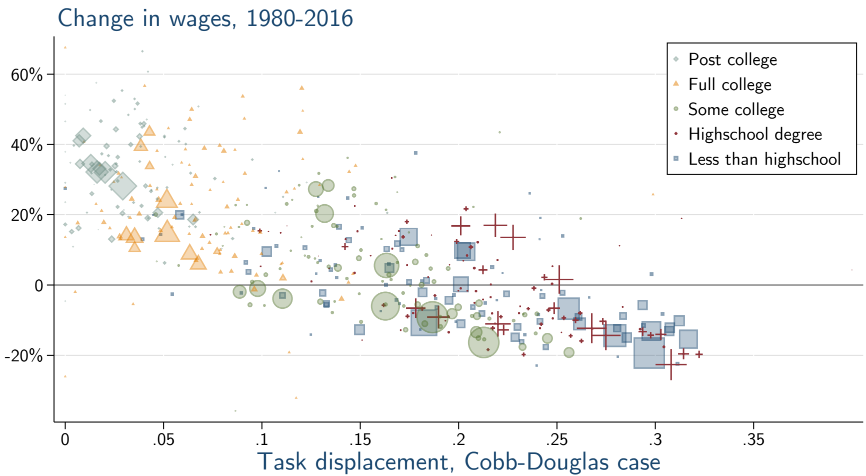
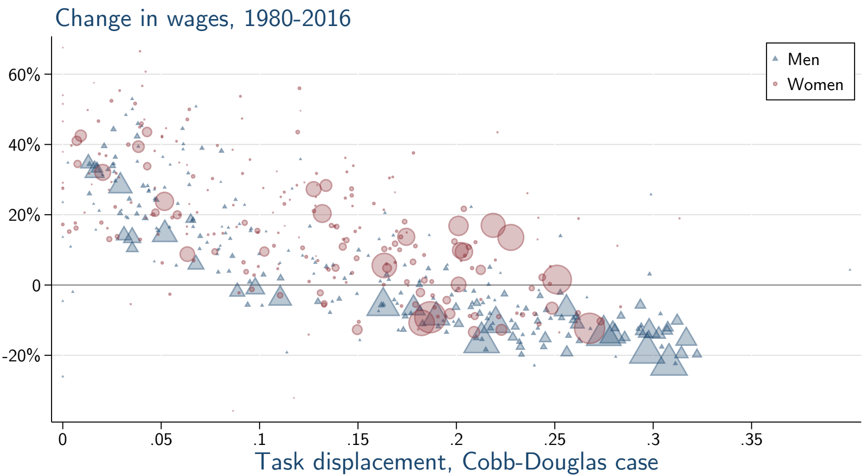


Figure: Reduced-form relation between task displacement and change in wages, 1980–2016.

Reduced-form evidence: Cobb-Douglas



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Reduced-form evidence: CES

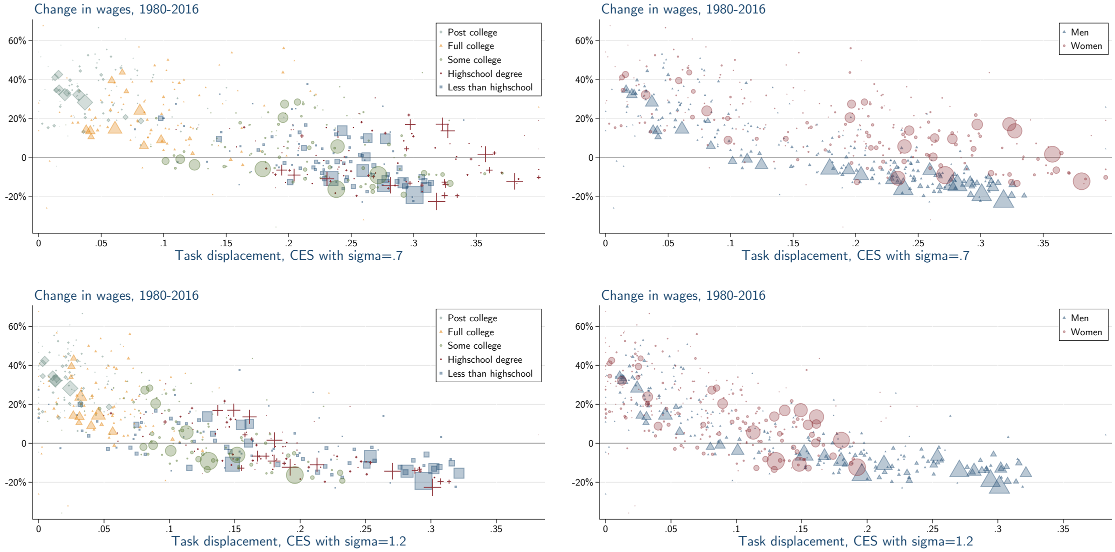

Figure: Reduced-form relation between task displacement and change in wages, 1980–2016.

Reduced-form evidence: Cobb-Douglas

	Dependent variable: change log hourly wages 1980-2016					
	(1)	(2)	(3)	(4)	(5)	(6)
Task displacement	-1.482	-1.132	-1.429	-1.243	-1.172	-1.032
	(0.096)	(0.162)	(0.302)	(0.219)	(0.218)	(0.205)
Sectoral expansion		0.214	0.099	0.111	0.117	0.652
		(0.076)	(0.084)	(0.079)	(0.075)	(0.155)
Industries with declining labor share			-0.416			
			(0.404)			
Relative specialization in routine jobs			0.060			
			(0.059)			
R-squared	0.62	0.66	0.70	0.77	0.79	0.81
Observations	500	500	500	500	500	500
Additional covariates:						
Broad group dummies				✓	✓	✓
Regional shares					✓	✓
Broad sectoral shares						✓

Technology or Rising Markups?

Industry correlates suggest technology important

- task displacement correlates with rising tfp and quantities, lower prices
- within manufacturing, task displacement correlates with automation and offshoring
- labor share declines mostly in manufacturing and industry

Reduced-form evidence

- as labor share declines, labor demand falling for routine workers but not for others

Takeaway

- markups might be important, but one needs a richer theory of their relationship to tfp, technology and demand for skills

Reduced-form evidence: Task displacement vs SBTC

	Dependent variable: change log hourly wages 1980-2016		
	(1)	(2)	(3)
Education: highschool	0.005	0.017	0.027
	(0.032)	(0.028)	(0.028)
Education: some college	0.032	-0.047	-0.054
	(0.035)	(0.037)	(0.039)
Education: full college	0.247	0.030	-0.045
	(0.029)	(0.053)	(0.060)
Education: more than college	0.395	0.142	0.016
	(0.027)	(0.056)	(0.074)
Gender: women	0.144	0.104	0.070
	(0.026)	(0.022)	(0.023)
Task displacement		-1.174	-1.032
		(0.195)	(0.205)
Sectoral expansion			0.652
			(0.155)
R-squared	0.68	0.76	0.81
Observations	500	500	500
Additional covariates:			
Regional and broad sectoral shares			✓

Reduced-form evidence: Robustness—CES case

	Dependent variable: change log hourly wages 1980-2016					
	$\sigma = 0.7$	$\sigma = 0.8$	$\sigma = 0.9$	$\sigma = 1$	$\sigma = 1.1$	$\sigma = 1.2$
	(1)	(2)	(3)	(4)		
Education: highschool	0.045	0.041	0.035	0.027	0.016	0.004
	(0.028)	(0.029)	(0.029)	(0.028)	(0.028)	(0.027)
Education: some college	-0.004	-0.019	-0.036	-0.054	-0.072	-0.088
	(0.033)	(0.035)	(0.037)	(0.039)	(0.040)	(0.040)
Education: full college	0.033	0.008	-0.019	-0.045	-0.067	-0.082
	(0.054)	(0.056)	(0.058)	(0.060)	(0.060)	(0.059)
Education: more than college	0.113	0.082	0.049	0.016	-0.013	-0.033
	(0.068)	(0.070)	(0.072)	(0.074)	(0.074)	(0.073)
Gender: women	0.144	0.124	0.099	0.070	0.038	0.007
	(0.020)	(0.020)	(0.021)	(0.023)	(0.027)	(0.030)
Task displacement	-0.736	-0.841	-0.943	-1.032	-1.095	-1.120
	(0.181)	(0.192)	(0.201)	(0.205)	(0.203)	(0.194)
Sectoral expansion	0.542	0.566	0.603	0.652	0.711	0.775
	(0.164)	(0.161)	(0.158)	(0.155)	(0.153)	(0.153)
R-squared	0.79	0.80	0.81	0.81	0.81	0.82
Observations	500	500	500	500	500	500
Additional covariates:						
Region and broad sector shares	✓	✓	✓	✓	✓	✓

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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:

$$d\ln w_g = \frac{1}{\lambda + \varrho_g} \cdot d\ln y + \frac{1}{\lambda}\Theta_g \cdot d\ln \zeta + \frac{1}{\lambda}\Theta_g \cdot d\ln \Gamma_L^{disp},$$

$$d\ln \zeta_g = \sum_i s_{gi}^L \cdot \left(d\ln s_i^Y(p, y) + (\lambda - 1) \cdot d\ln p_i\right),$$

$$d\ln p_i = s_i^L \cdot \sum_g s_{ig}^L \cdot \left(d\ln w_g + d\ln \Gamma_{gi}^{disp} \cdot \pi_{gi}\right)$$

$$d\ln tfp = -\sum_g s_g^L \sum_i s_{gi}^L \cdot d\ln \Gamma_{gi}^{disp} \cdot \pi_{gi}$$

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

Estimating Θ and ϱ: Approach

- Assume $\varrho_g = \varrho \Rightarrow$common elast of subs between capital and labor
  (see Dvorkin–Monge-Naranjo 2019 for approach with dif ϱ_g)
- $\beta_{gj} = \frac{1}{\lambda} \cdot \theta_{gj}/s_j^L$ is the per unit ripple effect from j to $g \Rightarrow \beta_{gj} = \beta_{jg}$
- Parametric assumption: $\theta_{gg} = \beta_{\text{own}} \geq 0$ 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 x_g^n are vectors of industry shares in 1980, occupational shares in 1980, state shares in 1980 and skill level
- Combine labor supply shocks (demographic trends), sectoral shifts (Bartik measure), and task displacement into a single shock to estimate β_{own} and $\beta_n \Rightarrow \widehat{\Theta}$

Estimating Θ and ϱ : 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
- own effects sizable and Θ has dominant diagonal
- estimate for $\lambda + \varrho = 0.9$ close to 1
- Next: CES industry structure with $\eta = 0.2$; $\lambda = 0.5$; $\pi = 30\%$

Estimates of Θ and ϱ

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]
$\lambda + \varrho$ (or σ)	0.91	

Quantitative Implications: Effects on Wages

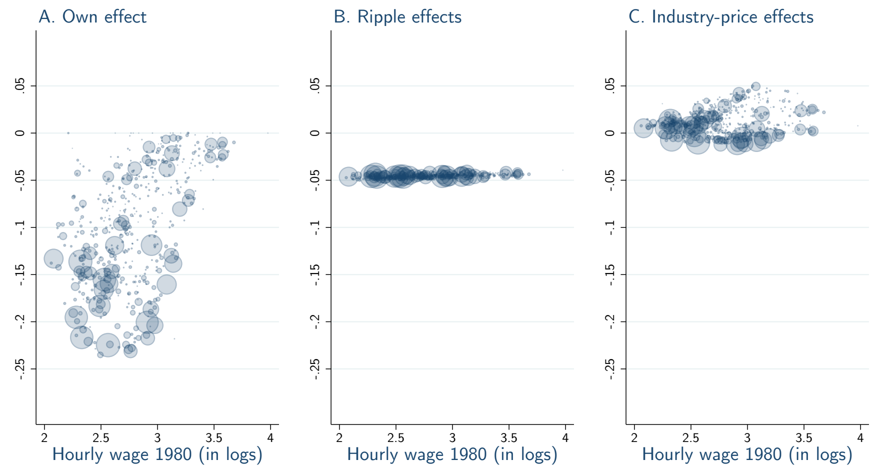

Figure: Effect on wages (not including rise in GDP).

Quantitative Implications: Combined Effect on Wages

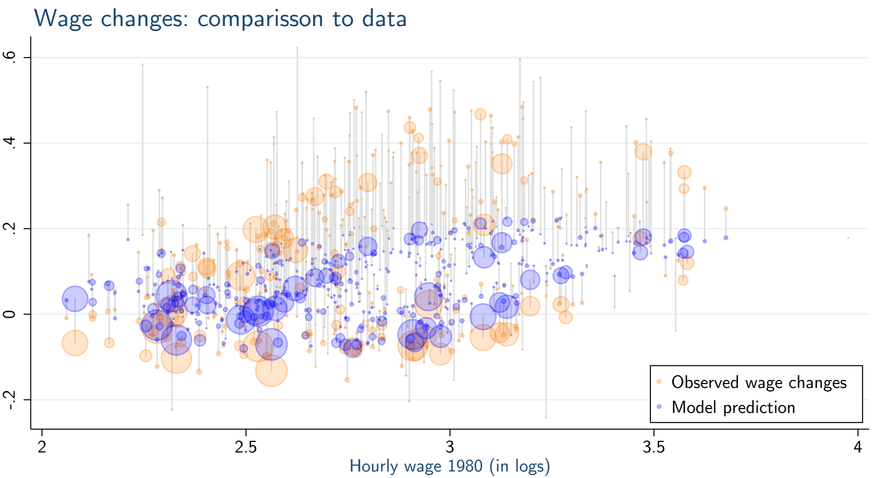

Figure: Combined effect on wages (including rise in GDP).

Quantitative Implications: Groups with Declining Wages

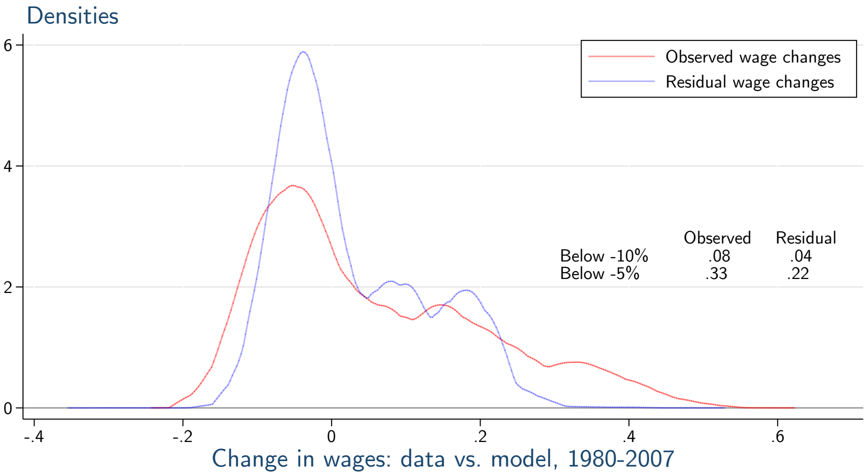

Figure: Observed wage changes and unexplained change in wages.

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 preliminary quantitative exercise

Work to do:

1. Much more to do regarding estimation of Θ...
2. Markups? direct measures of technology and estimation
3. Factor-augmenting technologies: bound effect on labor share
4. Repercussions for within-group inequality?

Appendix Model: Formal Definition of Equilibrium

back to model

Let $\mathcal{T}_g$ denote the set of tasks allocated to labor of type g and $\mathcal{T}_k$ the set of tasks allocated to capital.

Definition (Market equilibrium)

Given a supply of labor $\ell = (\ell_1, \ell_2, \ldots, \ell_G)$, a market equilibrium is given by wages $w = (w_1, w_2, \ldots, w_G)$, capital production decisions $\{k(x)\}$, and an allocation of tasks to factors $\{\mathcal{T}_k, \mathcal{T}_1, \ldots, \mathcal{T}_G\}$, such that:

- the allocation of tasks to factors minimizes the total cost of producing each task;
- the choice of capital maximizes net output;
- the market for capital and labor clears.

Why Focus on Task-Displacing Technologies?

1. **Rhetorical** point
   - compelling way of thinking about automation and offshoring
   - some tasks can now be automated or offshored; others not

2. **Mechanism** affecting wages
   - task-displacing techs directly change task-share boundaries
   - large distributional impact that is independent of elast. of subs.
   - effect of other techs mediated by $\lambda, \lambda + \varrho_g \lesseqgtr 1$

3. **Productivity** implications
   - task-displacing techs can have small effects on tfp if $\pi_g \approx 0$
   - other techs: prod gains and distributional effects coupled
     ▸ example: bounds on productivity ▸ example: SBTC

4. **Factor shares** implications
   - direct and intuitive effect on labor share that is independent of the elasticities of substitution $\lambda + \varrho_g$

Example I: Bounding Effects on Wage Inequality

back to main

Large G and uniform rise in inequality

- observed inequality $d\ln w_g = m_0 + \frac{1}{\lambda}\Theta_g \cdot m_g$, where $m_g \sim U[0, 2\delta]$
- how big is tech change required to explain this rise in inequality? (assuming no technological regress)

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▸ back to main

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Via task deepening

- $d \ln \mathrm{tfp} \geq \delta \cdot s^L / |1 - \lambda|$
- effects through $\lambda \in (0.5, 1) \Rightarrow$ subs across tasks

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Via labor-augmenting technologies

- $d \ln \mathrm{tfp} \geq \delta \cdot \sum_g s_g^L / |\sigma_g - 1|$, where $\sigma_g \geq \lambda$
- effects through $\sigma_g \in (1, 2) \Rightarrow$ subs across tasks and within marginal task

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- effects through $\sigma_g \in (1, 2) \Rightarrow$ subs across tasks and within marginal task

Via task displacement

- $d \ln \text{tfp} \geq \delta \cdot \sum_g s_g^L \cdot \pi_g$, where $\pi_g \geq 0$
- effects through changes in productivity at marginal tasks, π_g

Example II: Unpacking SBTC ▸ back to main

Canonical model

$$d\ln\frac{w_H}{w_L} = -\frac{1}{\sigma_L}\cdot d\ln\frac{H}{L} + \frac{\sigma_L - 1}{\sigma_L}\cdot d\ln\frac{A_H}{A_L}$$

Effects on TFP

$$d\ln \mathrm{tfp} = s^H \cdot d\ln A_H + s^L \cdot d\ln A_L$$

Tight link btn inequality, productivity, and real wages

- estimate of $\sigma_L = 1.5$
- explains skill premium with $d\ln A_H \geq d\ln A_H/A_L = 10\%$ p.a.
- but this implies $d\ln tfp \geq$2–3% p.a (vs 1–1.2% in data)
- and $d\ln w_L \geq$1.3–2% p.a (vs -0.2–0.2% in data)

Example II: Unpacking SBTC

back to main

Task model

$$d\ln\frac{w_H}{w_L} = -\frac{1}{\sigma_L}\cdot d\ln\frac{H}{L} + \frac{\sigma_L - 1}{\sigma_L}\cdot d\ln\frac{A_H}{A_L} - \frac{1}{\sigma}\cdot d\ln\Gamma_L^{\text{disp}},$$

$$\sigma_L := (\theta_{HH} - \theta_{LH})^{-1} = (\theta_{LL} - \theta_{HL})^{-1} > \lambda$$

Effects on TFP

$$d\ln \text{tfp} = s^H \cdot d\ln A_H + s^L \cdot d\ln A_L - s^L d\ln\Gamma_L^{\text{disp}} \cdot \pi_L$$

Decoupling of inequality, productivity, and real wages

- suppose $\sigma_L = 1.5$ and $\pi_L = 30\%$
- one can explain skill premium with $d\ln\Gamma_L^{\text{disp}} = -4.5\%$ p.a.
- this implies $d\ln tfp =$0.45% p.a (vs 1–1.2% in data)
- and $d\ln w_L =$-0.55% p.a (vs -0.2–0.2% in data)