UNIVERSITÀ DEGLI STUDI DI FERRARA
- EX LABORE FRUCTUS -

DEPARTMENT OF ECONOMICS & MANAGEMENT

# Economics of Innovation
## Innovation and Employment

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29/11/2018

# 1961, TIME magazine:

The number of jobs lost to more efficient machines is only part of the problem. What worries many job experts more is that automation may prevent the economy from creating enough new jobs. . . . Throughout industry, the trend has been to bigger production with a smaller work force. . . . Many of the losses in factory jobs have been countered by an increase in the service industries or in office jobs. But automation is beginning to move in and eliminate office jobs too. . . . In the past, new industries hired far more people than those they put out of business. But this is not true of many of today's new industries. . . . Today's new industries have comparatively few jobs for the unskilled or semiskilled, just the class of workers whose jobs are being eliminated by automation.

# Skill-Biased Technological Change

Changes in the demand for skilled labor within U.S. manufacturing

Berman, Bound & Griliches (1994)

# Introduction

- Earning differentials between high-school and college graduates rose by more than 10% over the 80s
  - Part due to slowdown in the rate of growth of college-educated population and continued growth in the demand for educated labour
- Employment of production workers in US manufacturing decrease by 15% in the 80s
- Nonproduction employment rose by 3%

- **Shift in labour demand** within manufacturing away from production and toward nonproduction labour

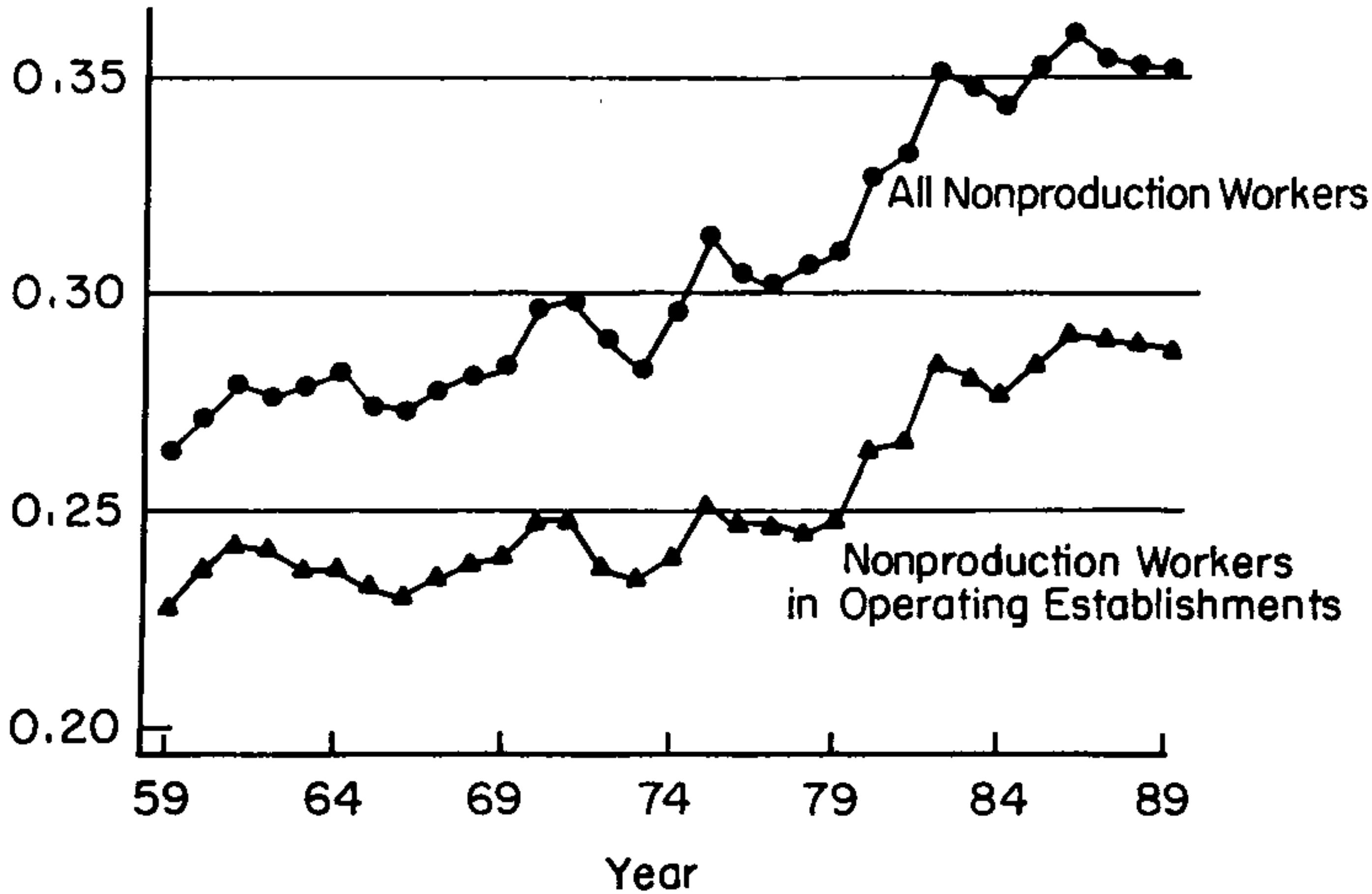



FIGURE I
Nonproduction Workers' Share in Total Employment

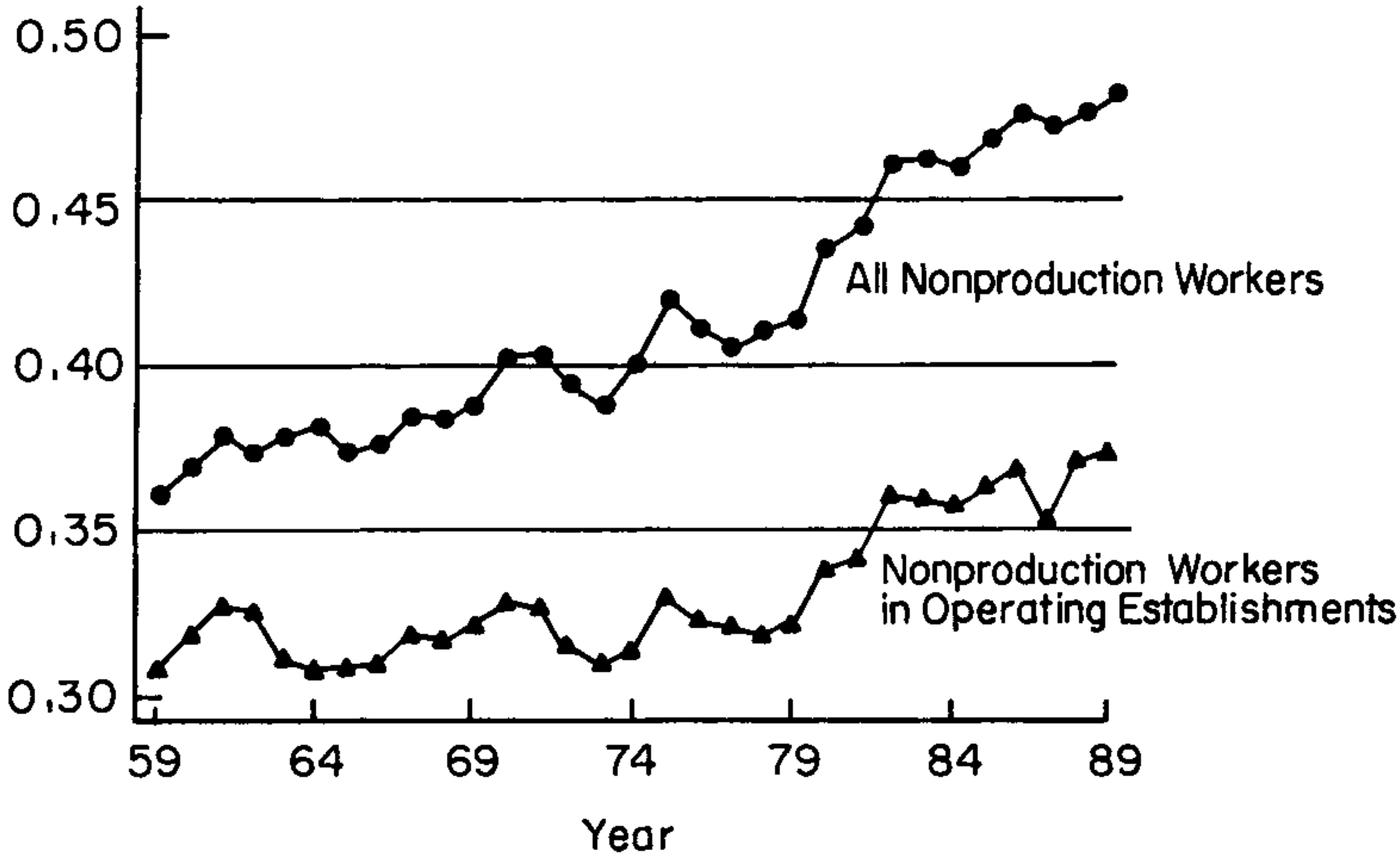



FIGURE II
Nonproduction Workers' Share in the Wage Bill

TABLE I
OCCUPATIONAL DISTRIBUTIONS WITHIN MANUFACTURING BY YEAR

| | 1973 | 1979 | 1987 |
|---|---|---|---|
| Total nonproduction | 28.3% | 30.9% | 35.4% |
| Percent in central offices | 17.3% | 19.7% | 18.4% |
| White-collar | 28.6% | 31.9% | 37.2% |
| Manager | 27.0 | 27.0 | 29.4 |
| Professional | 18.8 | 19.9 | 21.5 |
| Technician | 8.7 | 9.0 | 9.0 |
| Sales worker | 7.3 | 7.5 | 8.8 |
| Clerical worker | 38.1 | 36.6 | 31.4 |
| Subtotal | 100.0 | 100.0 | 100.0 |
| Blue-collar | 71.4% | 68.1% | 62.8% |
| Craft | 24.4 | 25.7 | 30.3 |
| Operative | 62.3 | 61.6 | 57.6 |
| Laborer | 9.8 | 9.5 | 9.0 |
| Service worker | 3.0 | 2.8 | 2.6 |
| Agricultural labor | 0.5 | 0.5 | 0.6 |
| Subtotal | 100.0 | 100.0 | 100.0 |

*Source.* Annual Survey of Manufacturing and CPS, May 1973, Outgoing Rotations, 1979 and 1987.

- The blue-collar/white-collar classification reflects educational classification of high school/college
- White-collar workers in clerical jobs dropped by 18%, managerial or professional jobs rose by 11%.
- Blue-collar working as operatives dropped by over 5 percent, while the fraction working in the more skilled crafts jobs rose by over 20 percent

# How much of skill upgrading is represented by the shift from blue- to white-collar occupations?

- Estimates indicate that 53% of the occupational upgrading that occurred between 1973 and 1987 is accounted for by shifts from blue- o white-collar occupations
- The same calculation using single years of education rather than occupation groups as predictors yields a figure of 27 percent

# Reasons

TABLE III
POSSIBLE CONTRIBUTORS TO THE INCREASED RELATIVE DEMAND FOR SKILLED LABOR

| | 1959 | 1973 | 1979 | 1987 |
|---|---|---|---|---|
| R & D expenditures as a fraction of manufacturing shipments | | | | |
| Total | 2.6 | 2.4 | 2.2 | 3.9 |
| Privately funded | 1.6 | 0.9 | 0.7 | 1.3 |
| Government funded | 1.1 | 1.5 | 1.5 | 2.6 |
| Share of high tech capital in total manufacturing capital stock | | | | |
| Total | 1.0 | 1.4 | 3.3 | 6.9 |
| Computing eq. | 0.3 | 0.2 | 0.5 | 2.3 |
| Communications eq. | 0.2 | 0.3 | 0.6 | 2.2 |
| Scientific eq. | 0.5 | 0.6 | 1.3 | 1.2 |
| Photocopy eq. | 0.0 | 0.3 | 1.0 | 1.2 |
| Imports and exports as a fraction of manufacturing shipments | | | | |
| Exports | 4.5 | 8.4 | 10.6 | 10.7 |
| Imports | 4.2 | 8.2 | 12.3 | 17.3 |
| Department of Defense purchases as a fraction of manufacturing shipments | | | | |
| Purchases | 5.9 | 2.1 | 2.0 | 4.2 |

*Source.* Rows 1–3, National Science Foundation [1991] and ASM; Rows 4–8, unpublished tabulations, Bureau of Economic Analysis; Rows 9–11 National Income and Products Accounts and ASM.

# Industry-level analysis and conclusions

- The shift is due mostly to increased use of skilled workers within industries rather than to a reallocation of employment between industries
- Trade and defence-demand are associated with only small employment reallocation effects
- Increased use of nonproduction workers is strongly correlated with investment in computers and in R&D

# The skill content of recent technological change

Autor, Levy & Murnane (2003)

How do computerization alters job skills demands?

# Introduction

- Positive relationship between adoption of computer-based technologies and the increased use of college-educated labour
- Various studies find evidence on industry level demand shifts and on firm and plan level shifts

→Evidence of **skill-biased technical change**

# Open questions

- What is that computers do?
- What is that people do with computers that causes educated workers to be relatively more in demand?

- How do computers change the task performed by workers at their jobs and ultimately the demand for human skills?

# Some introductory definitions

- **Routine tasks**: limited and well defined set of cognitive and manual activities
  - Can be accomplisedh by following explicit rules
- **Nonroutine tasks**: problem solving and complex communication activities
  - Rules are not sufficiently well understood  to be specified in computer code and executed by machines
- Rutine and nonroutine tasks are imperfect subsititutes

TABLE I

PREDICTIONS OF TASK MODEL FOR THE IMPACT OF COMPUTERIZATION ON FOUR CATEGORIES OF WORKPLACE TASKS

| | Routine tasks | Nonroutine tasks |
|---|---|---|
| | Analytic and interactive tasks | |
| Examples | • Record-keeping<br>• Calculation<br>• Repetitive customer service (e.g., bank teller) | • Forming/testing hypotheses<br>• Medical diagnosis<br>• Legal writing<br>• Persuading/selling<br>• Managing others |
| Computer impact | • Substantial substitution | • Strong complementarities |
| | Manual tasks | |
| Examples | • Picking or sorting<br>• Repetitive assembly | • Janitorial services<br>• Truck driving |
| Computer impact | • Substantial substitution | • Limited opportunities for substitution or complementarity |

# Conceptual model

- Because of its declining cost, computer-controlled machinery should have substantially substituted for workers in performing routine manual tasks
  - Similar to the mechanization that substituted human labour during the industrial revolution
- Computerization marks a qualitative enlargement in the set of tasks that machines can perform
  - Symbolic processing (storing, retrieving, and acting upon information) augment or supplant human cognition in a large set of information-processing tasks not amenable to mechanization

# Conceptual model

- This substitution marks an important reversal
  - Previous generations of high technology capital sharply increased demand for human input of routine information-processing tasks, as seen in the rapid rise of the clerking occupation in the nineteenth century [Chandler 1977; Goldin and Katz 1995]. Like these technologies, computerization augments demand for clerical and information-processing tasks. But in contrast to its nineteenth century predecessors, it permits these tasks to be automated

# Conceptual model

- However, the capability of computers to substitute for workers in carrying out cognitive tasks is limited
  – Tasks demanding flexibility, creativity, generalized problem-solving, and complex communications — what we call nonroutine cognitive tasks — do not (yet) lend themselves to computerization [Bresnahan 1999]. At present, the need for explicit programmed instructions appears a binding constraint
- Artificial Intelligence (AI) not considered

# Model implications

- Computer technology carries out routine tasks (more substitutable)
- Computer technology is relative complement to nonroutine tasks

- From a production function standpoint, outward shifts in the supply of routine informational inputs, both in quantity and quality, increase the marginal productivity of workers performing nonroutine tasks that demand these inputs

# Implications

- More tangibly, because repetitive, predictable tasks are readily automated, computerization of the workplace raises demand for problem-solving and communications tasks such as responding to discrepancies, improving production processes, and coordinating the activities of others
- Druker [1954] in the 1950s: “The technological changes now occurring will carry [the Industrial Revolution] a big step further. They will not make human labor superfluous. On the contrary, they will require tremendous numbers of highly skilled and highly trained men—managers to think through and plan, highly trained technicians and workers to design the new tools, to produce them, to maintain them, to direct them” [p. 22, brackets added]

# Postulates

- How computer capital interacts with human labour input:
    1. Computer capital is more substitutable for human labor in carrying out routine tasks than nonroutine tasks.
    2. Routine and nonroutine tasks are themselves imperfect substitutes.
    3. Greater intensity of routine inputs increases the marginal productivity of nonroutine inputs.

# Cobb-Douglas production function

$$Q = (L_R + C)^{1-\beta} L_N^{\beta}$$

- $L_R$ , $L_N$: Labour inputs for R and NR tasks (C computer capital)
- Computer capital and non-routine tasks are complementary
- Perfect substitution between C and $L_R$ (as in postulates 1 and 2).
- Marginal productivity of NR tasks increases with an increase in $L_R$ (3)

# Workers' choice

- One worker may supply R or NR tasks.

$$E_i = [r_i, n_i]$$

$$L_i = [\lambda_i r_i, (1 - \lambda_i) n_i]\,; 0 \leq \lambda \ \leq 1$$

- This supply depends on the elasticity of relative wages

# Equilibrium

- The assumption is that computers and R tasks are perfect substitutes. A decrease in the price of computers reduces the salary of R workers (not different from what's happening nowadays)

$$w_R = \rho$$

- The relative efficience for worker i between R and NR tasks:

$$\eta_i = \frac{n_i}{r_i} \qquad \text{in equilibrium} \qquad \eta^* = \frac{w_R}{w_N}$$

# Efficiency

- Individual *i* supplies routine labour $(\lambda_i = 1)$ if $\eta_i < \eta^*$
- Individual *i* will supply nonroutine labour otherwise
- To quantify labour supply we need to write function g(η) and h(η) which sum population endowments in efficiency units in routine and nonroutine tasks, respectively:

$$g(\eta) = \Sigma_i r_i \cdot I[\eta_i < \eta] \text{ and } h(\eta) = \Sigma_i n_i \cdot I[\eta_i \geq \eta]$$

# Efficiency

- Productive efficiency requires:

$$w_R = \frac{\partial Q}{\partial L_R} = (1-\beta)\theta^{-\beta} \quad \text{and} \quad w_N = \frac{\partial Q}{\partial L_N} = \beta\theta^{1-\beta}$$

- Where θ is the ratio of routine to nonroutine task input in production:

$$\theta \equiv (C + g(\eta^*))/h(\eta^*).$$

# Results

- From $[w_R = \rho]$ we can derive that, a decline in ρ reduces $w_R$: $\partial$ (ln $w_R$)/ $\partial$(ln ρ) = 1
- An increase in the demand for routine tasks can be faced by
  - An increase in computer capital
  - An increase in routine inputs
  - Combination of the two
- Increase in computer capital:
- The relative salary of NR workers increases when the price of computers decreases:

$$\frac{\partial \ln(\frac{w_N}{w_R})}{\partial ln\rho} = -\frac{1}{\beta}$$

- The marginal worker will reallocate their labour input from routine to nonroutine tasks

# Theoretical conclusions

- The monotonic decrease in the price of computers increases the marginal productivity of NR workers
- This leads to an shift in labour supply from R to NR workers
- This gap in the supply of R tasks is filled by computer capital that substitutes R workers

# Theoretical conclusions

- Computer capital is adopted in particular when its price decreases
- This is key in those industries that are R task intensive
- Computer capital satisfies the demand for R task inputs
- An increase in computer capital increases NR inputs
- This happens in many industries and also in some occupations (economists, engineers, etc.)

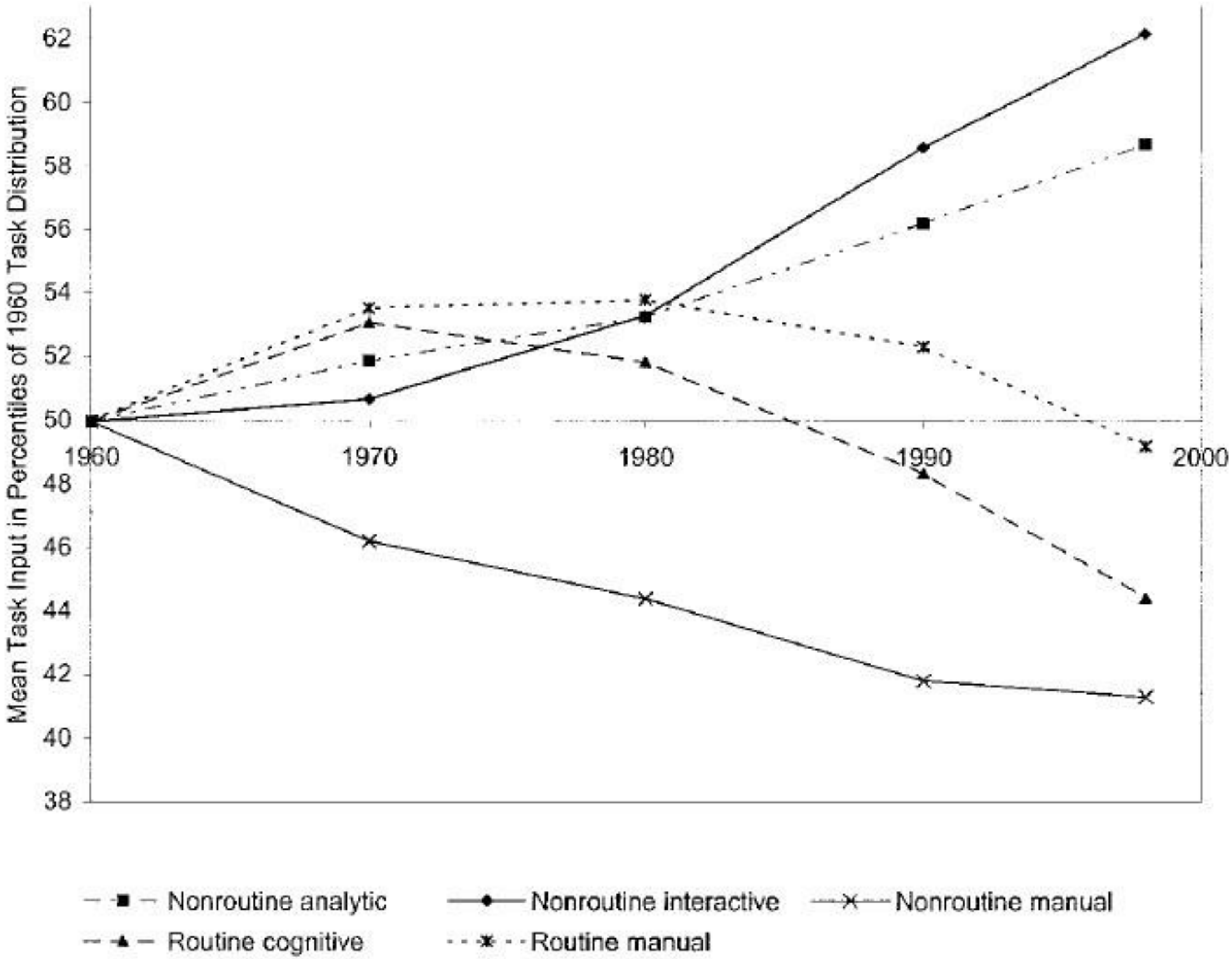
# Empirical issues

- The theoretical formalisation should be tested at the empirical level
- Problems:
  - How do we measure R and NR tasks?
  - What kind of data should we employ? Occupations? industries?

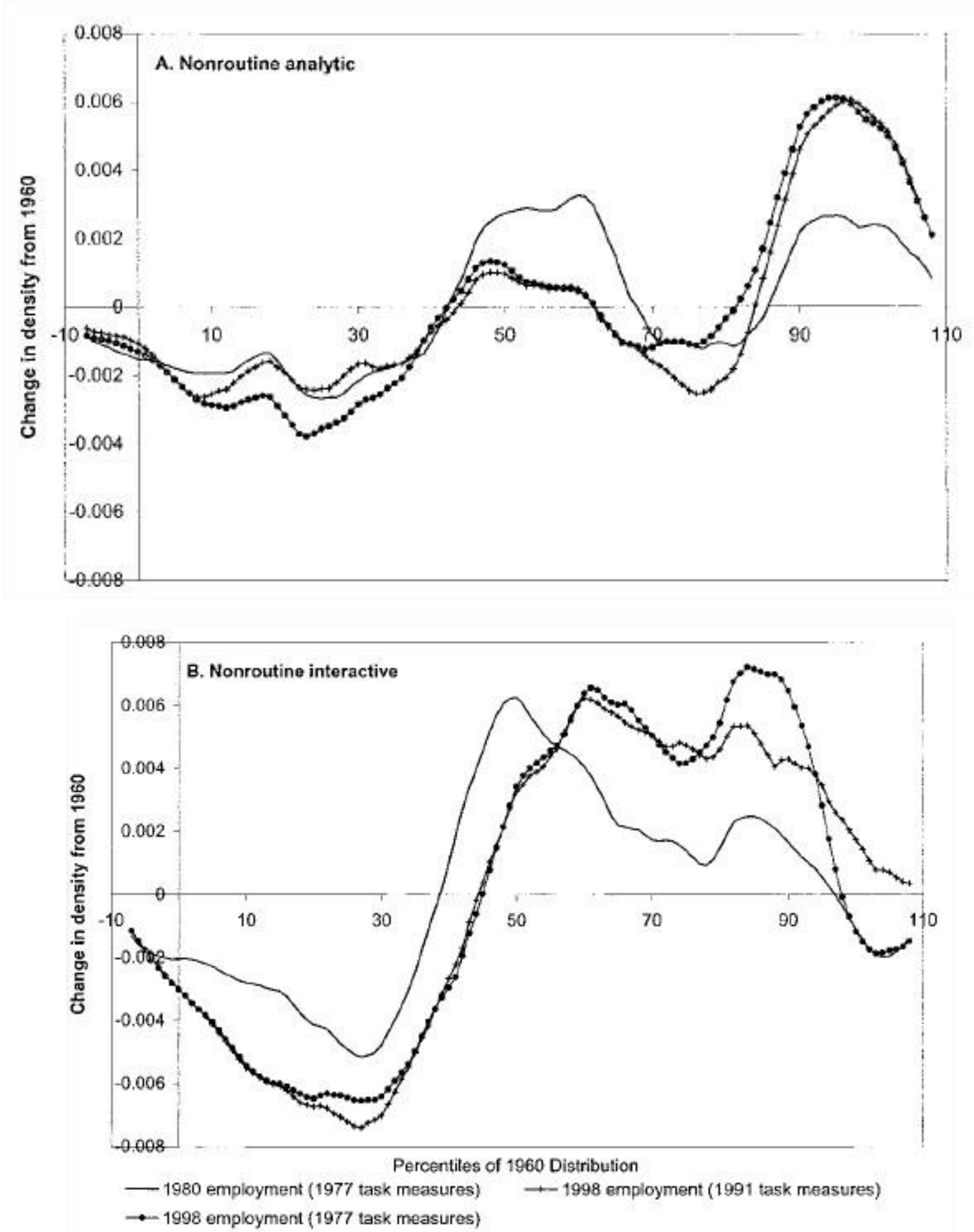
APPENDIX 1: DEFINITIONS OF TASK MEASURES FROM THE 1977 DICTIONARY OF OCCUPATIONAL TITLES

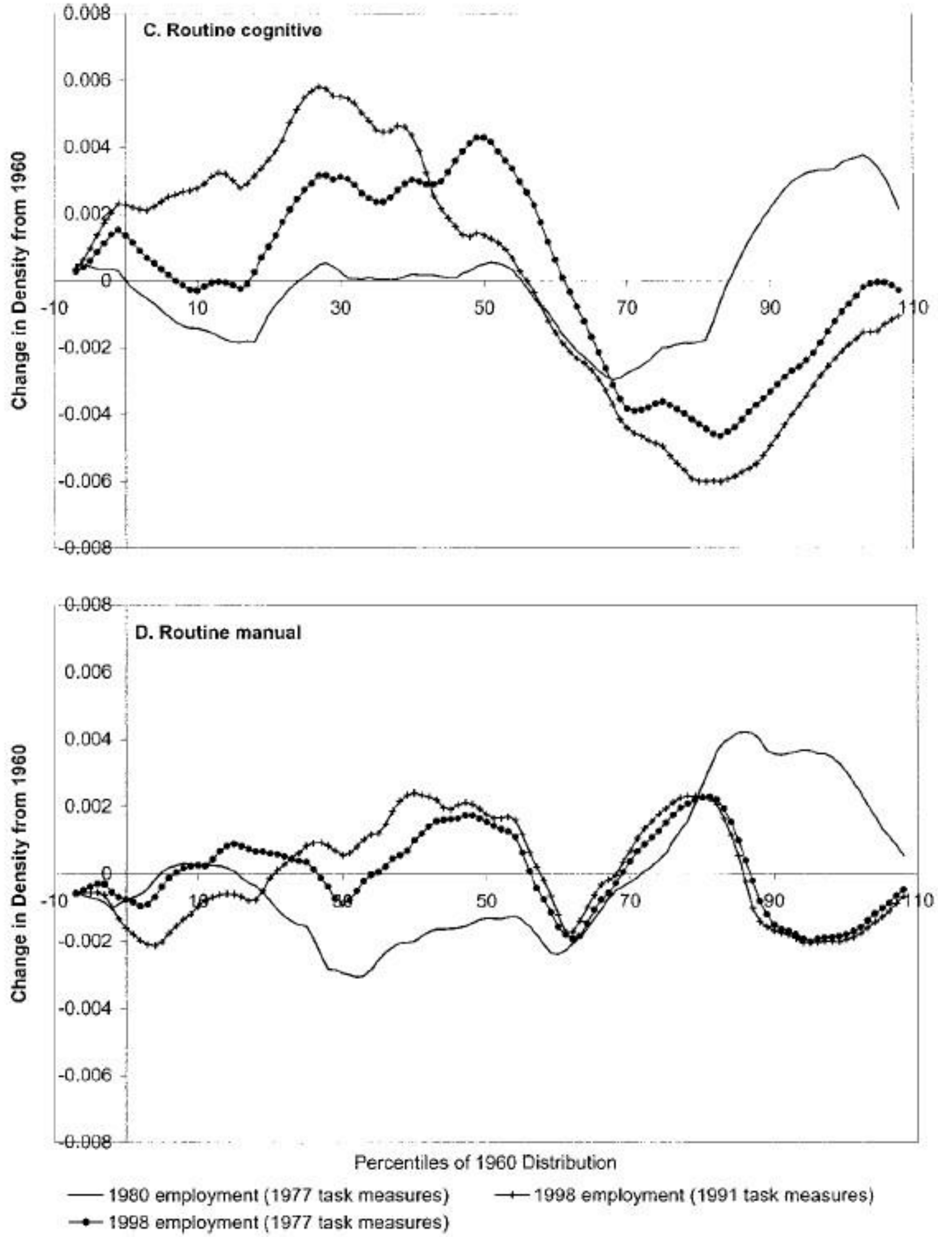
| Variable | DOT definition | Task interpretation | Example tasks from *Handbook for Analyzing Jobs* |
|---|---|---|---|
| 1. GED Math (MATH) | General educational development, mathematics | Measure of nonroutine analytic tasks | Lowest level: Adds and subtracts 2-digit numbers; performs operations with units such as cup, pint, and quart. Midlevel: Computes discount, interest, profit, and loss; inspects flat glass and compiles defect data based on samples to determine variances from acceptable quality limits. Highest level: Conducts and oversees analyses of aerodynamic and thermodynamic systems . . . to determine suitability of design for aircraft and missiles. |
| 2. Direction, Control, Planning (DCP) | Adaptability to accepting responsibility for the direction, control, or planning of an activity | Measure of nonroutine interactive tasks | Plans and designs private residences, office buildings, factories, and other structures; applies principles of accounting to install and maintain operation of general accounting system; conducts prosecution in court proceedings . . . gathers and analyzes evidence, reviews pertinent decisions . . . appears against accused in court of law; commands fishing vessel crew engaged in catching fish and other marine life. |
| 3. Set Limits, Tolerances, or Standards (STS) | Adaptability to situations requiring the precise attainment of set limits, tolerances, or standards | Measure of routine cognitive tasks | Operates a billing machine to transcribe from office records data; calculates degrees, minutes, and second of latitude and longitude, using standard navigation aids; measures dimensions of bottle, using gauges and micrometers to verify that setup of bottle-making conforms to manufacturing specifications; prepares and verifies voter lists from official registration records. |
| 4. Finger Dexterity (FINGDEX) | Ability to move fingers, and manipulate small objects with fingers, rapidly or accurately | Measure of routine manual tasks | Mixes and bakes ingredients according to recipes; sews fasteners and decorative trimmings to articles; feeds tungsten filament wire coils into machine that mounts them to stems in electric light bulbs; operates tabulating machine that processes data from tabulating cards into printed records; packs agricultural produce such as bulbs, fruits, nuts, eggs, and vegetables for storage or shipment; attaches hands to faces of watches. |
| 5. Eye Hand Foot Coordination (EYEHAND) | Ability to move the hand and foot coordinately with each other in accordance with visual stimuli | Measure of nonroutine manual tasks | Lowest level: Tends machine that crimps eyelets, grommets; next level: attends to beef cattle on stock ranch; drives bus to transport passengers; next level: pilots airplane to transport passengers; prunes and treats ornamental and shade trees; highest level: performs gymnastic feats of skill and balance. |

*Source:* U. S. Department of Labor, Manpower Administration, *Handbook for Analyzing Jobs* (Washington, DC, 1972).



62
60
58
56
54
52
50
48
46
44
42
40
38
1960
1970
1980
1990
2000
Mean Task Input in Percentiles of 1960 Task Distribution
Nonroutine analytic
Nonroutine interactive
Nonroutine manual
Routine cognitive
Routine manual


A. Nonroutine analytic
Change in density from 1960
0.008
0.006
0.004
0.002
0
-0.002
-0.004
-0.006
-0.008
-10
10
30
50
70
90
110
B. Nonroutine interactive
Change in density from 1960
0.008
0.006
0.004
0.002
0
-0.002
-0.004
-0.006
-0.008
-10
10
30
50
70
90
110
Percentiles of 1960 Distribution
1980 employment (1977 task measures)
1998 employment (1991 task measures)
1998 employment (1977 task measures)


C. Routine cognitive
Change in Density from 1960
0.008
0.006
0.004
0.002
0
-0.002
-0.004
-0.006
-0.008
-10
10
30
50
70
90
110
D. Routine manual
Change in Density from 1960
0.008
0.006
0.004
0.002
0
-0.002
-0.004
-0.006
-0.008
-10
10
30
50
70
90
110
Percentiles of 1960 Distribution
1980 employment (1977 task measures)
1998 employment (1991 task measures)
1998 employment (1977 task measures)

# Is this the end of the story?

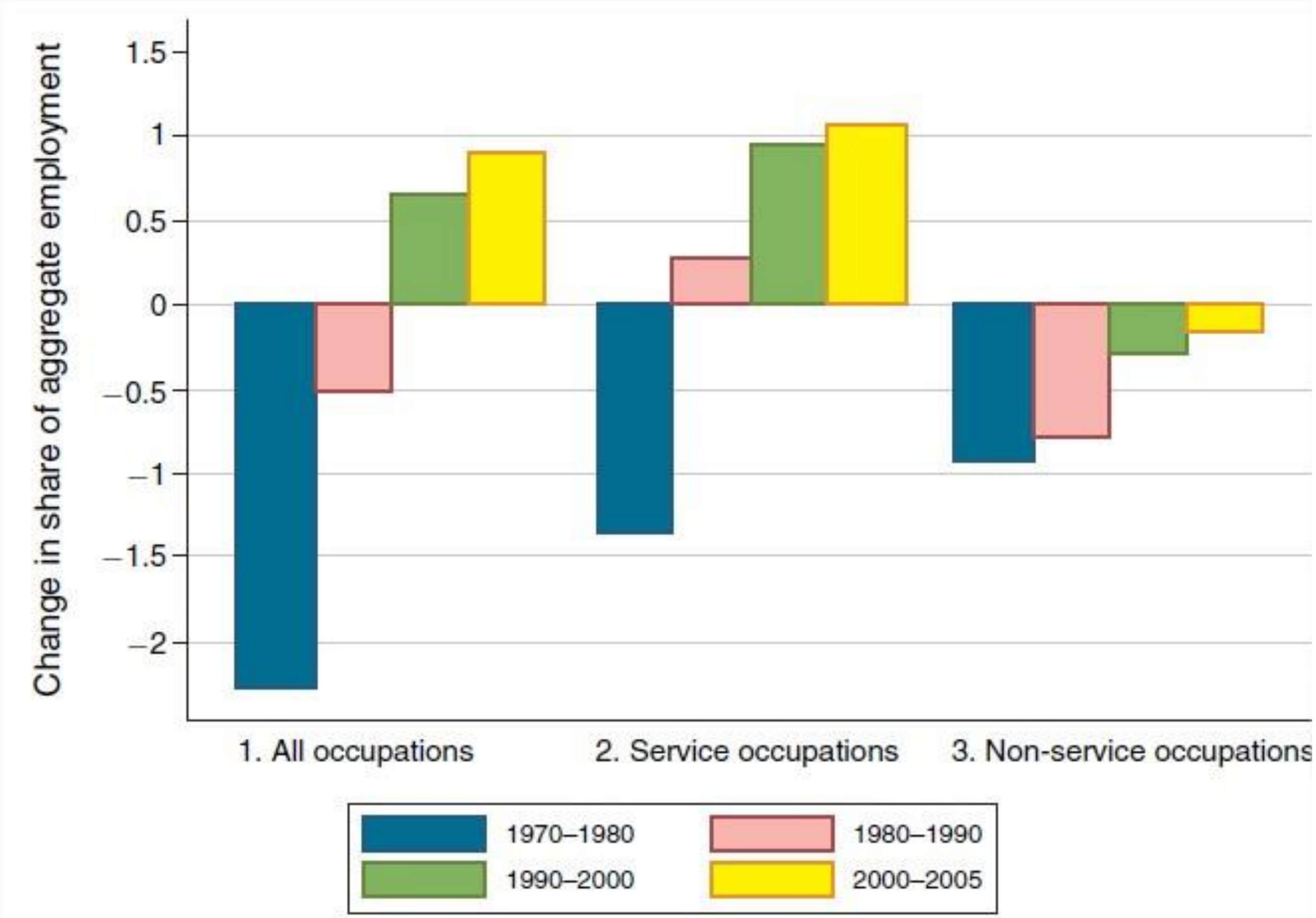


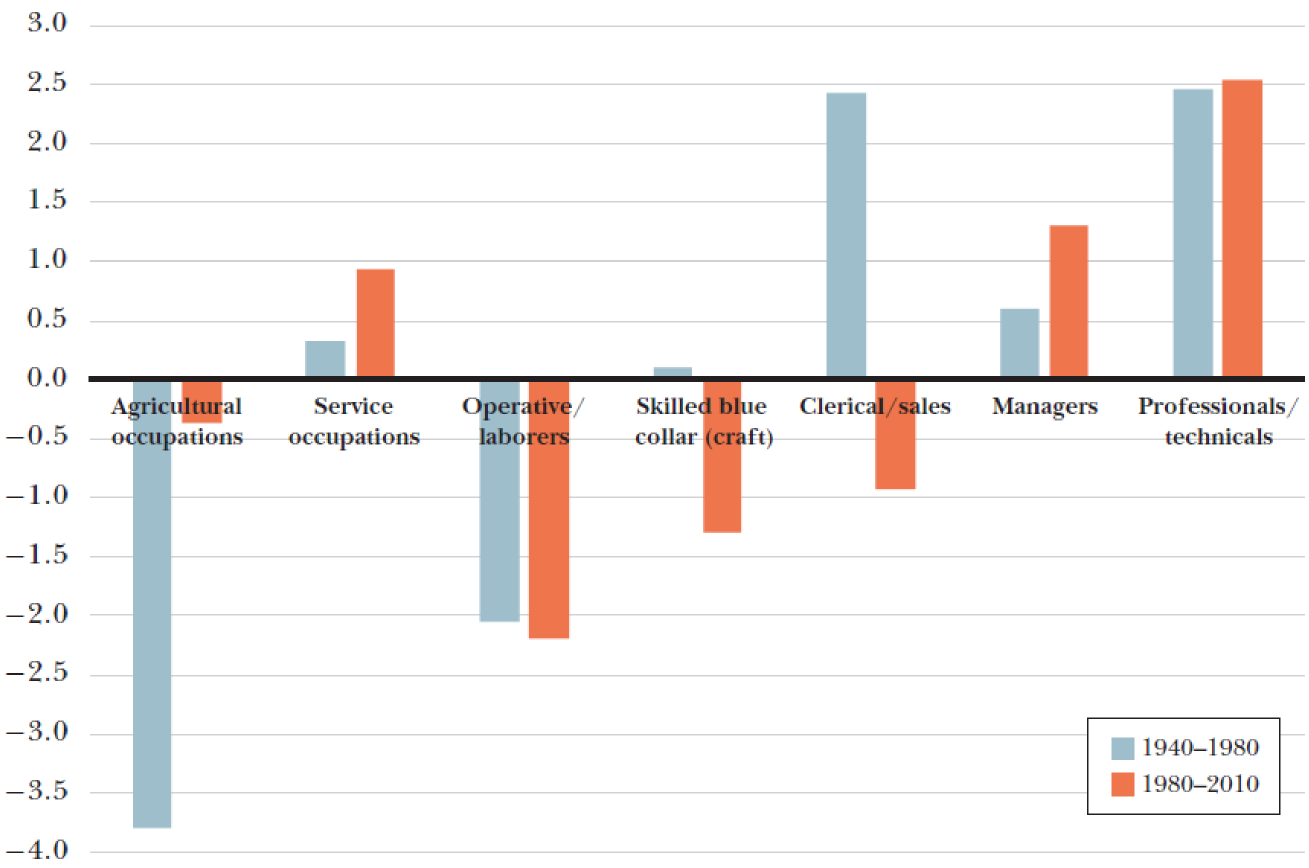

FIGURE 3. CHANGE IN AGGREGATE EMPLOYMENT SHARE BY DECADE 1970 THROUGH 2005 IN OCCUPATIONS COMPRISING THE LOWEST SKILL QUINTILE OF EMPLOYMENT IN 1980

Autor and Dorn, 2013

# Is this the end of the story?

*Figure 1*

**Average Change per Decade in US Occupational Employment Shares for Two Periods: 1940–1980 and 1980–2010**




*Source:* Based on Katz and Margo (2014), table 1.6, panel A, which is based upon the 1920 through 2000 Census of population IPUMS and 2010 American Community Survey.

*Figure 2*

**Change in Employment by Major Occupational Category, 1979–2012**

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

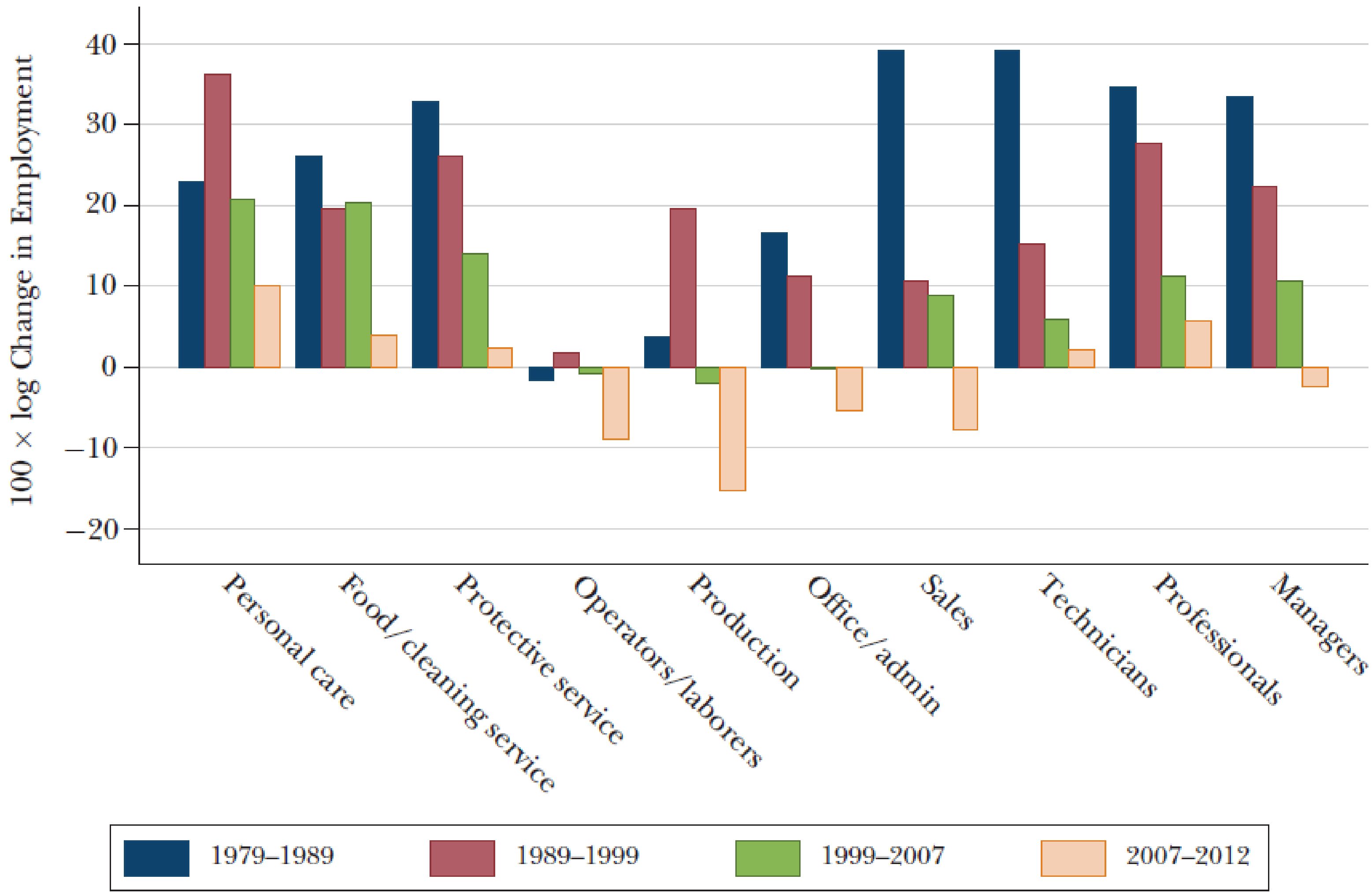
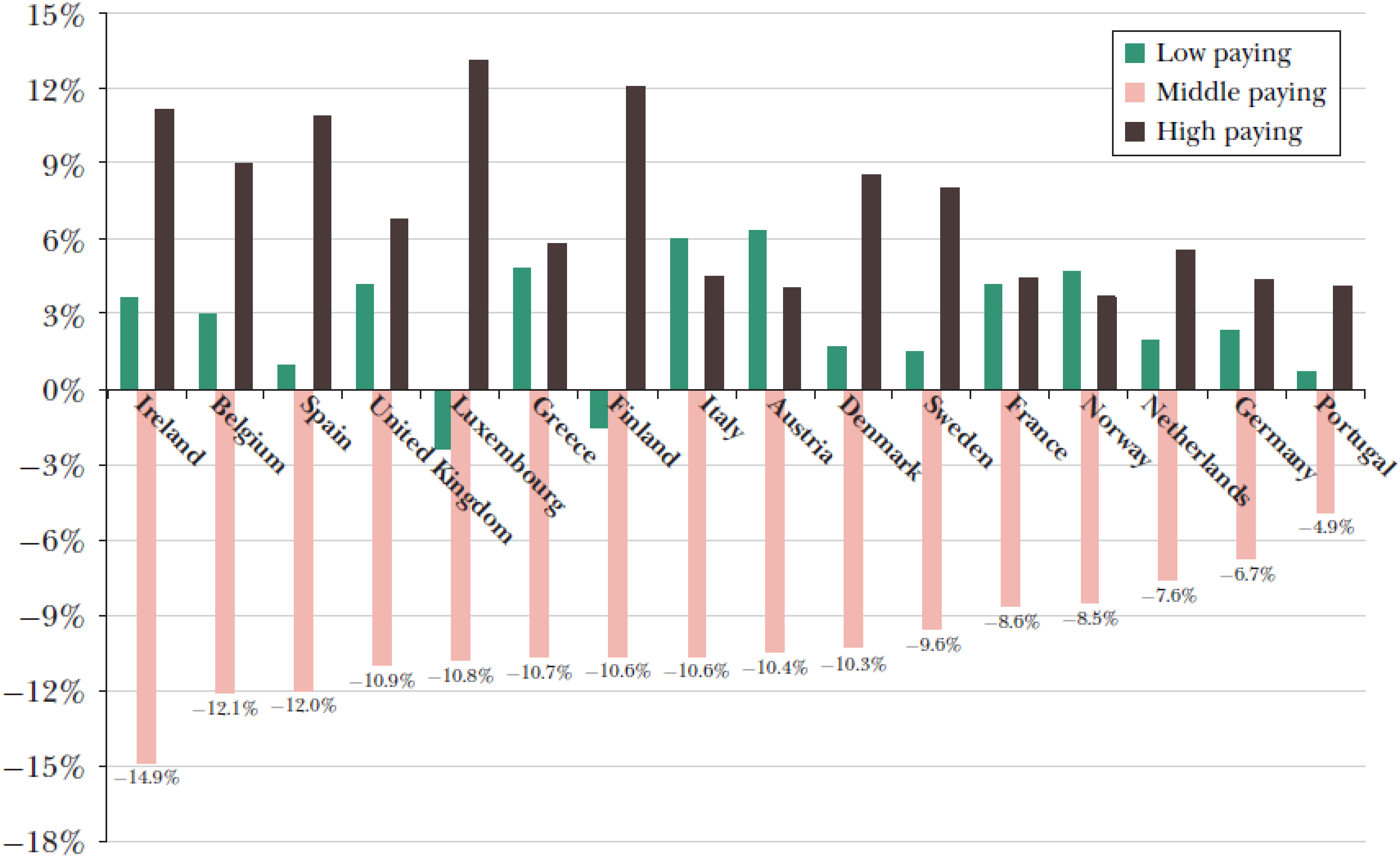


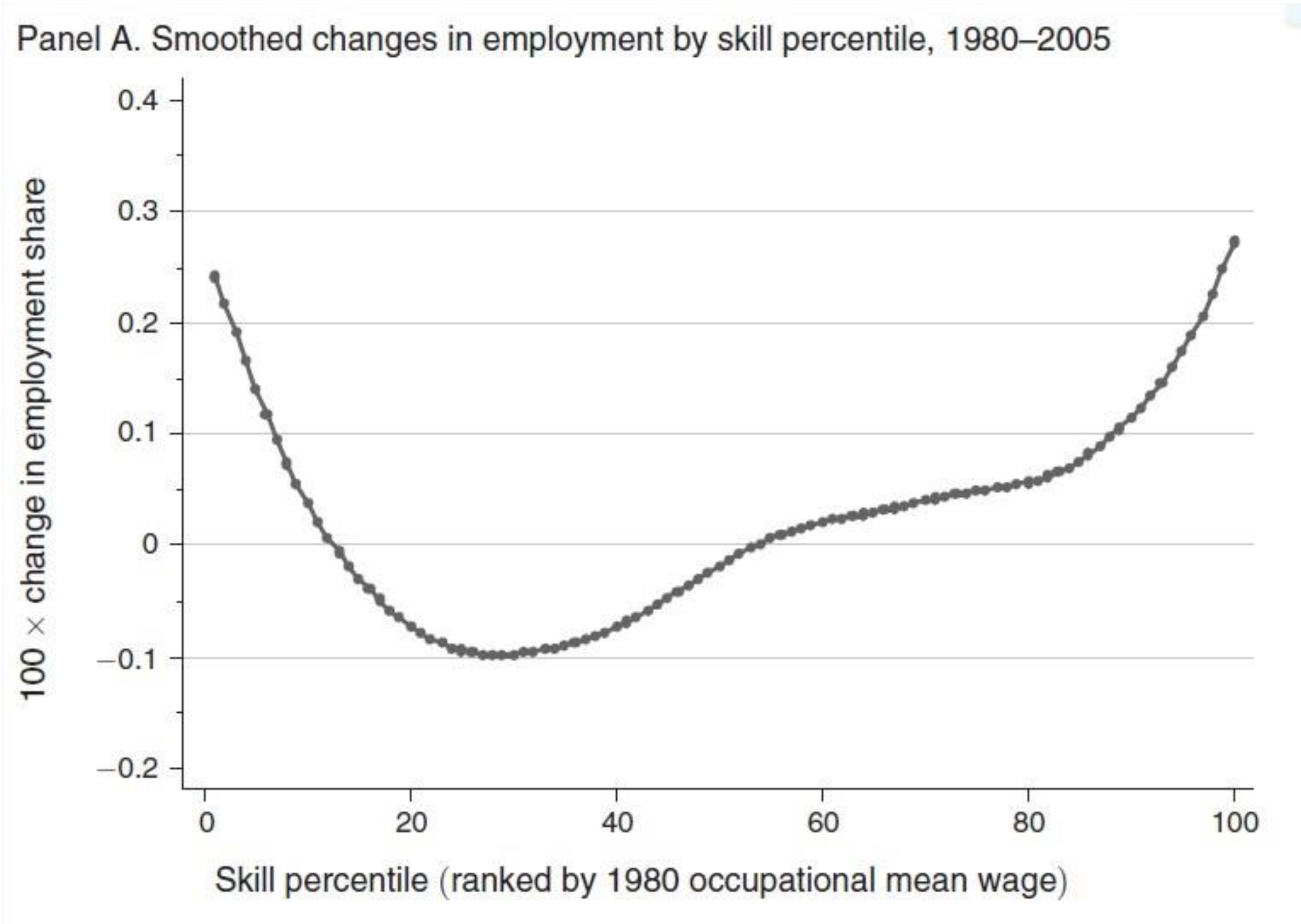
*Figure 3*

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



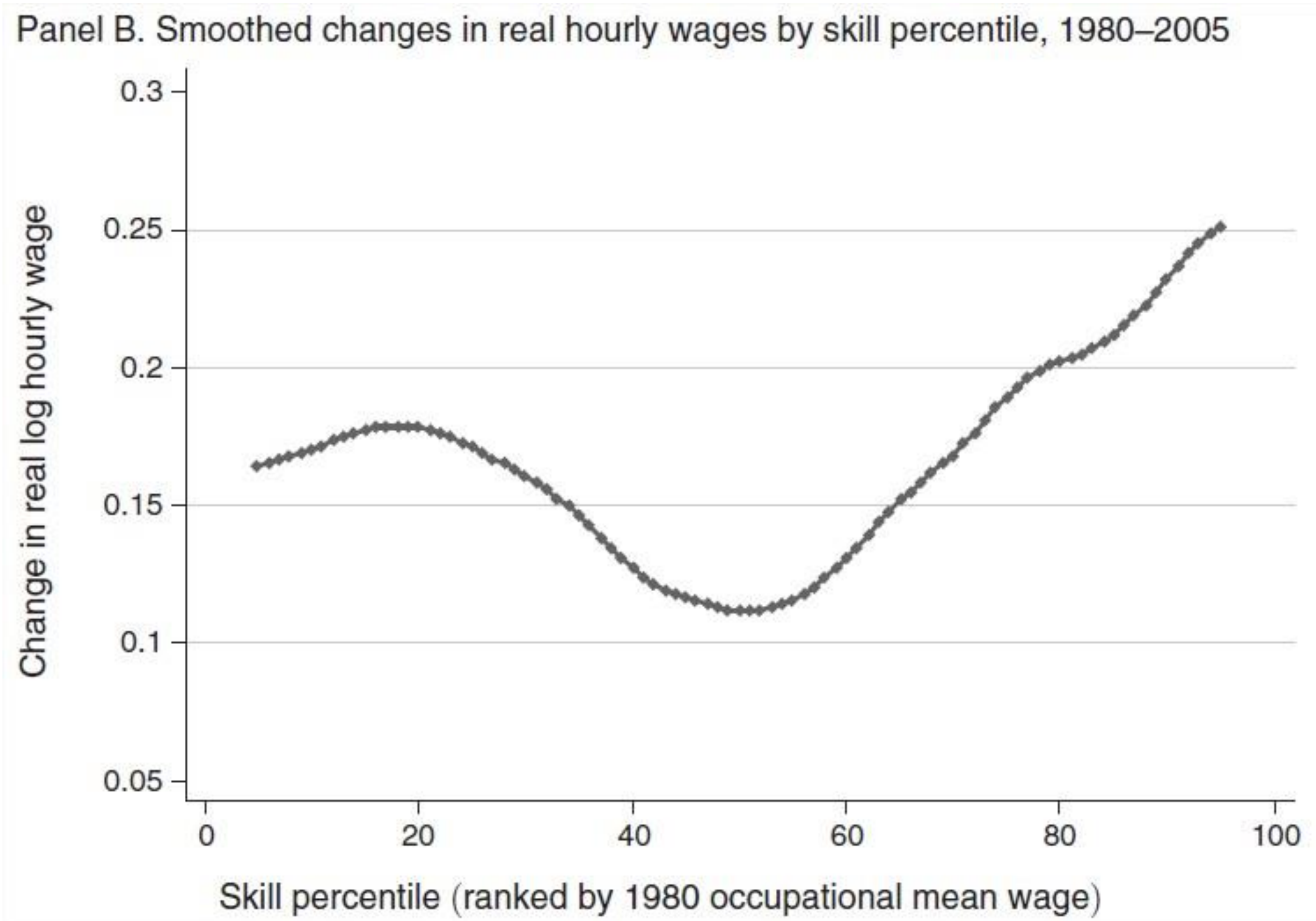

*Source:* Goos, Manning, and Salomons (2014, table 2).

# Polarisation




Autor and Dorn, 2013

# Polarisation




Autor and Dorn, 2013

*Figure 5*

**Smoothed Employment Changes by Occupational Skill Percentile, 1979–2012**

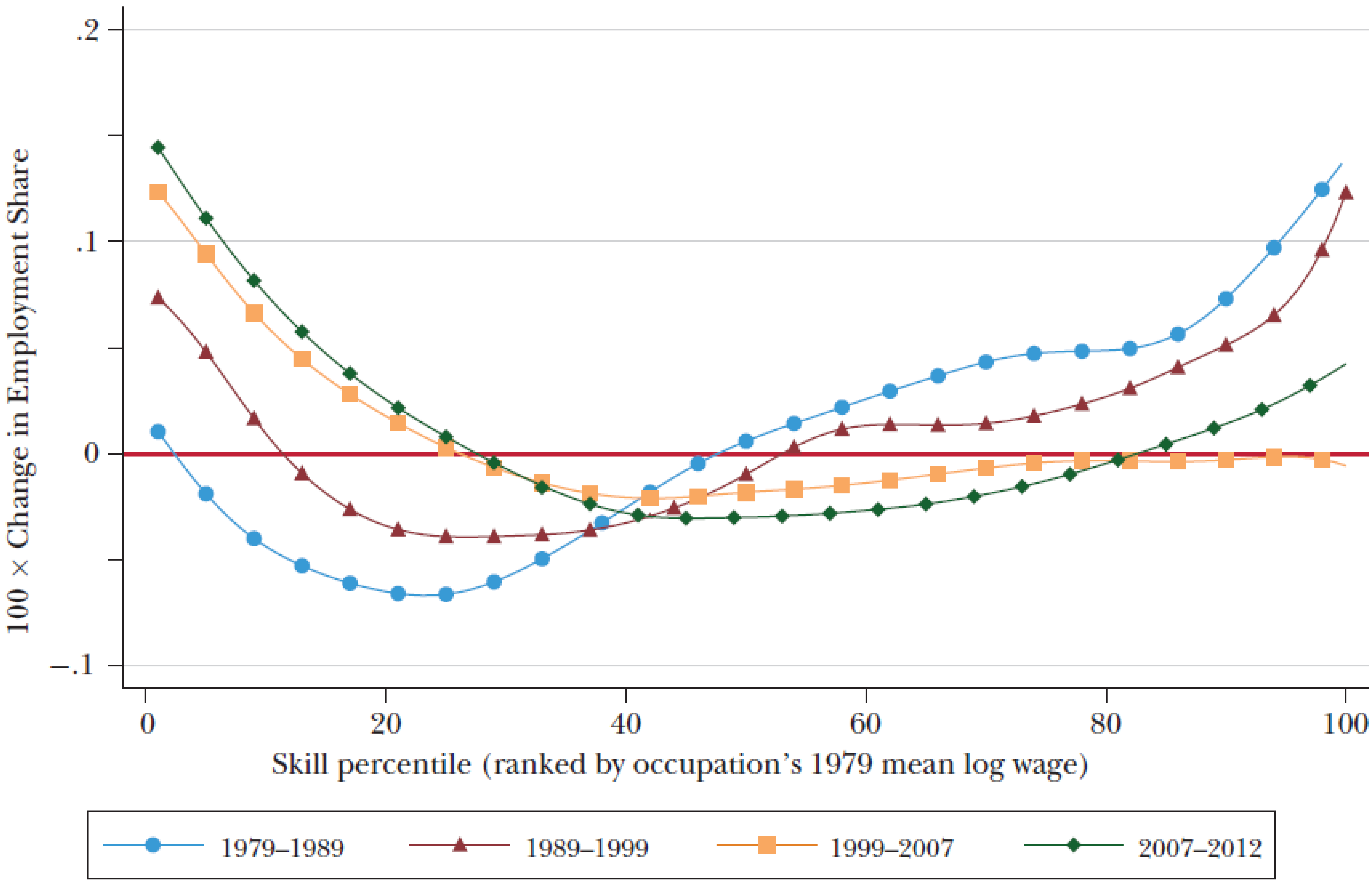
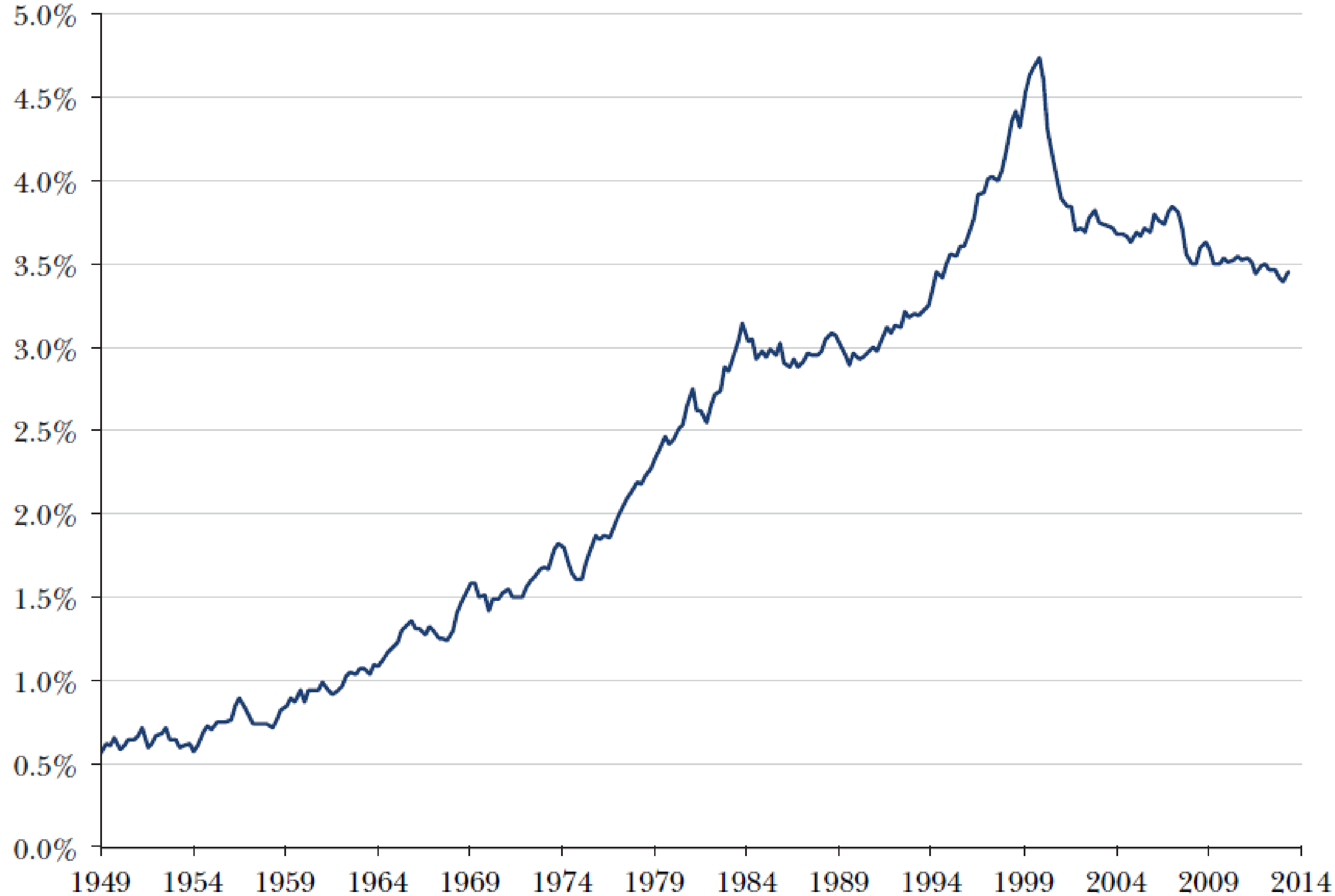


*Figure 6*

**Private Fixed Investment in Information Processing Equipment and Software as a Percentage of Gross Domestic Product, 1949–2014**




*Source:* FRED, Federal Bank of St. Louis. http://research.stlouisfed.org/fred2/graph/?g=GXc (accessed 8/3/2014).

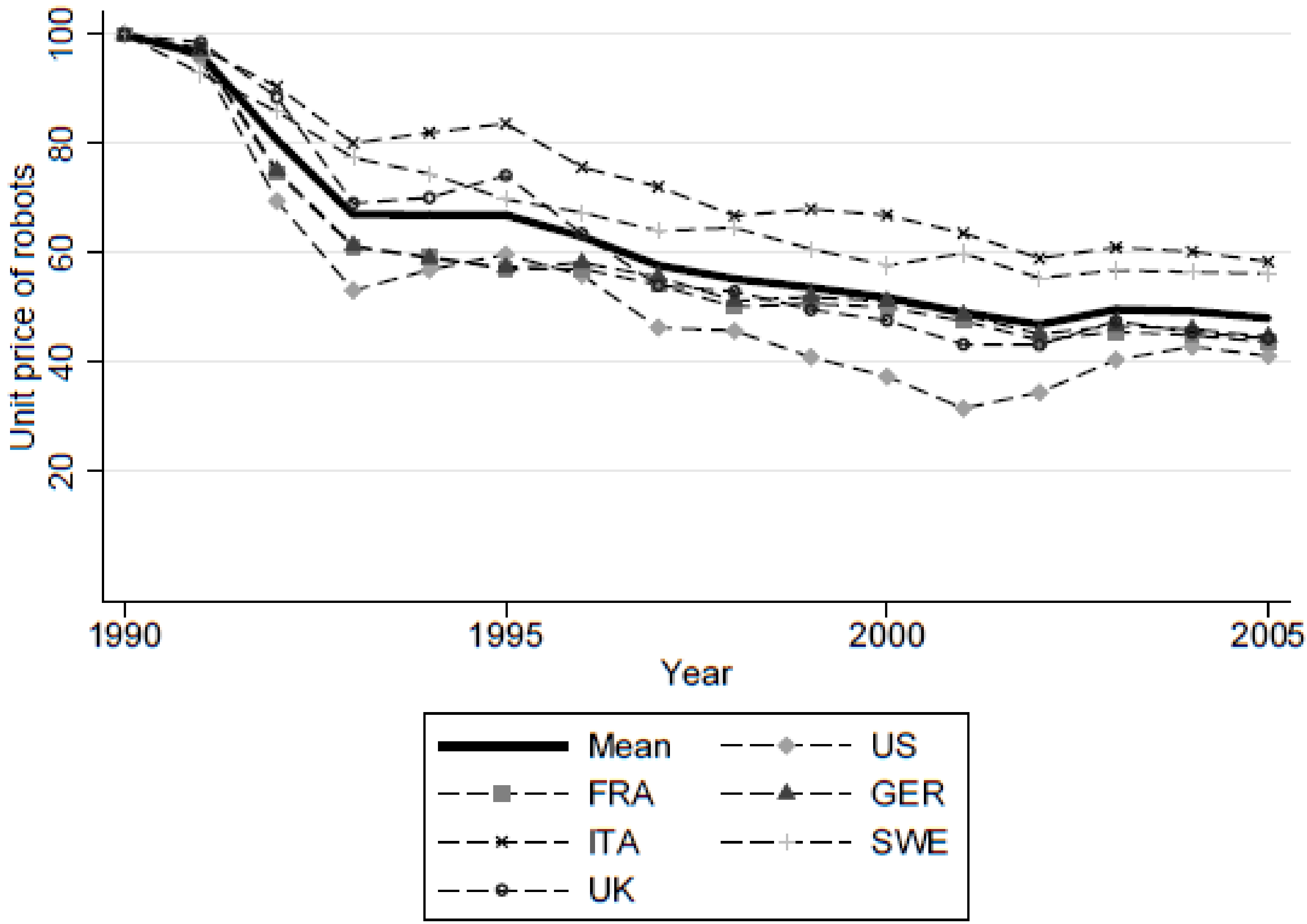
# Robots at work
# Graetz & Michaels, 2018

- Robots can now perform a fairly wide range of tasks, including welding, painting, and packaging with very little human intervention
- These capabilities set robots apart from earlier waves of automation and more conventional information and communication technologies (ICT), which left flexible movement in three dimensions firmly in human hands
- Poor evidence on the implications of increased robot use for labor productivity, total factor productivity, output prices, and the employment of workers with different skills across the developed world

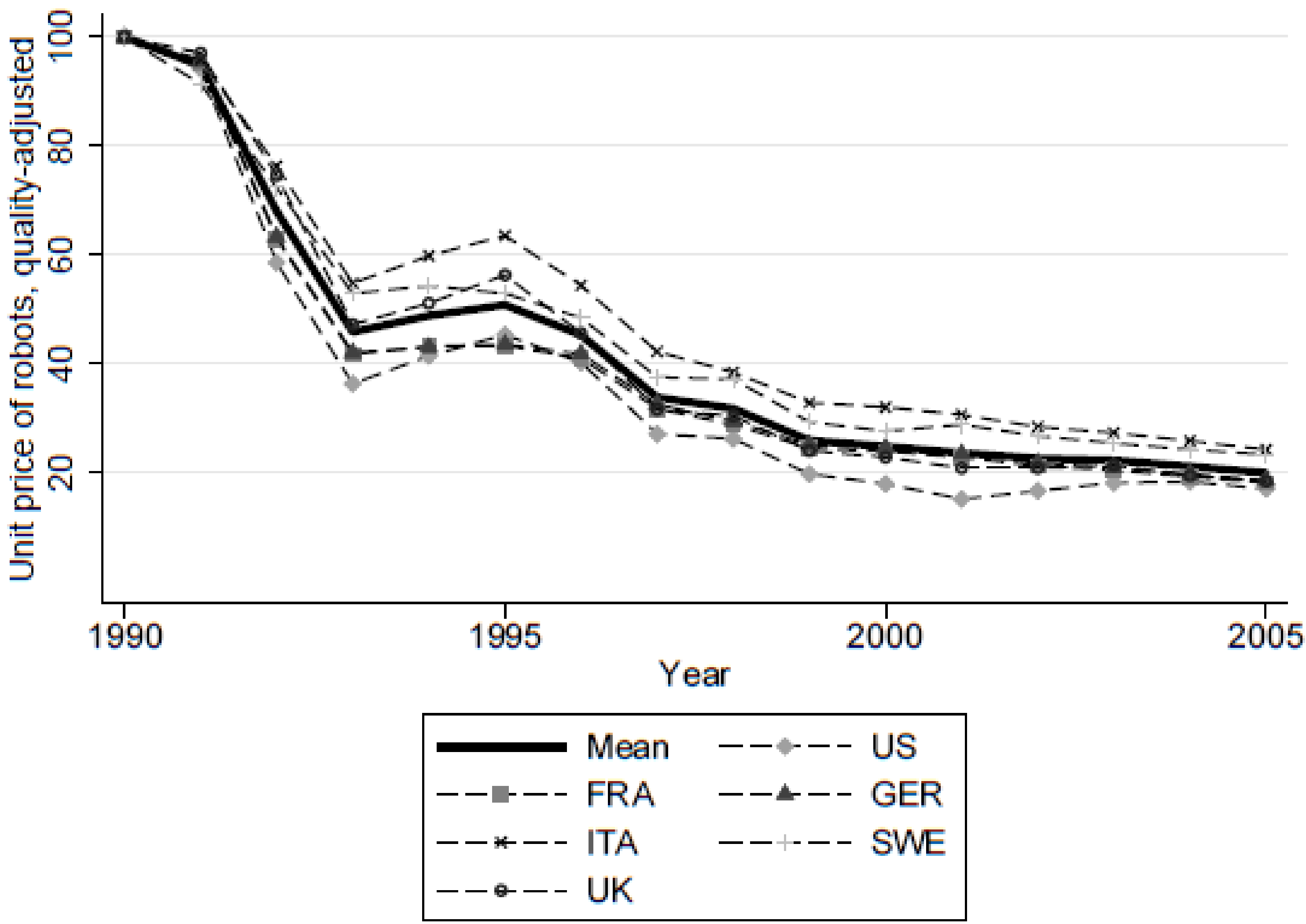
# Data source

- International Federation of Robotics (IFR).
- It measures the deliveries of “multipurpose manipulating industrial robots”
  - as defined by International Organization for Standardization (ISO): An automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications”

(a) Not adjusted for quality changes



(b) Adjusted for quality changes



# Empirical strategy

$$\Delta Y_{ci} = \beta_1 + \beta_2 f(robots_{ci}) + \beta_3 controls_{ci} + \varepsilon_{ci}$$

- Delta$Y_{ci}$ is the change in the outcome of interest, $Y_{ci}$ in industry *i* in country *c* from 1993-2007
- $f(robots_{ci})$ is some measure of the change in the use of robots, relative to the labor input
  - country fixed effects, initial (1993) wages and capital-labor ratios, as well as changes in other inputs, and in some cases also industry fixed effects.

# Productivity growth

(a) Percentile of Change in Robot Density

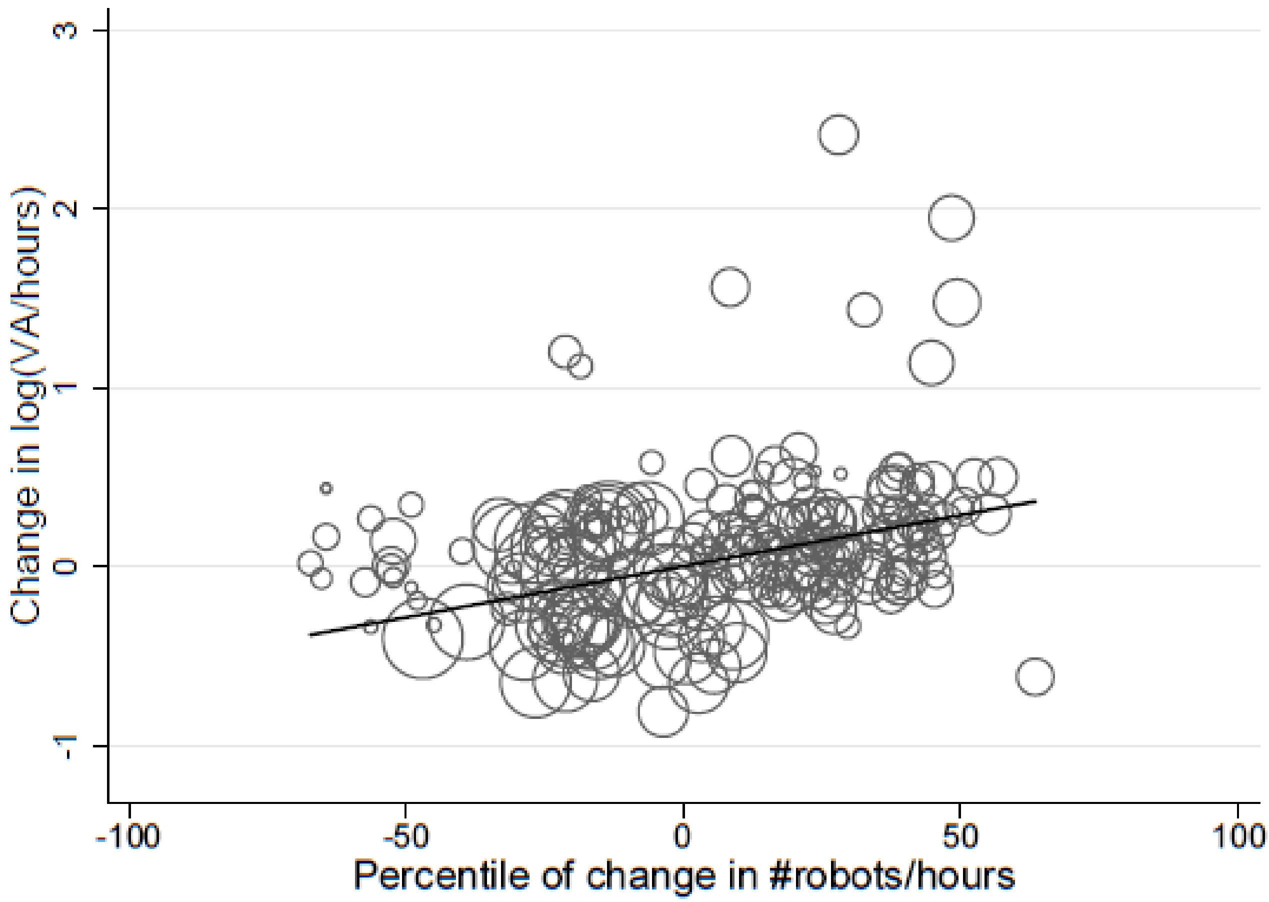


Table 2: Further Outcomes—TFP and Prices

| | $\Delta \ln(TFP)$ | | | $\Delta \ln(P)$ | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *A. OLS* | | | | | | |
| Robot adoption | 0.26 | 0.47 | 0.47 | -0.38 | -0.47 | -0.51 |
| | (0.20) | (0.19) | (0.19) | (0.18) | (0.20) | (0.21) |
| *B. IV: replaceable hours* | | | | | | |
| Robot adoption | 0.62 | 0.79 | 0.79 | -0.55 | -0.66 | -0.72 |
| | (0.40) | (0.32) | (0.32) | (0.47) | (0.35) | (0.35) |
| F-statistic | 47.7 | 32.7 | 35.0 | 41.8 | 33.9 | 36.8 |
| *C. IV: reaching & handling* | | | | | | |
| Robot adoption | 0.39 | 0.63 | 0.64 | -0.40 | -0.67 | -0.71 |
| | (0.46) | (0.37) | (0.36) | (0.56) | (0.43) | (0.38) |
| F-statistic | 39.3 | 17.3 | 17.2 | 30.1 | 16.1 | 19.3 |
| Country trends & controls | | ✓ | ✓ | | ✓ | ✓ |
| Changes in other capital | | | ✓ | | | ✓ |
| Observations | 210 | 210 | 210 | 238 | 238 | 224 |

Table 3: Further Outcomes—Hourly Wages

| | Δ ln(mean hourly wage) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *A. OLS* | | | | |
| Robot adoption | -0.010 | 0.057 | 0.042 | 0.039 |
| | (0.026) | (0.013) | (0.016) | (0.017) |
| *B. IV: replaceable hours* | | | | |
| Robot adoption | 0.067 | 0.097 | 0.085 | 0.087 |
| | (0.043) | (0.023) | (0.021) | (0.021) |
| F-statistic | 41.8 | 33.9 | 30.4 | 34.8 |
| *C. IV: reaching & handling* | | | | |
| Robot adoption | 0.075 | 0.142 | 0.119 | 0.118 |
| | (0.058) | (0.032) | (0.031) | (0.031) |
| F-statistic | 30.1 | 16.1 | 12.5 | 15.8 |
| Country trends & controls | | ✓ | ✓ | ✓ |
| Changes in skill mix | | | ✓ | ✓ |
| Changes in other capital | | | | ✓ |
| Observations | 238 | 238 | 238 | 224 |

Table 4: Further Outcomes—Share in Hours Worked by Skill Group

| | High | | Middle | | Low | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *A. OLS* | | | | | | |
| Robot adoption | 1.94 | 1.64 | 3.85 | 4.07 | -5.79 | -5.72 |
| | (1.91) | (1.85) | (3.23) | (2.89) | (1.63) | (1.65) |
| *B. IV: replaceable hours* | | | | | | |
| Robot adoption | 1.81 | 1.22 | 8.21 | 7.37 | -10.0 | -8.59 |
| | (3.11) | (2.84) | (5.58) | (4.36) | (3.44) | (2.68) |
| F-statistic | 33.9 | 36.8 | 33.9 | 36.8 | 33.9 | 36.8 |
| *C. IV: reaching & handling* | | | | | | |
| Robot adoption | 7.14 | 5.95 | 1.65 | 2.91 | -8.78 | -8.87 |
| | (3.40) | (3.09) | (4.83) | (4.21) | (3.38) | (3.56) |
| F-statistic | 16.1 | 19.3 | 16.1 | 19.3 | 16.1 | 19.3 |
| Country trends & controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Changes in other capital | | ✓ | | ✓ | | ✓ |
| Observations | 238 | 224 | 238 | 224 | 238 | 224 |

# Findings

- Moving from the bottom to the top of the ranking of changes in the robot density distribution corresponds to an increases in annual growth of 4.1 percentage points
- Robot adoption have been a more important driver of labor productivity growth at net of ICT adoption

# Findings

- Robot densification was associated with even higher increase in TFP, which is roughly two thirds as large as the increase in labor pro
- Positive effects of robot adoption on mean houarly wages
  - The magnitudes are however, much smaller than the TFP estimates, and they are typically around 10 percent of the labor productivity gains

# Findings

- Robot adoption increase the share of hours worked by high-skilled (usually college graduates) and middle-skilled workers (those with intermediate levels of schooling)
- Robot adoption reduce the share of hours worked by low skill (typically high school dropouts)

# Acemoglu & Restrepo (2017). Robots and Jobs: Evidence from US Labor Markets. *NBER*

- Analyze effect of industrial robot usage increase between 1990 and 2007 on US local labor markets
  - The local labor market effects of robots estimated by regressing the change in employment and wages on the **exposure to robots in each local labor market**—defined from the national penetration of robots into each industry and the local distribution of employment across industries
- Robots reduce employment and wages
  - one more robot per thousand workers reduces the employment to population ratio by about 0.18-0.34 percentage points and wages by 0.25-0.5 percent

# Arntz et al. (2016). The Risk of Automation for Jobs in OECD Countries OECD

- Estimation of the job automatibility of jobs for 21 OECD countries based on a task-based approach
  - In contrast to other studies, we take into account the heterogeneity of workers' tasks within occupations
- Find that 9 % of jobs are automatable
- The main conclusion is that automation and digitalisation are unlikely to destroy large numbers of jobs.
  - However, low qualified workers are likely to bear the brunt of the adjustment costs as the automatibility of their jobs is higher compared to highly qualified workers.
- The likely challenge for the future lies in coping with rising inequality and ensuring sufficient (re-)training especially for low qualified workers.