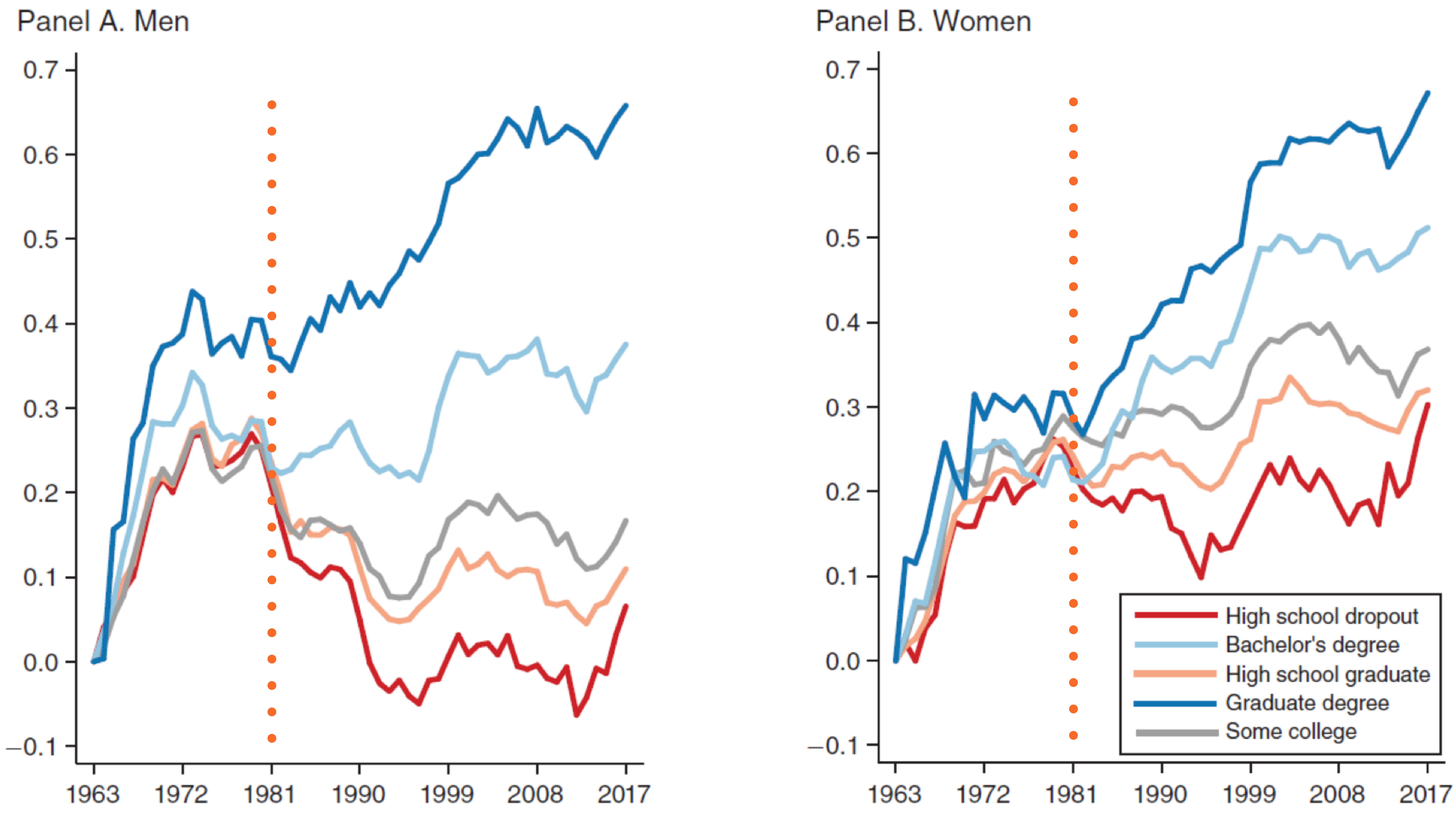
ACEMOGLU (MIT) & RESTREPO (BU)

TASKS, AUTOMATION, AND THE RISE IN US WAGE INEQUALITY

THE RISE IN US WAGE INEQUALITY



CUMULATIVE CHANGE IN THE LOG OF REAL WEEKLY WAGES (FROM AUTOR, 2020)

THIS PAPER

- Much of rise in US wage inequality due to uneven effects of **automation technologies** across groups of society
- Different from canonical skill-biased technical change (SBTC) theories, based on $Y = F(A_H \cdot H, A_L \cdot L)$ and A_H increasing.
- **This paper:** task framework to study effects of automation

1. real wage changes linked to task displacement
2. method to measure task displacement across groups
3. reduced-form and quantitative exercise: task displacement due to automation accounts for 50-70% of changes in US wage structure

A MODEL OF TASKS AND WAGE DETERMINATION

Output

$$y = \left(\frac{1}{M} \int_{\mathcal{T}} (M \cdot y(x))^{\frac{\lambda - 1}{\lambda}} \cdot dx \right)^{\frac{\lambda}{\lambda - 1}}$$

Factor-augmenting technologies

Tasks

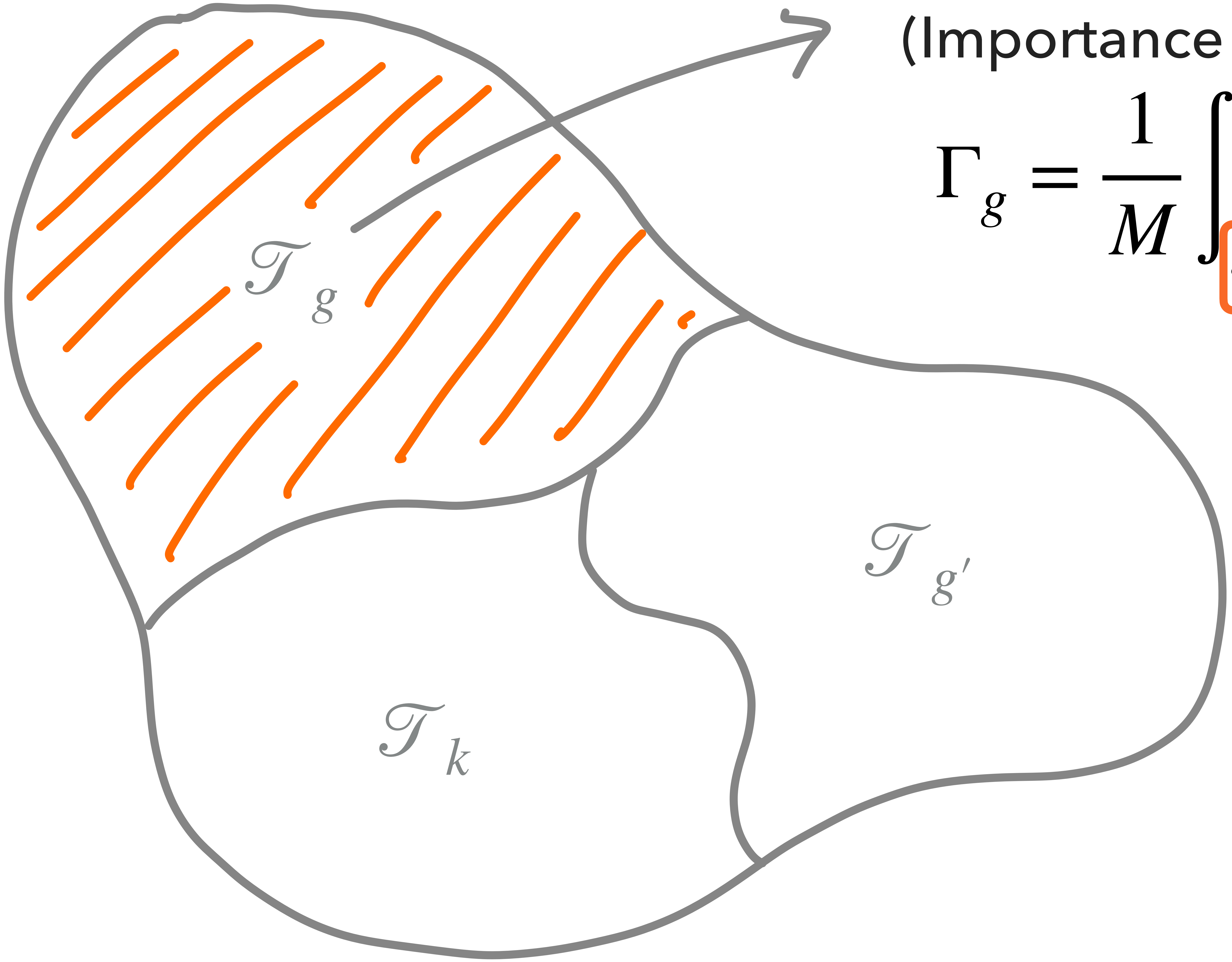
$$y(x) = \boxed{A_k} \cdot \boxed{\psi_k(x)} \cdot k(x) + \sum_g \boxed{A_g} \cdot \boxed{\psi_g(x)} \cdot \ell_g(x)$$

Task-specific technologies

Factors' supply & Equilibrium

- capital produced at rate $q(x)$ from the final good
- supply of labor fixed at ℓ_g
- Equilibrium given by allocation that maximizes net output

THE ALLOCATION OF TASKS AND TASK SHARES



Task shares

(Importance of tasks allocated to g)

$$\Gamma_g = \frac{1}{M} \int_{\boxed{\mathcal{T}_g}} \psi_g(x)^{\lambda-1} \cdot dx$$

Set of tasks allocated to g

EQUILIBRIUM AND TASK SHARES

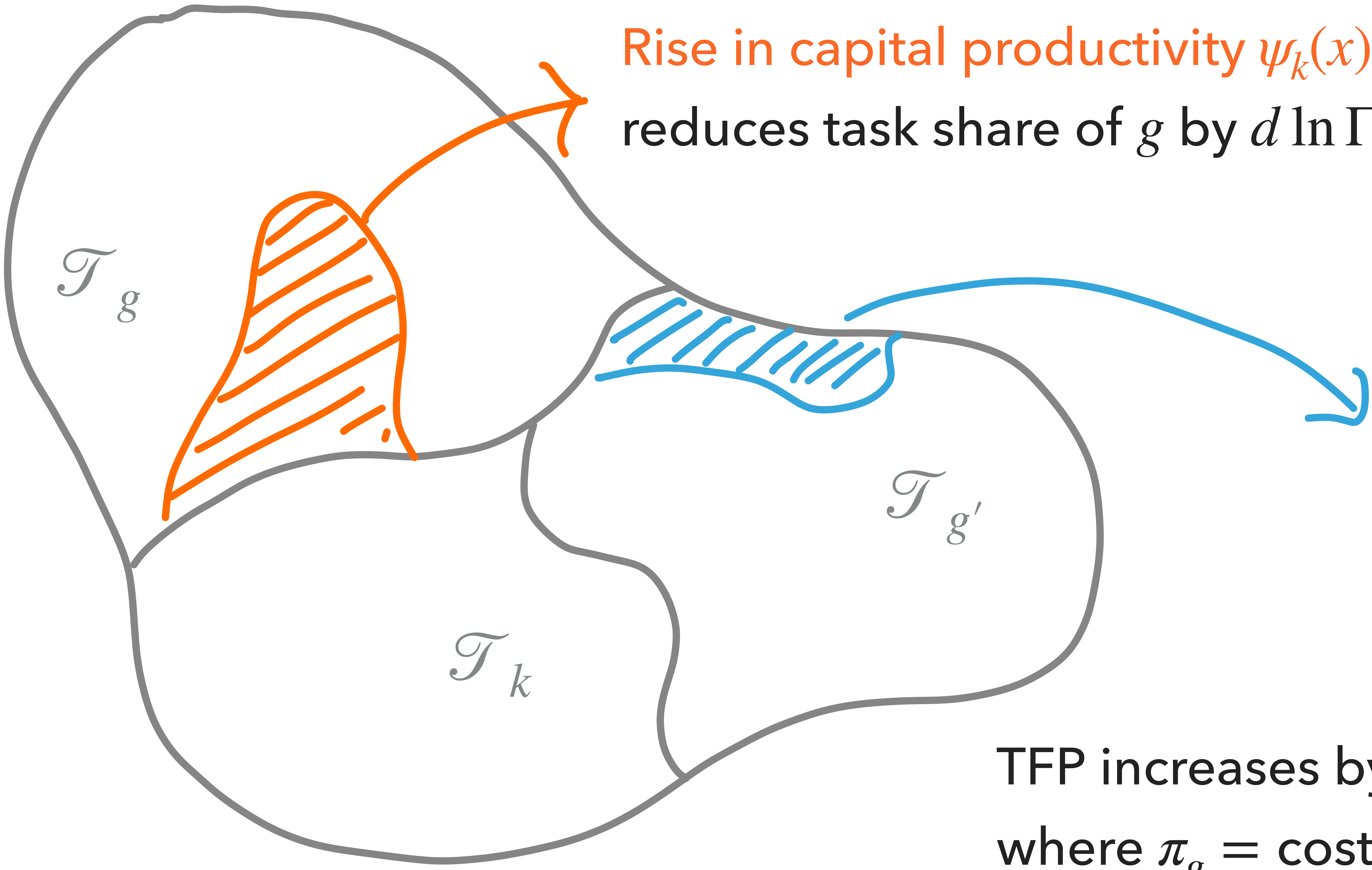
Output $$y = \left(1 - A_k^{\lambda-1} \cdot \Gamma_k\right)^{\frac{\lambda}{\lambda-1}} \cdot \left(\sum_g \boxed{\Gamma_g^{\frac{1}{\lambda}}} \cdot (A_g \cdot \ell_g)^{\frac{\lambda-1}{\lambda}}\right)^{\frac{\lambda}{\lambda-1}}$$

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

Labor share $$s_L = 1 - A_k^{\lambda-1} \cdot \boxed{\Gamma_k}$$

1. Task shares determine CES shares and wages
2. Elasticity of substitution between ℓ_g and other workers is $\sigma_g \geq \lambda$

EFFECTS OF AUTOMATION



Rise in capital productivity $\psi_k(x)$ at tasks in $\mathscr{T}_g$:
reduces task share of g by $d \ln \Gamma_g^d$ –task displacement

Ripple effects on g'

TFP increases by $s_g^L \cdot d \ln \Gamma_g^d \cdot \pi_g$
where π_g = cost-saving gains

EFFECTS OF TECHNOLOGY ON WAGES

- Change in wages due to automation and factor-augmenting technologies:

Direct effect from task displacement

$$d\ln w_g = \frac{1}{\lambda}\cdot d\ln y + \frac{\sigma_g - 1}{\sigma_g}\cdot d\ln A_g - \frac{1}{\lambda}\cdot \boxed{d\ln \Gamma_g^d} + \text{ripple effects}_g$$

$$d\ln \text{tfp} = \sum_g s_g^L \cdot \left(d\ln A_g + d\ln \Gamma_g^d \cdot \boxed{\pi_g}\right)$$

Productivity effects

- **Factor-augmenting:** small distributional effects and large productivity gains
- **Automation:** large direct displacement effects and small productivity gains

EFFECTS OF TECHNOLOGY IN MULTI-SECTOR ECONOMY

- Previous formula can be extended to a multi-sector economy.
- For now, we ignore ripple effects and return to them for quantification
- Key equation for our reduced-form analysis:

$$d\ln w_g = \frac{1}{\lambda}\cdot d\ln y + \underbrace{\boxed{\frac{\sigma_g - 1}{\sigma_g}\cdot d\ln A_g}}_{\text{Factor-augmenting technologies}} + \frac{1}{\lambda}\underbrace{\boxed{\sum_i \omega_{gi}\cdot \zeta_i}}_{\text{Industry shifters}} - \frac{1}{\lambda}\underbrace{\boxed{\sum_i \omega_{gi}\cdot d\ln \Gamma^d_{gi}}}_{\text{direct task displacement across industries}} + v_g$$

Factor-augmenting technologies

Proxied by group education dummies

Industry shifters

$\zeta_i \approx$ Increase in industry i value added share

direct task displacement across industries

MEASURING TASK DISPLACEMENT

- **Assumption:** only routine tasks automated and all workers displaced from routine tasks in an industry at the same rate.

$$\text{task displacement}_g^d = \sum_i \omega_{gi} \cdot \boxed{\frac{\omega_{gi}^R}{\omega_i^R}} \cdot \boxed{\text{automation-driven declines in } d\ln s_i^L}$$

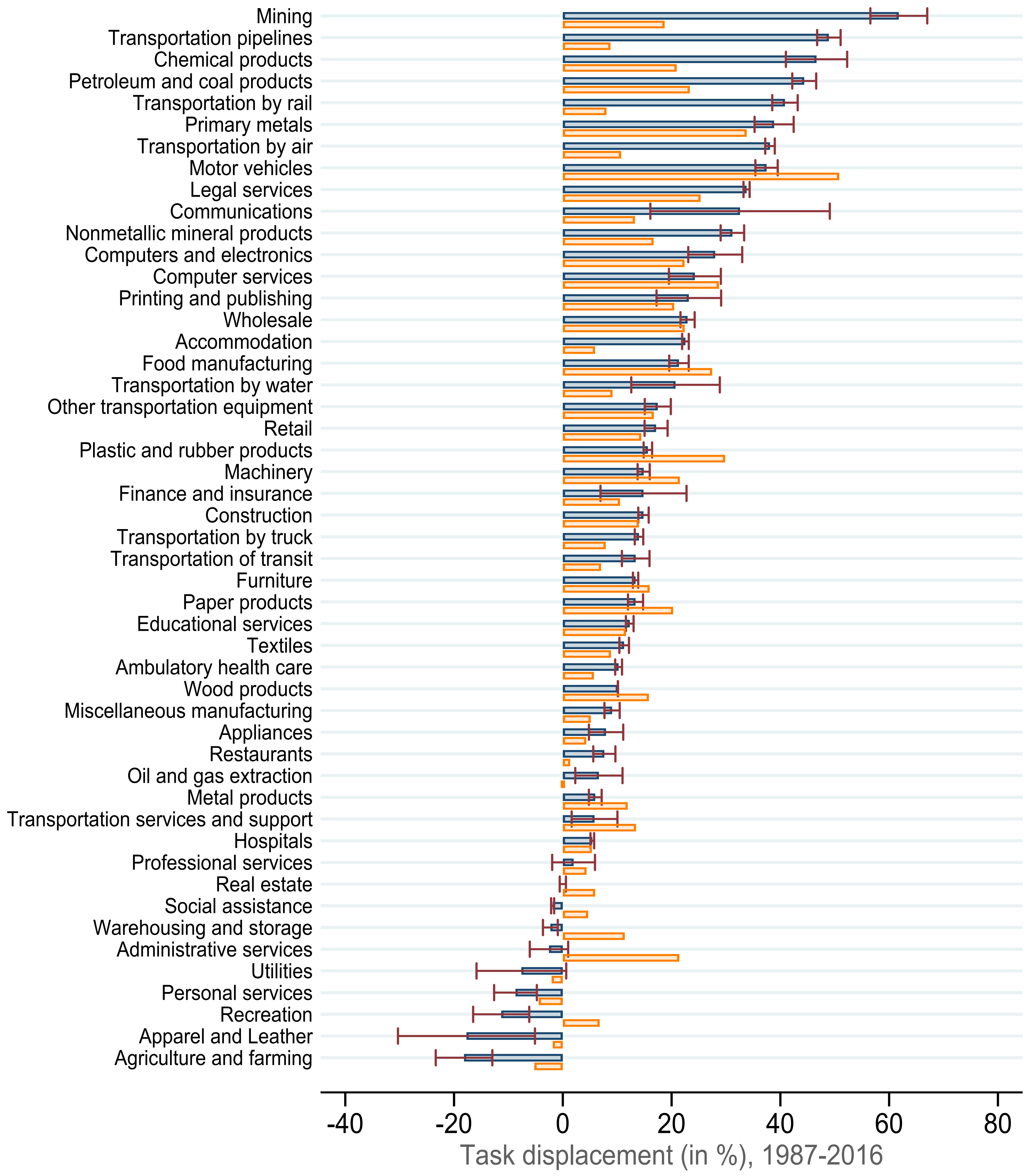
revealed comparative advantage in routine jobs in industry

measures total task displacement in industry i

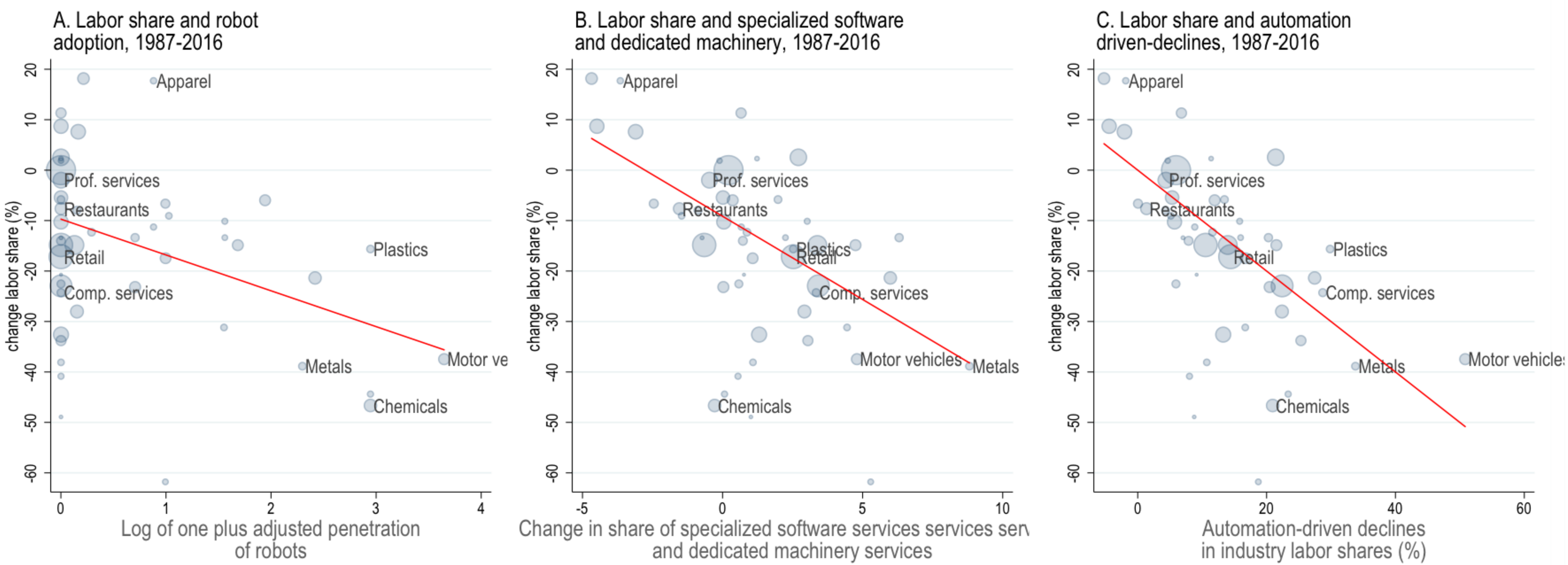
1. Use observed $-d\ln s_i^L$ (no markups/monopsony and CD; extensions in paper)
2. Use industry-level measures of automation (adoption of robots, specialized software and machinery) to estimate automation-driven declines $-d\ln s_i^{L,d}$

DATA

- Data on labor shares for 49 industries from the BEA for 1987–2016
- In blue, labor share decline
- In orange, part **due to specialized software and equipment, and robotics**
- These techs explain 50% of variation in labor share decline across industries



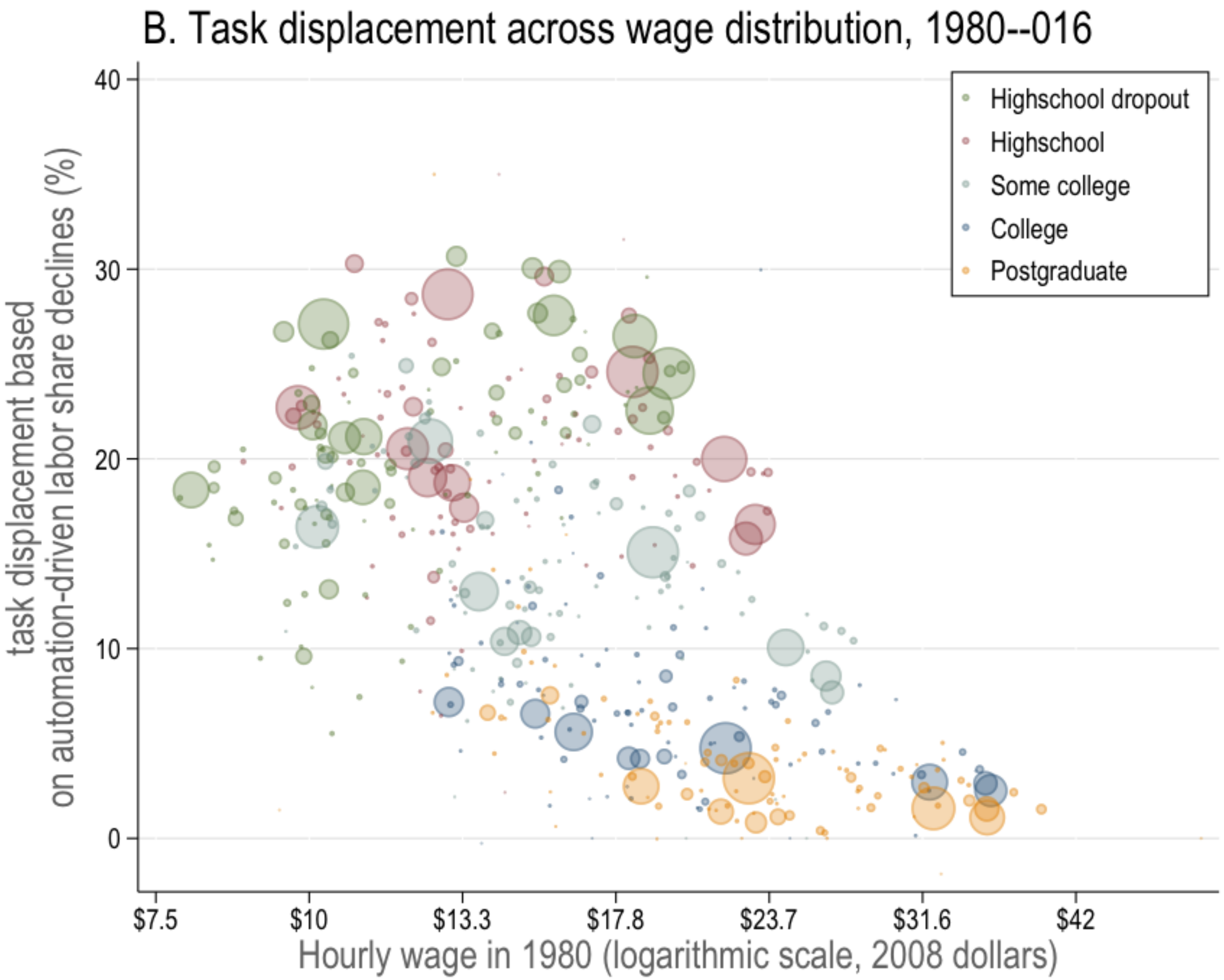
LABOR SHARE CHANGES AND AUTOMATION



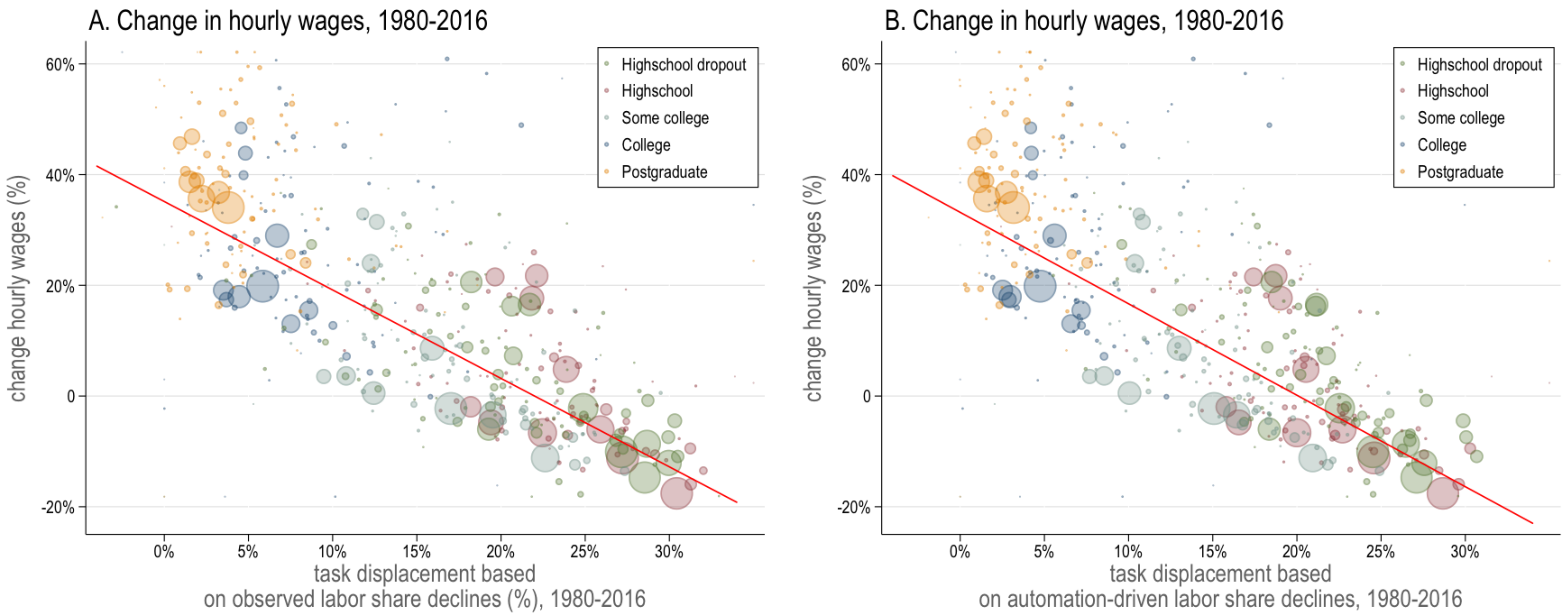
CROSS-INDUSTRY RELATIONSHIP BETWEEN LABOR SHARE CHANGES AND MEASURES OF AUTOMATION

GROUP MEASURE OF TASK DISPLACEMENT

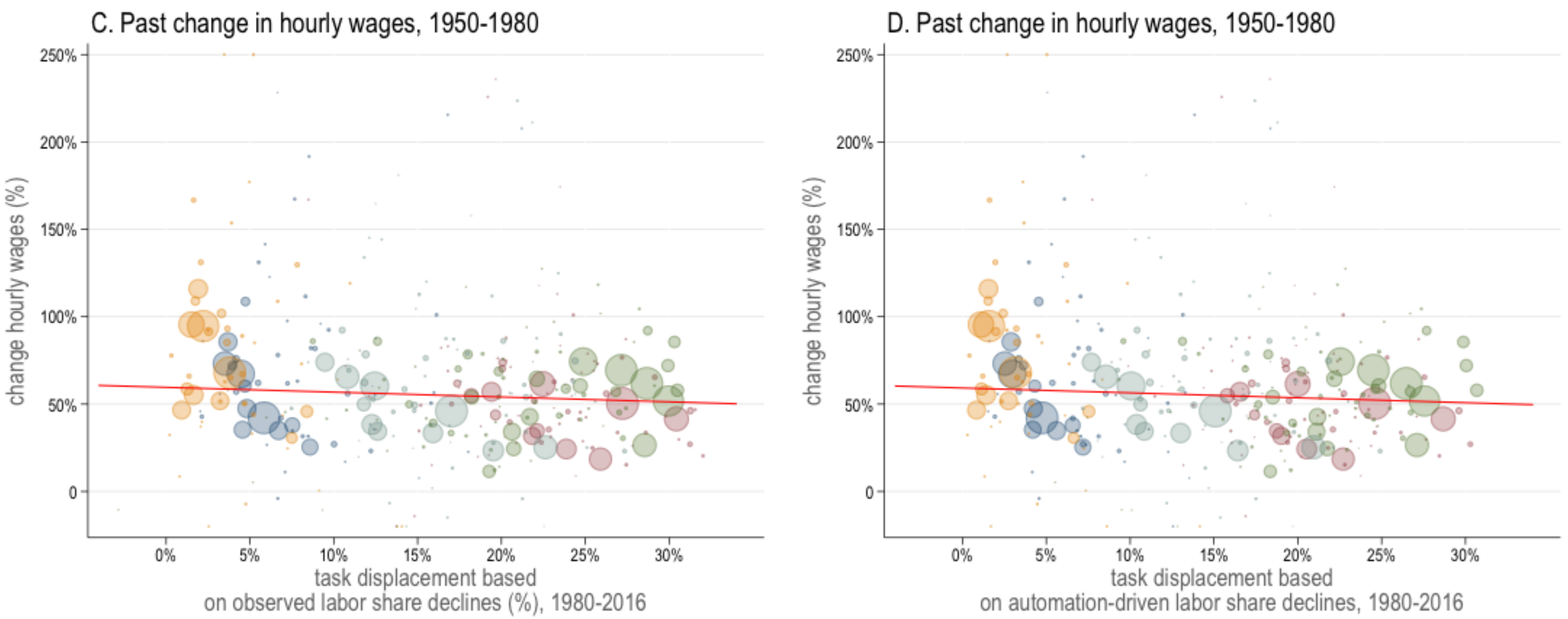
- Projected to 500 groups (education, gender, experience, race, place of birth) using wage shares from 1980 US Census
- Wages from Census–ACS
- Routine jobs defined using ONET as in Acemoglu and Autor (2011)– other measures in paper



DIRECT EFFECTS OF TASK DISPLACEMENT



DIRECT TASK DISPLACEMENT AND WAGES: 1950—1980



- No relationship between post-1980 task displacement and pre-1980 wage changes.

TASK DISPLACEMENT AND CHANGES IN HOURLY WAGES, 1980–2016

Table 1: Task displacement and changes in real hourly wages, 1980-2016.

	Dependent variable: change in hourly wages, 1980–2016					
	Task displacement based on labor share declines			Task displacement based on automaton-driven labor share declines		
	(1)	(2)	(3)	(4)	(5)	(6)
Task displacement	-1.60	-1.32	-1.66	-1.65	-1.33	-1.75
	(0.09)	(0.19)	(0.44)	(0.10)	(0.21)	(0.49)
Industry shifters		0.31	0.35		0.16	0.24
		(0.12)	(0.16)		(0.13)	(0.15)
College premium		-0.02	-0.01		-0.01	-0.01
		(0.05)	(0.05)		(0.05)	(0.04)
Postgraduate premium		0.08	0.10		0.09	0.11
		(0.06)	(0.06)		(0.06)	(0.06)
Exposure to industry labor share decline			0.18			-0.37
			(0.66)			(0.80)
Relative specialization in routine jobs			0.07			0.09
			(0.07)			(0.08)
Share variance explained by:						
-task displacement	67%	55%	70%	65%	52%	69%
-educational dummies		8%	9%		9%	10%
Observations	500	500	500	500	500	500
Other covariates:						
Manufacturing share, and education and gender dummies		✓	✓		✓	✓

TASK DISPLACEMENT AND CHANGES IN HOURLY WAGES, 1980–2016

TABLE 1: TASK DISPLACEMENT AND CHANGES IN REAL HOURLY WAGES, 1980-2016.

	DEPENDENT VARIABLE: CHANGE IN HOURLY WAGES, 1980–2016					
	TASK DISPLACEMENT BASED ON LABOR SHARE DECLINES			TASK DISPLACEMENT BASED ON AUTOMATON-DRIVEN LABOR SHARE DECLINES		
	(1)	(2)	(3)	(4)	(5)	(6)
Task displacement	-1.60	-1.32	-1.66	-1.65	-1.33	-1.75
	(0.09)	(0.19)	(0.44)	(0.10)	(0.21)	(0.49)
Industry shifters		0.31	0.35		0.16	0.24
		(0.12)	(0.16)		(0.13)	(0.15)
College premium		-0.02	-0.01		-0.01	-0.01
		(0.05)	(0.05)		(0.05)	(0.04)
Postgraduate premium		0.08	0.10		0.09	0.11
		(0.06)	[illegible]		(0.06)	(0.06)
Exposure to industry labor share decline						-0.37
						(0.80)
Relative specialization in routine jobs						0.09
						(0.08)
Share variance explained by:						
-task displacement	67%	55%	70%	65%	52%	69%
-educational dummies		8%	9%		9%	10%
Observations	500	500	500	500	500	500
Other covariates:						
Manufacturing share, and education and gender dummies		✓	✓		✓	✓

Unconditional changes :

Δcollege premium = 25 %

Δpostgraduate premium = 40 %

TASK DISPLACEMENT AND CHANGES IN HOURLY WAGES, 1980–2016

Table 1: Task displacement and changes in real hourly wages, 1980-2016.

	Dependent variable: change in hourly wages, 1980–2016					
	Task displacement based on labor share declines			Task displacement based on automaton-driven labor share declines		
	(1)	(2)	(3)	(4)	(5)	(6)
Task displacement	-1.60	-1.32	-1.66	-1.65	-1.33	-1.75
	(0.09)	(0.19)	(0.44)	(0.10)	(0.21)	(0.49)
Industry shifters		0.31	0.35		0.16	0.24
		(0.12)	(0.16)		(0.13)	(0.15)
College premium		-0.02	-0.01		-0.01	-0.01
		(0.05)	(0.05)		(0.05)	(0.04)
Postgraduate premium		0.08	0.10		0.09	0.11
		(0.06)	(0.06)		(0.06)	(0.06)
Exposure to industry			0.18			-0.37
labor share decline			(0.66)			(0.80)
Relative specialization			0.07			0.09
in routine jobs			(0.07)			(0.08)
Share variance explained by:						
-task displacement	67%	55%	70%	65%	52%	69%
-educational dummies		8%	9%		9%	10%
Observations	500	500	500	500	500	500
Other covariates:						
Manufacturing share, and education and gender dummies		✓	✓		✓	✓

ADDITIONAL EMPIRICAL RESULTS

1. Task displacement predicts a drop in employment and a rise in non-participation
2. Results not confounded by other rising markups, trade, declining unionization rates, and other sources of investment and TFP growth (and these other trends have small effects on relative wages once we control for task displacement and industry shifts)
3. More pronounced effects when controlling for changes in labor supply
4. Smaller role for offshoring, which explains 10% of variance
5. Similar results for stacked-differences for 1980–2000 and 2000–2016
6. Similar findings when exploiting differences in exposure across US regions
7. Similar results when using alternative measures of occupations that can be automated using robots and software (instead of routine jobs) from Webb (2020)

WAGE EFFECTS IN GENERAL EQUILIBRIUM

Following any shock z_g to the demand for g:

$$d \ln \boldsymbol{w} = \boldsymbol{z} + \boxed{\frac{1}{\lambda} \frac{\partial \ln \boldsymbol{\Gamma}}{\partial \ln \boldsymbol{w}}} \cdot d \ln \boldsymbol{w} \Rightarrow d \ln \boldsymbol{w} = \left(1 - \frac{1}{\lambda} \frac{\partial \ln \boldsymbol{\Gamma}}{\partial \ln \boldsymbol{w}}\right)^{-1} \cdot \boldsymbol{z}$$

Ripple effects due to task reallocation

Propagation matrix Θ

θ_{gj} : Extent to which j competes for tasks against g

encodes all information on how tasks are reallocated in response to z

GENERAL EQUILIBRIUM EFFECTS

$$d \ln w_g = \Theta_g \cdot \left(\frac{1}{\lambda} \cdot d \ln y + \frac{1}{\lambda} \cdot d\mathbf{ln}\, \zeta - \frac{1}{\lambda} \cdot \boxed{d\mathbf{ln}\, \mathbf{\Gamma}^d} \right)$$

Measured vector of task displacement across groups

Ripple effects

θ_{gj} parametrized as a function of similarity in the occupation and industry dist., and age and education. Then estimated via GMM.

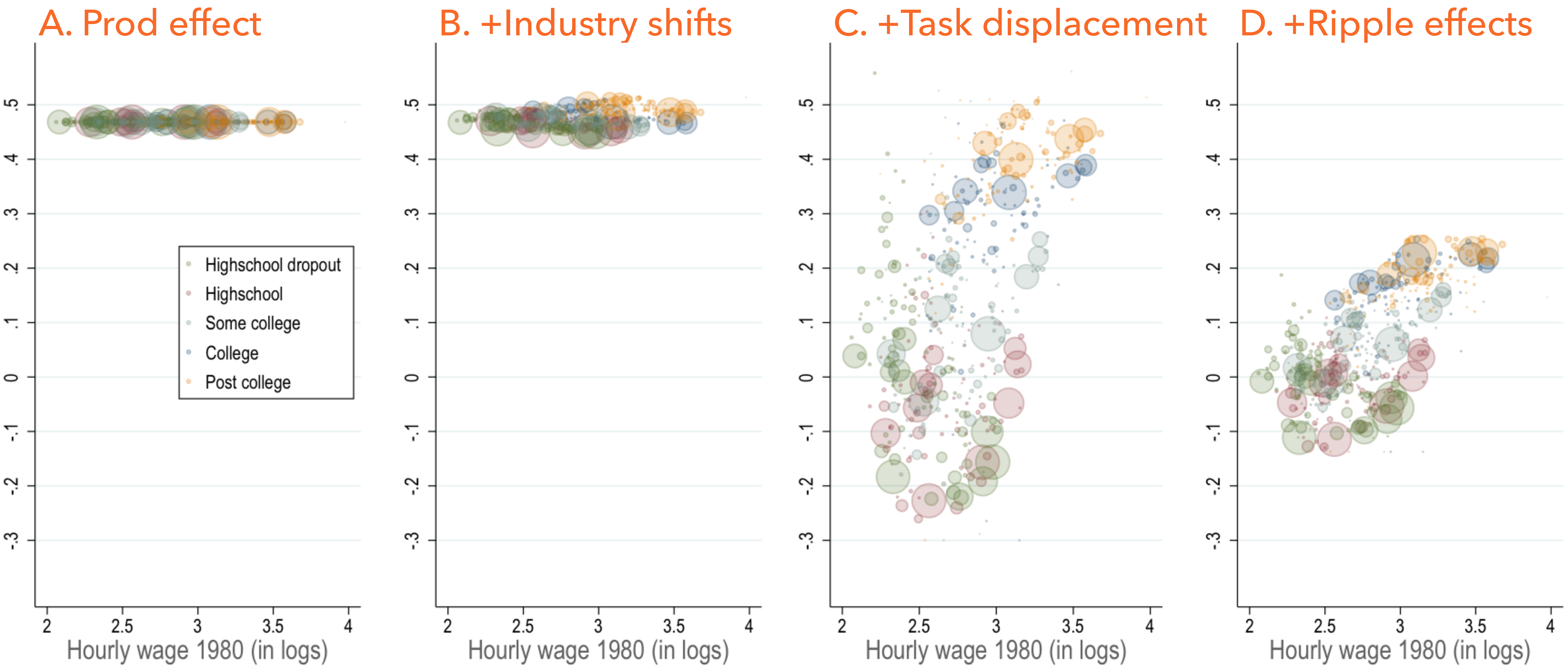
Productivity effects

Computed from formulas for TFP change and setting $\pi_{gi} = 30\,\%$ and $\lambda = 0.5$.

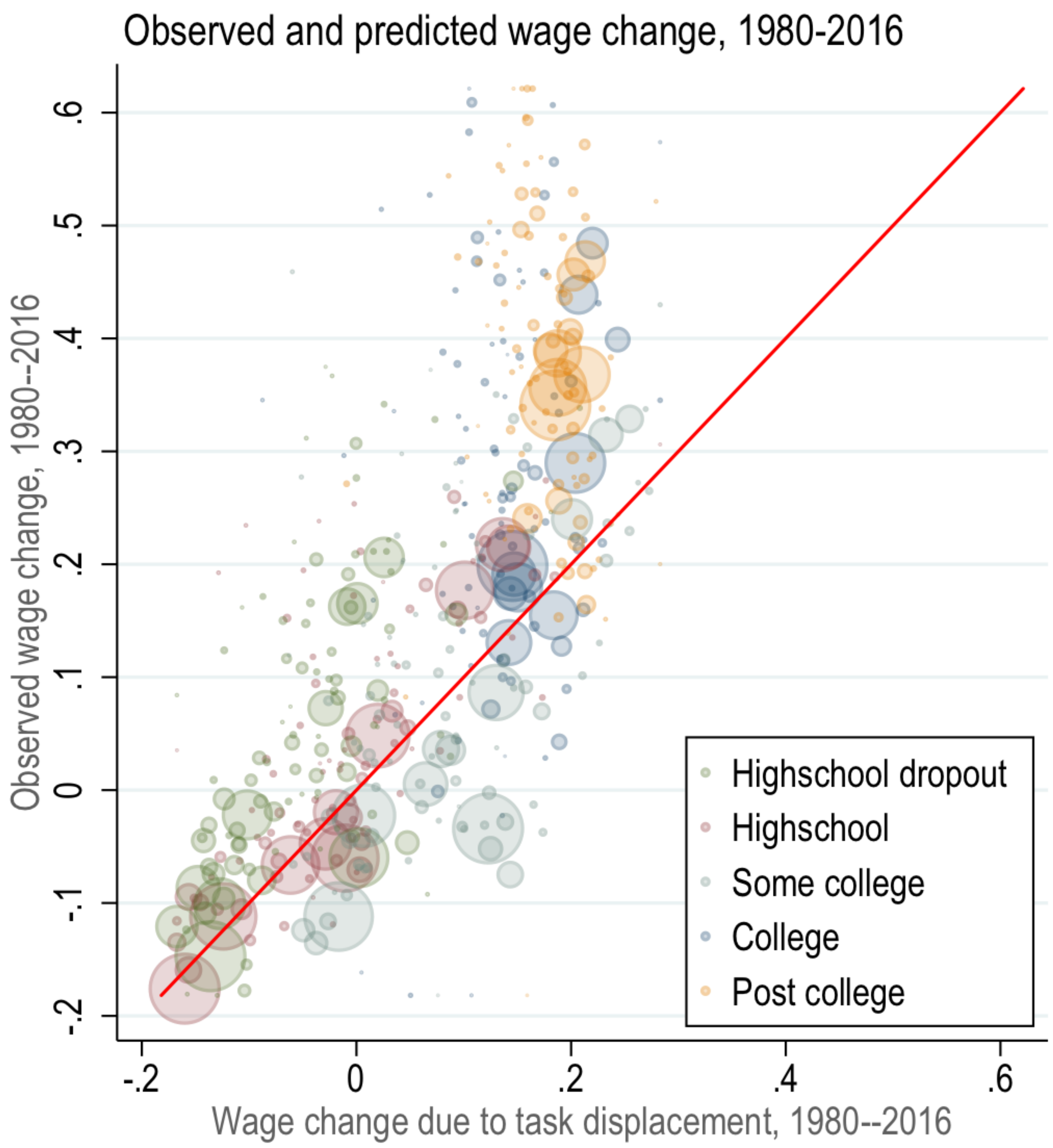
Industry shifts

Computed by assuming a CES demand across industries with elasticity 0.2

ACCOUNTING FOR GENERAL EQUILIBRIUM EFFECTS



ACCOUNTING FOR GENERAL EQUILIBRIUM EFFECTS



Summary of results:

- Explains 48% of observed wage changes
- Explains 80% of rise in college premium and 60% of rise in post-college premium
- Explains 80% of real wage declines
- Misses wage growth at top (other forces or direct complementarities with technology?)
- Increase in GDP of 20%, mean wage of 6%, and TFP of 4%

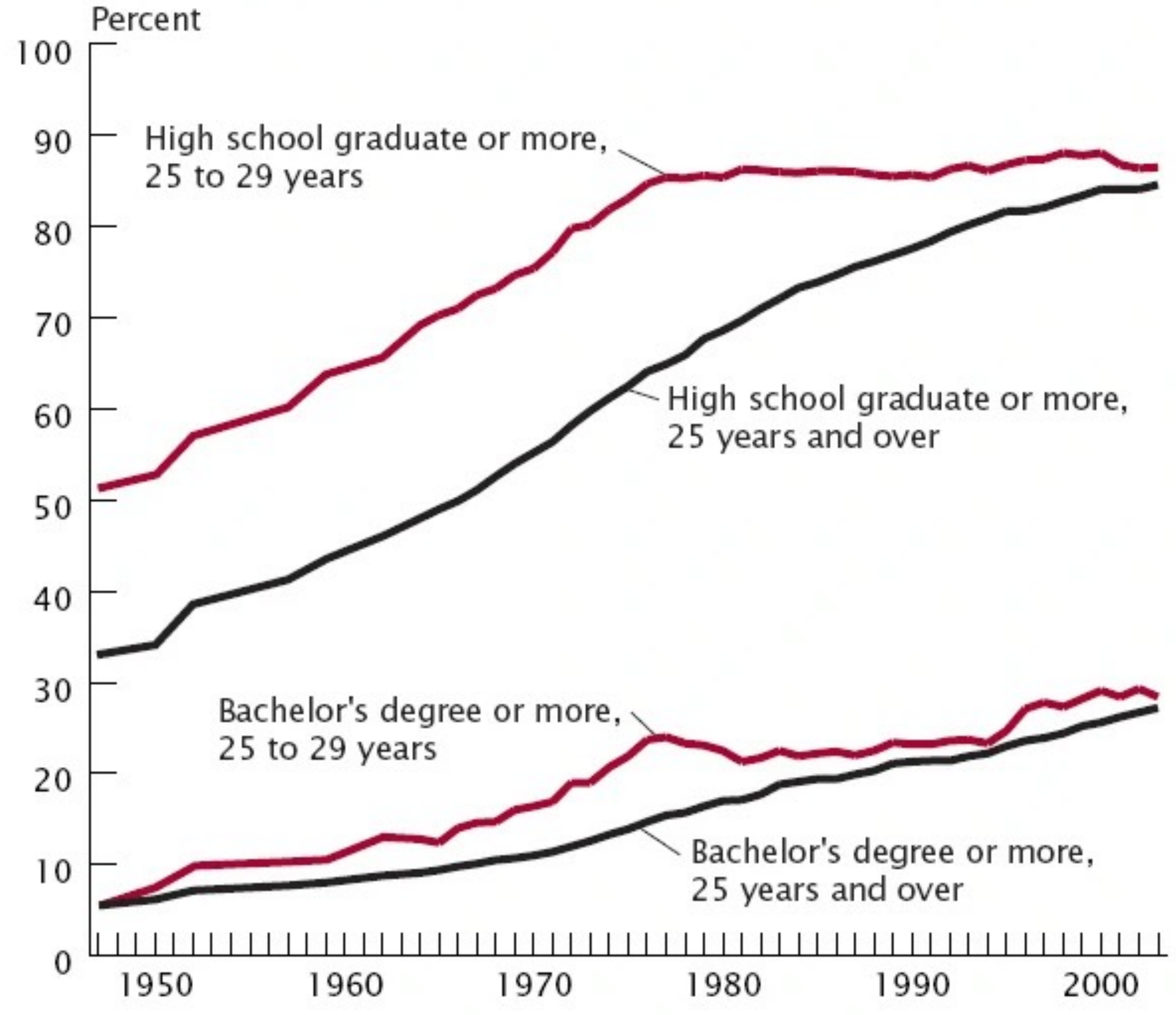
TO CONCLUDE

- Much of the rise in US wage inequality due to uneven effects of task displacement generated by automation
- Different from canonical explanations of SBTC:
    1. emphasizes task displacement and importance of industries and occupations above educational levels in mediating its effects
    2. better fit to data and high explanatory power
    3. explains lackluster TFP growth and declining real wages

APPENDIX MATERIAL

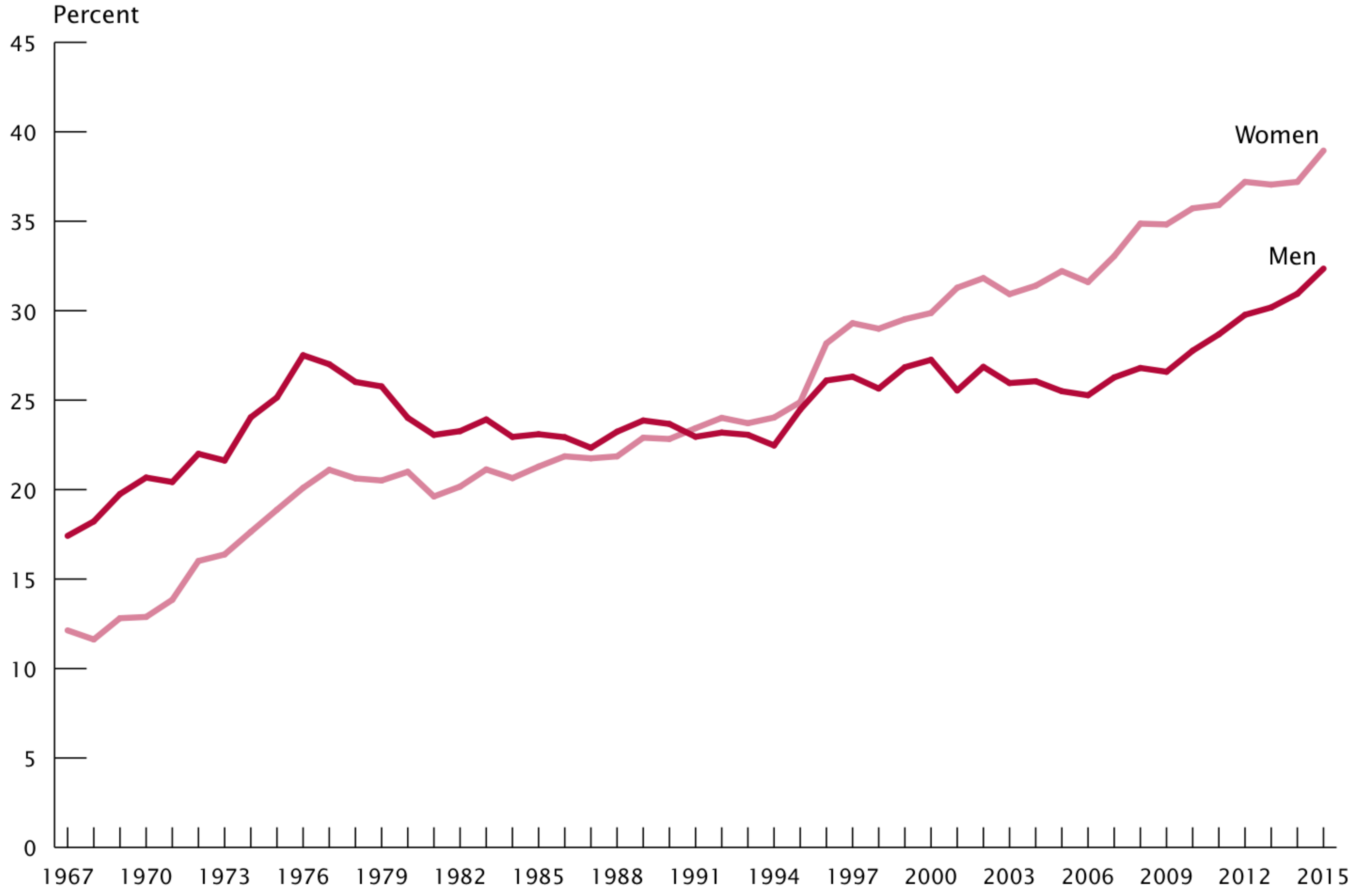
THE SUPPLY OF SKILLS

Figure 1.
Educational Attainment of the Population 25 Years and Over by Age: 1947 to 2003



Note: Prior to 1964, data are shown for 1947, 1950, 1952, 1957, 1959, and 1962.
Source: U.S. Census Bureau, Current Population Survey and the 1950 Census of Population.

Figure 7.
Percentage of the Population Aged 25 to 29 With a Bachelor's or Higher Degree, by Sex: 1967 to 2015



Source: U.S. Census Bureau, 1967–2015 Current Population Survey.

IV ESTIMATES

- Specifications exploiting our second measure very similar to IV using automation measures as instruments

Table 2: 2SLS estimates using automation and offshoring as instruments.

	Dependent variable: Change in hourly wages 1980–2016						
Instruments:	Robot APR, machinery, and software	Robot APR	Dedicated machinery	Specialized Software	Robot APR and software	Machinery and software	Offshoring
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Panel A. 2SLS estimates instrumenting task displacement with our automation and offshoring proxies						
Task displacement	-1.251	-1.216	-0.894	-1.480	-1.345	-1.216	-0.813
	(0.189)	(0.246)	(0.317)	(0.357)	(0.214)	(0.184)	(0.299)
Share variance explained by task displacement	0.48	0.30	0.16	0.17	0.47	0.42	0.09
R-squared	0.84	0.84	0.83	0.83	0.84	0.84	0.82
First-stage F	1209.41	98.00	44.98	67.40	439.92	831.72	30.62
Overid p-value	0.13				0.56	0.31	
Observations	500	500	500	500	500	500	500

AUTOMATION VS. SBTC

Table 3: Task displacement vs. SBTC, 1980–2016.

	Dependent variable: Change in hourly wages 1980–2016					
	SBTC by education level and gender			SBTC by wage level		
Task displacement measure		Labor share declines	Automation-driven declines		Labor share declines	Automation-driven declines
	(1)	(2)	(3)	(4)	(5)	(6)
Gender: women	0.173	0.104	0.120	0.245	0.154	0.167
	(0.019)	(0.020)	(0.019)	(0.024)	(0.026)	(0.027)
Education: no high school	0.016	0.023	0.036	0.051	0.039	0.047
	(0.024)	(0.020)	(0.020)	(0.023)	(0.018)	(0.020)
Education: some college	0.053	-0.070	-0.053	0.027	-0.057	-0.039
	(0.031)	(0.032)	(0.032)	(0.024)	(0.031)	(0.031)
Education: full college	0.245	-0.019	0.021	0.180	0.005	0.046
	(0.039)	(0.050)	(0.048)	(0.036)	(0.049)	(0.048)
Education: more than college	0.416	0.083	0.140	0.292	0.093	0.151
	(0.046)	(0.062)	(0.059)	(0.048)	(0.061)	(0.057)
Log of hourly wage in 1980				0.235	0.115	0.108
				(0.046)	(0.043)	(0.051)
Task displacement		-1.307	-1.334		-1.028	-1.006
		(0.188)	(0.210)		(0.185)	(0.230)
Share variance explained by:						
- educational dummies	0.55	0.08	0.15	0.37	0.09	0.16
- baseline wage				0.15	0.07	0.07
- task displacement		0.55	0.52		0.43	0.39
R-squared	0.76	0.84	0.83	0.81	0.85	0.84
Observations	500	500	500	500	500	500
Other covariates:						
Industry shifters and manufacturing share	✓	✓	✓	✓	✓	✓

EMPLOYMENT

- If our measures of task displacement are capturing changes in labor demand for groups, this should also explain differential changes in employment.

Table 4: Task displacement and employment outcomes, 1980-2016.

	Dependent variable: Labor market outcomes 1980–2016		
	Task displacement based on automation-driven labor share declines		
	(1)	(2)	(3)
Task displacement	-0.751	-0.443	-0.816
	(0.114)	(0.159)	(0.391)
Share variance explained by:			
- task displacement	0.35	0.20	0.38
- educational dummies		0.15	0.15
R-squared	0.35	0.77	0.78
Observations	500	500	500

Column 2 controls for education and gender dummies, industry shifters, and manufacturing wage shares.
Column 3 controls for exposure to industry labor share decline and relative specialization in routine jobs.

AUTOMATION VS. OTHER TECHNOLOGIES AND CAPITAL

TABLE 5: TASK DISPLACEMENT AND CHANGES IN REAL HOURLY WAGES—CONTROLLING FOR OTHER TRENDS, 1980-2016.

	DEPENDENT VARIABLE: CHANGE IN HOURLY WAGES 1980–2016			
	TASK DISPLACEMENT BASED ON AUTOMATION-DRIVEN LABOR SHARE DECLINES			
	CHANGES IN K/Y RATIO BY INDUSTRY (1)	CHANGES IN TFP BY INDUSTRY (2)	CHANGE IN CHINESE IMPORT COMPETITION (3)	DE-UNIONIZATION RATES (4)
Task displacement	-1.360	-1.382	-1.280	-1.321
	(0.201)	(0.216)	(0.218)	(0.226)
Exposure to industry shock	0.008	-0.114	0.022	-1.081
	(0.135)	(0.374)	(0.012)	(0.775)
Share variance explained by:				
- task displacement	0.53	0.54	0.50	0.51
- industry shock	0.00	0.01	-0.02	0.16
R-squared	0.83	0.83	0.83	0.83
Observations	500	500	500	500

All columns controls for education and gender dummies, industry shifters, and manufacturing wage shares.

AUTOMATION VS. MARKUPS

Table 6: Task displacement and changes in real hourly wages—controlling for changes in markups and industry concentration, 1980-2016.

	Dependent variable: Change in hourly wages 1980–2016			
	Task displacement based on automation-driven labor share declines			
	Change in sales concentration (1)	Markups from accounting approach (2)	Markups from materials share (3)	Markups from DLEU (2020) (4)
Task displacement	-1.398	-1.344	-1.397	-1.365
	(0.207)	(0.217)	(0.224)	(0.207)
Exposure to changes in markups or concentration	1.403	-0.896	-0.338	-0.674
	(1.497)	(1.371)	(0.427)	(1.079)
Share variance explained by:				
- task displacement	0.54	0.52	0.54	0.53
- markups/concetration	0.03	0.01	-0.03	0.01
R-squared	0.83	0.83	0.83	0.83
Observations	500	500	500	500

All columns controls for education and gender dummies, industry shifters, and manufacturing wage shares.