Industry Contribution to U.S. Wage Inequality

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Background

- Wage inequality has been on the rise in the United States over the last decades
  - what are the key drivers behind rising wage inequality in the literature?

① Employment polarization and Skill-Biased Technological Change (SBTC) theory

- up to the 1970s, prevalent *within-firm* dimension → explained by the *skill-premium*

➔ ***problem***: huge increase in relative supply of skilled workers, but skill-premium rose

② Role for the supply-side ⟶ pivotal is the *industry dimension*

- *between-firm* differences are clustered at the industry level

✍ Haltiwanger *et al.* (2023, 2024) → ***rising between-industry dispersion*** accounts for most of the overall change in wage inequality in USA {analogously in Briskar *et al.* (2022) for Italy}

▸ Graph

What's to come

Challenge: to address the determinants of real wages variance

Capture: dominant role of heterogeneity in the U.S. industry dimension

$\rightarrow$ disentanglement between a ***quantity*** and a ***structural*** effects

How:
① empirical motivation at 3-digit U.S. 2017 NAICS level

② general equilibrium model of structural transformations

③ structural estimation and counterfactual analysis

Question

What drives the industry-heterogeneous trend in wages?

The paper in one slide

① Empirics: industries exhibiting the largest growth in real wages are those ‣ Stylized facts

- significantly adopting ICT in physical capital, and . . .

  . . . where the substitution of routine with non-routine workers is most pronounced.

② Model ‣ Model overview

- wage premium from SBTC + workers' sorting and segregation effects
- it is able to address the observed between-industry wage inequality

③ Results: importance of *structural transformations* on U.S. wage inequality ‣ Take-aways

- differences in industry-level capital-labour substitution elasticities are the key drivers
- marginal role of sorting and segregation under heterogeneous elasticities
- alone, changes in factor endowments (*i.e.*, SBTC) explain 6-15%

Related literature

- Wage inequality in U.S. due to industrial composition {*e.g.*, Cullen (1956), Krueger and Summers (1988), Caselli (1999), Haltiwanger *et al.* (2023, 2024), Card *et al.* (2024); Briskar *et al.* (2022) for Italy}
  - → ***Contribution***: model that incorporates *structural* differences among U.S. industries
- Task-based literature {*e.g.*, Autor *et al.* (2006), Goos *et al.* (2009), Acemoglou and Autor (2011), Cortes *et al.* (2017), Cerina *et al.* (2021), Jaimovich *et al.* (2024)}
  - → ***Contribution***: distribution of labour into tasks + their substitutability on inequality
- Elasticity of substitution between capital and labour. In particular:
  - (*i*) secular decline in the labour share and role of industries {*e.g.*, Glover and Short (2023)}
  - (*ii*) structural transformation {*e.g.*, Buera and Kaboski (2012), Herrendorf *et al.* (2015)}
  - → ***Contribution***: routine share declines + capital-labour substitution elasticities < 1
- Skill-Biased-Technological-Change (SBTC) and wage inequality {*e.g.*, Krusell *et al.* (2000)}
  - → ***Contribution***: industry-level analysis and role of tasks

Motivating Evidence

US industries digitalization and labour force composition

- The `BEA Detailed Data for Fixed Assets` provides data on:
  - the stock of 96 different types of capital, classified in *intangible* capital, *digital equipment* and structures, and *physical* capital

▸ BEA construction

- The `BLS Occupational Employment and Wage Statistics` has data on:
  - more than 100 occupations according to the Standard Occupational Classification (SOC), classified in *routine* and *non-routine* tasks

▸ BLS construction

- *Unit*: 62 private 3-digits U.S. 2017 NAICS industries
- *Period*: 2003-2022, annual

Micro-econometrics methodology: panel data and quantile regressions, variance decompositions, shift-share

Structural transformations

Table 1: Combined regressions by groups, percentage changes

	$\Delta\, log(w_{s,t})$			
	0-25 quantile	*25-50 quantile*	*50-75 quantile*	*75-100 quantile*
$\beta_{\Delta k}$	-.693	.302***	.078	-.082*
	(.618)	(.072)	(.179)	(.042)
$\beta_{\Delta \ell}$	.041***	-.297	.015***	.052*
	(.004)	(.247)	(.003)	(.025)
$\beta_{\Delta k \times \Delta \ell}$	.876***	-1.304	-.643	1.560*
	(.100)	(2.945)	(.470)	(.789)

*Significance level at * (p<0.05), ** (p<0.01), *** (p<0.001). Standard error in parentheses. Analysis at 3-digit U.S. 2017 NAICS industries in 2003-2022. Each Fixed Effects (Fe) regression – performed on groups of industries clustered in quantiles (ω) according to their overall growth in real wage – , is of the form $y_\omega\ (\Delta\, log(w_{s,t}) \mid \mathcal{X}_{i,\omega t}, \mathcal{V}_{j,\omega t}) = \beta_{c,\omega} + \beta_{i,\omega}\mathcal{X}_{i,\omega t} + \delta_{j,\omega}\mathcal{V}_{j,\omega t} + u_{\omega t}$, with $\mathcal{X}_i$ representing the percentage change in both ICT-to-physical capital and non-routine-over-routine workers ratios, and $\mathcal{V}_j$ being a set of time-varying controls. Variables are all in log format. Constant not reported to save space. Source: BEA, BLS and own calculations.*

▸ Correlations

Possible interpretations

- *Quantile regressions*: not only a matter of isolated changes, but rather pivotal appears to be the interaction of these two ratios

- Wage inequality across industries could be the result of
  - a ***quantity*** effect, under different paths in factor of productions;
  - a ***structural*** effect, due to changes in technology parameters governing the relationship between capital and labour types.

☞ These general equilibrium issues will be addressed through the estimated model

▸ Fact 1: Capital gaps ▸ Fact 2: Labour force composition ▸ Fact 4: Contribution

Model

Households

- Unit mass of households, each labelled as i, split in types $a \in \{rt, nrt\}$ ▸ Intertemporal utility
  - each chooses consumption, invests in both capital types, and receives dividends

- Idiosyncratic productivity when working as type-a for firm h in industry s ▸ Indirect utility
  - drawn once from a *bivariate Frechét-type distribution* ... ▸ Frechét variability

    ... whose shape parameter identifies common productivity dispersion $\longleftrightarrow \quad \theta$

- Analytical form for the measure of each worker-type in firm (h, s)

$$\ell_h(a,s) = \left(\frac{w_h(a,s)}{\mathcal{W}_{\mathcal{H}}(a,\mathcal{S})} \; \frac{\mathcal{B}_h(a,s)}{\mathcal{B}_{\mathcal{H}}(a,\mathcal{S})} \right)^{\theta} \tag{1}$$

→ **Remark:** *sorting* and *segregation* effects in interaction with the *wage premium* ▸ Plot

▸ Validation: Employment

Market structure

- Three layers: (i) *final aggregator*, (ii) *sectoral bundler*, and (iii) *firms* ▸ Output aggregators

- *Technology* $\longrightarrow$ Cobb Douglas-Nested CES ▸ Production function

CES-1:	non-routine labour is complementary to ICT capital	$\longleftrightarrow$	ρ
CES-2:	routine labour is substitutable with *CES-1*	$\longleftrightarrow$	σ
C-D:	non-ICT capital together with *CES-2* part	$\longleftrightarrow$	α

- A monopolistically competitive firm (h, s) solves ▸ Firm problem

$$\max_{p_h(s), k_h(j,s), \ell_h(a,s)} \left[\mathcal{D}_h(s) \mid y_h(s) \right]$$

→ Optimal wages for *routine* and *non-routine* workers in industry s ▸ Wages

▸ Firms and Industry Levels ▸ Aggregation ▸ Equilibrium ▸ Validation: Wage

from Theory to Data

Calibration strategy

- Vector of parameters to calibrate: $\Theta = \Big(\alpha_s,\, \epsilon,\, \lambda_s,\, \mu_s,\, \theta,\, \rho_s,\, \sigma_s\Big)_{\forall s \in \{bot, mid, top\}}$
  1. *data and external calibration*. In particular:
     - ⋆ industries' shares of non-ICT capital, (α_s), directly from BEA tables, and offline calibration for ϵ;
  2. *estimating equations* for elasticity of substitution parameters, $(\rho_s, \sigma_s)_{\forall s}$; eqs. (8.1) and (8.2)
     - ⋆ identification: ***negative relationship between labour share and relative ICT stock***; ▸ Figure
  3. *Method of Simulated Moments* (MSM) for distributive weights parameters, $(\lambda_s, \mu_s)_{\forall s}$, and degree of labour market concentration (θ). In particular:
     - ⋆ $\lambda_s \longleftrightarrow$ industry-specific ICT capital in the aggregate stock;
     - ⋆ $\mu_s \longleftrightarrow$ routine workers in the data with that predicted by the model in eq. (1);
     - ⋆ $\theta \longleftrightarrow$ routine real *log*-wage premium of top relative to bottom groups.

→ **Model fit**: perfect targeting of observed wage inequality values ▸ Variances

▸ MSM targets ▸ MSM estimates

Calibration

Table 2: Summary of calibration

	parameter	value				source
		bottom	*middle*	*top*	*global*	
α	*physical capital, share of $y(s)$*	0.263	0.195	0.514		*data*
ϵ	*demand elasticity across firms*				6	*external*
μ	*weight of routine workers in $y(s)$*	0.676	0.495	0.337		*MSM*
λ	*weight of ICT capital in $q(s)$*	0.457	0.465	0.451		*MSM*
θ	*households' productivities dispersion*				11.3	*MSM*
ρ	*EoS, ICT capital and non-routine*	0.329	0.420	0.249		*estimation*
σ	*EoS, routine and ICT composite*	0.634	0.400	0.766		*estimation*

Set of estimated parameters of the model. "Data" implies that the values are directly computed from data sources, while in "external" I choose standard calibrated values from the literature. "MSM" refers to the Methods of Simulated Moments as in McFadden1989. "Estimation" refers to previously estimated values under a specific procedure; these values are taken from Table C.3.

▸ Model fit ▸ Variances ▸ Untargeted ▸ Correlations (1/2) ▸ Correlations (2/2) ▸ Quantiles ▸ Series (1/3) ▸ Series (2/3) ▸ Series (3/3)

Counterfactual analysis

→ What's next? *Counterfactual analysis*

- contribution of variations in parameters and/or series on *between-industry* wage inequality

- Either for total industry employment, and for routines and non-routines separately:
  1. changing one or more key parameters $(\rho_s, \sigma_s, \theta)$ at a time, fixing the others $(\alpha_s, \mu_s, \lambda_s)$;
     - ⋆ Tables C.12, C.14, C.16;
  2. keeping fixed the key parameters, while changing the others;
     - ⋆ Tables C.13, C.15, C.17;
  3. no changes in parameters, and let to vary only capital and labour series;
     - ⋆ Tables C.18, C.19, C.20;
  4. remove heterogeneous parameters, and let to vary only capital and labour series.
     - ⋆ Tables C.21, C.22.

▸ MSM re-estimates ▸ Models for counterfactuals ▸ Exogenous, series ▸ Exogenous, levels ▸ Exogenous, variances

Which parameters to pick?

- Selected parameters:

  (i) trend-differences in structural transformations $\longleftrightarrow$ ρ and σ;

  (ii) shifts in labour market concentration $\longleftrightarrow$ θ.

- Relevance of the changes occurred in the two elasticities of substitution ...
  - bottom $\longrightarrow$ $\rho\uparrow\uparrow$ and $\sigma\downarrow$;
  - middle $\longrightarrow$ $\rho\downarrow$ and $\sigma\uparrow$;
  - top $\longrightarrow$ $\rho\uparrow$ and $\sigma\downarrow$.

  ... considering two separate time windows, 2003-2012 and 2013-2022.

▸ Time-varying estimates

Increasing sorting and segregation effects, captured by θ

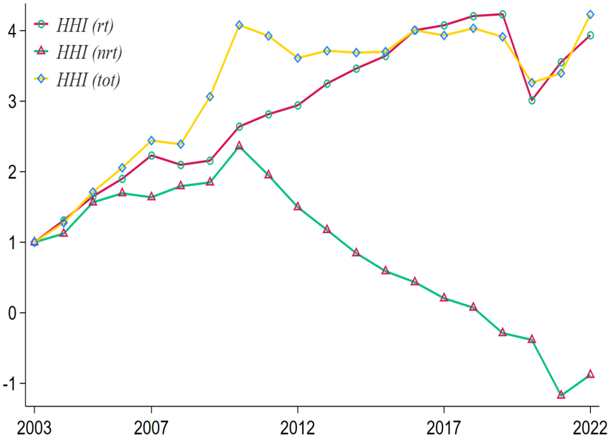
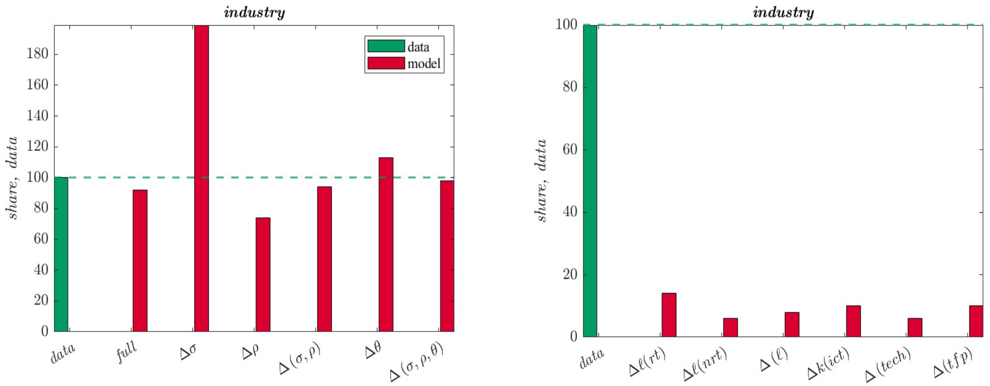


Figure 1: Labour market concentration

▸ HHI ▸ HHI industries

Model re-calibration counterfactuals



(a) Changing parameters

(b) Changing series, unique calibration

Figure 2: Impact on between-industry wage inequality

▸ Change ▸ Fixing ▸ SBTC and Series ▸ Productivity, mean ▸ Productivity, new

Conclusions

Take-away remarks

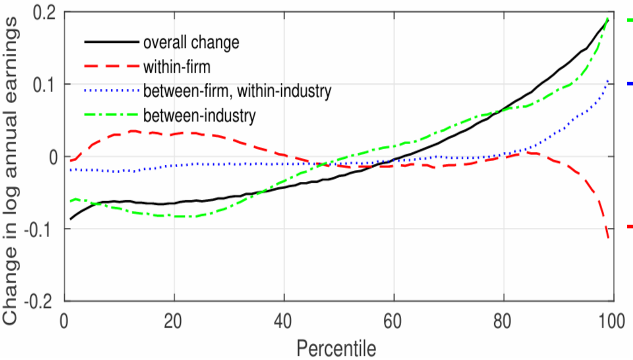
- Wage inequality in the U.S. economy since the 1990s has been substantial
  - → dominant driver of increasing inequality is ***between-industry*** dispersion in wages

- Pivotal role of *labour side* changes of industries' production structure

- Wage inequality is addressed by *structural transformations* across industries
  - → primarily driven up by uneven, industry-level substitutability between routine and non-routine workers;
  - → strengthen in sorting and segregation barely intensifies wage inequality;
  - → without its *structural effect*, SBTC does not address observed inequality.

Appendix

It's the industry, not the firm



Contribution to wage inequality

- 61.9% between-industry;
- 23.1% between-firm, within-industry;
- 14.9% within-firm.

Source: Haltiwanger *et al.* (2024), period 1996-2018

Go back

This paper: empirics ▸ Go back

Fact 1 (**Capital gaps**) *Dispersion in physical capital-labour ratio is decreasing across industries, while it is not that of ICT capital-labour ratio.*

Fact 2 (**Labour force composition**) *Increases in non-routine relative shares are determined by a substitution effect rather than by the size of industries.*

Fact 3 (**Structural transformations**) *Industries characterized by highest changes in real wages experience a substantial rise in their non-routine workers relative share along an increasing ICT capital ratio dynamics.*

Fact 4 (**Contribution**) *A small subset of industries drives the rise in wage inequality; these are in the tails of the industry-level wage growth distribution.*

This paper: model ▸ Go back

- ***Households***
  - Task heterogeneity: *routine* and *non-routine* households
  - Endogenous sorting into firms and industries given heterogeneous productivities
  - It gives rise to imperfectly elastic labour supply $\longleftrightarrow$ *sorting* and *segregation* effects
- ***Firms** and **Industries***
  - Monopolistically competitive firms in each industry
  - Two types of capital: *ICT* and *non-ICT* capital
  - Non-routine labour is complementary to ICT capital; routine labour is substitutable

This paper: results ▸ Go back

❊ Structural transformations drive most of the between-industry real wage inequality

Findings:

① industry-specific shifts in elasticities among capital and workers are pivotal
- ➔ 94% if combined shifts in elasticities;
- ➔ 88% when considering also weights of factors of production.

② major labour market concentration intensifies wage inequality
- ➔ 98% if combined with joint shifts in elasticities;

③ these patterns hold with routine and non-routine workers separately

④ wage inequality is not altered by monopsony power in wage-setting

Data from BEA

- Private non-residential capital types divided in gross categories[i]
  - each category contains different types of assets according to NIPA asset type code;
  - total of 96 different asset types.
- Classification:
  - (*i*) *digital equipment* is made of "Mainframes", "PCs", "DASDs", "Printers", "Terminals", "Tape Drives", "Storage Devices", and "System Integrators";
  - (*ii*) *intangible capital* coincides with "Total Intellectual Property Products" (IPP);
  - (*iii*) *ICT capital*, as the combination of *digital equipment* and *intangible capital*;
  - (*iv*) *physical* (or *non-ICT*) *capital* is the sum of all the remaining asset types.
- The value of each asset is expressed in millions of U.S. dollars

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[i] These are "Total Equipment", "Total Structures", and "Total Intellectual Property Products".

Dispersion in per worker wage and capital, cross-industries

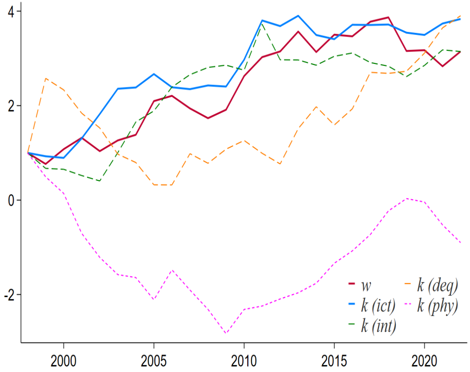

Figure A.1: Interquantile range, 90^{th}-10^{th}

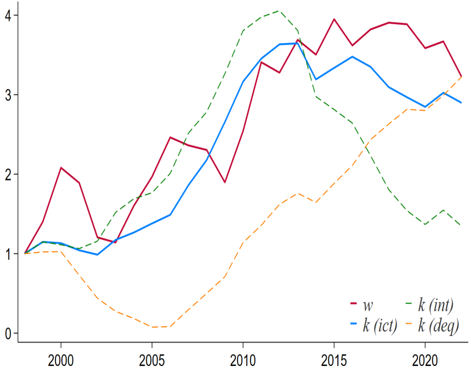

Figure A.2: Macro-complementarity at works

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Figure (aggregate) Table (2-digits) Figure (2-digits) Regressions (3-digits)

Measuring intensity in intangible capital

→ For each industry s,

$$INTint_{s,t} = \frac{INTstock_{s,t}}{TotCap_{s,t}}$$

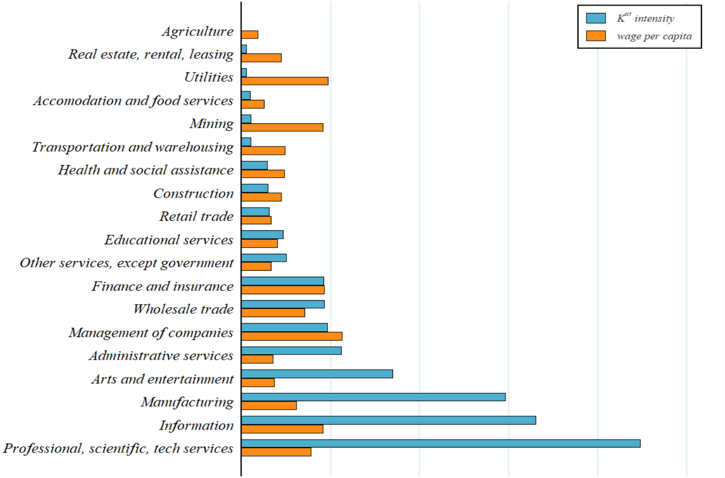

Figure A.3: Real wages per capita and intensity in intangible capital

▸ Table (2-digits) ▸ Figure (2-digits)

Table A.1: Percentage changes in intensity in intangible capital and real per capita wages

	Year													
Industry	1999		2002		2007		2012		2017		2022		***Overall***	
Accommodation and food services	-.04	[.]	-.11	[.]	-.11	[.]	.03	[.]	.68	[.]	.3	[.]	.72	[.36]
Administrative services	.33	[.]	.48	[.]	.13	[.]	.29	[.]	.15	[.]	-.05	[.]	2.1	[.50]
Agriculture	-.18	[.]	-.39	[.]	-.11	[.]	-.29	[.]	.74	[.]	.05	[.]	-.43	[.31]
Arts and entertainment	-.05	[.]	-.15	[.]	-.19	[.]	-.04	[.]	-.13	[.]	-.09	[.]	-.49	[.24]
Construction	.07	[.]	-.38	[.]	-.03	[.]	-.09	[.]	.16	[.]	.31	[.]	-.11	[.28]
Educational services	.03	[.]	.09	[.]	-.003	[.]	.32	[.]	.11	[.]	-.08	[.]	.52	[.19]
Finance and insurance	.09	[.]	.14	[.]	-.09	[.]	.19	[.]	.31	[.]	.33	[.]	1.36	[.39]
Health and social assistance	-.01	[.]	.19	[.]	-.28	[.]	.20	[.]	.26	[.]	.09	[.]	.41	[.19]
Information	.03	[.]	.02	[.]	.04	[.]	.01	[.]	.09	[.]	.01	[.]	.22	[.62]
Management of companies	.15	[.]	.29	[.]	.09	[.]	.67	[.]	-.09	[.]	-.18	[.]	1.03	[.25]
Manufacturing	.04	[.]	.04	[.]	.09	[.]	.67	[.]	-.09	[.]	-.17	[.]	.39	[.16]
Mining	.77	[.]	-.24	[.]	-.49	[.]	.02	[.]	.29	[.]	1.5	[.]	1.25	[.26]
Other services, no gov.	.01	[.]	.001	[.]	.02	[.]	.27	[.]	.35	[.]	.24	[.]	1.16	[.30]
Professional, scientific, technical services	.01	[.]	-.02	[.]	-.06	[.]	.04	[.]	.03	[.]	.05	[.]	.04	[.36]
Real estate, rental, leasing		[.]		[.]		[.]		[.]		[.]		[.]	.	[.35]
Retail trade	.12	[.]	.22	[.]	.07	[.]	.17	[.]	.42	[.]	.31	[.]	2.18	[.10]
Transportation	.07	[.]	-.003	[.]	-.39	[.]	-.05	[.]	.66	[.]	.06	[.]	.08	[.02]
Utilities	-.00	[.]	-.15	[.]	-.39	[.]	.14	[.]	.48	[.]	.39	[.]	.24	[.22]
Wholesale trade	.15	[.]	.36	[.]	.11	[.]	.08	[.]	.15	[.]	.08	[.]	1.32	[.25]
Aggregate economy	.	.	.	.	.	.	.	.	.	.	.	.	.	[.26]

Value in 1999 is computed given the level in 1998; values not in parenthesis are that of intangible capital percentage change, while [] refers to real wage per capita percentage change. Overall reports the total percentage change over the whole time span (1998-2022). 2-digit U.S. 2017 NAICS industries.

▸ Go back

Intensity in intangibles and real wage growth, by industry

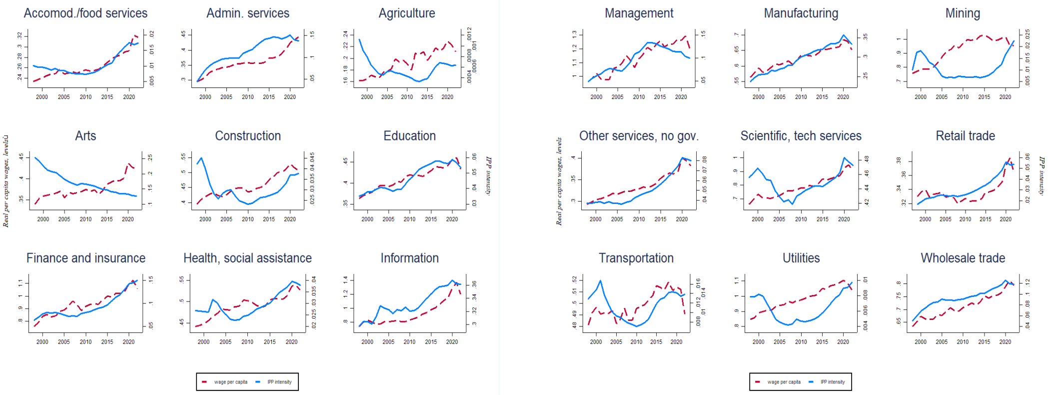

Figure A.4: Changes in *intangibles* intensity and real per capita wages

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Importance of per worker capital

Figure A.5: Evolution of capita-labour ratio and real per capita wages

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Table A.2: Capital-labour ratios and real per capita wages

	Overall					
Industry	k/ℓ	k^{phy}/ℓ	k^{ict}/ℓ	k^{ict}_{net}/ℓ	k^{int}/ℓ	w/ℓ
Accommodation and food services	1.43	1.41	3.04	2.50	3.18	.36
Administrative services	1.78	1.49	6.02	2.55	7.65	.50
Agriculture	2.03	2.04	.08	-.58	.73	.31
Arts and entertainment	2.36	2.94	.70	1.89	.68	.24
Construction	1.59	1.63	1.04	.06	1.32	.28
Educational services	1.95	1.89	3.07	.84	3.49	.19
Finance and insurance	1.65	1.45	3.18	.58	5.25	.39
Health and social assistance	1.34	1.32	1.96	.67	2.29	.19
Information	2.52	2.08	3.53	13.56	3.29	.62
Management of companies	.39	.32	1.53	.57	1.84	.25
Manufacturing	2.62	2.18	3.96	.65	4.06	.16
Mining	2.36	2.32	5.59	-.32	6.57	.26
Other services, no gov.	1.88	1.75	4.93	2.52	5.22	.30
Professional, scientific, and technical services	2.08	2.09	2.08	.92	2.19	.36
Real estate, rental, leasing	1.74	1.77	.72	-.20	6.37	.35
Retail trade	2.65	2.51	7.52	2.82	10.62	.10
Transportation	.64	.64	.46	-.23	.77	.02
Utilities	3.05	3.04	3.90	3.31	4.02	.22
Wholesale trade	1.85	1.71	3.39	.33	5.62	.25
Aggregate economy	1.94	1.96	3.21	1.40	3.22	0.26

Total percentage change over the whole time span (1998-2022) *for 2-digit U.S. 2017 NAICS industries.*

▸ Go back

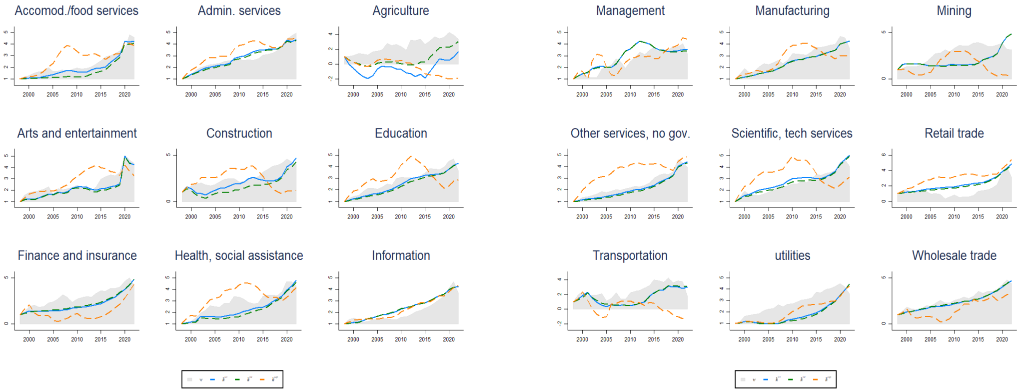

Figure A.6: Changes in capital-labour ratios and per real capita wages

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Table A.3: Regressions, capital stocks

	$log(w_{s,t})$			
	(1)	(2)	(3)	(4)
β_{kphy}	.134*** (3.48)	.122** (2.94)	.164*** (9.05)	.114*** (3.52)
β_{kict}	.052* (2.00)			.049* (2.27)
β_{kint}		.057* (2.03)		
β_{kdeq}		-.003 (-.26)		
$\beta_{kint} \times \beta_{kdeq}$			.009** (2.99)	.009** (2.80)
R^2	.461	.491	.287	.497

*t-statistics in parentheses. * ($p<0.05$), ** ($p<0.01$), *** ($p<0.001$). Analysis at 3/4-digit U.S. 2017 NAICS industries over 1998-2022 on $N = 1650$ observations. The Fixed Effects (Fe) regressions are of the form $y\left(log(w_{s,t}) \mid \mathcal{X}_{i,t}\right) = \beta_C + \beta_i \mathcal{X}_{i,t} + u_t$, with $\mathcal{X}_i$ representing the different capital-labour ratios considered. Results are robust even by controlling for the log size of the industries, or even taking capital series directly in levels. Variables are all in log format. Constant not reported to save space. Source: BEA and own calculations.*

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Data from BLS

- U.S. 2017 NAICS classification of industries only starting from 2003
- For each industry, occupations classified according to the U.S. SOC system
  - occupation based on the work performed and not on education or training
- I classify occupations by considering the "major" group:[ii]

  (*i*) *non-routine tasks* considers "Management", "Business and Financial Operations", "Computer and Mathematical", "Architecture and Engineering", "Life, Physical, and Social Science", "Community and Social Service", "Legal", "Educational Training and Library", and "Arts, Design, Entertainment, Sports, and Media" occupations;

  (*ii*) the rest of occupations is comprised in the set of *routine tasks*.

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[ii] These groups are a total of 22. I do not choose a more granular identification due to missing group definitions for some more detailed occupations.

Labour force composition: substitution or size? ▸ Go back

How much of the changing share of task-a is due to changing sizes of industries and how much is due to changes in workforce composition within those industries?

$$\Delta\left(\frac{\ell(a)}{\ell(a')}\right) = \underbrace{\sum_s \overline{\left(\frac{\ell(a,s)}{\ell(s)}\right)}\,\Delta\left(\frac{\ell(a,s)}{\ell(a',s)}\right)}_{\textit{within-industry: substitution effect}} + \underbrace{\sum_s \overline{\left(\frac{\ell(a,s)}{\ell(a',s)}\right)}\,\Delta\left(\frac{\ell(a,s)}{\ell(s)}\right)}_{\textit{between-industry: size effect}} \tag{A.1}$$

Table A.4: Labour force changes

	routine		***non-routine***	
Interval	*within*	*between*	*within*	*between*
2003-2008	83%	17%	38%	62%
2009-2015	81%	19%	58%	42%
2016-2022	78%	22%	69%	31%

▸ Figure (2-digits) ▸ Dynamics (3-digits) ▸ Shares (3-digits) ▸ Various (3-digits)

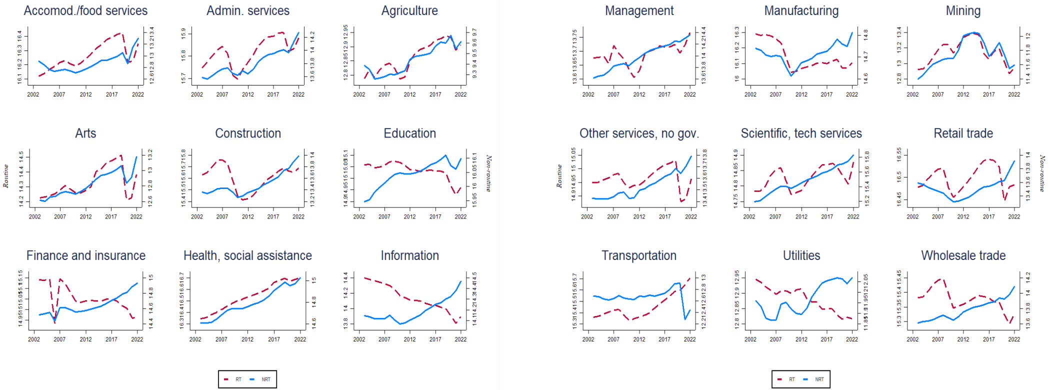


Figure A.7: Changes in routine and non-routine tasks

Go back

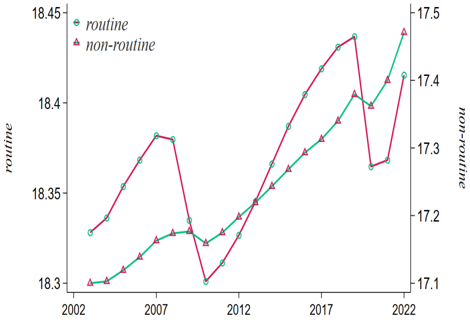


Figure A.8: Dynamics by tasks

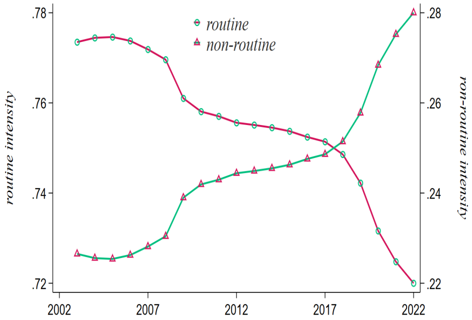
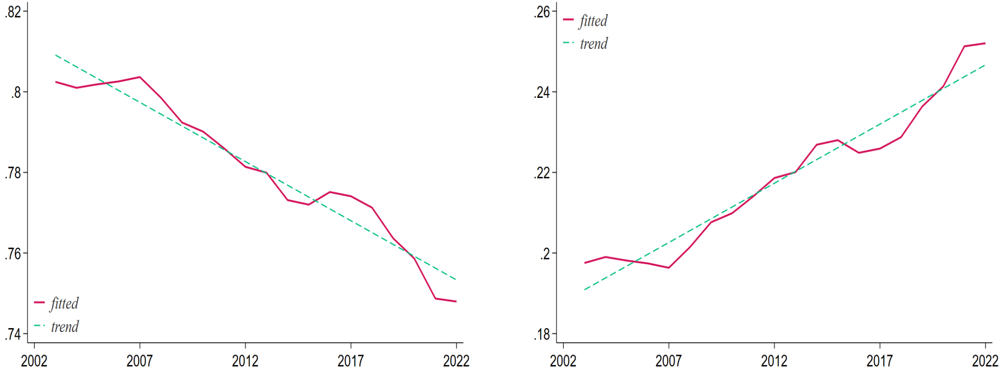


Figure A.9: Tasks' intensities over time

Go back



(a) Routine workers **(b)** Non-routine workers

Figure A.10: Labour shares pattern

Go back

Some patterns, occupations

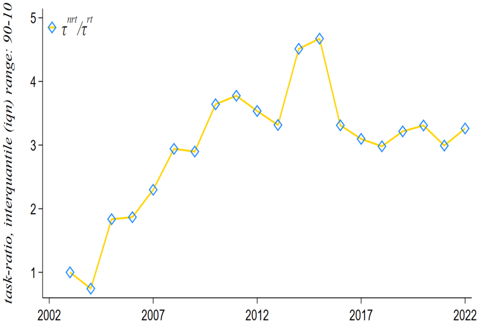


Figure A.11: Task ratio interquantile range

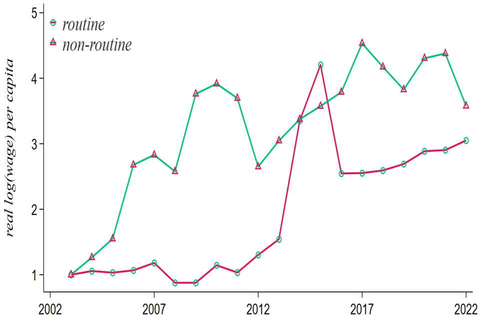


Figure A.12: Wage per capita, by tasks

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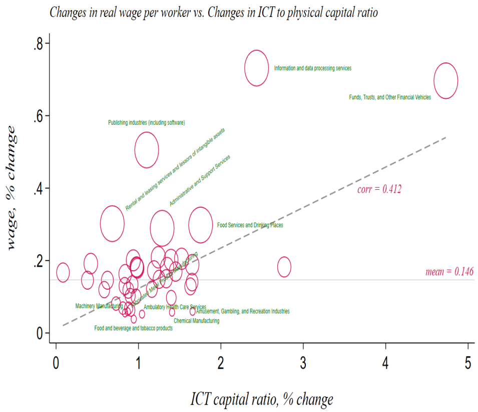


Figure A.13: Real wages vs. ICT capital ratio

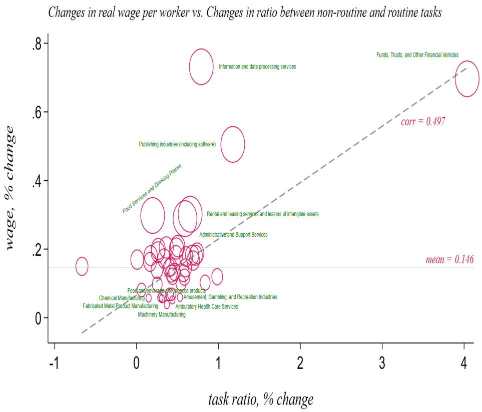
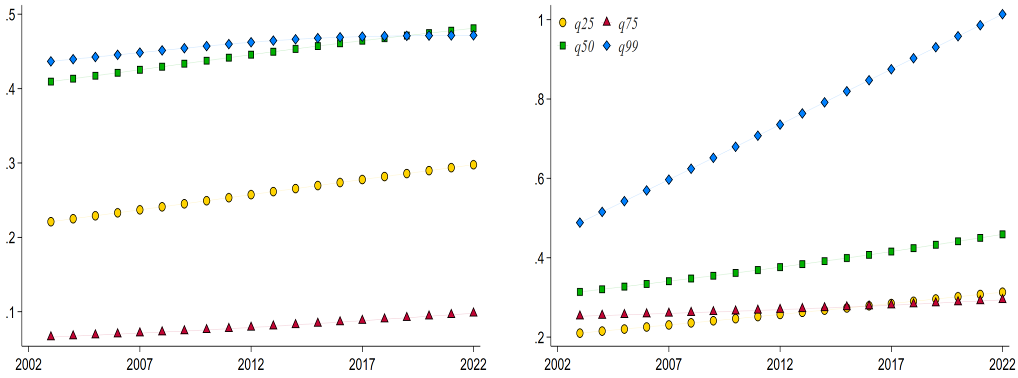


Figure A.14: Real wages vs. task ratio

▸ Quantiles, trend ▸ Regressions, changes ▸ Regressions, changes (groups) ▸ Regressions, levels ▸ Regressions, levels (std)

Trend by quantiles



(a) ICT capital ratio

(b) Task ratio

Figure A.15: Changes by percentiles

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Analysis by quantiles, interpretation

- Figure A.15 suggests that *top industries* (in terms of overall growth in real wages):

  (i) have increased either their own ICT capital ratio $\left(\frac{k(ict)}{k(phy)}\right)$ *and* their own task ratio $\left(\frac{\ell(nrt)}{\ell(rt)}\right)$;

  (ii) the other industries have not increased simultaneously these ratios.

- A theory for increasing wage dispersion across industries should display a study made through the lens of ***both*** changes in $\left(\frac{k(ict)}{k(phy)}\right)$ and $\left(\frac{\ell(nrt)}{\ell(rt)}\right)$
  - these results are in line with Table A.2, in which some industries display huge changes in $\frac{k(ict)}{\ell}$, but not in their real wage per capita

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Regressions, percentage changes

Table A.5: Combined regressions, percentage changes

	$\Delta\, log(w_{s,t})$		
	(1)	(2)	(3)
$\beta_{\Delta k}$	.054***		.009
	(.002)		(.008)
$\beta_{\Delta \ell}$	.035*		.035***
	(.018)		(.007)
$\beta_{\Delta k \times \Delta \ell}$		.982	.919***
		(.649)	(.152)
R^2	.030	.021	.037
N	1178	1178	1178

*t-statistics in parentheses. * (p<0.05), ** (p<0.01), *** (p<0.001). Analysis at 3-digit U.S. 2017 NAICS industries over 2003-2022. The Fixed Effects (Fe) regressions are of the form* $y\,(\Delta\, log(w_{s,t}) \mid \mathcal{X}_{i,t}, \mathcal{V}_j) = \beta_c + \beta_i \mathcal{X}_{i,t} + \delta_j \mathcal{V}_{j,t} + u_t$*, with* $\mathcal{X}_i$ *representing the percentage change in both ICT-to-physical capital and non-routine-over-routine workers ratios, and* $\mathcal{V}_j$ *being a set of time-varying controls. Variables are all in log format. Constant not reported to save space. Source: BEA, BLS and own calculations.*

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Table A.6: Combined regressions, levels

	$log(w_{s,t})$				
	Fe	*25th quantile*	*50th quantile*	*75th quantile*	*100th quantile*
β_k	.102**	.084***	.102***	.119***	.171*
	(.040)	(.029)	(.022)	(.027)	(.074)
β_ℓ	.299***	.269***	.300***	.328***	.416***
	(.078)	(.040)	(.030)	(.037)	(.104)
$\beta_{k\times\ell}$	.031	.029***	.031***	.034***	.041
	(1.89)	(.010)	(.008)	(.009)	(.025)

*Significance level at * (p<0.05), ** (p<0.01), *** (p<0.001). Standard error in parentheses. Analysis at 3-digit U.S. 2017 NAICS industries in 2003-2022 on N = 1240 observations. The Fixed Effects (Fe) regression is of the form* $y\left(log(w_{s,t}) \mid \mathcal{X}_{i,t}, \mathcal{V}_{j,t}\right) = \beta_C + \beta_i \mathcal{X}_{i,t} + \delta_j \mathcal{V}_{j,t} + u_t$, *with* $i = k, \ell$, *and* $\mathcal{V}_j$ *being a set of controls, and it has associated* $R^2 = .348$ *. Analogously, the conditional quantile regressions are then* $\mathcal{Q}_\omega\left(log(w_{s,t}) \mid \mathcal{X}_{i,\omega t}, \mathcal{V}_{j,\omega t}\right) = \beta_{i,\omega}\mathcal{X}_{i,\omega t} + \delta_{j,\omega}\mathcal{V}_{j,\omega t} + u_{\omega t}$, *where* ω *represents each quantile (defined on the independent variable). Variables are all in log format. Constant not reported to save space, while quantile regressions do not have the constant term. Source: BEA, BLS and own calculations.*

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Regressions by quantiles, levels in standard deviation

Table A.7: Combined regressions, standard deviations

	$sd(log(w_{s,t}))$				R^2	
	(1)		(2)			
	$\beta_{sd(k)}$	β_{ℓ}	β_k	$\beta_{sd(\ell)}$	(1)	(2)
25th quantile	.256***	.070***	.008***	.403***		
	(.054)	(.015)	(.002)	(.010)		
50th quantile	.121***	.051***	.008***	.404***		
	(.034)	(.009)	(.002)	(.008)		
75th quantile	.031	.038***	.008***	.405***		
	(.039)	(.011)	(.002)	(.010)		
100th quantile	-.127	.015	.008	.408***		
	(.112)	(.024)	(.005)	(.021)		
Fe	.149***	.055***	.008***	.404***	.324	.793
	(.031)	(.010)	(.002)	(.007)		

*Significance level at * ($p<0.05$), ** ($p<0.01$), *** ($p<0.001$). Standard error in parentheses. Analysis at 3-digit U.S. 2017 NAICS industries in 2003-2022 on $N = 1240$ observations. The Fixed Effects (Fe) regression is of the form $y\left(log(w_{s,t}) \mid \mathcal{X}_{i,t}, \mathcal{V}_{j,t}\right) = \beta_C + \beta_i \mathcal{X}_{i,t} + \delta_j \mathcal{V}_{j,t} + u_t$, with $i = k, \ell$, and $\mathcal{V}_j$ being a set of controls. Analogously, the conditional quantile regressions are then $\mathcal{Q}_\omega\left(log(w_{s,t}) \mid \mathcal{X}_{i,\omega t}, \mathcal{V}_{j,\omega t}\right) = \beta_{i,\omega}\mathcal{X}_{i,\omega t} + \delta_{j,\omega}\mathcal{V}_{j,\omega t} + u_{\omega t}$, where ω represents each quantile (defined on the independent variable). Variables are all in log or sd format Constant not reported to save space, while quantile regressions do not have the constant term. Source: BEA, BLS and own calculations.*

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Who drives increasing inequality?

- Industry $s \in \mathcal{S}$ contribution to wage inequality can be written as

$$\underbrace{\Delta\, var\left(w(s) - \overline{w}\right)}_{\substack{\text{between-industry} \\ \text{variance growth}}} = \sum_{s=1}^{\mathcal{S}} \overbrace{\Delta \underbrace{\left(\frac{\ell(s)}{\ell}\right)}_{\substack{\text{employment} \\ \text{share}}} \underbrace{\left(w(s) - \overline{w}\right)^2}_{\substack{\text{relative} \\ \text{wage}}}}^{\substack{\text{industry } s \text{ contribution to} \\ \text{between-industry variance}}} \tag{A.2}$$

- What portion of growth can be attributed to industry factors? *Shift-share analysis*

$$\underbrace{\Delta\left(\frac{\ell(s)}{\ell}\right)\left(w(s) - \overline{w}\right)^2}_{\substack{\text{industry-}s\text{ contribution to} \\ \text{between-industry variance}}} = \underbrace{\overline{\left(w(s) - \overline{w}\right)^2}\,\Delta\left(\frac{\ell(s)}{\ell}\right)}_{\text{shift share: employment}} + \underbrace{\overline{\left(\frac{\ell(s)}{\ell}\right)}\,\Delta\left(w(s) - \overline{w}\right)^2}_{\text{shift share: wage}} \tag{A.3}$$

➔ relative importance of wage $(w(s))$ changes vs. employment share $(\ell(s))$ changes

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Table A.8: Contribution to between-industry wage variance

				share	*shift-share*	
contribution	*industries*	*variance*		*employment*	*wage*	*employment*
$> 5\%$	3	.26	54%	8%	90%	10%
1% to 5%	7	.14	29%	18%	76%	24%
.05% to 1%	6	.05	10%	13%	124%	-24%
-.05% to .05%	46	.03	7%	61%	·	
quantiles						
0-25	15	.24	50%	31%	91%	9%
25-50	16	.04	8%	28%	77%	23%
50-75	16	.02	4%	15%	·	
75-100	15	.18	38%	26%	98%	2%

Estimates are referred to eq. (A.2) for 3-digit U.S. 2017 NAICS industries. The last two columns report a quantification of the components in eq. (A.3); not reported estimates '·' imply that the shift-share for employment is highly less than zero. Operator Δ in the equations is $x_t - x_{t-1}$, and not a percentage change. Industries are grouped according to their own contribution to between-industry wage inequality in the first part of the table while, in the second part, grouping follows the overall percentage change in real log-wage per capita of each industry. Source: BEA and own calculations.

Decomposing total change in variance of real *log*-wages

Total rise in wage inequality can be written also as

$$\underbrace{\Delta\,\widetilde{var}\left(w_{s,t}-\overline{w}_t\right)}_{\text{total, wages}} = \underbrace{\left(\frac{\ell_{g,0}}{\ell_0}\right)\left[\Delta\,\widetilde{var}\left(w_{s\in g,t}-\overline{w}_{g,t}\right)\right]}_{\text{within-group, wages}} + \underbrace{\sum_g\left[\Delta\,\widetilde{var}\left(\ell_{s,t}-\overline{\ell}_{g,t}\right)\right]\widetilde{var}\left(w_{s,0}-\overline{w}_{g,0}\right)}_{\text{between-groups, employment}}$$

$$+\underbrace{\sum_g\left[\Delta\,\widetilde{var}\left(w_{s,t}-\overline{w}_{g,t}\right)\right]\left[\Delta\,\widetilde{var}\left(\ell_{s,t}-\overline{\ell}_{g,t}\right)\right]}_{\text{between-groups, interaction}}$$

$$+\underbrace{\underbrace{\sum_{\mathcal{G}/g}\left(\frac{\ell_{\mathcal{G},0}}{\ell_0}\right)\left[\Delta\,\widetilde{var}\left(w_{s,t}-\overline{w}_{\mathcal{G},t}\right)\right]}_{\text{within-other groups, wages}} + \underbrace{\sum_g\left[\Delta\left(\frac{\ell_{g,t}}{\ell_t}\right)\widetilde{var}\left(\overline{w}_{g,t}-\overline{w}_t\right)\right]}_{\text{between groups, wages}}}_{\text{residual}} \tag{A.4}$$

where industries are partitioned in $g \in \mathcal{G}$ groups, and variances are *employment-weighted*. Estimates are presented in Table A.9

Quantifying variance group decomposition

Table A.9: Decomposition of the rise in wage inequality

	industry group g				
	(1)	(2)	(3)	(4)	(5)
share of the increase, wage variance	*tails*	*middle*	*services*	*manuf.*	*other*
rising variance within the group	79%	32%	58%	11%	27%
employment reallocation across groups	34%	34%	17%	51%	10%
comovement (variance, employment)	7%	7%	3%	4%	5%
residual	-20%	27%	-22%	-34%	58%
total change across all industries	*100%*	*100%*	*100%*	*100%*	*100%*

Estimates of each component in eq. (A.4) for 3-digit U.S. 2017 NAICS industries between 2003 and 2022 related to $\log(w_{s,t})$. Operator Δ in the equation is $x_t - x_{t-1}$, and not a percentage change. The first row shows the share of total increase in variance due to rising variance in the group of industries; the second row shows the share due to changes in employment between that group and the other industries in the sample (employment reallocation), holding constant the change in variance in each group; the third row shows the share that is due to the cross-product of rising variance and rising employment share; the fourth row is so that the sum for each column is 100%. "tails" and "middle" are referred to overall percentage changes distribution in industry real wage per capita; "manuf." stands for manufacturing industries, while "other" does not consider services and manufacturing industries. Source: BEA and own calculations.

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Frechéting-up the household problem

- Household i of type a in firm h in industry s owns an *indirect* utility

Intertemporal

$$\mathcal{U}_h^i(a,s) = -\, log\left[\mathcal{I}^i\left(b^i, k^i(j), \mathcal{D}^i\right)\right] + log\left[w_h(a,s)\right] + \varsigma\, log\left[\frac{1}{g_h(a,s)}\right] + \wp_h^i(a,s) \quad \text{(B.1)}$$

- Idiosyncratic *productivity* in firm (h,s) is drawn once from a Frechét distribution

$$F\left(\wp^i_{h,\ldots,H}(a,1),\ldots,\wp^i_{h,\ldots,H}(a,s),\ldots,\wp^i_{h,\ldots,H}(a,S)\right) = exp\left[-\sum_s\left(\int_h \wp_h^i(a,s)\,\mathrm{d}h\right)^{-\theta}\right]$$

- Upward-sloping labour supply curve of each (a,h,s) as in eq. (1)

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Frechét distribution variability and shape parameter

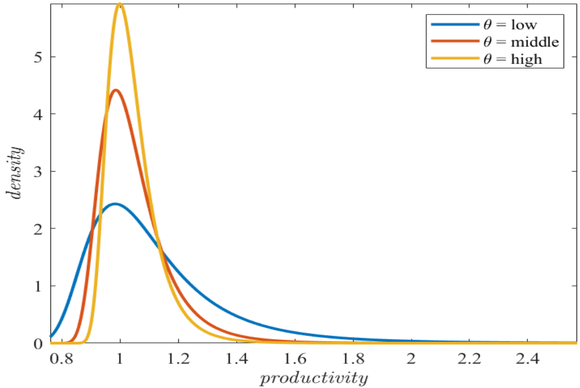
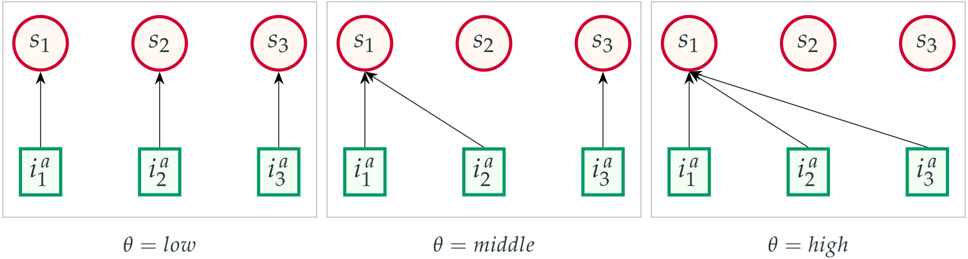


Figure B.1: Variability and the shape parameter

Go back

Productivity dispersion as a proxy of sorting and segregation

▸ Go back



- ✯ workers in the same task are "highly rival factors" (from Hicks 1932)

Household inter-temporal problem

- The problem implied by eq. (B.1) can be rewritten inter-temporally as

$$\max_{\mathcal{C}_t^i,\, b_{t+1}^i,\, \{k_{t+1}^i(j)\}_{\forall j}} \quad \mathcal{U}_{h,t}^i(a,s) = \sum_{t=0}^{\infty} \left[\beta^t\, log\left(\mathcal{C}_t^i\right)\right] + \wp_h^i(a,s)$$

$$s.t. \quad \mathcal{C}_t^i + I_t^i(phy) + I_t^i(ict) + b_{t+1}^i - (1 + r_t)\, b_t^i =$$

$$= w_{h,t}(a,s)\mathcal{B}_{h,t}(a,s)\ell_h^i(a,s) + R_t(phy)\, k_t^i(phy) + R_t(ict)\, k_t^i(ict) + \mathcal{D}_t^i$$

$$with \quad k_{t+1}^i(j) = \frac{I_t^i(j)}{\zeta_t^i} + (1 - \delta_j)\, k_t^i(j) \quad , \quad \forall j = \{phy, ict\}$$

- Optimality conditions are in order

$$\frac{1}{\mathcal{C}_t^i} = \beta^t\, (1 + r_{t+1})\, \frac{1}{\mathcal{C}_{t+1}^i}$$

$$R_t = (1 + r_{t+1})\, \zeta_t^i - (1 - \delta)\zeta_{t+1}^i \tag{B.2}$$

Go back

Final output and industry demand

- A final producer competitively combines outputs from intermediate industries $s \in \mathcal{S}$

$$Y = \left(\int_0^1 y(s)^{\frac{\eta-1}{\eta}} \, \mathrm{d}s \right)^{\frac{\eta}{\eta-1}}$$

→ resulting demand of each industry s is $y(s) = \left(\frac{p(s)}{P} \right)^{-\eta} Y$, with the aggregate price index being $P = \left(\int_0^1 p(s)^{1-\eta} \, \mathrm{d}s \right)^{\frac{1}{1-\eta}} = 1$ since final good is competitively aggregated

- Industry-level output combines outputs from firms $h \in \mathcal{H}$ in that industry

$$y(s) = \left(\int_0^1 y_h(s)^{\frac{\epsilon-1}{\epsilon}} \, \mathrm{d}h \right)^{\frac{\epsilon}{\epsilon-1}}$$

→ resulting demand of each firm (h, s) is thus $y_h(s) = \left(\frac{p_h(s)}{p(s)} \right)^{-\epsilon} y(s)$, with $p(s) = \left(\int_0^1 p_h(s)^{1-\epsilon} \, \mathrm{d}h \right)^{\frac{1}{1-\epsilon}} = 1$ since industry-level good is competitively aggregated

Go back

Production technology

- Firm h in industry s production function, $y = f\left(k^{phy}, k^{ict}, \ell^{rt}, \ell^{nrt}\right)$, is

$$y_h(s) = \left(k_h(phy,s)\right)^{\alpha}\left\{\mu\left(\ell_h(rt,s)\right)^{\varsigma} + \right.$$
$$\left. + (1-\mu)\underbrace{\left[\lambda\left(k_h(ict,s)\right)^{\varrho} + (1-\lambda)\left(\ell_h(nrt,s)\right)^{\varrho}\right]^{\frac{\varsigma}{\varrho}}}_{q_h(s)}\right\}^{\frac{1-\alpha}{\varsigma}} \quad \text{(B.3)}$$

- Elasticity indicators: $\varrho = \frac{\rho-1}{\rho}$ and $\varsigma = \frac{\sigma-1}{\sigma}$
  - capital-task complementarity requires that $\sigma > \rho$
  - parameters are all industry-specific

Go back

Firm problem

- The problem of firm h in industry s is

$$\max_{p_h(s),\{k_h(j,s)\}_{\forall j},\{w_h(a,s)\}_{\forall a}} p_h(s)y_h(s) - \left(\sum_j R(j)\, k_h(j,s) + \sum_a w_h(a,s)\, \ell_h(a,s)\right)$$

$$s.t. \quad y_h(s) = \left(\frac{p_h(s)}{p(s)}\right)^{\epsilon} y(s)$$

- Optimality conditions for capital types are in order

$$\begin{aligned} k_h\,(phy,s) &: p_h(s)F_{k_h(phy,s)} = \mathcal{M}R(phy) \\ k_h\,(ict,s) &: p_h(s)F_{k_h(ict,s)} = \mathcal{M}R(ict) \end{aligned} \tag{B.4}$$

$\longleftrightarrow$ pivotal to estimate the elasticities combination (ρ, σ) as given by eqs. (8.1)-(8.2)

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Optimal wages

- Optimal wages for *routine* and *non-routine* workers in industry s are, respectively,

$$w(rt,s) = \left[\Lambda(s)\,\chi(rt,s)\,\Big(k(phy,s)\Big)^{\alpha}\,\mathcal{Y}^{\frac{1-\alpha-\varsigma}{\varsigma}}\,\mathcal{B}(rt,s)^{\theta(\varsigma-1)}\,\mathcal{WB}(rt,\mathcal{S})^{\theta(1-\varsigma)}\right]^{\frac{1}{1+\theta-\theta\varsigma}}$$

$$w(nrt,s) = \left[\Lambda(s)\,\chi(nrt,s)\,\Big(k(phy,s)\Big)^{\alpha}\,\mathcal{Y}^{\frac{1-\alpha-\varsigma}{\varsigma}}\,\mathcal{Q}^{\frac{\varsigma-\varrho}{\varrho}}\,\mathcal{B}(nrt,s)^{\theta(\varrho-1)}\,\mathcal{WB}(nrt,\mathcal{S})^{\theta(1-\varrho)}\right]^{\frac{1}{1+\theta-\theta\varrho}}$$

where $\chi(rt,s) = (1-\alpha)\mu$ and $\chi(nrt,s) = (1-\alpha)(1-\mu)(1-\lambda)$, $\Lambda(s) = p(s)\,\mathcal{M}^{-1}$, and $w(s) = (\mathcal{A})^{-1}\sum_a w(a,s)$

→ Why do industry and firm levels coincide? ▸ Proposition ▸ Max-Stability

▸ Go back ▸ Validation: Wage ▸ Validation: Employment

Why do industry and firm levels coincide? ▸ Go back

- Firms within an industry are *homogeneous* (or *symmetric*)
- Given the labour supplies (eq. (1)) related to assumed productivity distribution, it can be proven that ▸ Proposition
  - → flexible movement of workers among firms in an industry implies a unique wage level
- More, the *max-stability property* of the *Frechét* distribution ensures that a worker, once choosing a workplace, will not move across industries ▸ Max-Stability

Why do industry and firm levels coincide?

Proposition 1 (Firm and industry layers)

In an economy characterized by a monopsonistic environment where the measure of workers in a given firm is mainly determined by its wage relative to the others, as long as

(a) *firms within an industry have the same size; or*

(b) *workers are perfectly mobile across firms within an industry,*

$$\frac{\partial \ell_h(a,s)}{\partial w_h(a,s)} = -\frac{\partial \ell_{h'}(a,s)}{\partial w_h(a,s)} \quad \text{and} \quad \frac{\partial w_h(a,s)}{\partial \ell_h(a,s)} = \frac{\partial w_{h'}(a,s)}{\partial \ell_{h'}(a,s)},$$

profit-maximizing wages set by firms in a specific industry are equal, and thus the unique optimal wage level can be directly written under industry notation. Moreover,

(c) *workers are immobile across firms between industries.*

▸ Go back

Remark 1 (Max stability and workers' movement)

As from eq. (B.1), a worker has no incentive to choose a workplace where performing worse since

$$\mathcal{U}_h^i(a,s) \mid \wp_h^i(a,s)_{max} \; > \; \mathcal{U}_h^i(a,s) \mid \forall \, \wp_h^i(a,s) \in \left[\wp_h^i(a,s)_{min} \, , \, \wp_h^i(a,s)_{max}\right)$$

is ensured by the selection of the maximal productivity by each worker for the (h,s) tuple. In addition, since firms are homogeneous within an industry, the sorting choice is uniquely driven by the dispersion of households' productivities across industries so that workers are free to move across firms within an industry.

▸ Go back

Aggregation

(a) *Labour market*

- aggregate labour supply is $L^S = \sum_a \sum_h \sum_s \ell_h(a,s)$
- aggregate labour demand is $L^D = \sum_a \sum_h \sum_s \ell_h(a,s)$ with $\ell_h(a,s) = \int_0^1 \ell_h^i(a,s)\mathrm{d}i$

(b) *Capital market* $\rightarrow K^D(phy) + K^D(ict) = K^S(phy) + K^S(ict)$

- capital types demands: $K^D(phy) = \sum_h \sum_s k_h(phy,s)$ and $K^D(ict) = \sum_h \sum_s k_h(ict,s)$
- capital types supplies: $K^S(phy) = \int_i k^i(phy)\mathrm{d}i$ and $K^S(ict) = \int_i k^i(ict)\mathrm{d}i$

(c) Aggregating the households' inter-temporal budget constraints and imposing the clearing conditions jointly with total quantities, the *aggregate resource constraint* at time t reads, given $\mathcal{B}_t = 1$, as

$$\mathcal{C}_t + I_t(phy) + I_t(ict) + b_{t+1} - (1+r_t)b_t = w_t\mathcal{B}_t L_t + R_t\Big(K_t(phy) + K_t(ict)\Big) + \mathcal{D}_t$$

Go back

Equilibrium conditions

An equilibrium for this economy is defined as a households' choice of tasks, a combination of factors' prices, $\left(w(a,s), R(phy), R(ict)\right)$, and a set of aggregate quantities, $\Omega = \left(Y, K(phy), K(ict), L(rt), L(nrt)\right)$ such that

(a) each household picks the firm-industry tuple that maximizes eq. (B.1);

(b) according to the occupational choice, each household maximizes its expected-utility version of the utility in eq. (B.1);

(c) final and sectoral good producers maximize their revenues;

(d) given the availability of workers in each job task as in eq. (1), optimal wages are determined by the equilibrium of labour demand and supply;

(e) firms choose also capital bundles to maximize their profits;

(f) all markets clear, shaping $\Omega\left(\cdot\right)$.

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Validating the wage equation

- Relevance of labour force composition on the industry-specific wage level

Table C.1: Industry wage and relative task size

	$log(w_{s,t})$		
	(1)	(2)	(3)
$\ell(rt/nrt)$	.016*** (.006)	.001 (.007)	-.020*** (.002)
$\ell(nrt/rt)$	.129*** (.036)	.250*** (.084)	.318*** (.043)
Industry FE	✓	✓	✗
Time FE	✗	✓	✗

*Significance level at * (p<0.05), ** (p<0.01), *** (p<0.001). Standard error in parentheses. Analysis at 3-digit U.S. 2017 NAICS industries in 2003-2022 on N = 1240 observations. The Fixed Effects (Fe) regressions are of the form* $(y \mid \mathcal{X}_{i,t}, \mathcal{V}_{j,t}) = \beta_c + \beta_i \mathcal{X}_{i,t} + \delta_j \mathcal{V}_{j,t} + u_t$, *with* $\mathcal{X}_i$ *being the regressors, and* $\mathcal{V}_j$ *a set of controls. All series are in logs. Constant not reported to save space. Source: BEA, BLS and own calculations.*

Go back

Validation: Employment

Validating the labour supply equation

- Relevance of relative wages on the industry-specific measures of worker types

Table C.2: Employment measures and tasks relative wages

	$log(\ell(rt,s))$			$log(\ell(nrt,s))$		
	(1)	(2)	(3)	(1)	(2)	(3)
$\ell(rt,s \mid w\mathcal{B})$	.765*	.657*	3.55***			
	(.32)	(.28)	(.17)			
$\ell(nrt,s \mid w\mathcal{B})$				5.76***	3.71***	29.4***
				(1.9)	(1.1)	(2.2)
Industry FE	✓	✓	✗	✓	✓	✗
Time FE	✗	✓	✗	✗	✓	✗

*Significance level at * ($p<0.05$), ** ($p<0.01$), *** ($p<0.001$). Standard error in parentheses. Analysis at 3-digit U.S. 2017 NAICS industries in 2003-2022 on $N = 1240$ observations. All the regressions are of the form $(y \mid \mathcal{X}_{i,t}, \mathcal{V}_{j,t}) = \beta c + \beta_i \mathcal{X}_{i,t} + \delta_j \mathcal{V}_{j,t} + u_t$, with $\mathcal{X}_i$ being the regressors, and $\mathcal{V}_j$ a set of controls. All series are in logs. Constant not reported to save space. Source: BLS and own calculations.*

Elasticities of substitution ▸ Go back

- A key implication of the *data* section is the divergence in elasticities of substitution
  - ☞ identification: ***negative relationship between labour share and relative ICT stock*** ▸ Figure
- Estimating equations (labour share *given* relative capital quantities):

$$\frac{s_\ell(nrt,s)}{1-s_\ell(nrt,s)}\widehat{s}_\ell(nrt,s)=\beta_c+(\rho-1)\,\widehat{\zeta}\,(s)+u \tag{8.1}$$

$$\frac{s_\ell(s)}{1-s_\ell(s)}\widehat{s}_\ell(s)=\beta_c+(\sigma-1)\,\widehat{\zeta}\,(s)+\beta_k\left(\frac{\widehat{\ell(nrt,s)}}{k(ict,s)}\right)+u \tag{8.2}$$

  - *note*: estimates of the following regressions are not $\beta_\zeta^{(\rho,\sigma)}=([\rho,\sigma]-1)\;\cdots$

    $\cdots$ but rather actual coefficients are $\beta_\zeta^{(\rho,\sigma)}=[\rho,\sigma]$

▸ Derivation ▸ Estimates

Derivation of estimating equations

- Method of Karabarbounis and Neiman (2014). Steps:

1. define a CES production function, $y(\cdot)$ and compute the related F.O.C.s. Equate them to the aggregated F.O.C.s of the intermediate monopolistically competitive industries;
2. define the following *income shares*. For a given labour force, ℓ and a given capital, k,

$$s_\ell = \left(\frac{1}{\mathcal{M}}\right)\left(\frac{w(\ell)\ell}{w(\ell)\ell + Rk}\right) \quad , \quad s_k = \left(\frac{1}{\mathcal{M}}\right)\left(\frac{Rk}{w(\ell)\ell + Rk}\right) \quad , \quad s_\pi = 1 - \frac{1}{\mathcal{M}}$$

3. by combining the F.O.C. for capital (either for labour) with all the above shares, one gets an equation whose left-hand side is $1 - s_\ell \mathcal{M}$. This should be then written in changes between two arbitrary periods, where changes in each element are $\widehat{x}$;
4. use eq. (B.2) to substitute $\widehat{R}$;
   - ⋆ From the Euler get $\widehat{(1+r)} = \frac{1}{\beta}$ so that, under constant β and δ, it holds that $\widehat{R} = \widehat{\zeta}$;
5. once substituting out $\widehat{R}$, take a linear approximation of the resulting equation around $\widehat{\zeta} = 0$, thus obtaining the estimating equation.

▸ Go back

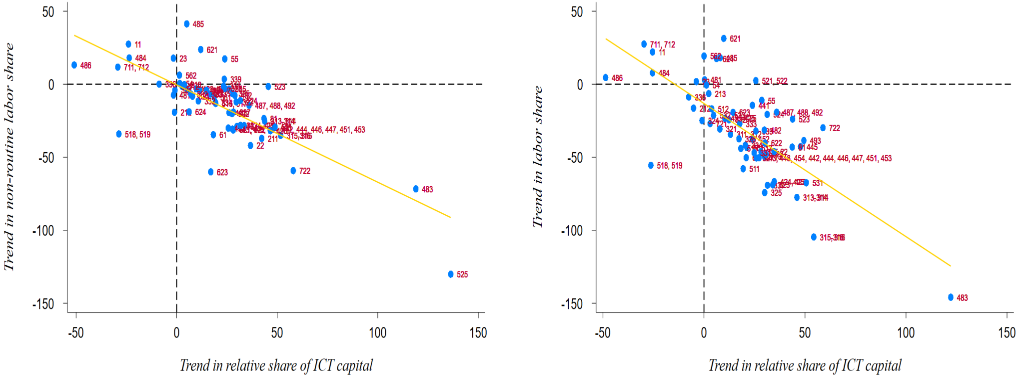
Table C.3: Baseline estimation

	β^{ρ}_{ζ}	*Std.Err.*	*95% CI*	β^{σ}_{ζ}	*Std.Err.*	*95% CI*	*Ind.*
bottom	.329	.04	[.250, .407]	.634	.08	[.482, .785]	16
middle	.420	.02	[.375, .466]	.400	.05	[.310, .491]	31
top	.249	.03	[.188, .310]	.766	.06	[.656, .877]	15

Estimation of the elasticities of substitution as given in eqs. (8.1) *and* (8.2)*, for 3-digit U.S. 2017 NAICS industries.* $\widehat{\rho}$ *refers to the estimate of the pair* $\left(\ell_s^{nrt}\,;\,k_s^{ict}\right)$*, and it exploits the degree of substitutability between non-routine workers and ICT capital;* $\widehat{\sigma}$ *relates to the pair* $\left(\ell^{rt}\,;\,\left[\ell_s^{nrt},\,k_s^{ict}\right]\right)$*, and it is the degree of substitutability between routine workers and the joint combination of non-routine workers and ICT capital. "Ind." is the number of industries in each group.*

▸ Go back

Negative relationship



(a) Estimates for ρ, $corr_{\rho}$ = -0.76 (b) Estimates for σ, $corr_{\sigma}$ = -0.75

Figure C.1: Correlation between elasticities and relative ICT capital

Table C.4: Time-varying estimation

	2003-2012		2013-2022		
	β_ζ^ρ	β_ζ^σ	β_ζ^ρ	β_ζ^σ	*ind.*
bottom	.355 [.12]	.366 [.12]	.819 [.05]	.326 [.06]	16
middle	.431 [.04]	.429 [.08]	.345 [.04]	.438 [.09]	31
top	.408 [.04]	.367 [.12]	.508 [.06]	.358 [.05]	15

Estimation of the elasticities of substitution as given in eqs. (8.1) and (8.2) over different time span (2003-2012 and 2013-2022), in absolute values, for 3-digit U.S. 2017 NAICS industries. Standard errors in parenthesis, [·], and 95% confidence interval significant but not reported. $\widehat{\rho}$ refers to the estimate of the pair $(\ell_s^{nrt}\,;\,k_s^{ict})$, and it exploits the degree of substitutability between non-routine workers and ICT capital; $\widehat{\sigma}$ relates to the pair $(\ell^{rt}\,;\,[\ell_s^{nrt}, k_s^{ict}])$, and it is the degree of substitutability between routine workers and the joint combination of non-routine workers and ICT capital. "ind." is the number of industries in each group.

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Targeting moments for MSM

① Share parameters, λ and μ

- λ is matched with the industry-specific ICT capital in the aggregate stock;
- the weight of routine workers (μ) is used to bridge the share of routine workers in the data with that predicted by the model, *i.e.*, I implement the following identity

$$\ell_{model}(a,s) = \left(\frac{w(a,s)}{\mathcal{W}(a,\mathcal{S})} \frac{\mathcal{B}(a,s)}{\mathcal{B}(a,\mathcal{S})} \right)^{\theta} \approx \ell_{data}(a,s)$$

② Households' productivities dispersion parameter, θ

- it directly relates to the *between-industry* wage difference for worker-a: *wage premium* of type-rt working in *top* industry (s) relative to its counterpart in the *bottom* industry (s'):

$$\frac{w(rt,s)}{w(rt,s')} = \frac{\left[\Lambda(s)\,\chi(rt,s)\,\big(k(phy,s)\big)^{\alpha(s)}\,\mathcal{Y}(s)^{\frac{1-\alpha(s)-\varsigma(s)}{\varsigma(s)}}\,\mathcal{B}(rt,s)^{\theta[\varsigma(s)-1]}\,\mathcal{WB}(rt,\mathcal{S})^{\theta[1-\varsigma(s)]} \right]^{\frac{1}{1+\theta-\theta\varsigma(s)}}}{\left[\Lambda(s')\,\chi(rt,s')\,\big(k(phy,s')\big)^{\alpha(s')}\,\mathcal{Y}(s')^{\frac{1-\alpha(s')-\varsigma(s')}{\varsigma(s')}}\,\mathcal{B}(rt,s')^{\theta[\varsigma(s')-1]}\,\mathcal{WB}(rt,\mathcal{S})^{\theta[1-\varsigma(s')]} \right]^{\frac{1}{1+\theta-\theta\varsigma(s')}}}$$

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MSM ESTIMATES

- Vector $\tilde{\Theta} = \{\lambda_s , \mu_s , \theta\}$ to match key moments of the production structure

$\longleftrightarrow$ minimize the *loss function* $\mathcal{L}(\tilde{\Theta}) = \left(\hat{m}(\tilde{\Theta}) - \tilde{m}\right)' \mathbf{W} \left(\hat{m}(\tilde{\Theta}) - \tilde{m}\right)$ to estimate $\tilde{\Theta}$

Table C.5: Method of Simulated Moments, results

	parameter	*value*	***moment to match***	*fit* data	*fit* model
μ_{bot}	weight of routines in $y(bot)$	0.6763	routine share, bottom	.0858	.0434
μ_{mid}	weight of routines in $y(mid)$	0.4953	routine share, middle	.1357	.0458
μ_{top}	weight of routines in $y(top)$	0.3366	routine share, top	.0985	.0199
λ_{bot}	weight of ICT in $Q(bot)$	0.4565	ICT share, bottom	.3968	.3968
λ_{mid}	weight of ICT in $Q(mid)$	0.4645	ICT share, middle	.3042	.3042
λ_{top}	weight of ICT in $Q(top)$	0.4514	ICT share, top	.2990	.2990
θ	productivity dispersion	11.302	wage premium, $w(a, [s, s'])$	.9945	.9945

Estimated values and related matched moment using the Methods of Simulated Moments by McFadden1989.

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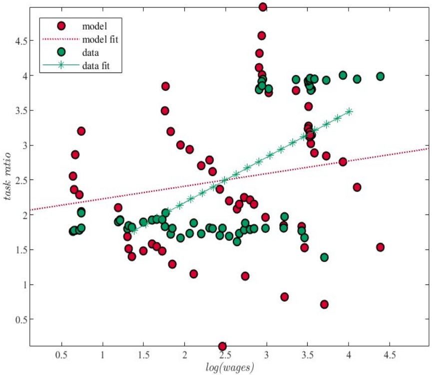
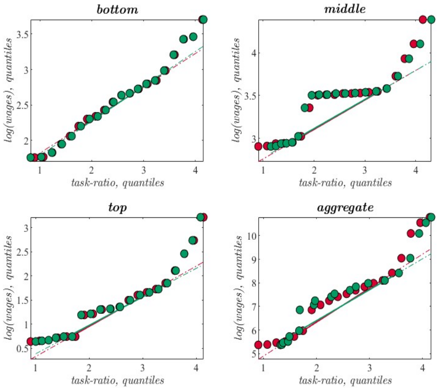


(a) Task Ratio vs. Wages



(b) Quantiles

Figure C.2: Model and data comparison

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Steady-state discussion: implied variances

Table C.6: Implied fit of wage variances

moment	*data*	*model*
routine wage variance, across industries	2.285	2.289
non-routine wage variance, across industries	2.314	2.311
between-industry wage variance	2.299	2.300

Comparison of the model fitting against data for moments related to 3-digit U.S. 2017 NAICS between-industry real log wage variance structure over the period 2003-2022; variances are computed according to eq. (A.2). The first two rows compute this measure for routine and non-routine tasks, while the last row directly reports the wage dispersion across industries.

▸ Go back, calibration strategy ▸ Go back, calibration

Steady-state discussion: untargeted moments

Table C.7: Model fit, untargeted moments

moment	*fit*	
	data	*model*
aggregate task-premium	.001	.005
aggregate wage	-.008	-.073
routine wage, bottom	-.016	-.070
routine wage, middle	-.001	-.051
routine wage, top	-.007	-.079
non-routine wage, bottom	-.019	-.060
non-routine wage, middle	.003	-.074
non-routine wage, top	-.010	-.046

Untargeted moments to match to validate the calibration strategy. All moments, referred to real log-wages, are taken as percentage changes throughout the series.

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Steady-state correlations

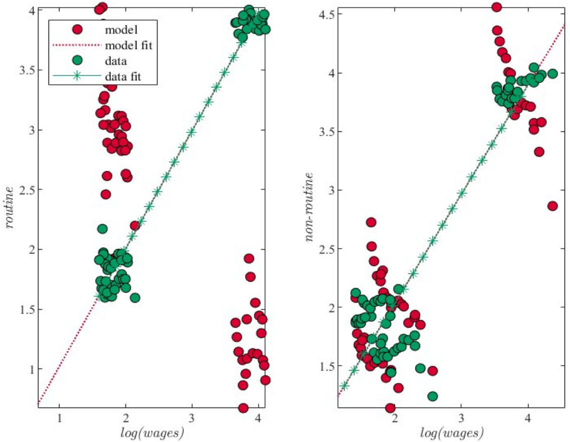
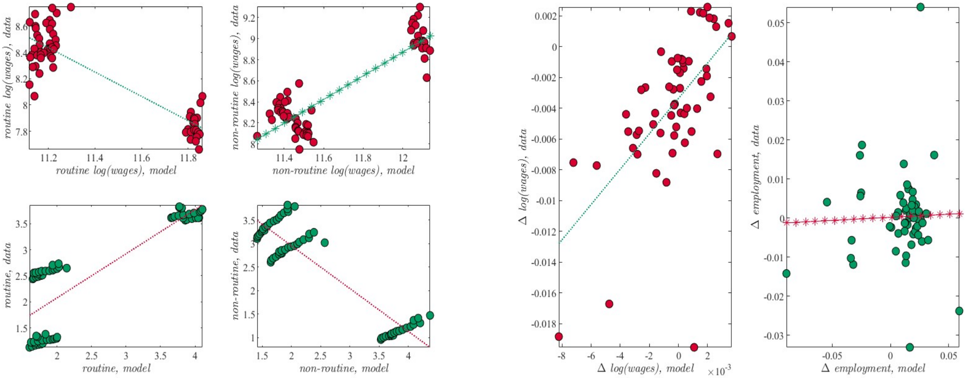


Figure C.3: Model and data comparison (1/3)

Go back

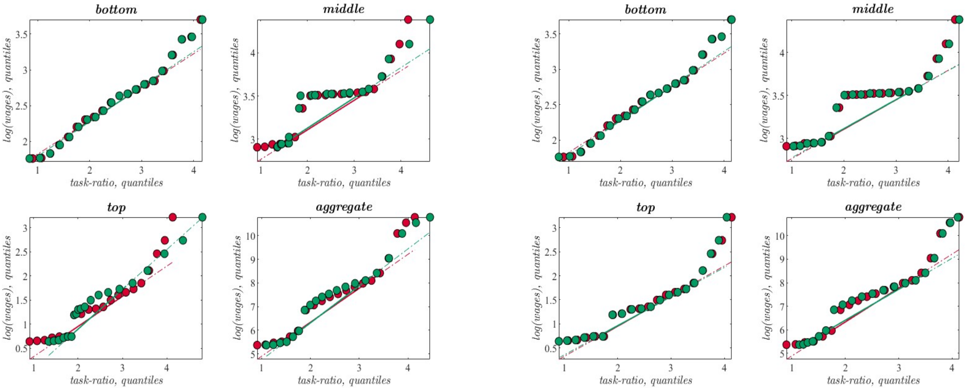


(a) Various series

(b) Changes

Figure C.4: Model and data comparison (2/3)

Go back



(a) Routines, quantiles

(b) Non-routines, quantiles

Figure C.5: Model and data comparison (3/3)

Steady-state real *log*-wages

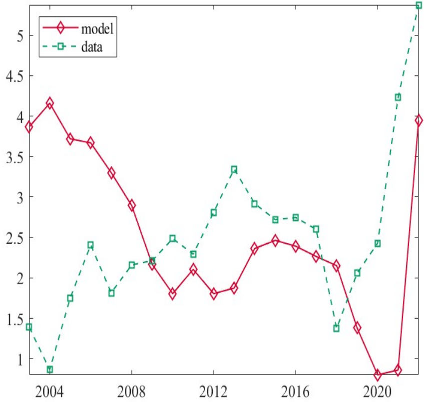


Figure C.6: Top-bottom real *log*-wage ratio, model vs. data

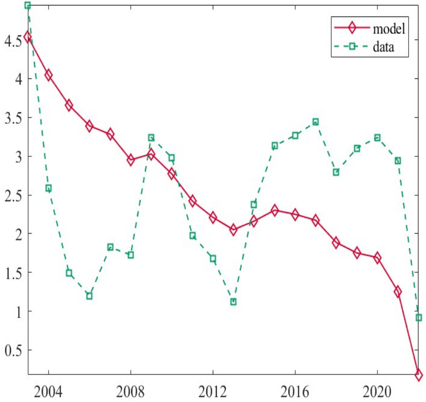


Figure C.7: Real *log*-wage series, model vs. data (1/3)

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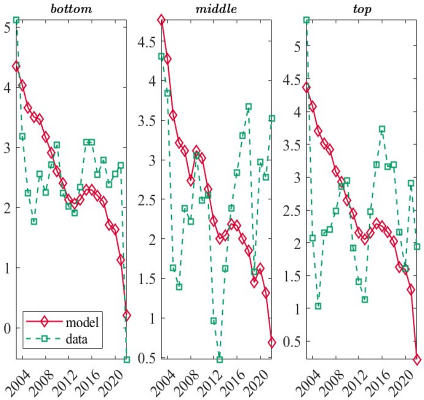
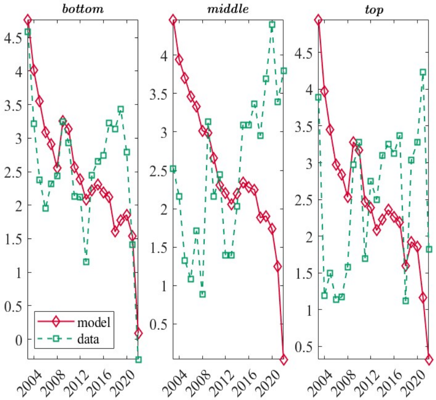
Steady-state real *log*-wages



(a) Wages, routines



(b) Wages, non-routines

Figure C.8: Wage series, model vs. data (2/3)

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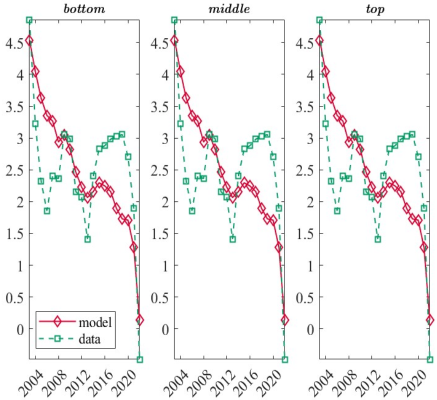
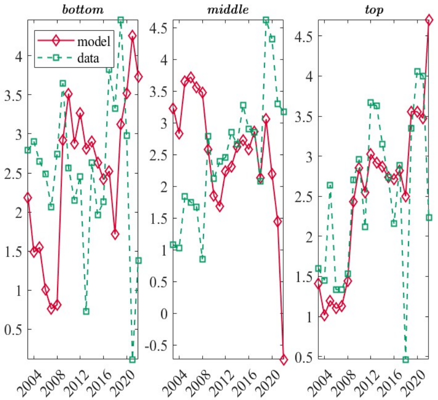
STEADY-STATE REAL *log*-WAGES



(a) Wages, industry groups



(b) Task premium

Figure C.9: Wage series, model vs. data (3/3)

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Herfindahl-Hirschman Index (HHI)

- The *Herfindahl-Hirschman Index* (HHI) is computed to account for market concentration of labour force at the industry level
- Market-level concentration for task-a is defined as

$$HHI_{\ell(a)} = \sum_{s_{|g}} \left(\frac{\ell(a, s_{|g})}{\ell(a)} \right)^2$$

  where the sum is over individual industries (s), or over a group of industries $\left(s_{|g}\right)$
- Total employment concentration is defined by $HHI_{\ell} = \sum_a HHI_{\ell(a)}$
- The index is $HHI \in [0, 1]$:
  - a value of 1 identifies maximum market concentration, a single monopsonist;
  - conversely, a value of 0 results in a perfectly competitive environment.

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(a) Bottom **(b)** Middle **(c)** Top

Figure C.10: Market concentration by groups of industries

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Table C.8: Method of Simulated Moments, splitting results

	moment to match	2003-2012 *value*	2003-2012 *data*	2003-2012 *model*	2013-2022 *value*	2013-2022 *data*	2013-2022 *model*
μ_{bot}	routine share, bottom	0.196	0.087	0.097	0.415	0.085	0.051
μ_{mid}	routine share, middle	0.486	0.132	0.057	0.506	0.140	0.030
μ_{top}	routine share, top	0.902	0.100	0.013	0.608	0.097	0.083
λ_{bot}	ICT share, bottom	0.650	0.399	0.399	0.786	0.395	0.395
λ_{mid}	ICT share, middle	0.530	0.314	0.314	0.490	0.295	0.295
λ_{top}	ICT share, top	0.185	0.287	0.287	0.327	0.311	0.311
θ	wage premium, $w(a,[s,s'])$	7.259	0.994	0.994	7.787	0.995	0.995

Estimated values and related matched moment using the Methods of Simulated Moments by McFadden1989 for first and second half of the sample.

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Table C.9: Model vs. data counterfactual, series

	data	***model***	***model*** $\mid \Delta\, x$				
			$\Delta\ell(rt)$	$\Delta\ell(nrt)$	$\Delta\,(\ell)$	$\Delta k(ict)$	$\Delta\,(tech)$
Wages, variance							
routine	2.285	2.289	2.55	2.42	2.24	2.78	2.45
non-routine	2.314	2.311	2.78	2.44	2.37	2.78	2.39
industry	2.299	2.300	2.66	2.43	2.30	2.78	2.42

Changes in variances in real log-wages in the model induced by variations in one or more series, keeping fixed the others, and imposing the parameters to be that in the full baseline calibration. $\Delta\,(\ell)$ *refers to joint variations in routine and non-routine series, while* $\Delta\,(tech)$ *is associated to simultaneous changes in both ICT capital and non-routine workers.*

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Model vs. data counterfactual, levels

Table C.10: Model vs. data counterfactual, levels

			model $\mid \Delta\, x(j)_{\in\Theta}$				
	data	***model***	$\Delta\sigma$	$\Delta\rho$	$\Delta\,(\sigma,\rho)$	$\Delta\theta$	$\Delta\,(all)$
Wages, level $(\Delta_{\%})$							
routine	-.008	-.067	-.031	-.033	-.031	-.033	-.032
non-routine	-.007	-.061	-.030	-.029	-.029	-.031	-.030
industry	-.007	-.067	-.031	-.032	-.031	-.033	-.031
bottom	-.017	-.065	-.030	-.031	-.030	-.032	-.031
middle	.001	-.070	-.032	-.033	-.031	-.034	-.032
top	-.006	-.065	-.031	-.032	-.031	-.032	-.031
Employment, level $(\Delta_{\%})$							
routine	.006	.087	.055	.058	.055	.057	.054
non-routine	.025	.061	.044	.042	.044	.041	.043
industry	.018	.074	.051	.053	.051	.052	.051

Changes in key moments of real log-wages and nominal employment measures in the model induced by an exogenous variation (which is assumed to be homogeneous across groups of industries) in a specific parameter; such shift is computed at the initial period, so that the change identifies the transition from the initial (2003) to the final (2022) steady state level. In the first two columns, the variation is computed throughout the period-by-period percentage differential thus identifying overall changes in empirical trends implied both by the data and the model, while the last three columns are just the percentage difference between the two steady states.

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Table C.11: Model vs. data counterfactual, parameters

	data	model	$\Delta\sigma$	$\Delta\rho$	$\Delta(\sigma,\rho)$	$\Delta\theta$	$\Delta(all)$
			model $\mid \Delta x(j)_{\in\Theta}$				
Wages, variance							
routine	2.285	2.289	2.31	2.16	2.31	2.20	2.36
non-routine	2.314	2.311	2.29	2.18	2.29	2.19	2.32
industry	2.299	2.300	2.30	2.17	2.30	2.20	2.34

Changes in variances in real log-wages in the model induced by an exogenous variation (which is assumed to be homogeneous across groups of industries) in a specific parameter; such shift is computed at the initial period, so that the change identifies the transition from the initial (2003) to the final (2022) steady state level. In the first two columns, the variation is computed throughout the period-by-period percentage differential thus identifying overall changes in empirical trends implied both by the data and the model, while the last five columns are just the percentage difference between the two steady states.

▸ Go back

Models for counterfactual analysis

① Changing main parameters, fixing the others, and series over time

$$\Delta var\left(w(s)-\overline{w}\right)=f\left(\Phi_s\left(x,\tau_1\right),\Theta_s(p,\tau_1),\Phi_s\left(x,\tau_2\right)\,\middle|\,\Delta\Theta_s\left(p_{\tau_2}^{\{\rho,\sigma,\theta\}},-p_{\tau_1}\right)\right) \quad \text{(Model A)}$$

② Fixing main parameters, changing the others, and series over time

$$\Delta var\left(w(s)-\overline{w}\right)=f\left(\Phi_s\left(x,\tau_1\right),\Theta_s(p,\tau_1),\Phi_s\left(x,\tau_2\right)\,\middle|\,\Delta\Theta_s\left(p_{\tau_2},-p_{\tau_1}^{\{\rho,\sigma,\theta\}}\right)\right) \quad \text{(Model B)}$$

③ Fixing all parameters, and changing one or more series over time

$$\Delta var\left(w(s)-\overline{w}\right)=f\left(\Phi_s\left(x,\tau_1\right),\Delta\Phi_s\left(x_{\tau_2},-x_{\tau_1}\right)\,\middle|\,\Theta_s\left(p,\tau_1\right)\right) \quad \text{(Model C)}$$

④ Impose same parameters, fixing them, and changing one or more series over time

$$var\left(w(s)-\overline{w}\right)=f\left(\Delta\Phi_s\left(x\right),\Phi_s\left(-x,\tau_0\right)\,\middle|\,\Theta_{=\forall s}\left(p\right)\right) \quad \text{(Model D)}$$

▸ Go back

Model re-calibration counterfactual, change

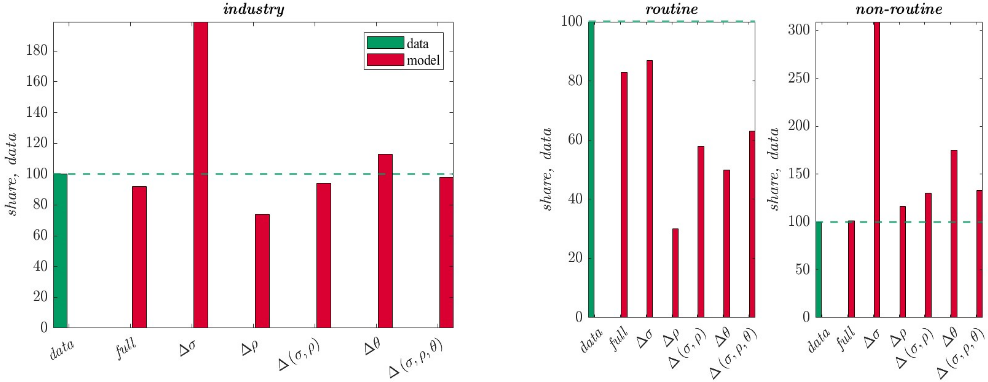

Figure C.11: Impact on between-industry wage inequality

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Model re-calibration counterfactual, fixing c

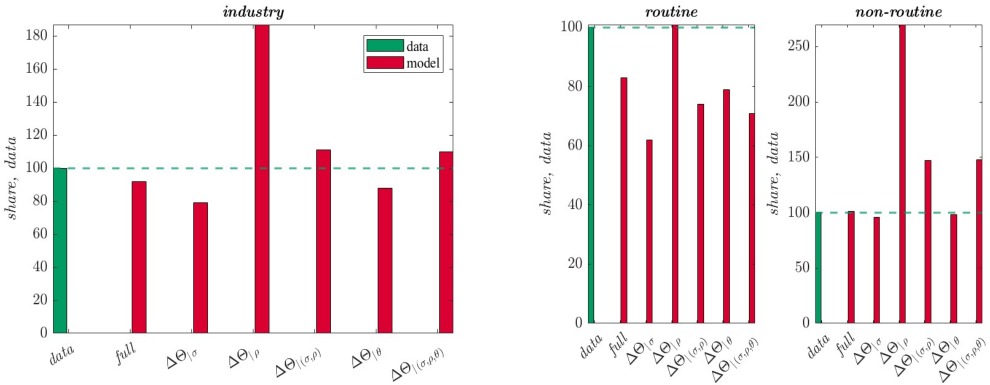

Figure C.12: Impact on between-industry wage inequality

▸ Go back

- Between-industry real *log*-wage variance if only a specific parameter changes from period 1 to period 2, keeping the remaining parameters fixed at their initial level

Table C.12: Model counterfactual, change

		Δ ***model*** $\mid \Delta\, m\left(\Phi(x,\tau_2), \Theta = \{p_{\tau_2}, -p_{\tau_1}\}\right)$		
industry wages	$var(w)_{p_2}$	*level*	*share, model*	*share, data*
Data	1.18			
Model	1.09			
$\Delta\sigma$		2.37	2.18	1.99
$\Delta\rho$		.88	.81	.74
$\Delta(\sigma,\rho)$		1.12	1.03	.94
$\Delta\theta$		1.34	1.23	1.13
$\Delta(\sigma,\rho,\theta)$		1.16	1.07	.98

Quantification of Model A. Model implied between-industry real log-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to the aggregate economy considering bottom, middle, and top industries' groups.

▸ Go back

Model re-calibration counterfactual, fixing

- Between-industry real *log*-wage variance if only a specific parameter is fixed at its initial level, letting the remaining parameters to change from period 1 to period 2

Table C.13: Model counterfactual, fixing

		Δ ***model*** $\mid \Delta\, m\left(\Phi(x,\tau_2),\Theta = \{p_{\tau_2}, -p_{\tau_1}\}\right)$		
industry wages	$var(w)_{p_2}$	*level*	*share, model*	*share, data*
Data	1.18			
Model	1.09			
$\Delta\Theta_{\mid\sigma}$		.94	.87	.79
$\Delta\Theta_{\mid\rho}$		2.21	2.04	1.87
$\Delta\Theta_{\mid(\sigma,\rho)}$		1.31	1.21	1.11
$\Delta\Theta_{\mid\theta}$		1.04	.96	.88
$\Delta\Theta_{\mid(\sigma,\rho,\theta)}$		1.30	1.20	1.10

Quantification of Model B. Model implied between-industry real log-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to the aggregate economy considering bottom, middle, and top industries' groups.

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Model re-calibration counterfactual, routine change

- Between-industry routine real *log*-wage variance if only a specific parameter changes from period 1 to period 2, keeping the remaining parameters fixed at their initial level

Table C.14: Model counterfactual, routine change

		Δ ***model*** $\mid \Delta\, m\left(\Phi(x,\tau_2),\Theta=\{p_{\tau_2},-p_{\tau_1}\}\right)$		
routine wages	$var(w)_{p_2}$	*level*	*share, model*	*share, data*
Data	1.14			
Model	.95			
$\Delta\sigma$		.99	1.04	.87
$\Delta\rho$		.35	.37	.30
$\Delta(\sigma,\rho)$		.66	.70	.58
$\Delta\theta$		.57	.60	.50
$\Delta(\sigma,\rho,\theta)$		.71	.76	.63

Quantification of Model A. Model implied between-industry routine workers real log-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to the aggregate economy considering bottom, middle, and top industries' groups.

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- Between-industry routine real *log*-wage variance if only a specific parameter is fixed at its initial level, letting the remaining parameters to change from period 1 to period 2

Table C.15: Model counterfactual, routine fixing

		Δ ***model*** $\mid \Delta\, m\Big(\Phi(x,\tau_2), \Theta = \{p_{\tau_2}, -p_{\tau_1}\}\Big)$		
routine wages	*var*$(w)_{p_2}$	*level*	*share, model*	*share, data*
Data	1.14			
Model	.95			
$\Delta\Theta_{\mid\sigma}$		.71	.75	.62
$\Delta\Theta_{\mid\rho}$		1.15	1.22	1.01
$\Delta\Theta_{\mid(\sigma,\rho)}$		.84	.89	.74
$\Delta\Theta_{\mid\theta}$		.90	.95	.79
$\Delta\Theta_{\mid(\sigma,\rho,\theta)}$		.81	.86	.71

Quantification of Model B. Model implied between-industry routine workers real log-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to the aggregate economy considering bottom, middle, and top industries' groups.

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- Between-industry non-routine real *log*-wage variance if only a specific parameter changes from period 1 to period 2, keeping the remaining parameters fixed at their initial level

Table C.16: Model counterfactual, non-routine change

		Δ ***model*** $\mid \Delta\, m\Big(\Phi(x,\tau_2),\Theta = \{p_{\tau_2}, -p_{\tau_1}\}\Big)$		
non-routine wages	$var(w)_{p_2}$	*level*	*share, model*	*share, data*
Data	1.21			
Model	1.22			
$\Delta\sigma$		3.74	3.06	3.09
$\Delta\rho$		1.41	1.15	1.16
$\Delta(\sigma,\rho)$		1.57	1.28	1.30
$\Delta\theta$		2.11	1.73	1.75
$\Delta(\sigma,\rho,\theta)$		1.61	1.31	1.33

Quantification of Model A. Model implied between-industry non-routine workers real log-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to the aggregate economy considering bottom, middle, and top industries' groups.

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- Between-industry non-routine real *log*-wage variance if only a specific parameter is fixed at its initial level, letting the remaining parameters to change from period 1 to period 2

Table C.17: Model counterfactual, non-routine fixing

		Δ ***model*** $\mid \Delta\, m\Big(\Phi(x,\tau_2), \Theta = \{p_{\tau_2}, -p_{\tau_1}\}\Big)$		
non-routine wages	$var(w)_{p_2}$	*level*	*share, model*	*share, data*
DATA	1.21			
MODEL	1.22			
$\Delta\Theta_{\mid\sigma}$		1.16	.95	.96
$\Delta\Theta_{\mid\rho}$		3.27	2.67	2.70
$\Delta\Theta_{\mid(\sigma,\rho)}$		1.78	1.45	1.47
$\Delta\Theta_{\mid\theta}$		1.18	.97	.98
$\Delta\Theta_{\mid(\sigma,\rho,\theta)}$		1.79	1.46	1.48

Quantification of Model B. Model implied between-industry routine workers real log-wage variance changes between two time spans differently calibrated, and changes also according to variations in some parameters; values are referred to the aggregate economy considering bottom, middle, and top industries' groups.

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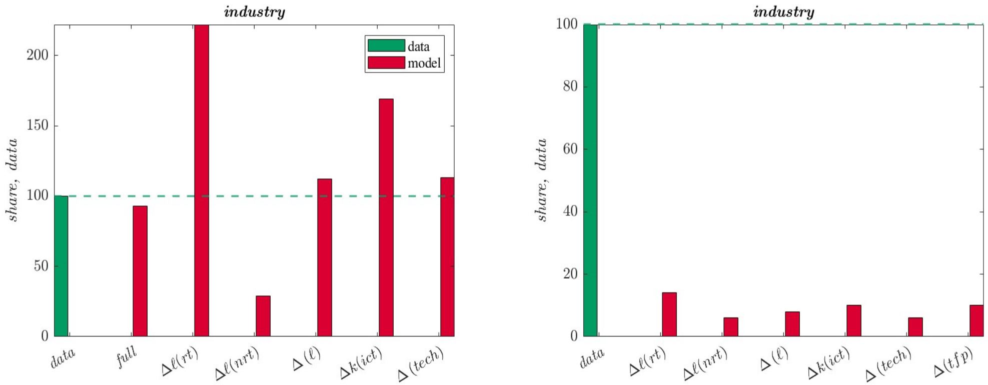

(a) Changing series, industry-specific calibration

(b) Changing series, unique calibration

Figure C.13: Impact on between-industry wage inequality

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Model re-calibration counterfactual, SBTC

- Between-industry real *log*-wage variance if only a specific series changes from period 1 to period 2, keeping the remaining parameters fixed at their initial level

Table C.18: Model counterfactual, SBTC

industry wages	$var(w)_{\tau_2}$	Δ ***model*** $\mid \Delta\, m\Big(\Phi = \{x_{\tau_2}, -x_{\tau_1}\}\ \Big\vert\, \Theta(p,\tau_1)\Big)$ *level*	*share, model*	*share, data*
Data	1.18			
Model	1.09			
$\Delta\ell(rt)$		2.62	2.42	2.22
$\Delta\ell(nrt)$		.35	.32	.29
$\Delta\ell$		1.32	1.22	1.12
$\Delta k(ict)$		1.99	1.84	1.69
$\Delta(\ell, ict)$		1.34	1.23	1.13

Quantification of Model C. Model implied between-industry routine workers real log-wage variance changes between two time spans uniformly calibrated, with changes according to variations in some series; values are referred to variance levels considering bottom, middle, and top industries.

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MODEL RE-CALIBRATION COUNTERFACTUAL, ROUTINE SBTC

- Between-industry routine real *log*-wage variance if only a specific series changes from period 1 to period 2, keeping the remaining parameters fixed at their initial level

Table C.19: Model counterfactual, routine SBTC

		Δ ***model*** $\mid \Delta\, m\left(\Phi = \{x_{\tau_2}, -x_{\tau_1}\} \,\middle|\, \Theta(p, \tau_1)\right)$		
routine wages	$var(w)_{\tau_2}$	*level*	*share, model*	*share, data*
DATA	1.14			
MODEL	.95			
$\Delta\ell(rt)$		1.21	1.28	1.06
$\Delta\ell(nrt)$		.20	.21	.18
$\Delta\ell$		.56	.59	.49
$\Delta k(ict)$		.86	.91	.75
$\Delta(\ell, ict)$		.53	.56	.47

Quantification of Model C. Model implied between-industry routine workers real log-wage variance changes between two time spans uniformly calibrated, with changes according to variations in some series; values are referred to variance levels considering bottom, middle, and top industries.

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- Between-industry non-routine real *log*-wage variance if only a specific series changes from period 1 to period 2, keeping the remaining parameters fixed at their initial level

Table C.20: Model counterfactual, non-routine SBTC

		Δ ***model*** $\mid \Delta\, m\left(\Phi = \{x_{\tau_2}, -x_{\tau_1}\} \,\middle|\, \Theta(p, \tau_1)\right)$		
non-routine wages	$var(w)_{\tau_2}$	*level*	*share, model*	*share, data*
DATA	1.21			
MODEL	1.22			
$\Delta\ell(rt)$		4.04	3.30	3.34
$\Delta\ell(nrt)$		.50	.40	.41
$\Delta\ell$		2.09	1.70	1.73
$\Delta k(ict)$		3.13	2.56	2.59
$\Delta(\ell, ict)$		2.14	1.75	1.77

Quantification of Model C. Model implied between-industry non-routine workers real log-wage variance changes between two time spans uniformly calibrated, with changes according to variations in some series; values are referred to variance levels considering bottom, middle, and top industries.

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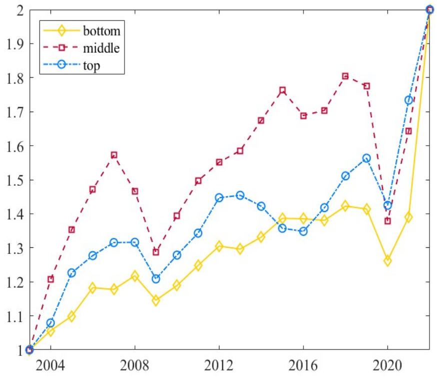
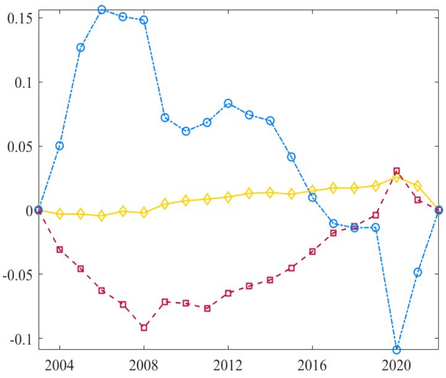


(a) Unique calibration, mean



(b) Difference with baseline

Figure C.14: Estimated productivities

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Model re-calibration counterfactual, series

- Between-industry real *log*-wage variance if only a specific series (or a combination) changes over time, keeping the remaining parameters fixed at their initial level, given the same (***mean***) calibration across industries

Table C.21: Model counterfactual, series

		model $\mid \Delta\,\Phi(x)$						
							$\Delta\,(tfp)$	
	data	$\Delta\ell(rt)$	$\Delta\ell(nrt)$	$\Delta\,(\ell)$	$\Delta k(ict)$	$\Delta\,(tech)$	*mean*	*baseline*
Wages, variance								
routine	2.285	.35	.16	.22	.24	.15	.25	.22
non-routine	2.314	.32	.12	.17	.23	.13	.21	.23
industry	2.299	.33	.14	.19	.23	.14	.23	.23

Quantification of Model D. Changes in variances in real log-wages in the model induced by variations in one or more series, keeping fixed the others, and imposing the mean parameters to be homogeneous across industries.

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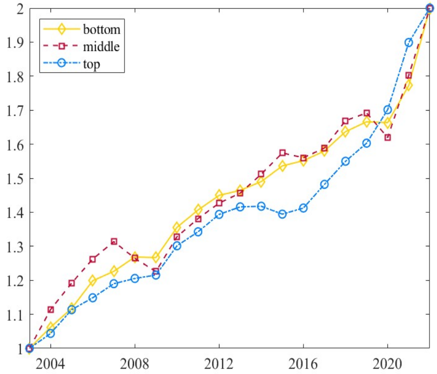
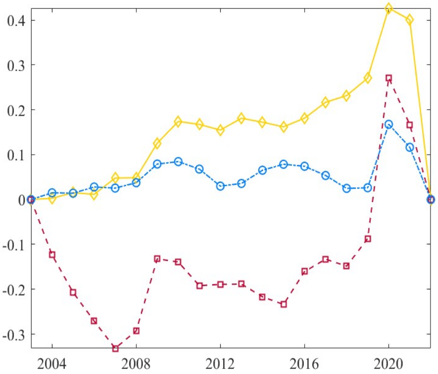
Productivity series under unique and *new* calibration



(a) Unique calibration, newly



(b) Difference with baseline

Figure C.15: Estimated productivities

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Model re-calibration counterfactual, series

- Between-industry real *log*-wage variance if only a specific series (or a combination) changes over time, keeping the remaining parameters fixed at their initial level, given the same (***new***) calibration across industries

Table C.22: Model counterfactual, series

		model $\vert \Delta\,\Phi(x)$						
							$\Delta\,(tfp)$	
	data	$\Delta\ell(rt)$	$\Delta\ell(nrt)$	$\Delta\ell$	$\Delta k(ict)$	$\Delta\,(\ell, ict)$	*newly*	*baseline*
Wages, variance								
routine	2.285	.62	.41	.46	.54	.40	.57	.34
non-routine	2.314	.07	.02	.02	.04	.03	.02	.09
industry	2.299	.35	.22	.24	.29	.21	.30	.22

Quantification of Model D. Changes in variances in real log-wages in the model induced by variations in one or more series, keeping fixed the others, and imposing the newly estimated parameters to be homogeneous across industries..

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Employment Cyclicality

Employment, relative wages and business cycle

- The analysis so far has been focused on explaining the *trend*
- Heathcote *et al.* (2023): importance of the *cycle*
  - dispersion at the top has increased steadily;
  - dispersion at the bottom features a strong cyclical component.
- Model eq. (1) well suited to analyze the evolution of employment combined with that in wages

$$\ell_h(a,s) = \left(\frac{w_h(a,s)}{\mathcal{W}_{\mathcal{H}}(a,\mathcal{S})} \, \frac{\mathcal{B}_h(a,s)}{\mathcal{B}_{\mathcal{H}}(a,\mathcal{S})} \right)^{\theta}, \quad \text{when} \quad \mathcal{B}_h(a,s) = 1 \;\; \forall a,h,s$$

→ changes in employment in the data with vs. changes in employment implied by the model (directly linked with changes in industries *relative* wage)

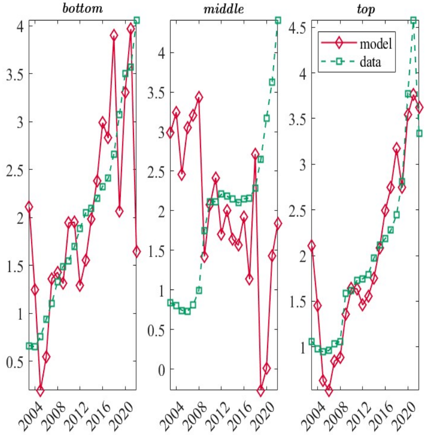

Figure .1: Task ratio, by industry-groups

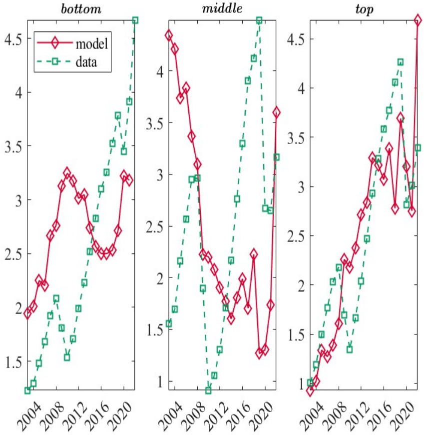

Figure .2: Employment, by industry-groups

▸ Aggregate ▸ Tasks

Cyclicality: aggregate series

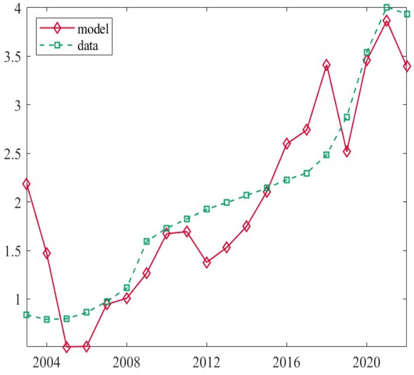

Figure .3: Aggregate task ratio

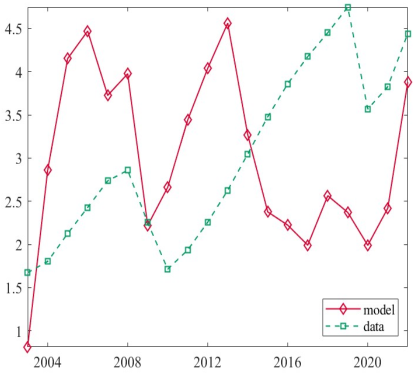

Figure .4: Aggregate employment

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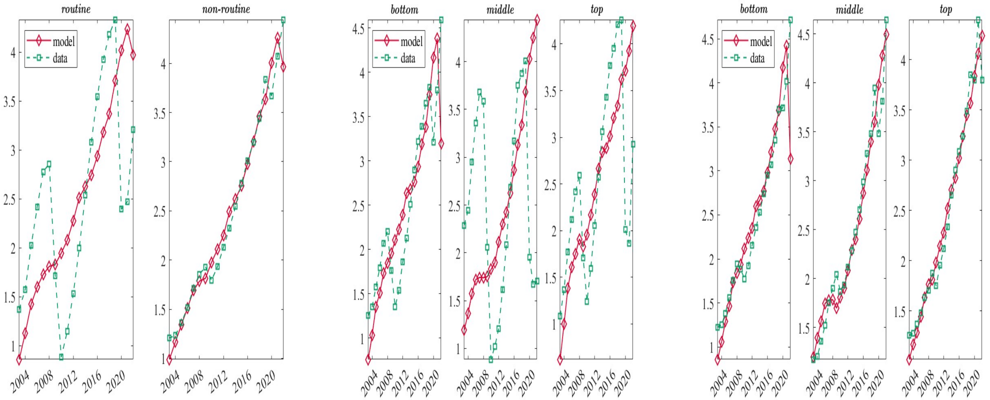
Cyclicality: employment by Tasks



(a) Employment, by tasks

(b) Employment, routines

(c) Employment, non-routines

Figure .5: Employment, by tasks and industries

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