Unlocking frontier technologies in firms

How firms' (organizations) mediate technology impact:

- changes in the structure and level of wages
- changes in industry structure
- productivity growth

Claire LELARGE

université PARIS-SACLAY

Roadmap (open to discussion!)

1. CHALLENGE / Review of stylized facts to be understood:
   - Wage distribution, including top managerial wages (specific literature on this); occupations
   - Firm size and scope, with implications in terms of industry concentration
   - Labor share (generality of pattern is debated)
2. Alternative possible explanations (with quantification goal)
   - China shock, trade
   - Skill biased technological change: no firms
   - Automation (task-based models)
   - Communication technologies (models of optimal hierarchies)
3. Open questions / implications of ML/AI technologies?

1. Macro stylized facts

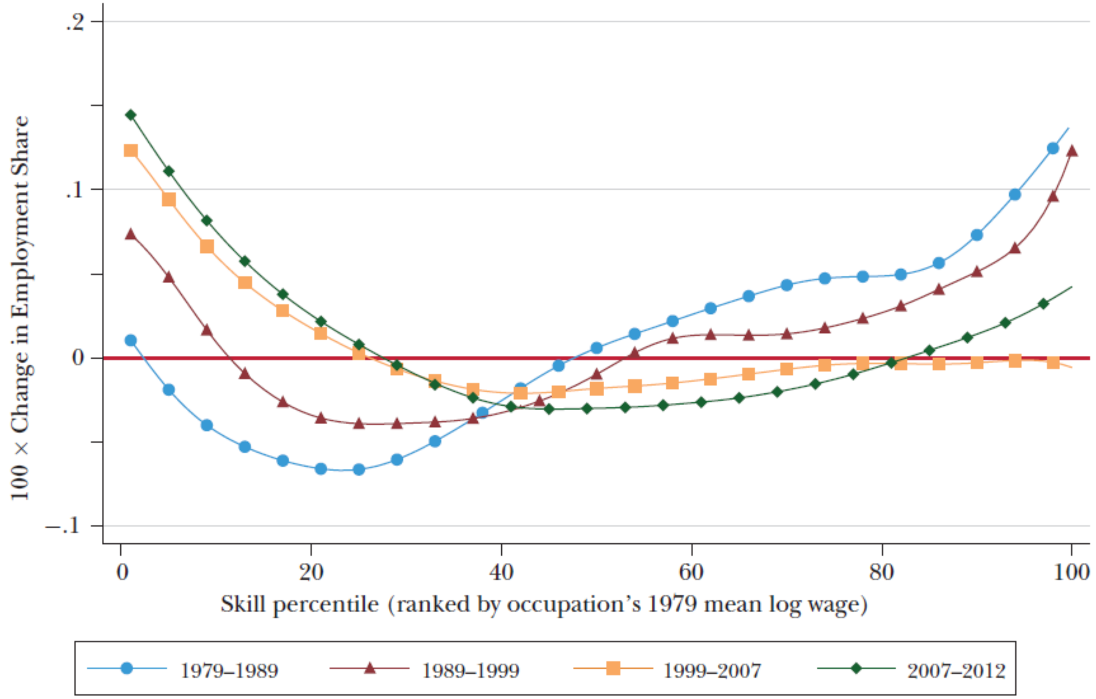
Debates in macro / organizational economics

Firm dimension often missing

A/ Wage and employment polarization

Autor and Dorn, AER, 2013, updated in Autor JPE 2014

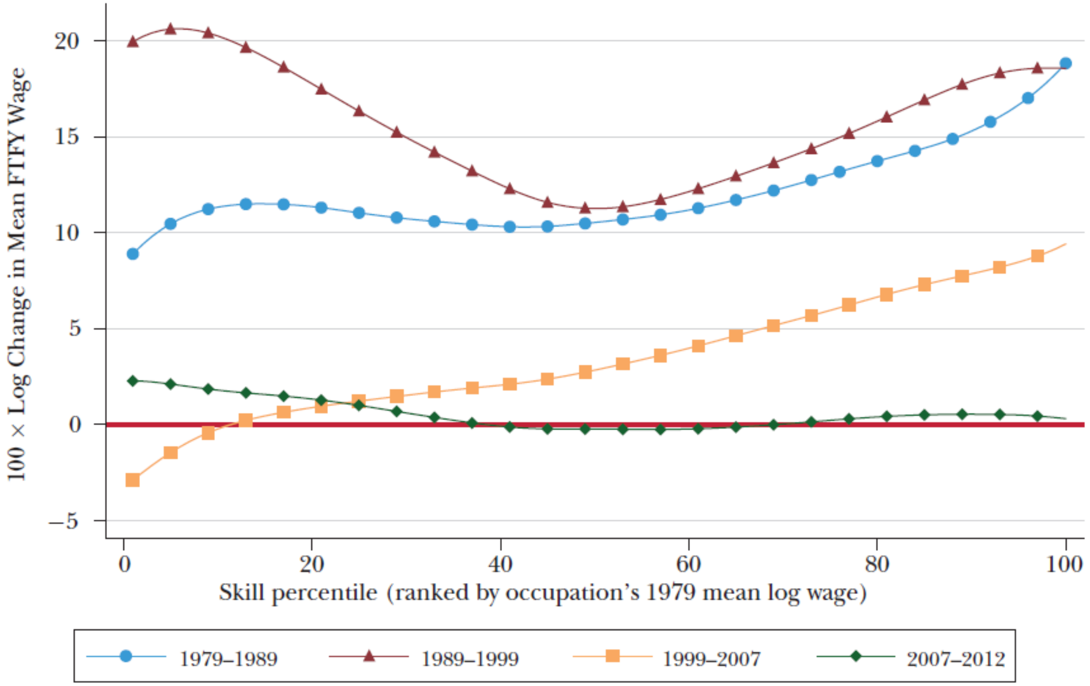
Smoothed Employment Changes by Occupational Skill Percentile, 1979–2012



Sources: Author, calculated using 1980, 1990, and 2000 Census Integrated Public Use Microdata Series (IPUMS) files; American Community Survey combined file 2006–2008, American Community Survey 2012.
Notes: The figure plots changes in employment shares by 1980 occupational skill percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), where skill percentiles are measured as the employment-weighted percentile rank of an occupation's mean log wage in the Census IPUMS 1980 5 percent extract. Employment in each occupation is calculated using workers' hours of annual labor supply times the Census sampling weights. Consistent occupation codes for Census years 1980, 1990, and 2000, and 2008 are from Autor and Dorn (2013).

Changes in Mean Wages by Occupational Skill Percentile among Full-Time, Full-Year (FTFY) Workers, 1979–2012

(the y-axis plots 100 times log changes in employment, which is nearly equivalent to percentage points for small changes)

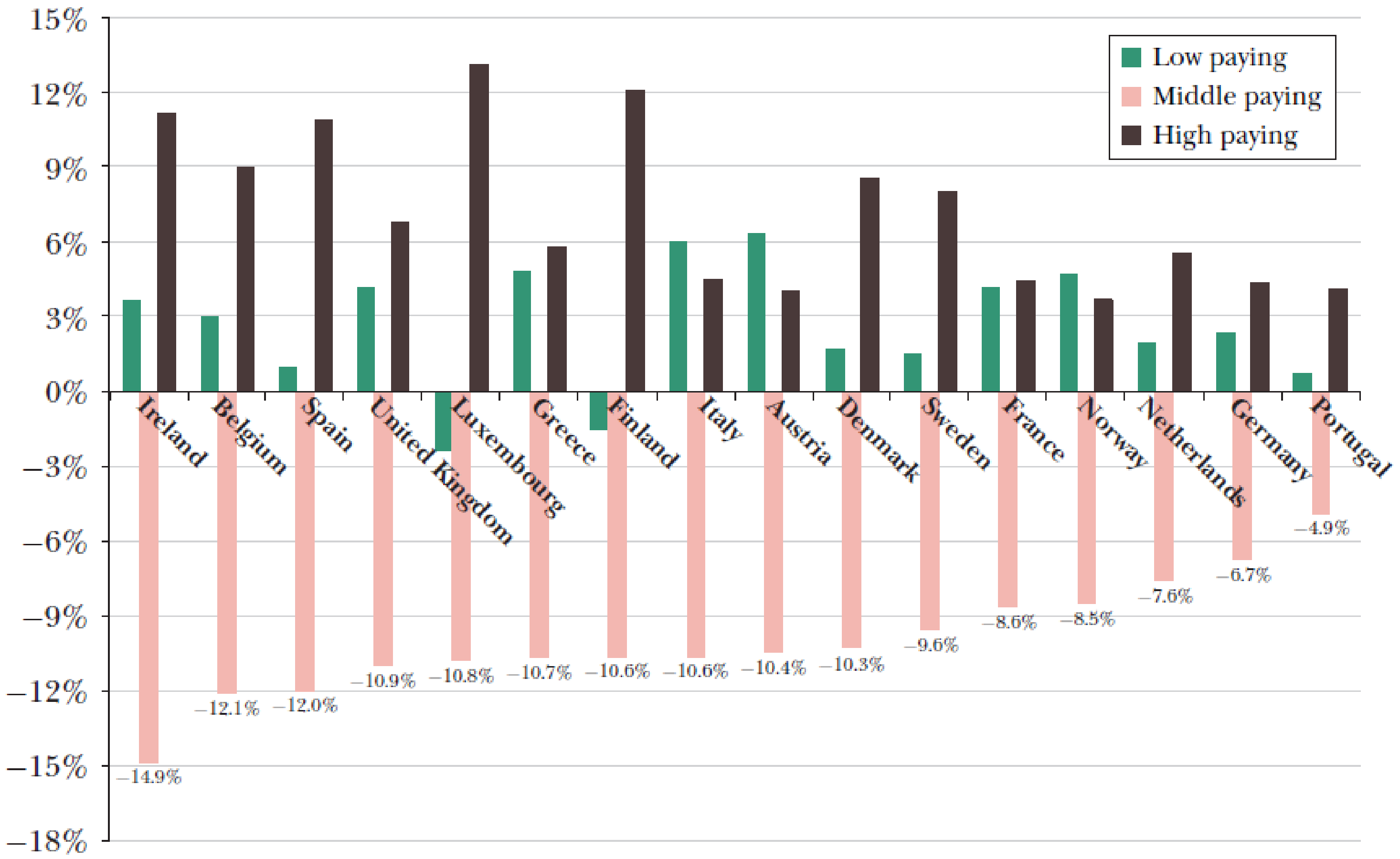


Sources: Author, calculated using 1980, 1990, and 2000 Census IPUMS files; American Community Survey combined file 2006–2008, American Community Survey 2012.
Notes: The figure plots changes in mean log wages over each period, by 1979 occupational skill percentile rank using a locally weighted smoothing regression (bandwidth 0.8 with 100 observations), where skill percentiles are measured as the employment-weighted percentile rank of an occupation's mean log wage in the Census IPUMS 1980 5 percent extract. The sample includes the working-age (1–64) civilian non-institutionalized population with 48+ annual weeks worked and 35+ usual weekly hours. Weekly wages are calculated as annual earnings divided by weeks worked.

A/ Holds across all countries

Goos, Manning, Salomons, AER 2014

Change in Occupational Employment Shares in Low, Middle, and High-Wage Occupations in 16 EU Countries, 1993–2010



Source: Goos, Manning, and Salomons (2014, table 2)

A/ Evolution of skill premium

Acemoglu and Autor, JEL, 2012

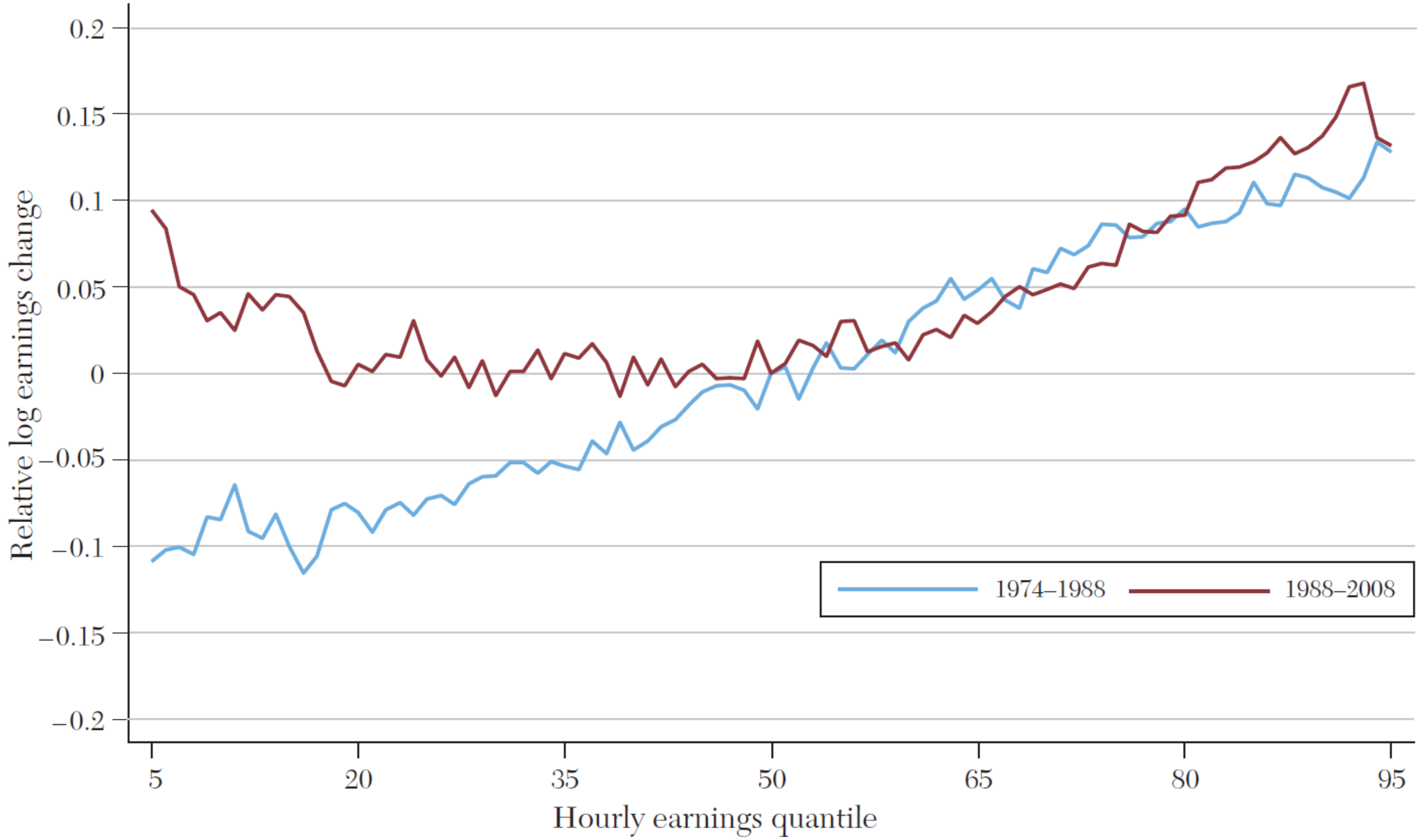
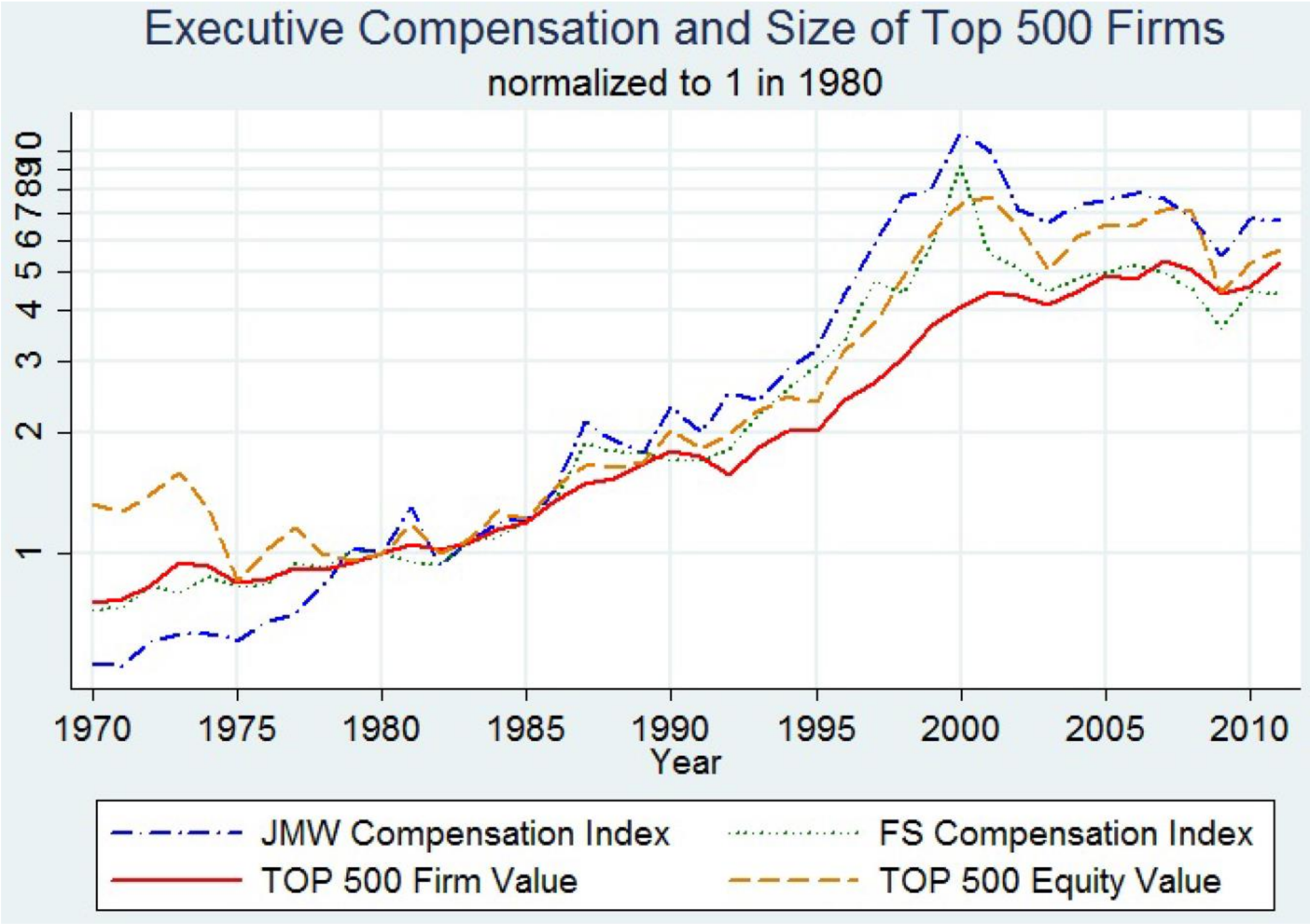


Figure 4. Changes in Male Log Hourly Wages by Percentile Relative to the Median

Source: May/ORG CPS data for earnings years 1973–2009. The data are pooled using three-year moving averages (i.e., the year 1974 includes data from years 1973, 1974, and 1975). For each denoted time period, the change in the 5th–95th percentile of log weekly wages is calculated.

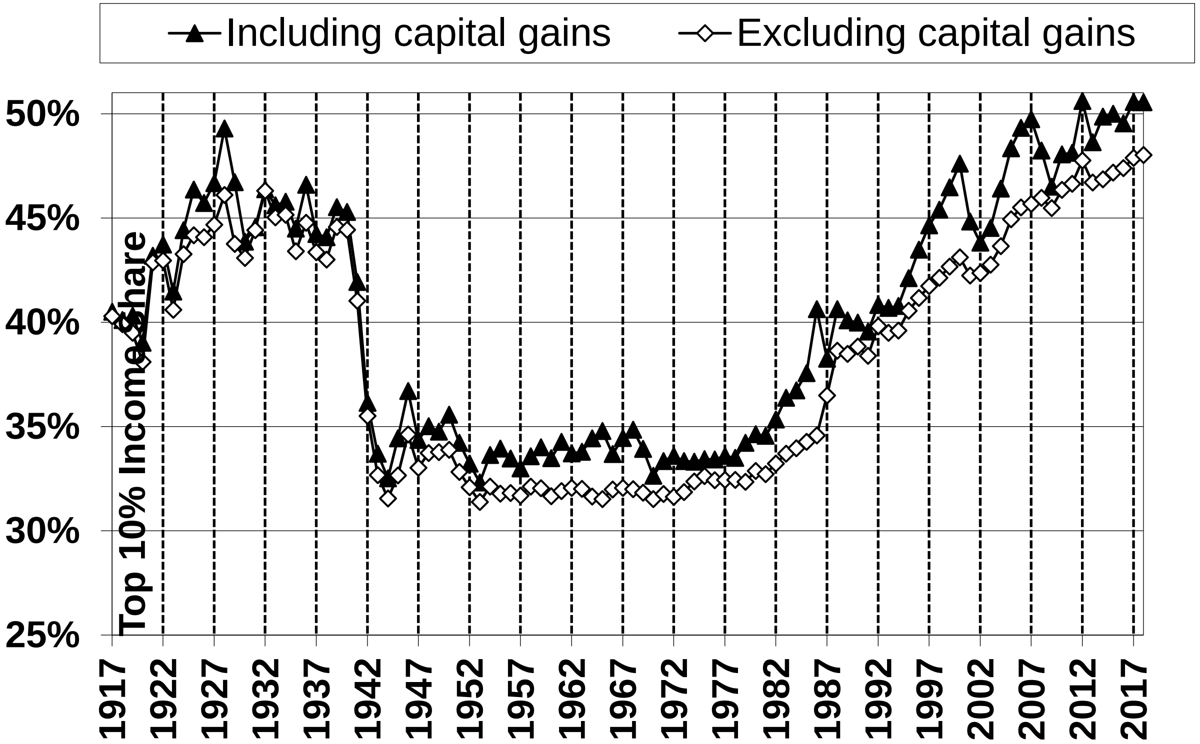
A/ At the top of the distribution (1)

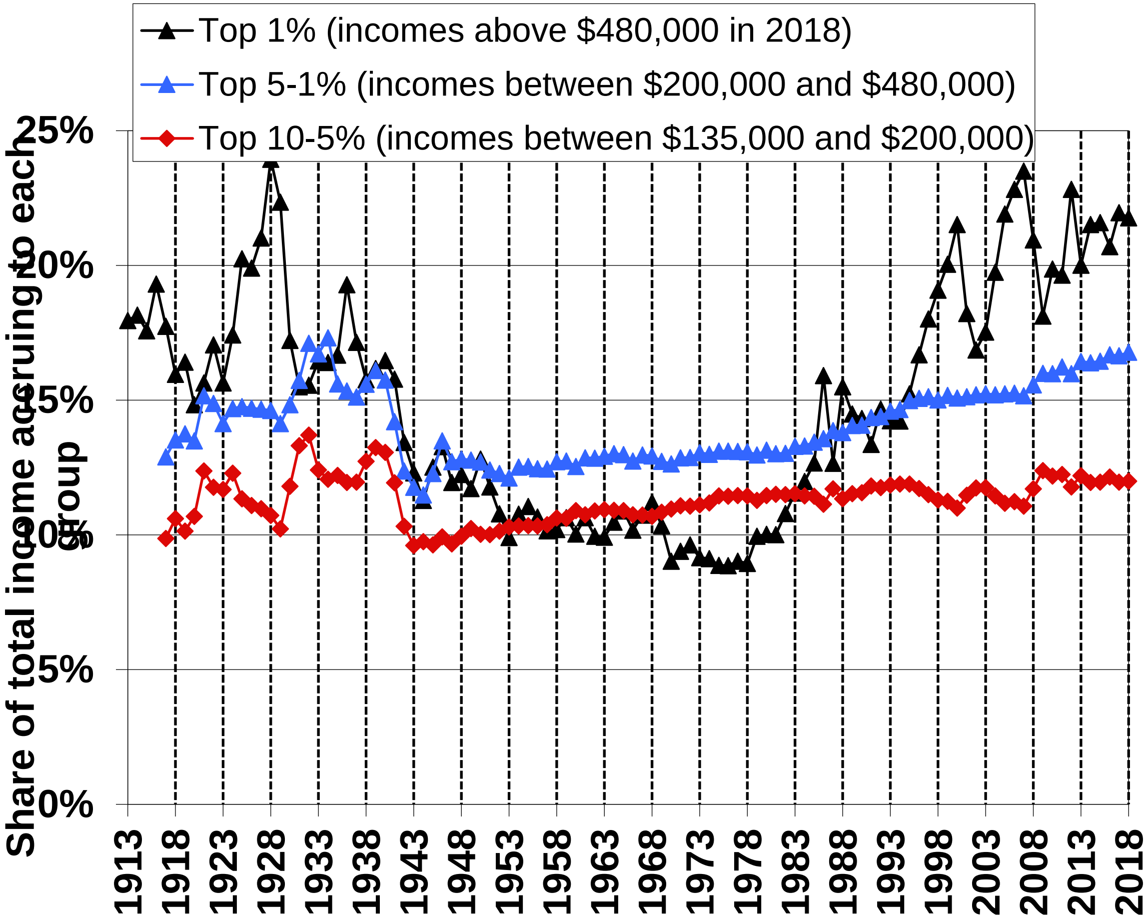
Executive compensation of largest firms: update of Gabaix Landier, QJE 2008



A/ At the top of the distribution (2)

Piketty and Saez, 2008 and updates

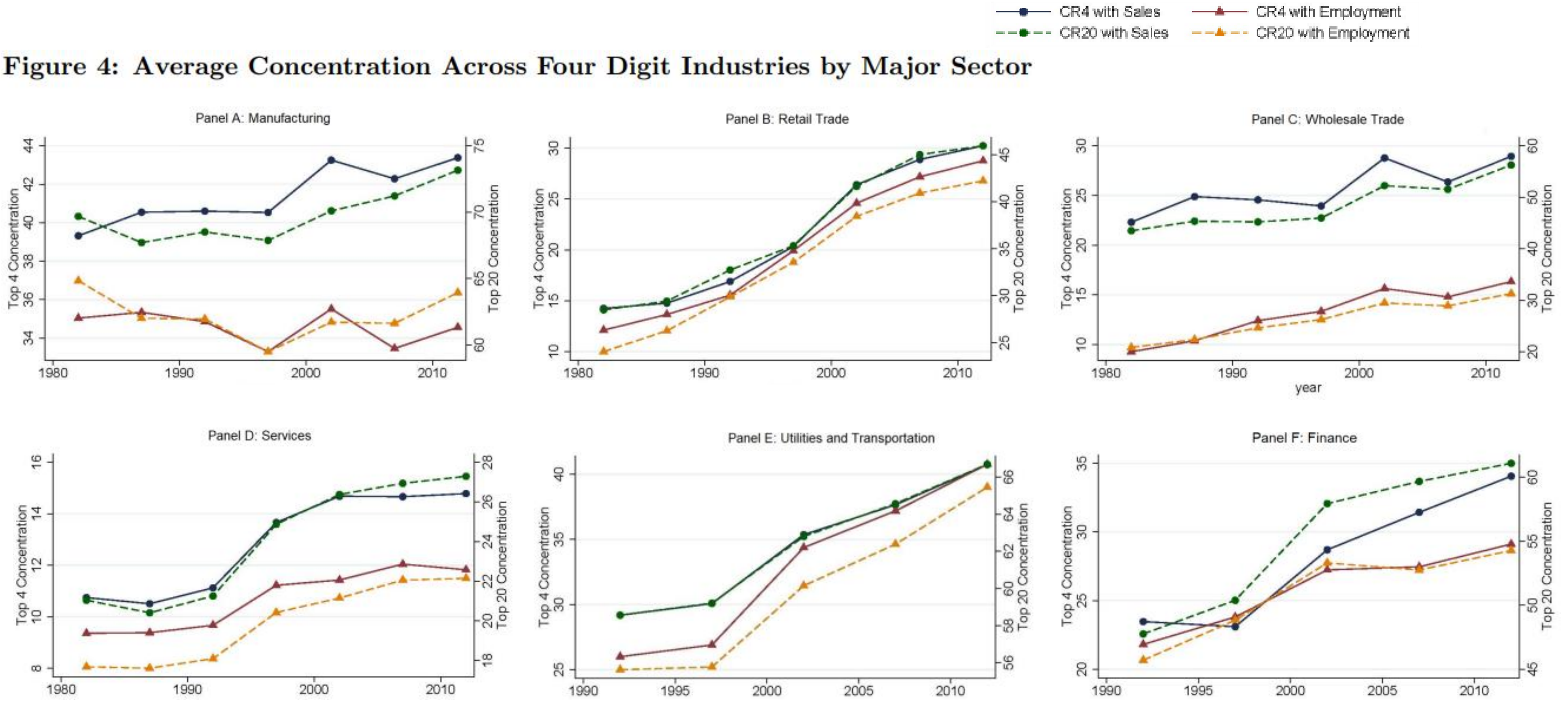




B/ Increased market concentration…

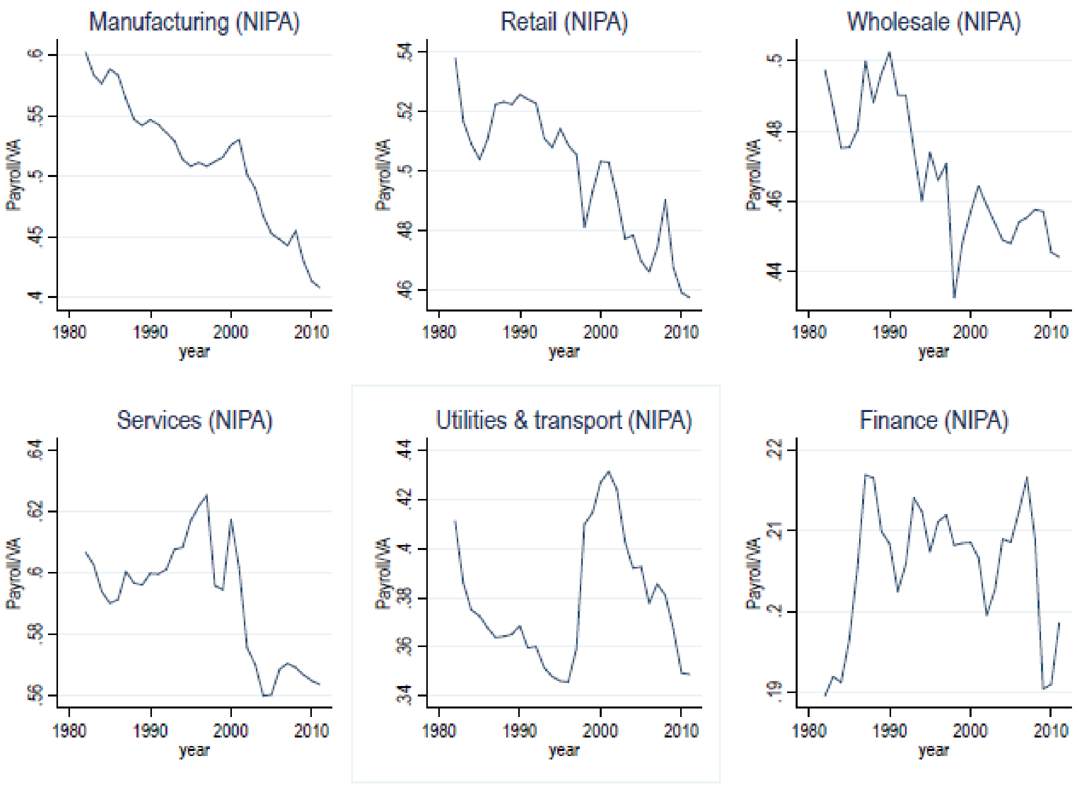
Autor, Dorn, Katz, Patterson, Van Reenen et al., QJE 2020 (''Concentrating on the Fall of the Labor Share", Superstar firms)

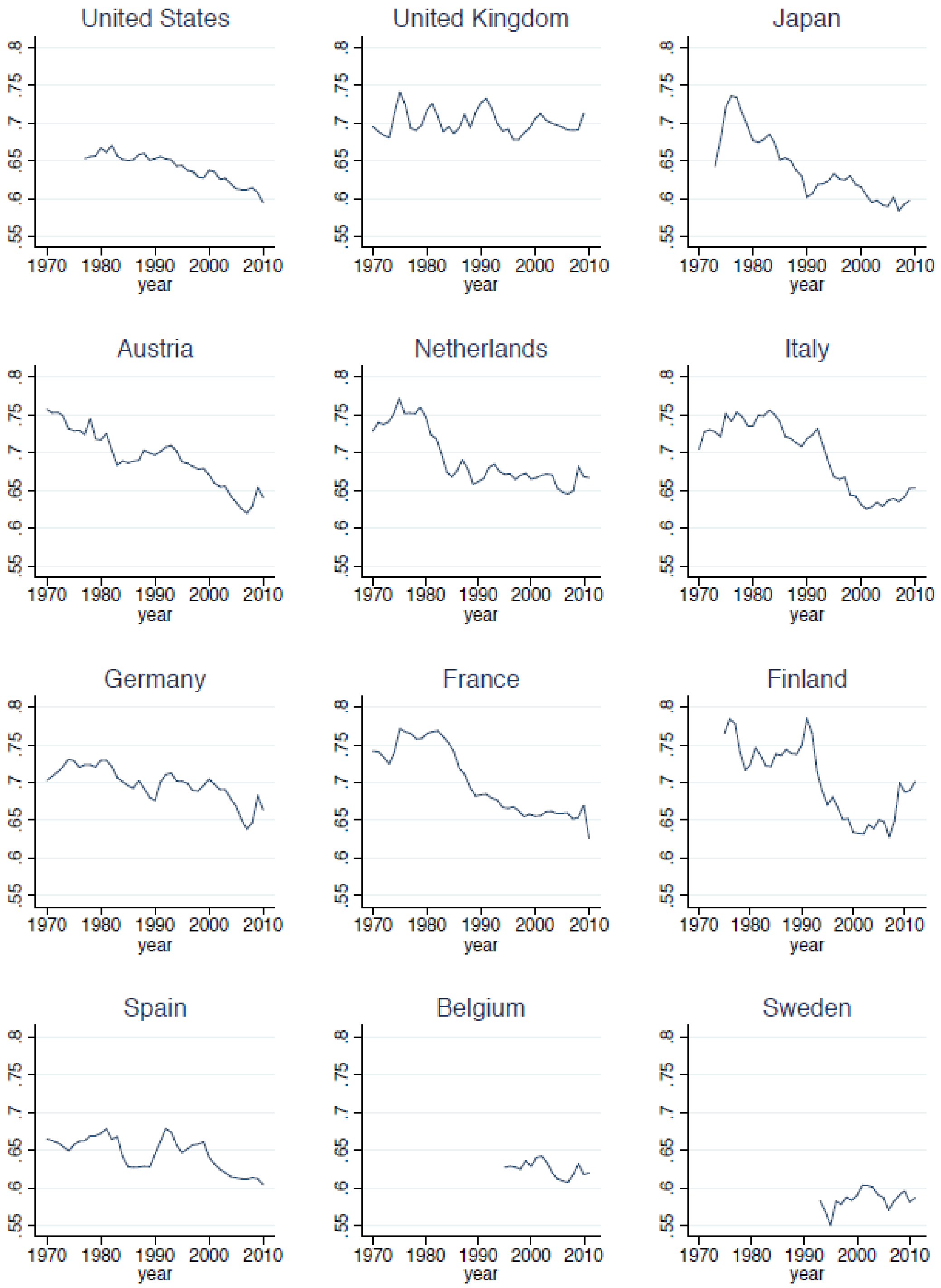
Figure 4: Average Concentration Across Four Digit Industries by Major Sector



C/ Labor shares

(Autor et al, 2020)





B+C/ Covariance btw LS and concentration

Table 2: Industry-Level Regressions of Change in Share of Labor on Change in Concentration, Manufacturing

	5-year Changes						10-year Changes					
	CR4		CR20		HHI		CR4		CR20		HHI	
	(1)		(2)		(3)		(4)		(5)		(6)	
1 Baseline	-0.148	***	-0.228	***	-0.213	**	-0.132	***	-0.153	***	-0.165	*
	(0.036)		(0.043)		(0.085)		(0.040)		(0.055)		(0.093)	
2 Compensation Share of Value Added	-0.177	***	-0.266	***	-0.256	**	-0.139	***	-0.151	**	-0.183	
	(0.045)		(0.056)		(0.110)		(0.053)		(0.071)		(0.125)	
3 Deduct Service Intermediates from Value Added in Labor Share	-0.339	***	-0.514	***	-0.502	***	-0.261	***	-0.353	***	-0.303	
	(0.064)		(0.074)		(0.175)		(0.056)		(0.065)		(0.275)	
4 Value Added-based Concentration	-0.219	***	-0.337	***	-0.320	***	-0.210	***	-0.251	***	-0.289	***
	(0.028)		(0.045)		(0.060)		(0.037)		(0.054)		(0.075)	
9 Employment-Based Concentration Measure	0.036		0.024		0.160	**	0.018		0.029		0.082	
	(0.036)		(0.033)		(0.075)		(0.035)		(0.040)		(0.083)	

How to account for all of these facts?

Parsimoniously but quantitatively…

A/ Trade and China shock?

Trade or technology?

A. China shock

- Only accounts for inequality
- Does not explain the rest

Figure 3.4. Share of Manufacturing in Aggregate Employment and Output
(Percent)

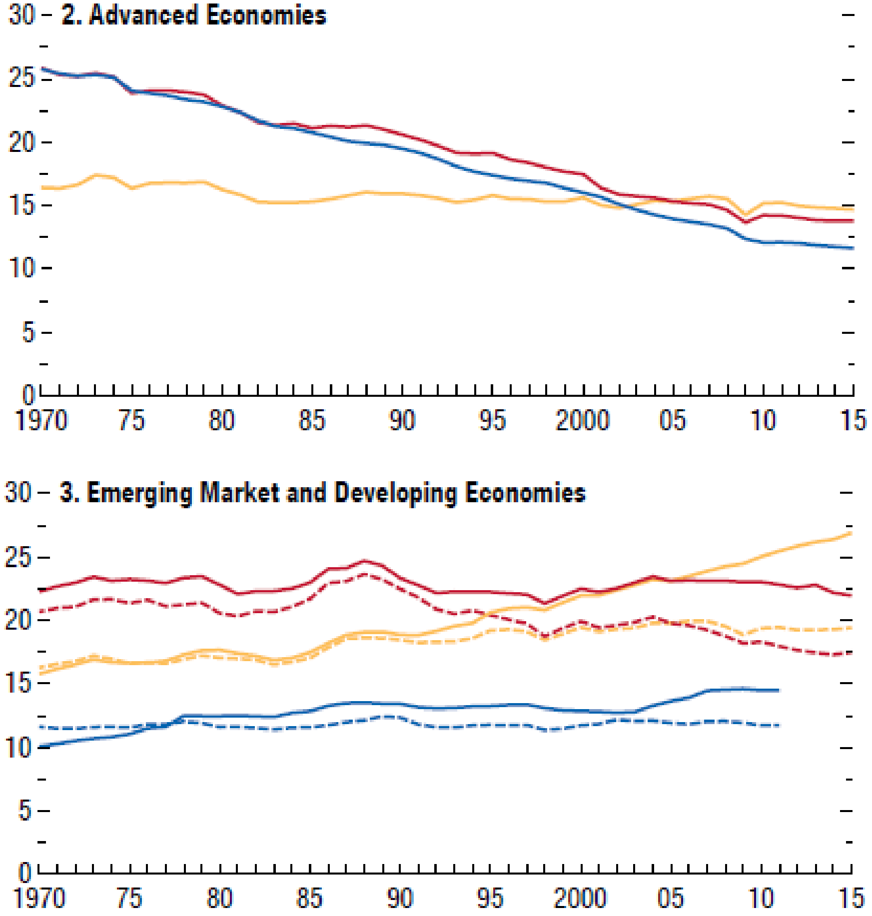
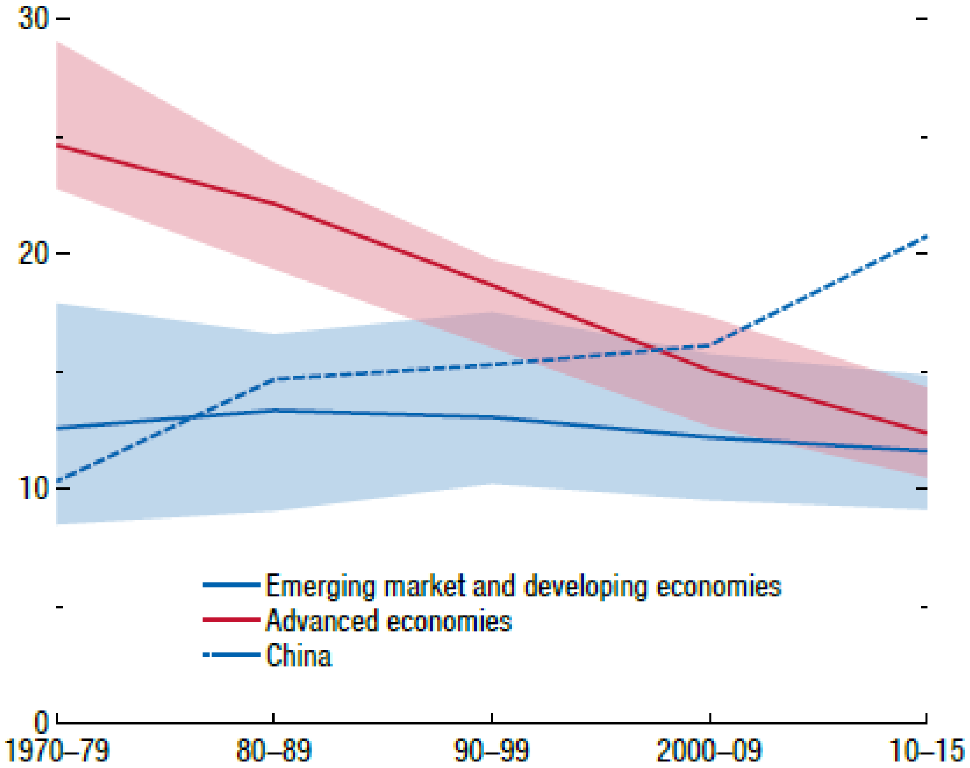


Figure 3.1. Share of Manufacturing in Aggregate Employment
(Percent)

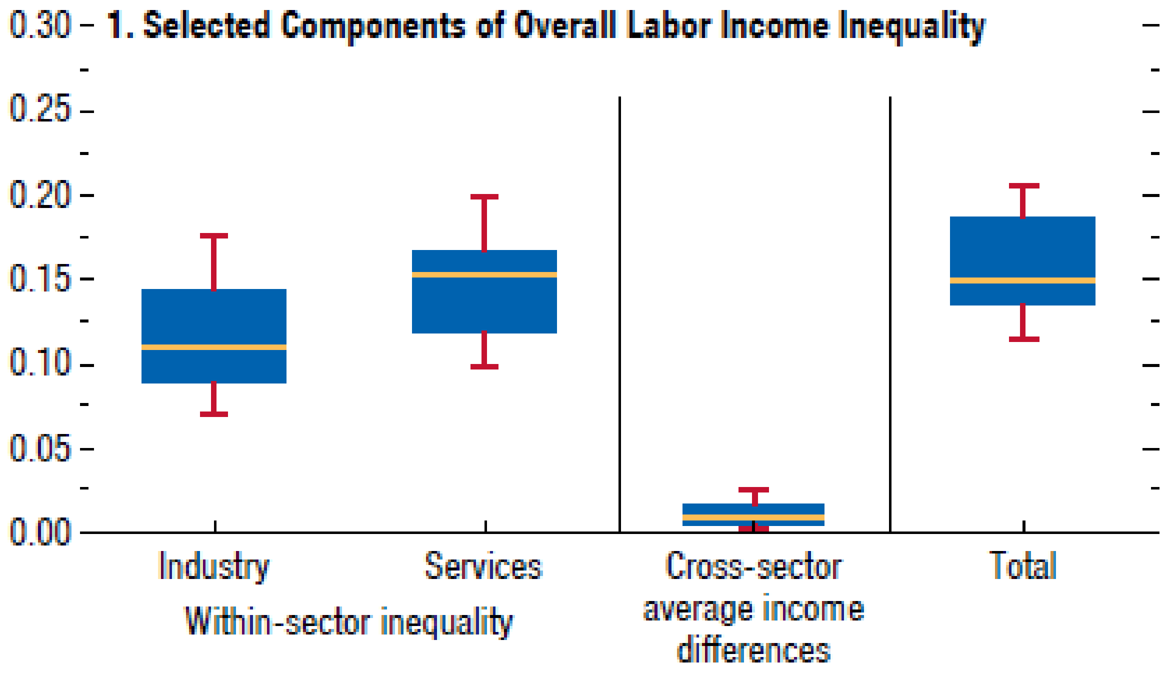
Manufacturing employment has been in relative decline for nearly five decades in advanced economies, and it seems to be peaking at low shares of total employment among more recent developers.



Source: IMF staff calculations. WEO 2018
Note: The solid lines and shaded areas denote the simple average and the interquartile range across economies, respectively. The sample comprises 21 advanced economies and 44 emerging market and developing economies with sectoral employment data since 1970. See Annex 3.1 for data sources and country coverage.

A. China shock

- The China shock can't explain the rise in **WITHIN industry inequality**
- Globalization and Wage Inequality, E. Helpman, NBER Working Paper No. 22944, 2016 (survey):
- "*Trade played an appreciable role in increasing wage inequality, but [its] cumulative effect has been modest […] globalization does not explain the preponderance of the rise in wage inequality within countries.*"



B/ Skill biased technological change?

B. Skill biased technological change (1)

$$Y(t) = \left[\gamma_H \left(A_H(t)H(t)\right)^{\frac{\sigma-1}{\sigma}} + \gamma_L \left(A_L(t)L(t)\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \qquad \sigma > 0$$

- H-augmenting productivity $A_H(t)$ and L-augmenting productivity $A_L(t)$.
- Constant elasticity of substitution $\sigma > 0$. Gross complements if $\sigma < 1$, gross substitutes if $\sigma > 1$. For H and L standard estimares are $\sigma \in (1, 2)$.
- Allows us to formalize Tinbergen's (1974) argument that the evolution of the skill premium depends on a 'race' between the demand for skilled labor and the supply of it due to increased schooling [cf., Goldin and Katz (2010) *The Race Between Education and Technology*].

B. Skill biased technological change (2)

- Implies relative demand curve, in logs

$$\log \frac{w_H(t)}{w_L(t)} = \log \frac{\gamma_H}{\gamma_L} + \frac{\sigma - 1}{\sigma} \log \left(\frac{A_H(t)}{A_L(t)} \right) - \frac{1}{\sigma} \log \left(\frac{H(t)}{L(t)} \right)$$

- Following Tinbergen (1974), suppose linear trend in relative productivity

$$\log \left(\frac{A_H(t)}{A_L(t)} \right) = \alpha_0 + \alpha_1 t$$

- Katz-Murphy (1992) estimate the time-series regression

$$\log \frac{w_H(t)}{w_L(t)} = \text{constant} + \frac{\sigma - 1}{\sigma} \alpha_1 t - \frac{1}{\sigma} \log \left(\frac{H(t)}{L(t)} \right)$$

on annual data from 1963-1987 (25 observations!) and obtain

$$\log \frac{w_H(t)}{w_L(t)} = \text{constant} + \underset{(0.007)}{0.033}\, t - \underset{(0.150)}{0.709} \log \left(\frac{H(t)}{L(t)} \right)$$

implying a point estimate of $\sigma \approx 1/0.709 = 1.41$.

B. Skill biased technological change (3)

- Modest amount of substitutability between H and L plus exogenous trend in A_H/ A_L rationalizes trend in skill premium.
- But some issues:
  - implied degree of skill-bias is *very large*, gap between $A_H(t)$ and $A_L(t)$ growing at annual rate of

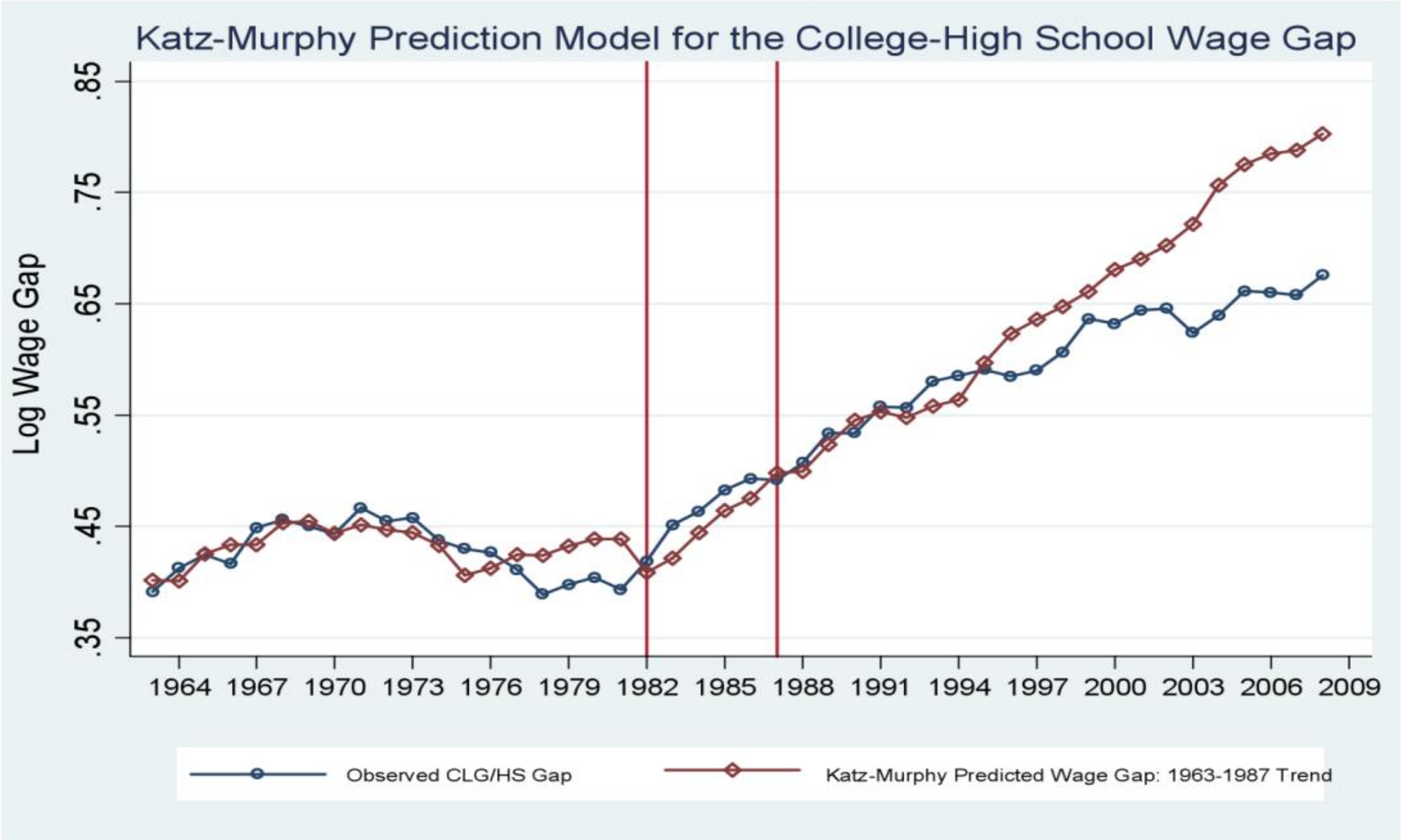
    $$\alpha_1 = \frac{\sigma}{\sigma - 1}(0.033) = 0.1135$$

    that is, more than 10% per year
  - implies counterfactually high rates of aggregate TFP growth
  - e.g., given aggregate labor share of $2/3$ and skilled worker share of 0.25, implies aggregate TFP growth is at least $(0.1135)(0.25)(2/3) = 0.0189$, say 1.9% per year, substantially larger than standard 1% estimates

B. Skill biased technological change (4)

Out of sample, the model over-predicts growth in skill premium

- With more data, estimates of σ rise from 1.4 to 2.9
- Trend growth falls from 0.033 to 0.016



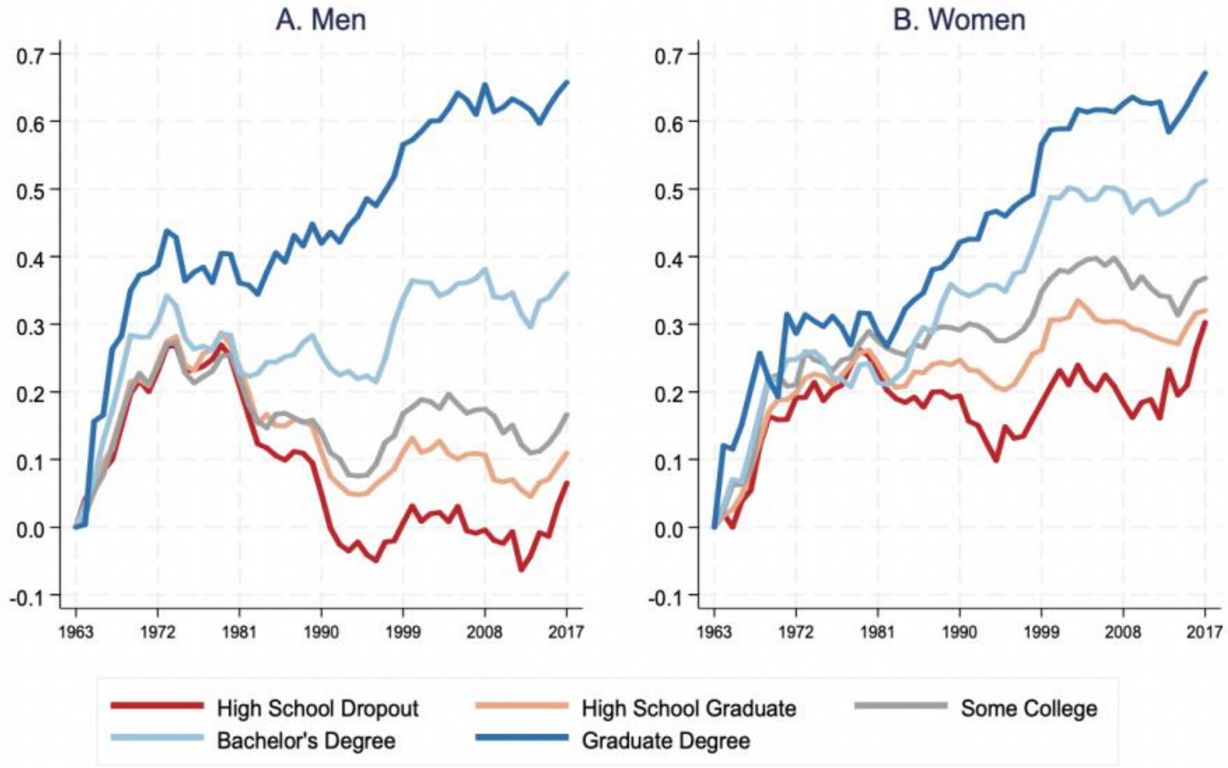
Composition-adjusted college wage premium. Source: Acemoglu-Autor (2011).

B. Skill biased technological change (5)

Hard to understand why real wages have declined for some workers:

- while skill-biased technological change can rationalize increase in skillpremium,
- **actual wage levels should not decline**

Figure 1: Cumulative Change in Real Weekly Earnings of Working Age Adults Ages 18-64, 1963-2017



If workers are substitutes, absent technological *regress*, we should not see declining wages for any group. Source: Autor (2019).

C/ Task-based models

Motivation (1)

- Given the difficulties with standard model: an alternative perspective.
- Introduced by Zeira (1998) and Acemoglu and Zilibotti (1999). See Acemoglu and Autor (2011) for a review.
- Recent developments by Acemoglu and Restrepo (2018/2023)
  - **Automation** (e.g., adoption of industrial robots) is at the root of most of the sweeping labor market trends of the last three decades
  - Its impacts can be understood via changes in the labor share, but not using the standard framework with factor-augmenting technologies;
  - Rise in inequality also intimately linked to changes in task content.
- Longer term perspective: automation in the last 200 years…
  1. horse-powered reapers, harvesters, and threshing machines replaced manual labor
  2. machine tools replaced labor-intensive artisan techniques
  3. industrial robotics automated welding, machining, assembly, and packaging
  4. software automated routine tasks performed by white-collar workers
  5. AI- based technologies?

Motivation (2)

- Hard to map to canonical production function factor-augmenting technologies:

$$Y = F(A_L L, A_K K).$$

- Once we write $F(A_L L, A_K K)$
  - allocation of tasks to factors remain unchanged, and
  - technological change makes capital (or labor) uniformly more productive in all tasks.
- But technologies other than $\{A_L, A_K\}$ change allocation of tasks:
  - capital outperforms labor in a few tasks and industries
  - it becomes feasible to use capital at certain tasks —automation.

Formalization (1)

Acemoglu and Restrepo, AER, 2018

Elast of substitution

$$Y = \left(\int_{N-1}^{N} \mathcal{Y}(z)^{\frac{\sigma-1}{\sigma}} dz \right)^{\frac{\sigma}{\sigma-1}}$$

Output Task services

- Tasks can be produced using capital or labor:

$$\mathcal{Y}(z) = \begin{cases} A^L \gamma^L(z)\ell(z) + A^K \gamma^K(z)k(z) & \text{if } z \in [N-1, I] \\ A^L \gamma^L(z)\ell(z) & \text{if } z \in (I, N]. \end{cases}$$

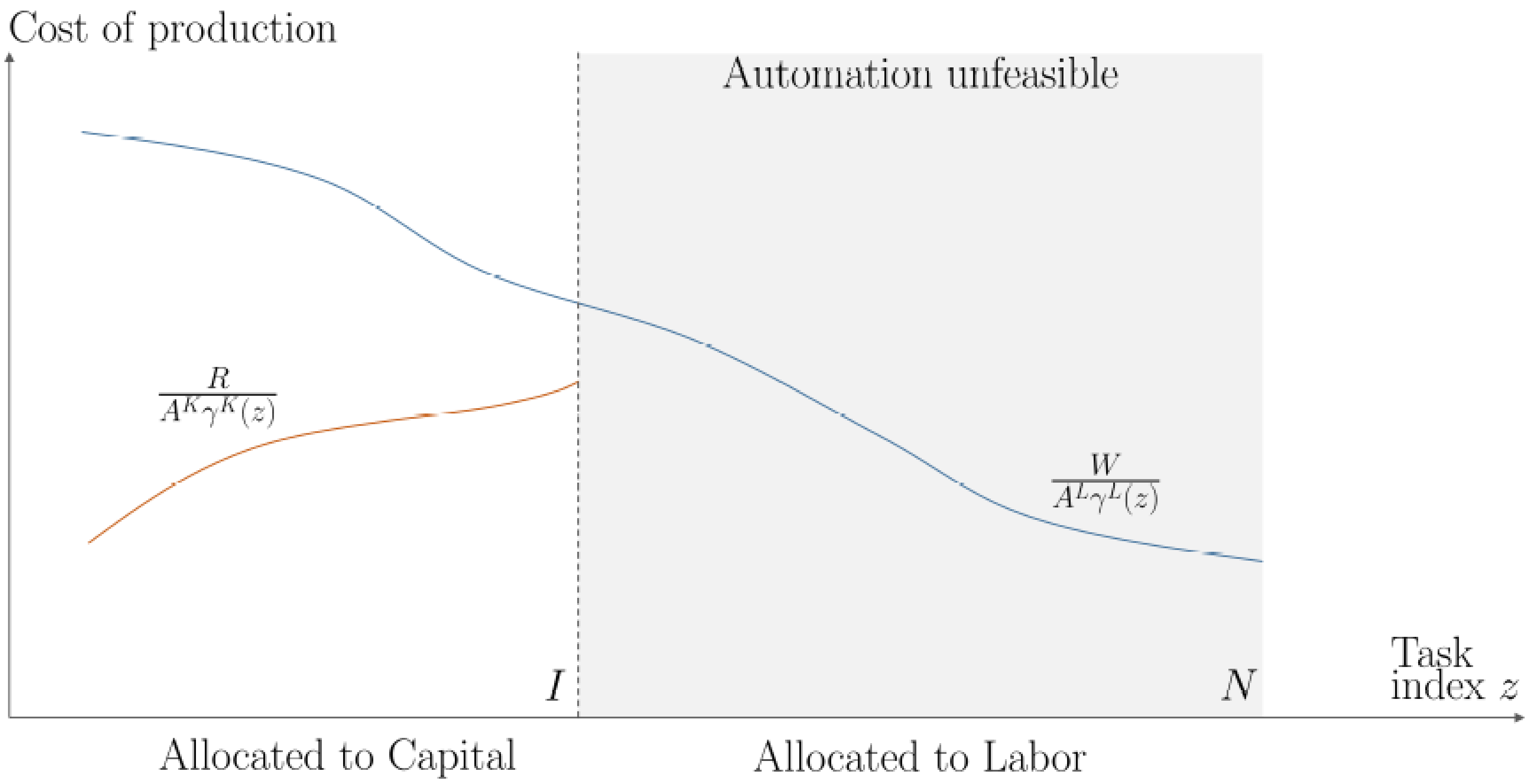
Feasible to automate

New tasks

- Comparative advantage: $\gamma^L(z)/\gamma^K(z)$ and $\gamma^L(z)$ increasing in z.

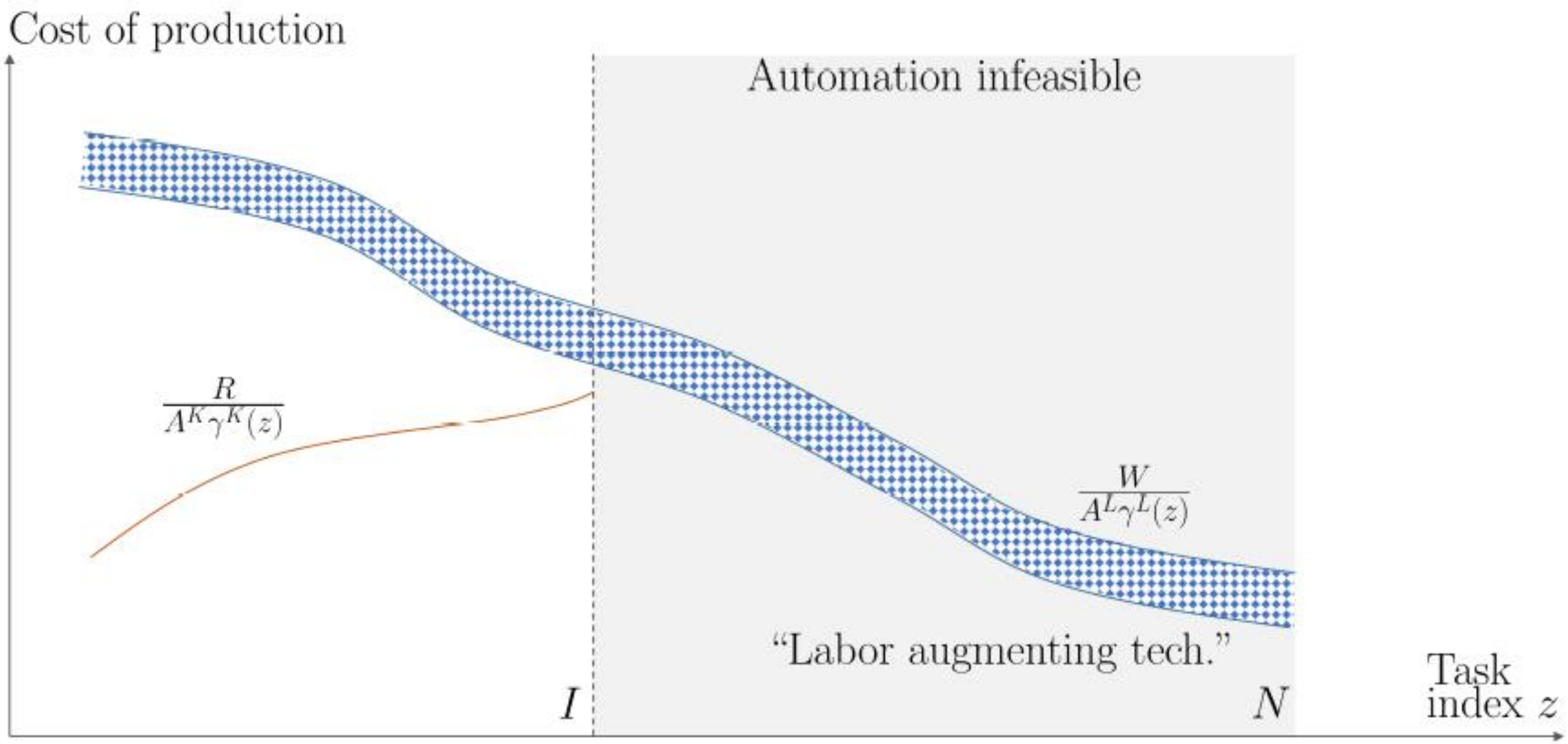
Allocation of tasks

Acemoglu and Restrepo, AER, 2018



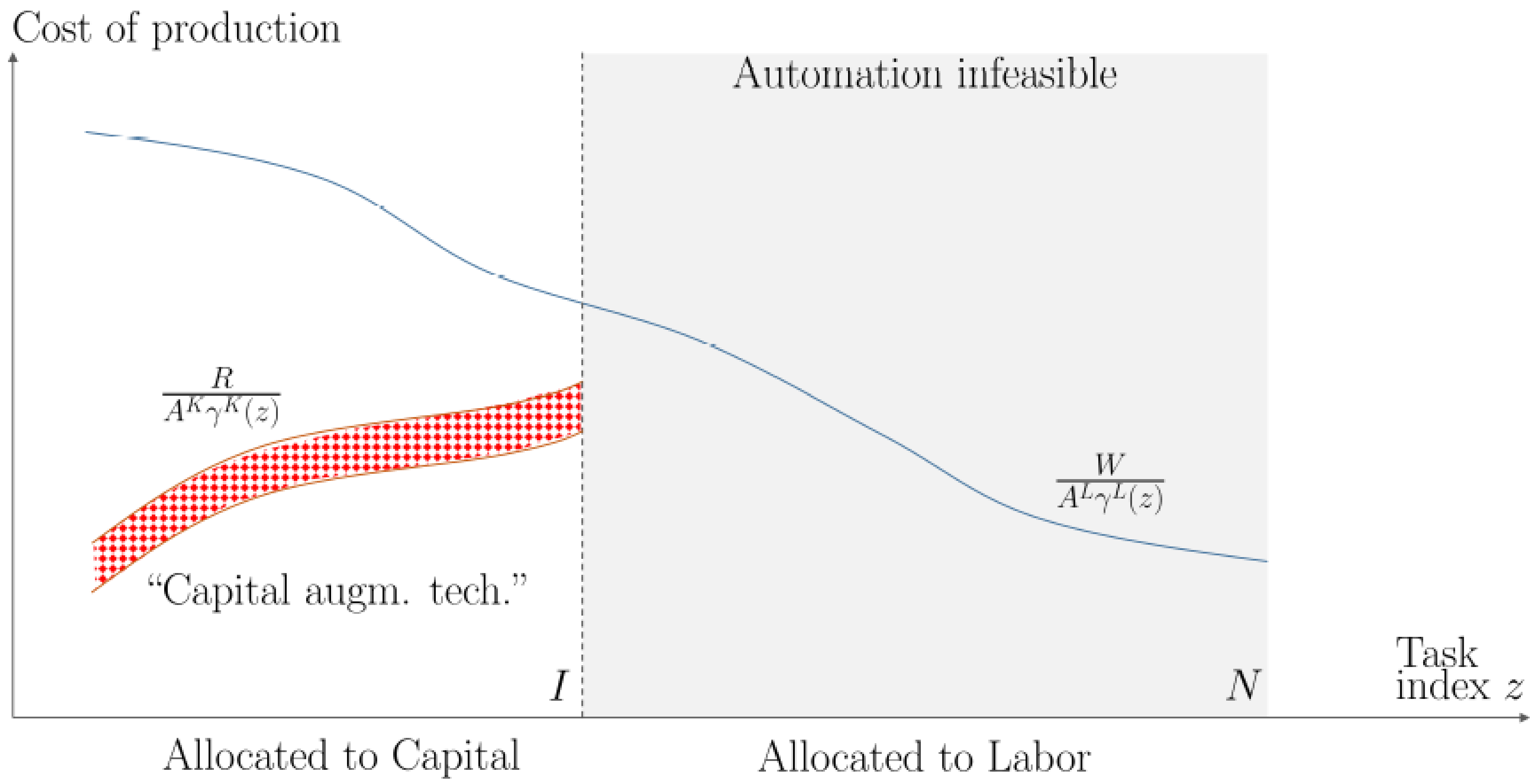
Labor augmenting technology

Acemoglu and Restrepo, AER, 2018



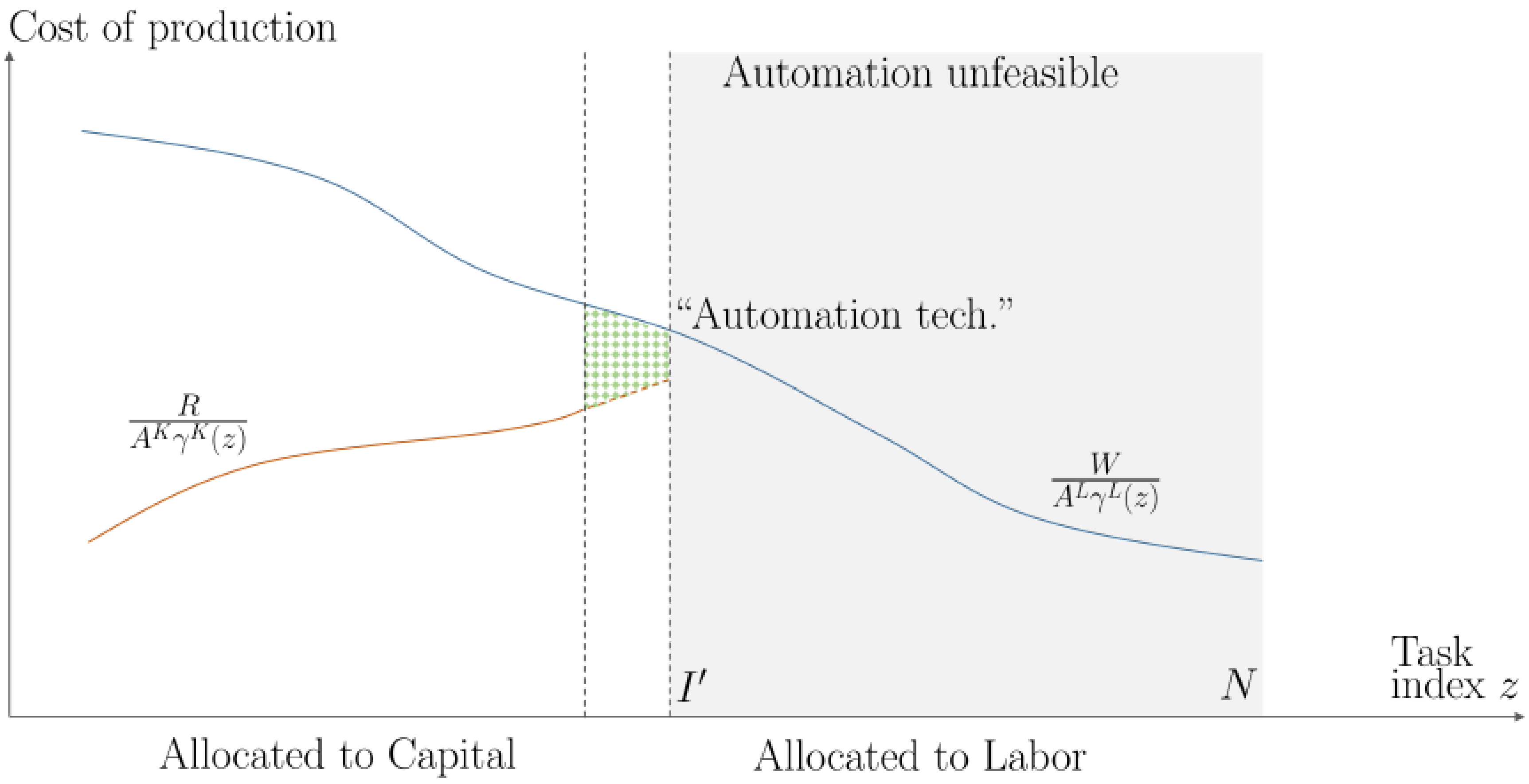
Capital augmenting technology

Acemoglu and Restrepo, AER, 2018



Automation technology

Acemoglu and Restrepo, AER, 2018



Formalization (2)
Acemoglu and Restrepo, AER, 2018

$$Y(L,K) = \left(\left(\int_{N-1}^{I} \gamma^K(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}} (A^K K)^{\frac{\sigma-1}{\sigma}} + \left(\int_{I}^{N} \gamma^L(z)^{\sigma-1} dz \right)^{\frac{1}{\sigma}} (A^L L)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}$$

- The labor share is given by

$$s^L = \frac{\Gamma(N,I)(W/A^L)^{1-\sigma}}{(1-\Gamma(N,I))(R/A^K)^{1-\sigma} + \Gamma(N,I)(W/A^L)^{1-\sigma}}$$

$$\text{Task content } \Gamma = \frac{\int_I^N \gamma^L(z)^{\sigma-1} dz}{\int_{N-1}^I \gamma^K(z)^{\sigma-1} dz + \int_I^N \gamma^L(z)^{\sigma-1} dz}$$

Task-price subs.

- When $\sigma = 1$ or $\gamma^L(z) = \gamma^K(z) = 1$, then $\Gamma = N - I$.
- Factor-augmenting technologies and automation work through different channels: task content vs task-price substitution
- Automation always reduces the labor share regardless of the value of σ.

Labor demand:
with automation technologies

$$WL = Y \times s^L$$

$$\frac{\partial \ln WL}{\partial I} = \frac{1}{\sigma - 1}\left[\left(\frac{R}{A^K \gamma^K(I)}\right)^{1-\sigma} - \left(\frac{W}{A^L \gamma^L(I)}\right)^{1-\sigma}\right] \quad \text{(Productivity effect>0)}$$

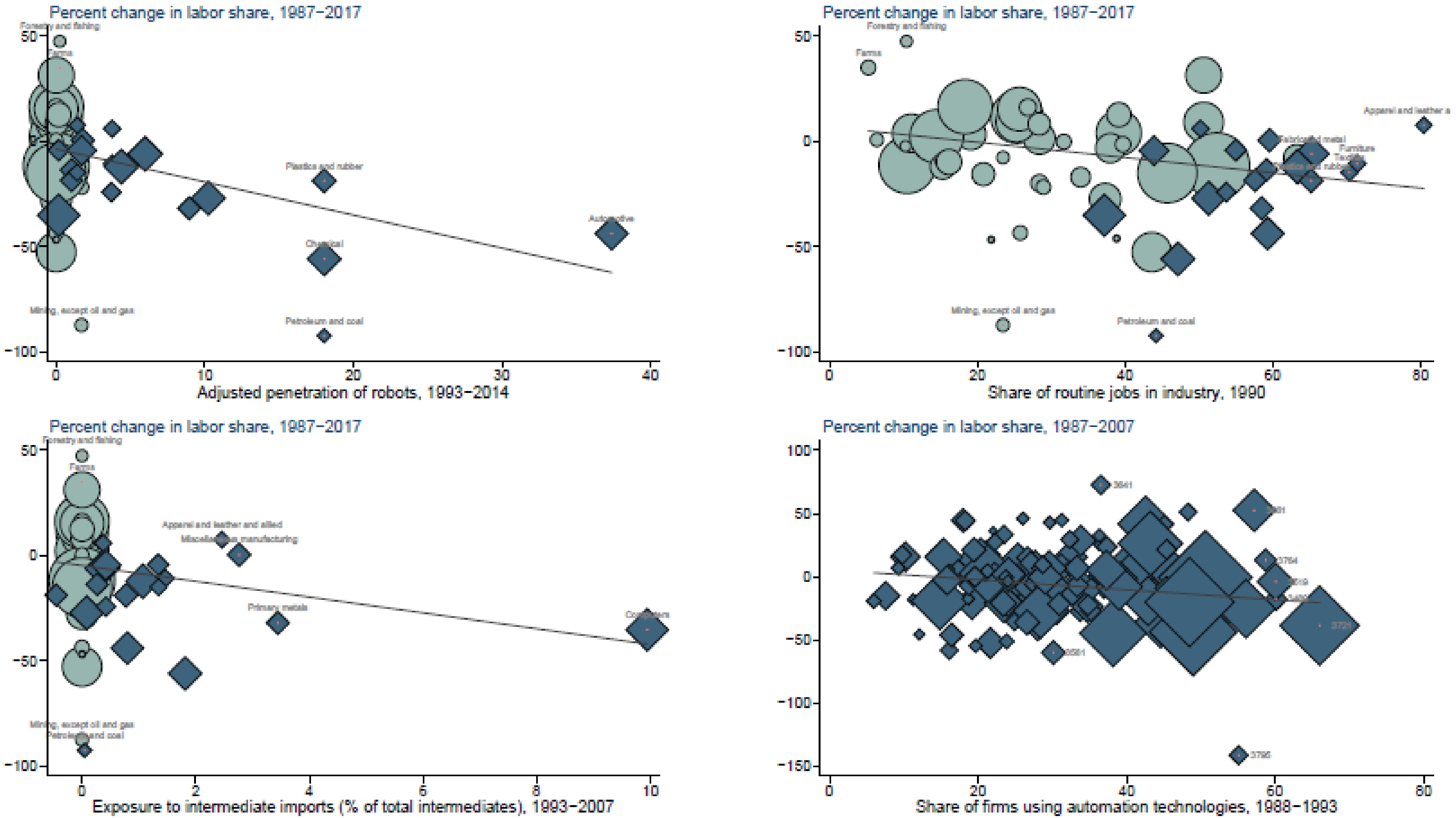
$$+ \frac{1}{\sigma}\frac{1 - s^L}{1 - \Gamma(N, I)}\frac{\partial \ln \Gamma(N, I)}{\partial I} \quad \text{(Displacement effect<0)}$$

- In the absence of the displacement effect, the wage bill changes proportionately to output, and the labor share is constant.
- Because the displacement effect is negative, wage bill increases less than output.
- Net effect on wage bill depends on technology/context:

Labor demand: with factor augmenting technologies

$$WL = Y \times s^L$$

$$\begin{aligned}
\frac{\partial \ln WL}{\partial \ln A^L} =& s^L && \text{(Productivity effect)} \\
&+ \frac{\sigma - 1}{\sigma}(1 - s^L) && \text{(Task-price substitution),} \\
\frac{\partial \ln WL}{\partial \ln A^K} =& (1 - s^L) && \text{(Productivity effect)} \\
&+ \frac{1 - \sigma}{\sigma}(1 - s^L) && \text{(Task-price substitution).}
\end{aligned}$$


Percent change in labor share, 1987-2017
Forestry and fishing
Farms
Plastics and rubber
Automotive
Chemical
Mining, except oil and gas
Petroleum and coal
Adjusted penetration of robots, 1993-2014
Percent change in labor share, 1987-2017
Forestry and fishing
Farms
Apparel and leather a
Furniture
Textiles
Mining, except oil and gas
Petroleum and coal
Share of routine jobs in industry, 1990
Percent change in labor share, 1987-2017
Forestry and fishing
Farms
Apparel and leather and allied
Miscellaneous manufacturing
Primary metals
Computers
Mining, except oil and gas
Petroleum and coal
Exposure to intermediate imports (% of total intermediates), 1993-2007
Percent change in labor share, 1987-2007
Share of firms using automation technologies, 1988-1993

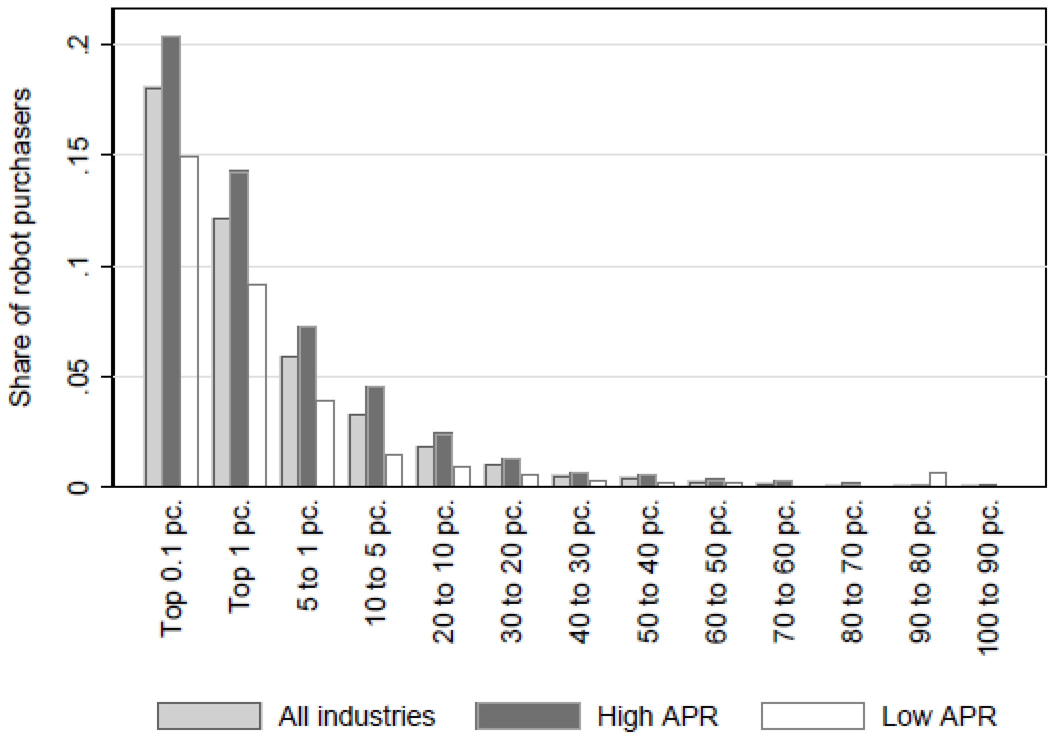
Synthesis so far…

- Explains well changes in **occupation and wages**
- So far, little to say about **firm-level concentration**
  - This requires firm-level data…

Firm-level data about robotization

- From Acemoglu, Lelarge and Restrepo (AER, P&P 2020).
- Sample of 55,390 firms that were active from 2010 to 2015 in the French manufacturing sector. Subset of 598 firms that purchased industrial robots in this period.
- Identified from several sources:
  - survey by the French Ministry of Industry
  - clients' lists provided by French robot suppliers and integrators
  - customs data on imports of industrial robots by firm
  - fiscal files with information on robot depreciation allowances
- Although only 1% of the firms purchased robots in 2010-2015, these firms account for 20% of total manufacturing employment.

Robot adoption: only very few firms



- Robot adopters are larger and concentrate in high APR industries—those where there are major advances in robotics technology and rapid spread of robots in other countries.

(Descriptive) impact on industry structure

- Estimating equation:

$$
\begin{aligned}
\Delta \ln y_f \quad = \quad & \beta \cdot \text{Robot}_f + \eta \cdot \text{Adoption by competitors}_f \qquad (1) \\
& \gamma \cdot X_f + \alpha_{i(f)} + \delta_{c(f)} + \varepsilon_f .
\end{aligned}
$$

where

$$
\begin{array}{l}\text{Adoption by} \\ \text{competitors}_f\end{array} = \sum_i m_{fi} \cdot \sum_{f' \neq f} s_{if'} \cdot \text{Robot}_{f'} .
$$

- First sum over all 4-digit industries; m_{fi} is the share of firm f sales in industry i.
- The second sum is over all firms other than f and $s_{if'}$ is the share of industry i sales accounted for by firm f'.
- Measure of adoption by competitors gives the overlap in terms of sales across 4-digit industries between a firm and all robot adopters in the economy.
- Unweighted and baseline employment-weighted OLS estimates (no firm-level exogenous source of variation in robot adoption).

Table: Estimates of robot adoption on adopters and competitors

	Unweighted estimates			*Employment-weighted estimates*		
	(1)	(2)	(3)	(4)	(5)	(6)
	Δ log employment (in hours)	Δ log value added	Δ labor share	Δ log employment (in hours)	Δ log value added	Δ labor share
Robot adoption by competitors	-0.105	-0.100	0.002	-0.250	-0.209	-0.008
	(0.047)	(0.051)	(0.015)	(0.107)	(0.159)	(0.040)
Robot adopter	0.106	0.201	-0.043	0.035	0.078	-0.027
	(0.020)	(0.030)	(0.009)	(0.022)	(0.029)	(0.012)
R^2	0.093	0.083	0.161	0.190	0.217	0.274

Magnitudes and Interpretation

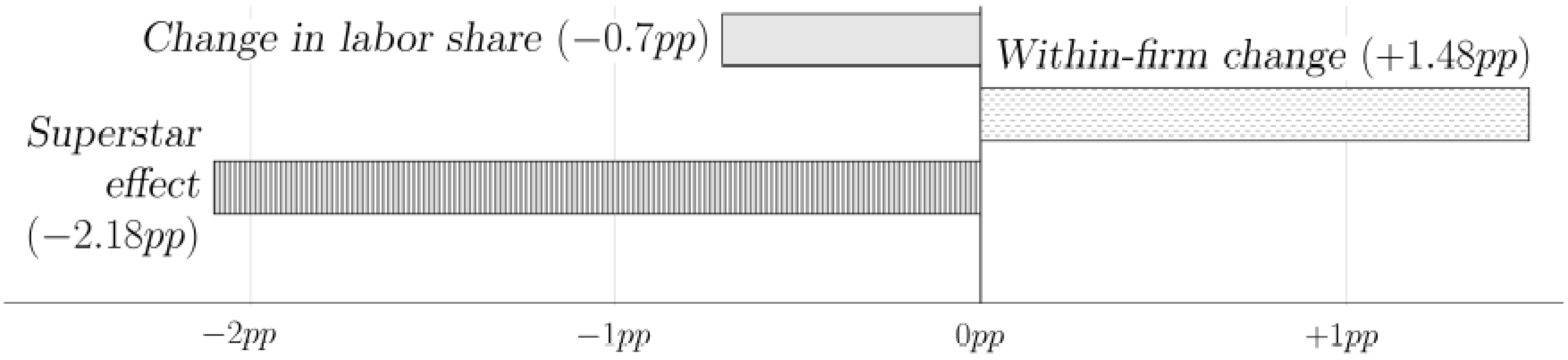
- Most striking result: robot adoption is associated with increases in firm employment but significant declines in the employment of competing firms.
- Equally important for our focus: robot adoption associated with a 4.3 pp reduction in the labor share of a firm (and no effect from competitors).
- Robot adopters make up 20% of value added, and thus their decline in labor share accounts for a 0.86 pp decline in the manufacturing labor share.
- This is approximately the decline in French manufacturing over this time period.
- Consistent with theory, competitors' adoption has no impact on own labor share.

Superstar Effects and the Labor Share (1)

- The impact of robot adoption on overall labor share is greater than impact on own labor share—because of reallocation documented above.
- The issue is very similar to that studied by Autor et al. (2019).
- They propose the following decomposition (only for surviving firms here)

$$\begin{array}{c}\text{Change in}\\\text{labor share}\end{array} = \begin{array}{c}\text{Within firm change:}\\\text{Change in}\\\text{unweighted mean}\end{array} + \begin{array}{c}\text{Superstar effect:}\\\text{Change in covariance between}\\\text{labor share and value added}\end{array}$$

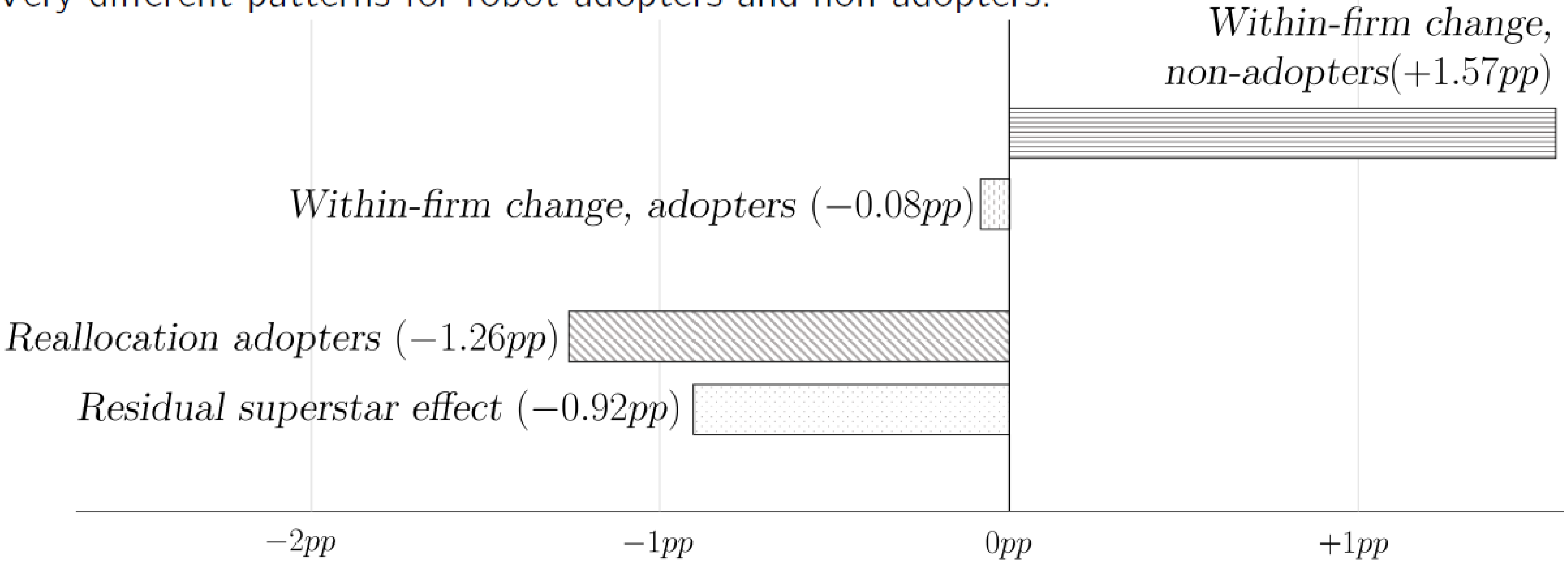
Superstar Effects and the Labor Share (2)



- This is quantitatively similar to the findings from the US in Autor et al. (2019).
- But we can now further understand the role of automation in this process.

Superstar Effects and the Labor Share (3)

- Very different patterns for robot adopters and non-adopters.



- The superstar effect for adopters is mostly about the fact that labor share declines in these firms that account for a large fraction of value added.
- No "pure reallocation effect"—driven by shifts in value-added towards lower labor share firms—because no baseline differences in labor share between adopters and non-adopters (74% versus 76% in the two groups).

D/ Communication technologies in optimal hierarchies

Models of optimal hierarchies

- Main intuition: **human capital is the scarcest resource** (“skills” ≈ “knowledge”)
  - How to save on it??

- **Main references**:
  - Lucas (1978) span of control model: the observed size distribution of firms is a solution to the problem: allocate productive factors over managers of different ability so as to maximize output.
  - Rosen (1981) Economics of superstars; Rosen (1982) Authority, Control and the Distribution of Earnings
  - Garicano (JPE 2000); G and Rossi-Hansberg (AER 2004, QJE 2006, ARE 2015), empirical studies with Caliendo on French and Portuguese data

- Drop in cost of **communication technologies (CT)** leverages the skill of the best managers:
  - They will match with other best managers / workers
  - They will apply their knowledge (skill) to larger problems
  - **Cheaper communications** allow for more **“leverage” of talent**
  - Can account for a wide range of the previous stylized facts

  - **IT improvements** have contrasted effects! (GRH, 2006, Bloom et al, 2014)

Impact of ICT technologies

Counterfactual wage distribution

Mechanism generating skewed distribution of income:

Scale of operation effect

- Those with higher ability are assigned larger ressources
- But this scale of operations affects the marginal value of ability
  - Earnings of entrepreneurs are skewed, because only the more talented have a positive span of control, and the differences in ability are multiplied by this span.

Emergence of firms’ organizations (1)

- **Knowledge (talent)** is the really scarce asset
  - Essential determinant of the productive efficiency of an organization
- The organizational problem arises because knowledge is embedded in individuals who have limited time to work (time is limited)
  - One way to relax this time constraint is to **work in teams**
    - Economizing on the time of experts
    - Allowing them to specialize on giving directions on the harder tasks, ie **VERTICAL SPECIALIZATION**

  - Alfred Sloan: *‘’We do not do much routine work with details. They never get up to us. I work fairly hard, but it is on exceptions… not on routine or petty details’’*
  - **The key determinant of this team technology is communication**

Emergence of firms’ organizations (2)

Organizations determine:

- Who knows what
- Who do they communicate with
- How many workers of each type are required
- … In order to minimize the cost of producing a certain output

Hierarchies as a specific form of organization are a way to acquire and utilize knowledge efficiently:

- **Optimization of the use of knowledge across layers**
    - Routine [common] tasks/problems at the bottom
    - Exceptions at the top
    - Allows differentiation of roles
    - Higher levels help lower levels solve problems

Details of the production function specification (1)

- Workers:
  - Each worker uses her unit of time to generate a production possibility that can yield A units of output
  - For output to be realized the worker needs to solve a problem
  - Problems are drawn from $F(z) = 1 - e^{-\lambda z}$
    - $\lambda > 0$ regulates how common are the problems faced in production
  - Workers learn how to solve an interval of knowledge $[0, z_L^0]$
    - If the problem they face is in this interval production is realized
    - Otherwise they could ask a manager one layer above

Details of the production function specification (2)

- Managers
  - Specialize in solving problems
  - Spend h units of time with each problem that gets to her
    - ★ So each manager can deal with $1/h$ problems
  - A manager of layer 1 tries to solve the problems workers could not solve
    - ★ So problems that require knowledge larger than z_L^0
    - ★ Learns how to solve problems in the interval $\left[z_L^0, z_L^0 + z_L^1\right]$
    - ★ So the firm needs $n_L^1 = hn_L^0\left(1 - F\left(z_L^0\right)\right)$ of these managers
    - ★ Unsolved problems can be sent to a manager one layer above
  - In general, managers in layer l learn $\left[Z_L^{l-1}, Z_L^l\right]$ and there are $n_L^l = hn_L^0(1 - F(Z_L^{l-1}))$ of them, where $Z_L^l = \sum_{\ell=0}^{l} z_L^\ell$

Details of the production function specification (3)

Central cost minimization problem

- Consider a firm that produces a quantity q. The *variable* cost function is given by

$$C(q; w) = \min_{L \geq 0} \{C_L(q; w)\}$$

where $C_L(q; w)$ is the minimum cost of producing q with an organization with $L+1$ layers, namely,

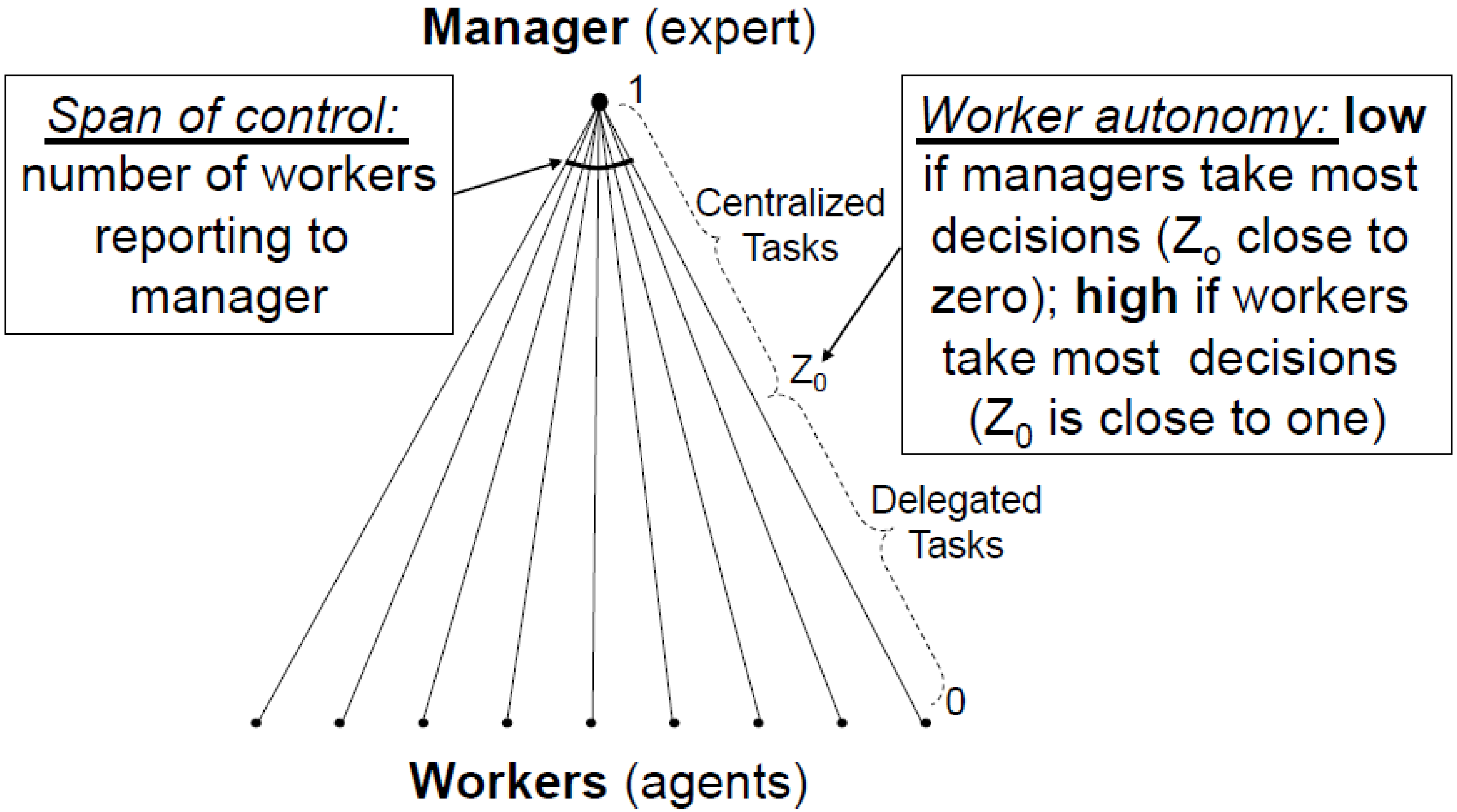
$$C_L(q; w) = \min_{\{n_L^l, z_L^l\}_{l=0}^L \geq 0} \sum_{l=0}^L n_L^l w \left(c z_L^l + 1\right)$$

subject to

$$\begin{aligned} q &\leq F(Z_L^L) A n_L^0, \\ n_L^l &= h n_L^0 (1 - F(Z_L^{l-1})) \text{ for } L \geq l > 0, \\ n_L^L &= 1 \end{aligned}$$

Inserting a layer is equivalent to paying an additional fixed cost to achieve lower marginal costs

Span of control vs. Autonomy (1)



Span of control vs. Autonomy (2)

The relation between the two is the ‘’scale of operations’’ effect:

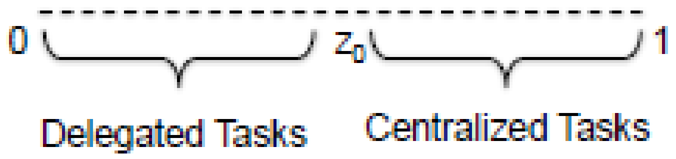
- The marginal value of an agent’s ability is given by the **amount of resources he manages**
- Absent distorsions (eg. monopsony power), it determines **her/his wage**

One essential application of the organizational problem described above is to understand the impact of ***economy-wide*** changes in technologies that affect the acquisition and communication of knowledge…

Impact of a change in communication costs:
Increases the number of "centralized tasks"

Lower communication costs increase the number of "**direct reports**"…

- The cost of passing problems to the top decreases
- Example: meetings
- 0: most routine (frequent) vs. 1 not routine



Notes: $z \in [0, z_0]$ Performed by lower level agents
$z \in (z_0, 1]$ Passed on to the higher level

- Implies increases in wages at the top, decreases at the bottom
- (Complicated in-between…)

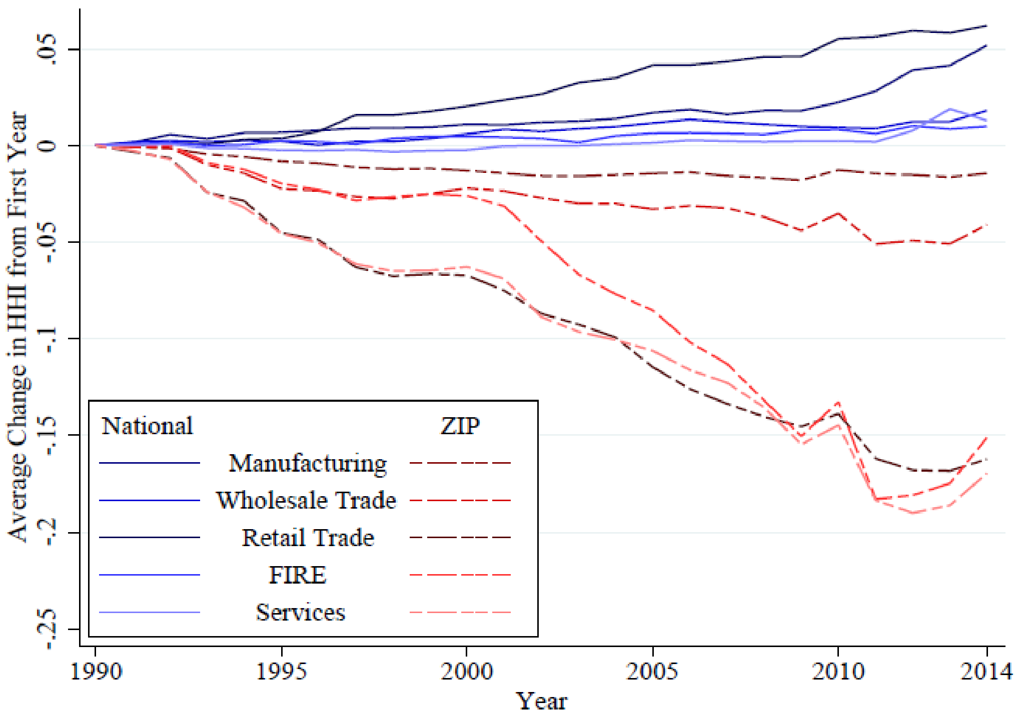
Impact of a change in communication costs:
Amplification of superstar effects (1)

Increase in the « scale of operations » effect :

- **Able to rationalize increase in CEO pay** : similar to Gabaix and Landier (2008) (NB: credible, but debated)
- Probably able to rationalize **increase in concentration**

- Consistent with the availability of **new sets of fixed-cost technologies that enable adopters to produce at lower marginal costs in all markets**.
- Mechanism proposed to rationalize ''Diverging Trends in National and Local Concentration'' (2021, Rossi-Hansberg, Sarte and Trachter, NBER Macro Annual)
- ''The Industrial Revolution in Services'' (JPE Macro, forth), Rossi-Hansberg and Hsieh

Figure 2: Diverging division-level national and local concentration trends

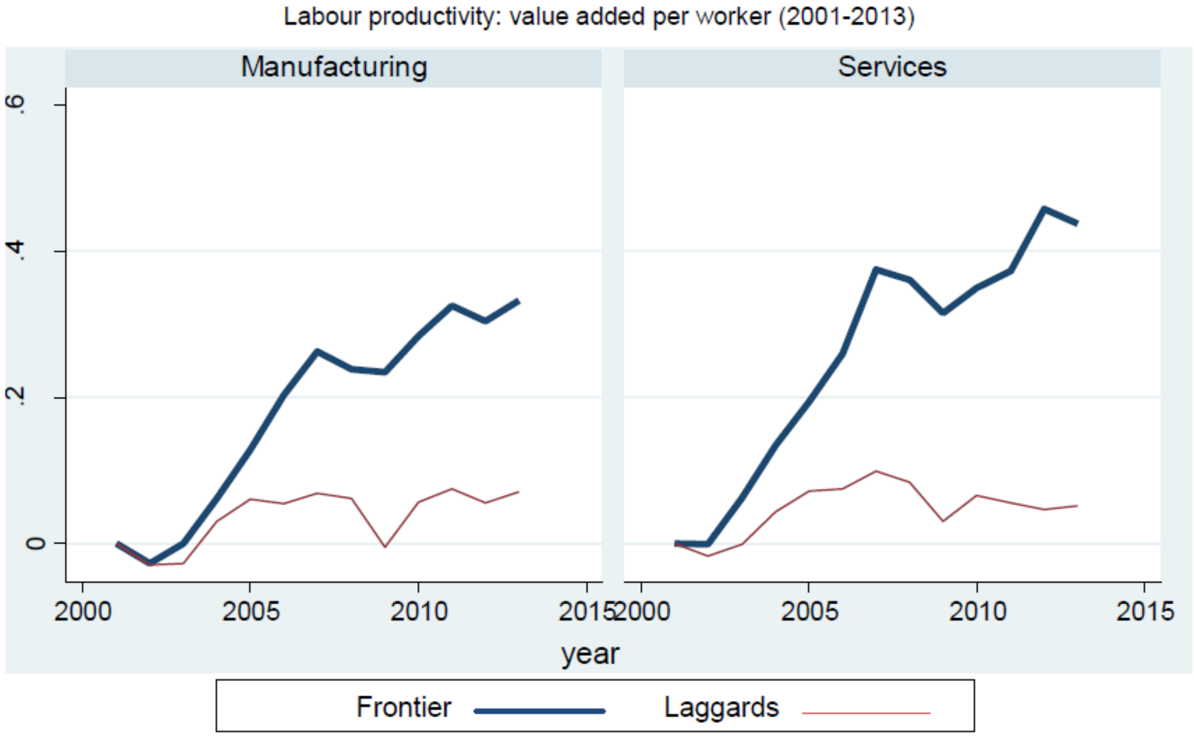


Impact of a change in communication costs:
Amplification of superstar effects (2)

Increase in the « scale of operations » effect :

- **Able to rationalize increase in CEO pay** : similar to Gabaix and Landier (2008) (NB: credible, but debated)
- Probably able to rationalize **increase in concentration**
- Also consistent with additional **"super-star" effect in terms of FIRMS 'productivity**

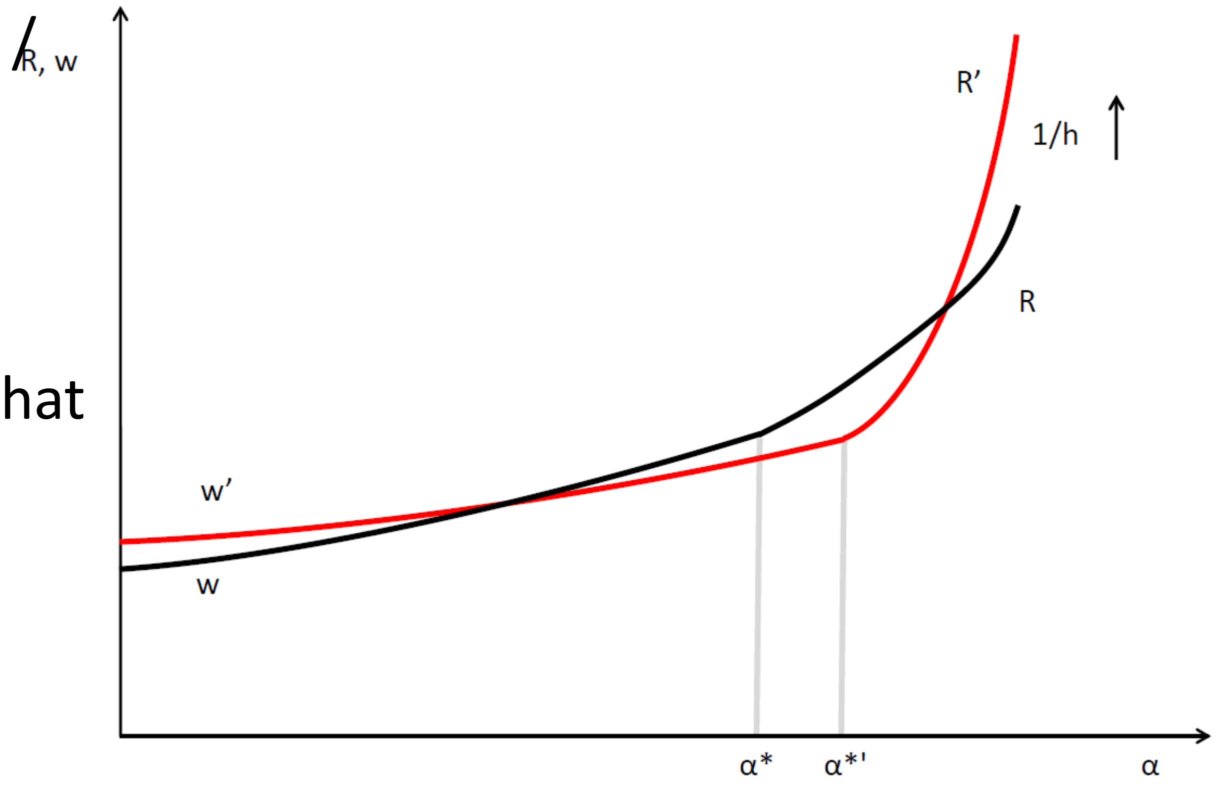
Andrews, D., Criscuolo C., and Gal P. N., "**The Best versus the Rest: The Global Productivity Slowdown, Divergence across Firms** and the Role of Public Policy", OECD Productivity Working Papers, 2016-05, OECD Publishing, Paris



Impact of a change in communication costs:
Implications for wages (GRH, AER 2006)

Reallocation of tasks/problems across workers / managers implying that:

- Workers become **less differentiated**
- Top managers **earn a lot more**
- **''Shadow of the superstars''** on the workers that used to be the ones exclusively working with them:
  - Medium knowldege and skill matter less (knowledge effect)
  - They lose demand to superstar (demand effect)



Impact of a change in communication costs:
Attempt to rationalize lower labor shares…

The compensation to top talents could be mismeasured:

- Stock options and stock based rewards to CEO and top managers/top workers.
- Would be measured as capital rather than labor compensation
- They are in fact a return to the knowledge

- (Is it enough to rationalize the empirical pattern? not sure….)

Future Research?

Many challenges…

Still limitations of the 2 main frameworks presented here

Task-based approach:

- Extension about why some firms adopt new technologies, why others don’t to be developed
  - Would involve integrating some source of firm heterogeneity
- => Still incomplete understanding of why automation would affect concentration, IO aspects
- Would also improve identification: IV for technology adoption

Optimal hierarchies :

- Somewhat specific production functions: only suitable to think about IT/CT
- Still : probably relevant to think about AI- based technologies
- Does not seem to fully capture the labor replacement effect and overall impact on labor shares
- Difficult to use as a macro quantitative framework:
  - Attempt in Lawson, Lelarge and Spanos, 2023