Technology and Labor Displacement: Evidence from Linking Patents with Worker-Level Data

L. Kogan[1,3] D. Papanikolaou[2,3] L. Schmidt[1] B. Seegmiller[2]

[1]MIT Sloan

[2]Kellogg School of Management

[3]NBER

Big Picture

Question: How do technological improvements to capital affect the earnings of exposed individual workers?

Big Picture

Question: How do technological improvements to capital affect the earnings of exposed individual workers?

Complications:

Big Picture

Question: How do technological improvements to capital affect the earnings of exposed individual workers?

Complications:

1. Capital (tangible or intangible) can substitute or complement labor. Same technology can substitute some tasks and complement others.

Big Picture

Question: How do technological improvements to capital affect the earnings of exposed individual workers?

Complications:

1. Capital (tangible or intangible) can substitute or complement labor. Same technology can substitute some tasks and complement others.
2. How to measure exposure to substitution or complementarity?

Big Picture

Question: How do technological improvements to capital affect the earnings of exposed individual workers?

Complications:

1. Capital (tangible or intangible) can substitute or complement labor. Same technology can substitute some tasks and complement others.
2. How to measure exposure to substitution or complementarity?
3. Even if it is a complement, new technologies can displace workers if they require skills incumbents lack.

Big Picture

Question: How do technological improvements to capital affect the earnings of exposed individual workers?

Complications:

1. Capital (tangible or intangible) can substitute or complement labor. Same technology can substitute some tasks and complement others.
2. How to measure exposure to substitution or complementarity?
3. Even if it is a complement, new technologies can displace workers if they require skills incumbents lack.

What we do

1. Using textual analysis of patent data and occupation task descriptions, directly measure whether a given technological improvement substitutes or complements a given occupation's tasks.
2. Estimate impact on individual worker earnings using administrative tax data (first such evidence in United States)
3. Interpret coefficient estimates using both worker-level and aggregate data through the lens of a structural model.
4. Use model to speculate on the impact of AI on worker earnings.

What we find

1. Automation/labor-saving technology improvements:
   - Pervasively large **negative** effects on incumbent individual worker earnings.
   - Negative effects on aggregate employment and wages.
   - Industry-level productivity $\uparrow$ and labor share $\downarrow$

What we find

1. Automation/labor-saving technology improvements:
   - Pervasively large **negative** effects on incumbent individual worker earnings.
   - Negative effects on aggregate employment and wages.
   - Industry-level productivity $\uparrow$ and labor share $\downarrow$

2. Complementary improvements:
   - Small negative average effects on incumbent individual workers.
   - Significant **heterogeneity**: entirely concentrated among older and most highly paid workers
   - Positive effects on aggregate employment and wages.
   - Industry-level productivity $\uparrow$ and labor share $\uparrow$
   - Patterns consistent with increased labor demand at expense of skill displacement of incumbent workers.

Comparison to the Literature

1. Routine Task Intensity (RTI) (Autor, Levy, and Murnane, 2003; Autor and Dorn, 2013)
   - RTI measures the *potential* for automation, and is a time-invariant occupation characteristic.
   - Our measure reflects actual technological developments that could automate tasks and is therefore dynamic.
     - Varies by occupation $\times$ industry and year
2. Software and Robot Exposure (Webb, 2020)
   - Also based on overlap between patent text and task descriptions.
   - Does not differentiate between routine and non-routine tasks
   - Also time-invariant

Both of these measures are time-invariant, so they would be absorbed in occupation fixed effects in our analysis.

Outline

Model

Measurement

Aggregate Outcomes

Individual Workers

Model Estimation

Conclusion

Conceptual Framework

Industry output a CES combination of many tasks indexed by j (cross-task elasticity of substitution ψ)

Conceptual Framework

Industry output a CES combination of many tasks indexed by j (cross-task elasticity of substitution ψ)

- Task j combines labor $l(j)$ & capital $k(j)$ w/ elasticity of substitution ν_j

Conceptual Framework

Industry output a CES combination of many tasks indexed by j (cross-task elasticity of substitution ψ)

- Task j combines labor $l(j)$ & capital $k(j)$ w/ elasticity of substitution ν_j
  - If j is a **routine** task $\nu_j = \nu_R > 1$; if j is **non-routine**, $\nu_j = \nu_N < 1$

Conceptual Framework

Industry output a CES combination of many tasks indexed by j (cross-task elasticity of substitution ψ)

- Task j combines labor $l(j)$ & capital $k(j)$ w/ elasticity of substitution ν_j
  - If j is a **routine** task $\nu_j = \nu_R > 1$; if j is **non-routine**, $\nu_j = \nu_N < 1$
  - $k(j)$ has exogenous price $q(j)$.
  - Technology shock = fall in the price of task-specific capital: $\Delta \log q(j) = -\varepsilon(j)$
    - Labor-saving for routine tasks; labor-complementing for a non-routine task

Conceptual Framework

Industry output a CES combination of many tasks indexed by j (cross-task elasticity of substitution ψ)

- Task j combines labor $l(j)$ & capital $k(j)$ w/ elasticity of substitution ν_j
  - If j is a **routine** task $\nu_j = \nu_R > 1$; if j is **non-routine**, $\nu_j = \nu_N < 1$
  - $k(j)$ has exogenous price $q(j)$.
  - Technology shock = fall in the price of task-specific capital: $\Delta \log q(j) = -\varepsilon(j)$
    - Labor-saving for routine tasks; labor-complementing for a non-routine task
- Occupations o are a mix of routine and non-routine tasks and partition the task space.

Details

Model-Implied Technology Exposure

Worker's technology exposure in occupation o summarized by

$$\xi^R(i) \equiv \sum_{j \in J_R} s(i,j)\varepsilon(j) = \underbrace{\theta(i)}_{\text{Share of R tasks}} \underbrace{\sum_{j \in J_R} \tilde{s}^R(i,j)\varepsilon(j)}_{\text{R-task exposure}}$$

$$\xi^N(i) \equiv \sum_{j \in J_N} s(i,j)\varepsilon(j) = \underbrace{(1-\theta(i))}_{\text{Share of N tasks}} \underbrace{\sum_{j \in J_N} \tilde{s}^N(i,j)\varepsilon(j)}_{\text{N-task exposure}}$$

Depends on:

- Relevance of technological improvements to occupation tasks
- Relevance of routine or non-routine tasks to a worker's occupation

Model implications for aggregate labor demand

Occupational wage growth:

$$\Delta \log W(o) \approx \underbrace{\left[\frac{\psi - \nu_R}{\nu_R + \zeta_R} \Gamma_R\right] \xi^R(o)}_{\text{Direct Effect of Automation}}$$

Model implications for aggregate labor demand

Occupational wage growth:

$$\Delta \log W(o) \approx \underbrace{\left[\frac{\psi - \nu_R}{\nu_R + \zeta_R}\Gamma_R\right]\xi^R(o)}_{\substack{\text{Direct Effect of} \\ \text{Automation}}} + \underbrace{\left[\frac{\psi - \nu_N}{\nu_N + \zeta_N}\Gamma_N\right]\xi^N(o)}_{\substack{\text{Direct Effect of} \\ \text{Complementary Technologies}}}$$

Model implications for aggregate labor demand

Occupational wage growth:

$$\Delta \log W(o) \approx \underbrace{\left[\frac{\psi - \nu_R}{\nu_R + \zeta_R}\Gamma_R\right]\xi^R(o)}_{\substack{\text{Direct Effect of}\\ \text{Automation}}} + \underbrace{\left[\frac{\psi - \nu_N}{\nu_N + \zeta_N}\Gamma_N\right]\xi^N(o)}_{\substack{\text{Direct Effect of}\\ \text{Complementary Technologies}}}$$

$$+ \underbrace{\left[(A_R - A_N)\theta(o) + A_N\right]\Delta \log X}_{\text{Aggregate Productivity Spillovers}}$$

Model implications for aggregate labor demand

Occupational wage growth:

$$\Delta \log W(o) \approx \underbrace{\left[\frac{\psi - \nu_R}{\nu_R + \zeta_R}\Gamma_R\right]\xi^R(o)}_{\substack{\text{Direct Effect of}\\ \text{Automation}}} + \underbrace{\left[\frac{\psi - \nu_N}{\nu_N + \zeta_N}\Gamma_N\right]\xi^N(o)}_{\substack{\text{Direct Effect of}\\ \text{Complementary Technologies}}}$$

$$+ \underbrace{\left[(A_R - A_N)\theta(o) + A_N\right]\Delta \log X}_{\text{Aggregate Productivity Spillovers}}$$

Extensive margin of labor supply: Aggregate labor supply to task j is upward-sloping with elasticity ζ_j. $\implies$ Occupational employment growth:

$$\Delta \log L(o) \approx \zeta_R \left[\frac{\psi - \nu_R}{\nu_R + \zeta_R}\,\Gamma_R\right]\xi^R(o) + \zeta_N \left[\frac{\psi - \nu_N}{\nu_N + \zeta_N}\,\Gamma_N\right]\xi^N(o)$$

$$+ \Big(\zeta_R A_R \theta(o) + \zeta_N A_N (1 - \theta(o))\Big)\Delta \log X,$$

Wage bill growth is the sum of the two.

Model Implications at the Industry Level

Define $\overline{\xi}_R$ $\left(\overline{\xi}_N\right)$ as industry compensation-weighted average of worker-level R (N) exposure. Then:

- Both predict productivity growth: $\Delta \log X \propto \overline{\xi}_R + \overline{\xi}_N$
- $\overline{\xi}_R$ predicts declines in labor share and total labor compensation, opposite for $\overline{\xi}_N$

Outline

Steps

Model-consistent technology exposure (assuming equal task weights):

$$\xi^R(o) \equiv \underbrace{\theta(o)}_{\text{Share of R tasks}} \times \underbrace{\sum_{j \in J_R} \varepsilon(j)\, \mathbb{1}_{j \in J_R(o)}}_{\text{R-task exposure}}$$

$$\xi^N(o) \equiv \underbrace{(1-\theta(o))}_{\text{Share of N tasks}} \times \underbrace{\sum_{j \in J_N} \varepsilon(j)\, \mathbb{1}_{j \in J_N(o)}}_{\text{N-task exposure}}$$

We need to:

1. Identify major technological improvements (large ε)
2. Classify each task (from Dictionary of Occupational Titles) performed by occupation o into R and N
3. Identify which technologies relate to R or N tasks performed by o
   - Exposure depends on product between technology improvements ε and tasks performed by occupation

Measuring Technology: Broad Idea

Use breakthrough patents to measure innovation. We follow Kelly, Papanikolaou, Seru, and Taddy (2021) and identify important patents as those that:

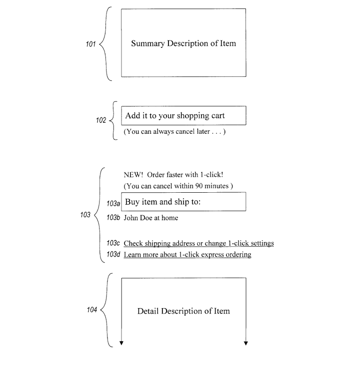
- Novel and impactful: are distinct from previous patents but are related to subsequent patents based on textual similarity
- Breakthroughs: patents in the top 10 percent of the unconditional distribution of impact/novelty

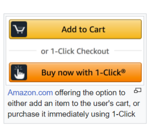
Historical trends by technology class

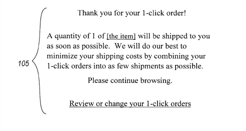
Breakthrough Patents, Examples

Method and system for placing a purchase order via a communications network

One-click buying, US Patent 5,960,411 (issued to Jeff Bezos in 1997):







“The server system receives purchaser information including identification of the purchaser, payment information, and shipment information from the client system. The server system then assigns a client identifier to the client system and associates the assigned client identifier with the received purchaser information.”

Routine vs Non-Routine Tasks

Computer Programmers (SOC Code 151131)

- Converts detailed logical flow chart to language processable by computer.
- Enters program codes into computer system.
- Inputs test data into computer.
- Observes computer monitor screen to interpret program operating codes.
- Prepares detailed workflow chart and diagram to illustrate sequence of steps that program must follow and to describe input, output, and logical operations involved.
- Corrects program errors, using methods such as modifying program or altering sequence of program steps.
- Analyzes, reviews, and rewrites programs to increase operating efficiency or to adapt program to new requirements.
- Confers with supervisor and representatives of departments concerned with program to resolve questions of program intent, data input, output requirements, and inclusion of internal checks and controls.

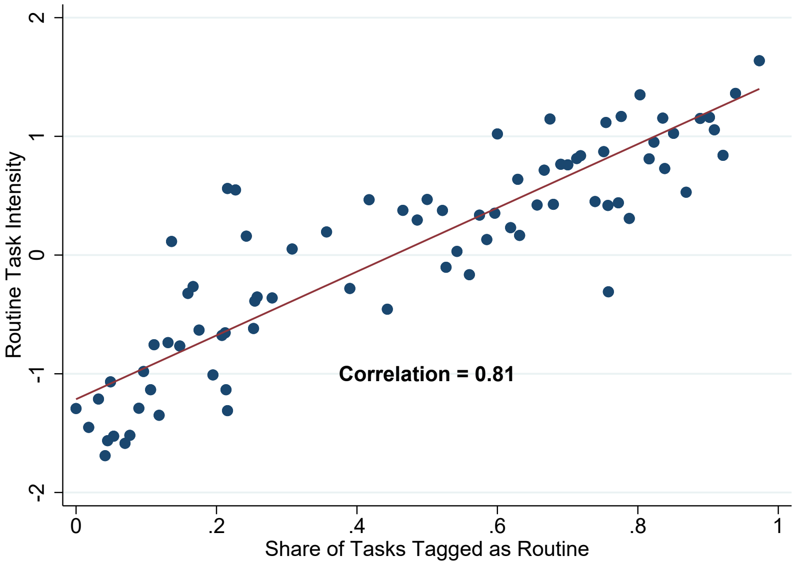
Routine vs Non-Routine Tasks: Tagged by GPT4

Computer Programmers (SOC Code 151131)

- Converts detailed logical flow chart to language processable by computer.
- Enters program codes into computer system.
- Inputs test data into computer.
- Observes computer monitor screen to interpret program operating codes.
- Prepares detailed workflow chart and diagram to illustrate sequence of steps that program must follow and to describe input, output, and logical operations involved.
- Corrects program errors, using methods such as modifying program or altering sequence of program steps.
- Analyzes, reviews, and rewrites programs to increase operating efficiency or to adapt program to new requirements.
- Confers with supervisor and representatives of departments concerned with program to resolve questions of program intent, data input, output requirements, and inclusion of internal checks and controls.

GPT4 Prompt

Validation with Routine-Task Intensity



Measuring patent-occupation similarity

Using textual analysis (word embeddings) we obtain a similarity measure ρ between each *breakthrough* patent *p* and each occupation *o* subset of R and NR tasks

Patent Text

US006948168B1

(12) **United States Patent**
Kuprionas

(10) **Patent No.: US 6,948,168 B1**
(45) **Date of Patent: Sep. 20, 2005**

(54) **LICENSED APPLICATION INSTALLER**

(75) Inventor: **Paul Kuprionas**, Nanticoke, PA (US)

(73) Assignee: **International Business Machines Corporation**, Armonk, NY (US)

(*) Notice: Subject to any disclaimer, the term of this patent is extended or adjusted under 35 U.S.C. 154(b) by 0 days.

(21) Appl. No.: **09/539,859**

(22) Filed: **Mar. 30, 2000**

(51) **Int. Cl.**[7] **G06F 9/445**

(52) **U.S. Cl.** **717/178**; 709/218; 709/219; 709/242; 709/249; 710/8; 710/52

(58) **Field of Search** 717/168–178; 709/200–250; 710/8, 52

(56) **References Cited**

U.S. PATENT DOCUMENTS

4,953,209 A		8/1990	Ryder, Sr. et al.	
5,005,122 A		4/1991	Griffin et al.	
5,138,712 A	*	8/1992	Corbin	717/176
5,337,357 A		8/1994	Chou et al.	
5,421,009 A		5/1995	Platt	
5,638,513 A		6/1997	Ananda	
5,666,501 A		9/1997	Jones et al.	
5,708,709 A		1/1998	Rose	
5,835,911 A		11/1998	Nakagawa et al.	
5,864,620 A		1/1999	Pettitt	
5,881,236 A	*	3/1999	Dickey	717/168
5,903,650 A		5/1999	Ross et al.	
5,905,860 A		5/1999	Olsen et al.	
5,919,247 A		7/1999	Van Hoff et al.	
5,953,532 A	*	9/1999	Lochbaum	717/176
6,056,786 A	*	5/2000	Rivera et al.	717/168
6,189,146 B1	*	2/2001	Misra et al.	717/177
6,202,209 B1	*	3/2001	Bartholomew	717/168
6,493,871 B1	*	12/2002	McGuire et al.	717/173

FOREIGN PATENT DOCUMENTS

EP	0 841 615 A2	5/1998
JP	04-100148	4/1992
JP	08-190529	7/1996
JP	09069044 A	3/1997
JP	10040098 A	2/1998
JP	10143357 A	5/1998
JP	10-283270	10/1998
JP	11-024918	1/1999
JP	11-110209	4/1999
JP	11-238038	8/1999

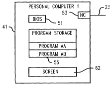
* cited by examiner

Primary Examiner—Tuan Dam
Assistant Examiner—Chuck Kendall
(74) *Attorney, Agent, or Firm*—DeLio & Peterson, LLC; Kelly M. Reynolds; James J. Cioffi

(57) **ABSTRACT**

A method and system of installing licensed software on an end user's computer comprising having a program storage device and a unique computer identifier distinguishing the end user computer from other computers, e.g., a BIOS serial number or a network adapter address. The network computer contains a plurality of different software for license to end users and a database listing computer identifiers licensed to run the software. The end user computer sends to the network computer a command to run a program identifying to the end user computer the software listed as licensed by the computer identifier of the end user computer. The network computer contacts the end user computer and determine its end user computer identifier, verifies listing of the end user computer identifier in the network computer database, and identifies to the end user computer all of the software on the network computer program storage device listed as licensed by the computer identifier of the end user computer using an executable program on the network computer. The end user computer sends to the network computer a selection of the software to be downloaded. The network computer downloads the selected software and installs it on the end user computer program storage device.

17 Claims, 4 Drawing Sheets



Occupation Task Description

Computer Programmers (SOC Code 151131)

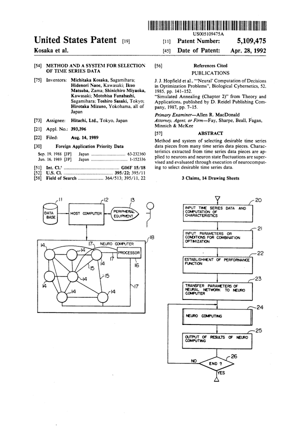
- Prepares detailed workflow chart and diagram to illustrate sequence of steps that program must follow and to describe input, output, and logical operations involved.
- Analyzes workflow chart and diagram, applying knowledge of computer capabilities, subject matter, and symbolic logic.
- Confers with supervisor and representatives of departments concerned with program to resolve questions of program intent, data input, output requirements, and inclusion of internal checks and controls.
- Converts detailed logical flow chart to language processable by computer.
- Enters program codes into computer system.
- Inputs test data into computer.
- Observes computer monitor screen to interpret program operating codes.
- Corrects program errors, using methods such as modifying program or altering sequence of program steps.
- Writes instructions to guide operating personnel during production runs.
- Analyzes, reviews, and rewrites programs to increase operating efficiency or to adapt program to new requirements.
- Compiles and writes documentation of program development and subsequent revisions.
- May train workers to use program.
- May direct and coordinate work of others to write, test, and modify computer programs.
- Confers with other engineering and technical personnel to resolve problems of intent, inaccuracy, or feasibility of computer processing.
- Enters program into computer system.
- Reviews results of computer runs with interested personnel to determine necessity for modifications or reruns.
- Develops new subroutines or expands program to simplify statement, programming, or coding of future problems.
- Plans, schedules, and directs preparation of programs to process data and solve problems by use of computers.
- Consults with managerial and systems analysis personnel to clarify program intent, identify problems, suggest changes, and determine extent of programming and coding required.
- Assigns, coordinates, and reviews work of programming personnel.
- Develops programs from workflow charts or diagrams, considering factors, such as computer storage capacity and speed, extent of peripheral equipment, and intended use of output data.
- Converts workflow charts to language processable by computer.
- Enters program codes into computer.
- Enters test data into computer.
- Analyzes test runs on computer to correct or direct correction of coded program and input data.
- Revises or directs revision of existing programs to increase operating efficiency or adapt to new requirements.
- Compiles documentation of program development and subsequent revisions.
- Trains subordinates in programming and program coding.
- Prescribes standards for terms and symbols used to simplify interpretation of programs.
- Collaborates with computer manufacturers and other users to develop new programming methods.
- Prepares records and reports.

"**Licensed application installer**" (US Patent 6,948,168): more related to computer programmers' routine tasks validation

Measuring patent-occupation similarity

Using textual analysis (word embeddings) we obtain a similarity measure ρ between each *breakthrough* patent *p* and each occupation *o* subset of R and NR tasks

Patent Text



United States Patent [19] | US005109475A | [11] Patent Number: 5,109,475
Kosaka et al. | [45] Date of Patent: Apr. 28, 1992

[54] METHOD AND A SYSTEM FOR SELECTION OF TIME SERIES DATA

[75] Inventors: Michitaka Kosaka, Sagamihara; Hidenori Naoe, Kawasaki; Ikuo Matsuba, Zama; Shinichiro Miyaoka, Kawasaki; Motohisa Funabashi, Sagamihara; Toshiro Sasaki, Tokyo; Hirotaka Mizuno, Yokohama, all of Japan

[73] Assignee: Hitachi, Ltd., Tokyo, Japan

[21] Appl. No.: 393,396

[22] Filed: Aug. 14, 1989

[30] Foreign Application Priority Data

Sep. 19, 1988 [JP] Japan 63-232360
Jun. 16, 1989 [JP] Japan 1-152336

[51] Int. Cl.⁵ G06F 15/18
[52] U.S. Cl. 395/22; 395/11
[58] Field of Search 364/513; 395/11, 22

[56] References Cited

PUBLICATIONS

J. J. Hopfield et al., "'Neural' Computation of Decisions in Optimization Problems", Biological Cybernetics, 52, 1985, pp. 141–152.
"Simulated Annealing (Chapter 2)" from Theory and Applications, published by D. Reidel Publishing Company, 1987, pp. 7–15.

Primary Examiner—Allen R. MacDonald
Attorney, Agent, or Firm—Fay, Sharpe, Beall, Fagan, Minnich & McKee

[57] ABSTRACT

Method and system of selecting desirable time series data pieces from many time series data pieces. Characteristics extracted from time series data pieces are applied to neurons and neuron state fluctuations are supervised and evaluated through execution of neurocomputing to select desirable time series data.

3 Claims, 14 Drawing Sheets

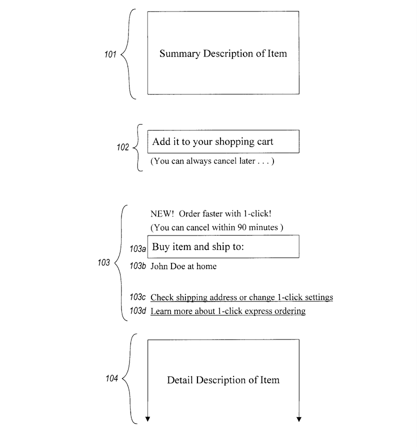
Occupation Task Description

Computer Programmers (SOC Code 151131)

- Prepares detailed workflow chart and diagram to illustrate sequence of steps that program must follow and to describe input, output, and logical operations involved.
- Analyzes workflow chart and diagram, applying knowledge of computer capabilities, subject matter, and symbolic logic.
- Confers with supervisor and representatives of departments concerned with program to resolve questions of program intent, data input, output requirements, and inclusion of internal checks and controls.
- Converts detailed logical flow chart to language processable by computer.
- Enters program codes into computer system.
- Inputs test data into computer.
- Observes computer monitor screen to interpret program operating codes.
- Corrects program errors, using methods such as modifying program or altering sequence of program steps.
- Writes instructions to guide operating personnel during production runs.
- Analyzes, reviews, and rewrites programs to increase operating efficiency or to adapt program to new requirements.
- Compiles and writes documentation of program development and subsequent revisions.
- May train workers to use program.
- May direct and coordinate work of others to write, test, and modify computer programs.
- Confers with other engineering and technical personnel to resolve problems of intent, inaccuracy, or feasibility of computer processing.
- Enters program into computer system.
- Reviews results of computer runs with interested personnel to determine necessity for modifications or reruns.
- Develops new subroutines or expands program to simplify statement, programming, or coding of future problems.
- Plans, schedules, and directs preparation of programs to process data and solve problems by use of computers.
- Consults with managerial and systems analysis personnel to clarify program intent, identify problems, suggest changes, and determine extent of programming and coding required.
- Assigns, coordinates, and reviews work of programming personnel.
- Develops programs from workflow charts or diagrams, considering factors, such as computer storage capacity and speed, extent of peripheral equipment, and intended use of output data.
- Converts workflow charts to language processable by computer.
- Enters program codes into computer.
- Enters test data into computer.
- Analyzes test runs on computer to correct or direct correction of coded program and input data.
- Revises or directs revision of existing programs to increase operating efficiency or adapt to new requirements.
- Compiles documentation of program development and subsequent revisions.
- Trains subordinates in programming and program coding.
- Prescribes standards for terms and symbols used to simplify interpretation of programs.
- Collaborates with computer manufacturers and other users to develop new programming methods.
- Prepares records and reports.

"**Method and a System for Selection of Time Series Data**" (US Patent 5,109,475): more related to computer programmers' non-routine tasks validation

Back to Jeff Bezos...

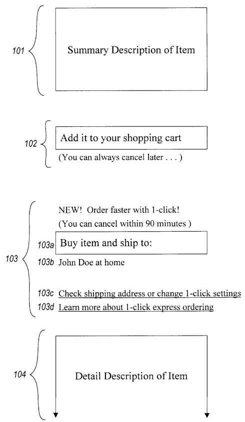


Most similar routine task occupation: Order clerks.

Examples of order clerk routine tasks:

- "Processes orders for material or merchandise received by mail, telephone, or personally from customer"
- "Writes or types order form, or enters data into computer, to determine total cost for customer."

Back to Jeff Bezos...



Most similar routine task occupation: Order clerks.

Examples of order clerk routine tasks:

- "Processes orders for material or merchandise received by mail, telephone, or personally from customer"
- "Writes or types order form, or enters data into computer, to determine total cost for customer."

One-click buying patent early part of the e-commerce wave of the late 1990s

Wages subsequently declined due to increased technology exposure Details

Technology Exposure

We then construct our empirical measure as:

Technology Exposure

We then construct our empirical measure as:

$$\xi^j(k,o,t) = \underbrace{\theta^j(o)}_{\substack{\text{Occ Share of} \\ \text{R/N tasks}}}$$

Technology Exposure

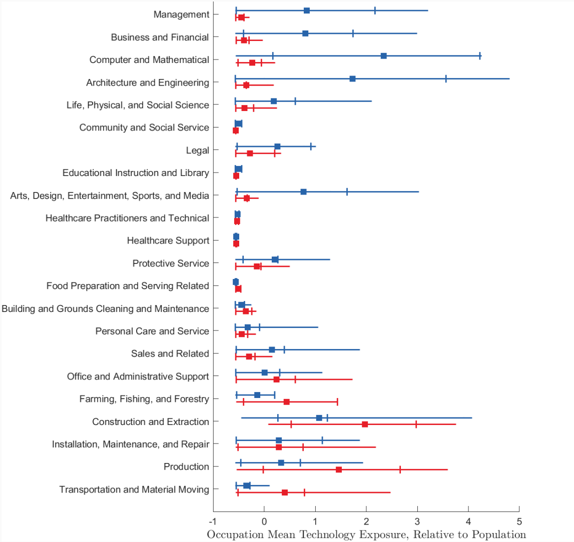
We then construct our empirical measure as:

$$\xi^j(k,o,t) = \underbrace{\theta^j(o)}_{\substack{\text{Occ Share of} \\ \text{R/N tasks}}} \times \underbrace{\log\left(1 + \sum_{b \in \mathcal{B}_{k,t}} \tilde{\rho}^j(o,b)\right)}_{\substack{\text{Similarity of Occ R/N tasks} \\ \text{to Ind Breakthrough innovations}}}, \qquad j \in \{R, N\}$$

Notes:

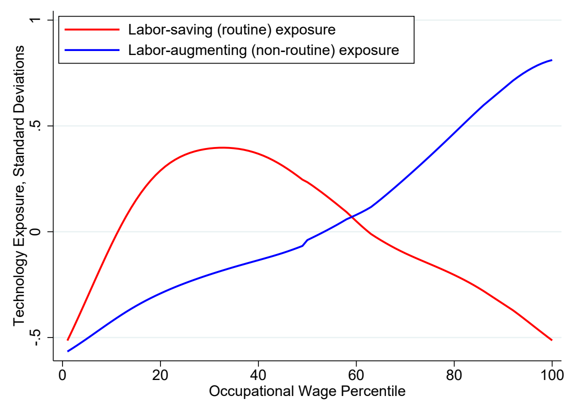
- Varies across industry k, occupation o and time t
- Allows us to have industry $\times$ year and occupation $\times$ year FEs in our empirical specifications.
- Patents are included when they are issued rather than filed (3 year average lag between filing year and issue year)

Which occupations are most exposed?



Labor-Saving Labor-Augmenting

Which occupations are most exposed?



- Labor-saving innovations primarily affect occupations in the middle of the skill distribution ('polarization')
- Labor-augmenting innovations primarily affect high-skill occupations ('skill-bias')

Outline

Aggregate Outcomes: Occupation$\times$Industry-level

Occupation$\times$Industry-level:	Employment	Avg Hourly Wage	Total Wage Bill
	(1)	(2)	(3)
Exposure to labor-saving (ξ^R)	-0.44	-0.00	-0.46
	(-3.52)	(-1.13)	(-3.69)
Exposure to labor-augmenting (ξ^N)	0.91	0.01	1.01
	(5.59)	(2.04)	(6.13)

Model prediction: sign of coefficient depends on $\psi - \nu_j$ for $j \in \{R, NR\}$

Dependent variable: annualized growth rate (10-year horizon) in occupation-industry employment, wages or wagebill (data from ACS/Decennial Census)

Controls: occupation $\times$ year + industry $\times$ year FEs, demographics

Aggregate Outcomes: Industry-level

Industry-level:	Productivity		Labor share	Wage Bill
	(1)	(2)	(3)	(4)
Overall Technology Exposure ($\bar{\xi}$)		1.06		
		(6.09)		
Exposure to labor-saving ($\bar{\xi}^R$)	0.50		-0.51	-0.63
	(1.67)		(-3.37)	(-2.88)
Exposure to labor-augmenting ($\bar{\xi}^N$)	0.63		0.14	0.29
	(3.01)		(1.31)	(1.49)

Model predictions:

- Both $\overline{\xi}_R$ and $\overline{\xi}_N$ predict productivity growth: $\Delta \log X \propto \overline{\xi}_R + \overline{\xi}_N$
- $\overline{\xi}_R$ predicts declines in labor share and wage bill, opposite for $\overline{\xi}_N$

Dependent variable: annualized growth rate (5-year horizon) in industry productivity, labor share, or wage bill (data from BLS)

Controls: 2 digit industry $\times$ year FEs, log lagged industry employment, lagged growth rates

Outline

Impact of innovation on individual workers

Aggregate wage and employment effects can be very different than for individual workers due to new entry and composition effects.

Impact of innovation on individual workers

Aggregate wage and employment effects can be very different than for individual workers due to new entry and composition effects.

Track individual workers over time: panel of individuals in the Current Population Survey linked with W2 tax data (Detailed Earnings Record, 1981-2016)

Impact of innovation on individual workers

Aggregate wage and employment effects can be very different than for individual workers due to new entry and composition effects.

Track individual workers over time: panel of individuals in the Current Population Survey linked with W2 tax data (Detailed Earnings Record, 1981-2016)

Calculate growth in age-adjusted (cumulative) W2 earnings

$$\Delta w^i_{t+h} \equiv w^i_{t+1,t+h} - w^i_{t-2,t}$$

where

$$w_{i,t:t+h} \equiv \log\left(\frac{\sum_{j=0}^{h} \text{W2 wage}_{i,t+j}}{\sum_{j=0}^{h} D(\text{age}_{i,t+j})}\right)$$

Notes:

- Growth in cumulative earnings emphasizes permanent income changes.
- Subsequent earnings include earnings from other jobs or non-employment (zero W2 earnings).

Specification

Basic regression model:

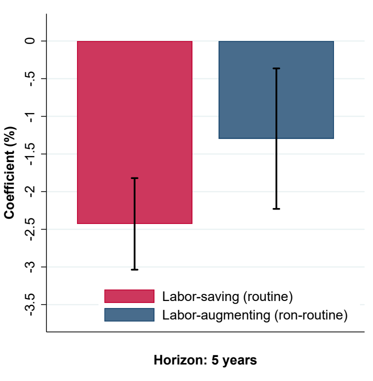
$$\Delta w^i_{t+h} = \gamma \xi^R_{i,t} + \delta \xi^N_{i,t} + c\,\mathbf{Z}_{i,t} + u_{i,t}.$$

$Z_{i,t}$ includes set of flexible non-parametric controls for worker age and the level of past worker earnings as well as recent earnings growth rates.

Also industry$\times$year and occupation$\times$ year fixed effects

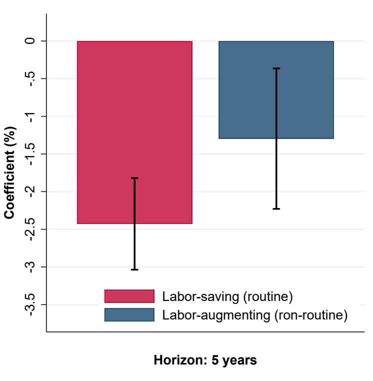
Allow the estimated coefficients γ and δ to vary across different sectors, job types, or worker characteristics.

Exposure Marginal Effects: Homogenous



Magnitudes: Moving from 50th to 90th percentile of tech exposure.

Exposure Marginal Effects: Homogenous and Heterogeneous



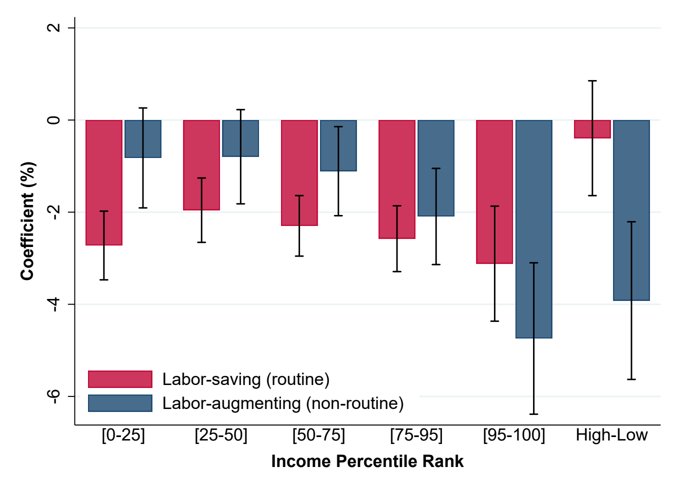
Magnitudes: Moving from 50th to 90th percentile of tech exposure.

Labor-augmenting marginal effects on earnings growth are highly heterogeneous. Concentrated among:

- Service industries
- Cognitive task-intensive occupations
- College-educated workers
- Older workers

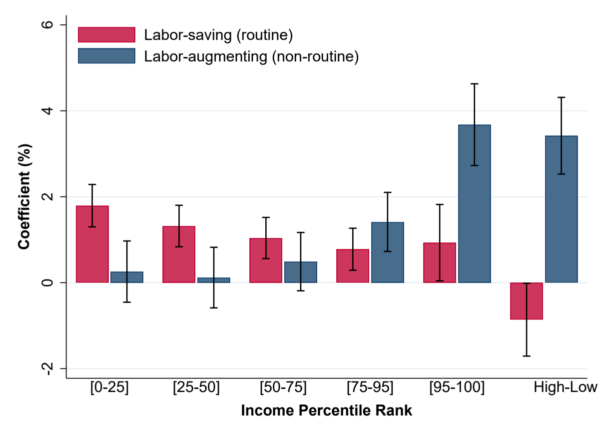
No such patterns for labor-saving exposure (strongly negative everywhere except for interpersonal occupations) Details

Effects Vary with Worker Income



Prior Income: relative to industry and occupation. Robust to sorting on income residual of age, gender, occupation, industry, firm, and union status.

Effects driven by heightened probability of job loss



- **Job Loss:** Leave firm within 5 years + income growth below 20th prctile.
- Increased probability of job loss accounts for
  - 3/4 of the impact of complementary technologies on top workers.
  - 1/2 to 2/3 of the impact of automation on worker earnings.

Directed Innovation? Prior wage growth and future technology exposure

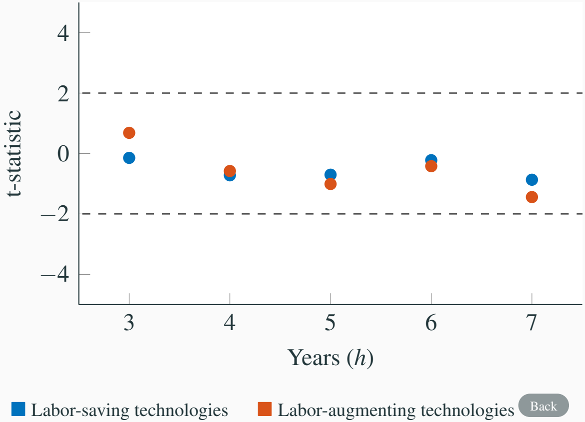
Estimate:

$$\xi_{i,t+5+h} = b\,\Delta w^{i}_{t+5} + c\,\mathbf{Z}_{i,t} + u_{i,t}.$$

Directed Innovation? Prior wage growth and future technology exposure

Estimate:

$$\xi_{i,t+5+h} = b\,\Delta w^{i}_{t+5} + c\,\mathbf{Z}_{i,t} + u_{i,t}.$$



Back

Worker-level Productivity Spillovers

Industry productivity increases labor demand for all workers

- Productivity spillovers absorbed by 4-digit industry $\times$ year FEs
- Move to 2-digit industry $\times$ year FEs to capture spillovers.
- **Model:** Productivity's effect on earnings is proportional to industry-level average of $\bar{\xi} \equiv \xi^R + \xi^N$.

Worker-level Productivity Spillovers

Industry productivity increases labor demand for all workers

- Productivity spillovers absorbed by 4-digit industry $\times$ year FEs
- Move to 2-digit industry $\times$ year FEs to capture spillovers.
- **Model:** Productivity's effect on earnings is proportional to industry-level average of $\bar{\xi} \equiv \xi^R + \xi^N$.

Empirical Estimates:

$$\Delta w^i_{t+h} = \underbrace{\underset{(-7.84)}{-0.030}}_{\text{Automation}} \xi^R(i) + \underbrace{\underset{(-2.75)}{-0.017}}_{\text{Complementary tech}} \xi^N(i) + \underbrace{\underset{(5.41)}{0.025}}_{\text{Spillovers}} \bar{\xi}$$

Outline

Can model square aggregate and worker-level results?

Labor-saving tech exposure: strongly and (mostly) uniformly predicts $\downarrow$ labor demand

Complementary tech exposure: predicts $\uparrow$ aggregate labor demand, but $\downarrow$ for <u>incumbent</u> worker earnings, with heterogeneity by prior expertise.

How to square the two?

Can model square aggregate and worker-level results?

Labor-saving tech exposure: strongly and (mostly) uniformly predicts $\downarrow$ labor demand

Complementary tech exposure: predicts $\uparrow$ aggregate labor demand, but $\downarrow$ for incumbent worker earnings, with heterogeneity by prior expertise.

How to square the two? $\implies$ Incorporate skill displacement into model.

Can model square aggregate and worker-level results?

Labor-saving tech exposure: strongly and (mostly) uniformly predicts $\downarrow$ labor demand

Complementary tech exposure: predicts $\uparrow$ aggregate labor demand, but $\downarrow$ for incumbent worker earnings, with heterogeneity by prior expertise.

How to square the two? $\implies$ Incorporate skill displacement into model.

Non-routine tasks require specialized skills. When technology improves:

Can model square aggregate and worker-level results?

Labor-saving tech exposure: strongly and (mostly) uniformly predicts $\downarrow$ labor demand

Complementary tech exposure: predicts $\uparrow$ aggregate labor demand, but $\downarrow$ for incumbent worker earnings, with heterogeneity by prior expertise.

How to square the two? $\implies$ Incorporate skill displacement into model.

Non-routine tasks require specialized skills. When technology improves:

- Incumbent workers may lack skills to utilize new vintage
  - Allow for some average amount of skill loss (β)
- May erode advantage of incumbent workers who were relatively skilled in prior vintage
  - Allow for some mean-reversion in relative skill ranking (ω)

Can model square aggregate and worker-level results?

Labor-saving tech exposure: strongly and (mostly) uniformly predicts ↓ labor demand

Complementary tech exposure: predicts ↑ aggregate labor demand, but ↓ for incumbent worker earnings, with heterogeneity by prior expertise.

How to square the two? $\implies$ Incorporate skill displacement into model.

Non-routine tasks require specialized skills. When technology improves:

- Incumbent workers may lack skills to utilize new vintage
  - Allow for some average amount of skill loss (β)
- May erode advantage of incumbent workers who were relatively skilled in prior vintage
  - Allow for some mean-reversion in relative skill ranking (ω)

Wage Earnings Growth for Incumbent Workers

$$\Delta \log W(i) \approx \underbrace{\left[\frac{\psi - \nu_R}{\nu_R + \zeta_R}\Gamma_R\right]}_{\substack{\text{Direct Effect of} \\ \text{Automation}}} \xi^R(i)$$

$$+ \left[\underbrace{\frac{\psi - \nu_N}{\nu_N + \zeta_N}\Gamma_N}_{\substack{\text{Direct Effect of} \\ \text{Complementary Technologies}}} \right] \xi^N(i)$$

$$+ \underbrace{\left[(A_R - A_N)\theta(i) + A_N\right]\Delta \log X}_{\text{Aggregate Productivity Spillovers}}$$

Wage Earnings Growth for Incumbent Workers

$$
\begin{aligned}
\Delta \log W(i) \approx\ & \underbrace{\left[\frac{\psi - \nu_R}{\nu_R + \zeta_R}\Gamma_R\right]}_{\substack{\text{Direct Effect of}\\ \text{Automation}}} \xi^R(i) \\
& + \left[\underbrace{\frac{\psi - \nu_N}{\nu_N + \zeta_N}\Gamma_N}_{\substack{\text{Direct Effect of}\\ \text{Complementary Technologies}}} \quad \underbrace{-\beta - \omega\left[\log \bar{l}(i) - E_i[\log \bar{l}(i)]\right]}_{\text{Incumbent Skill Displacement}} \right] \xi^N(i) \\
& + \underbrace{\left[(A_R - A_N)\theta(i) + A_N \right] \Delta \log X}_{\text{Aggregate Productivity Spillovers}}
\end{aligned}
$$

- Effect of automation is symmetric across all workers.
- Effect of complementary technologies is heterogeneous.

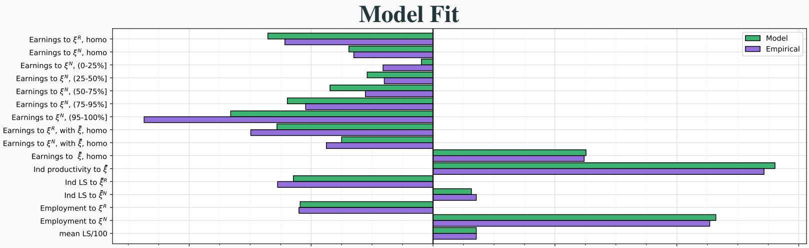
Model Estimation and Fit

Are our empirical estimates consistent with a common set of parameters?

Model Estimation and Fit

Are our empirical estimates consistent with a common set of parameters?

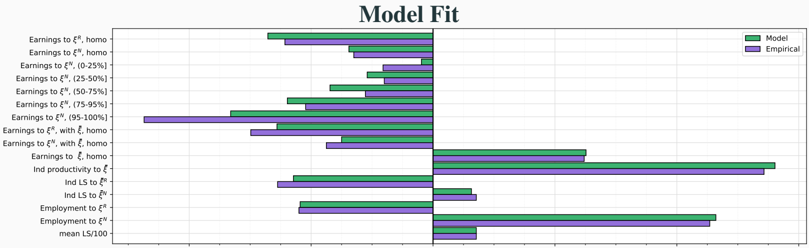
Estimate parameters via GMM: 11 parameters identified by 16 moments + 2 cross-equation restrictions. Details



Model Estimation and Fit

Are our empirical estimates consistent with a common set of parameters?

Estimate parameters via GMM: 11 parameters identified by 16 moments + 2 cross-equation restrictions. Details



Key parameter estimates:

- $\nu_R = 1.439$ (routine labor/capital elasticity of substitution)
- $\nu_N = 0.928$ (non-routine labor/capital elasticity of substitution)
- $\beta = 0.052$ (average skill loss)
- $\omega = 0.014$ (relative skill loss)
- $\psi = 1.191$ (elasticity of substitution across tasks)

Outline

Conclusion

- Introduce a direct, time-varying measure of exposure to labor-saving and complementary technologies
- Automation has large, pervasive, and persistent effect on earnings of individual workers and in the aggregate
- Modest negative earnings response to complementary technologies, but with significant heterogeneity: suggests role for skill displacement
  - Future cohorts reap benefits of complementary technologies
- Application of model to AI suggests AI automates office admin jobs and production; exposes sales, admin, and business professionals to skill displacement

Census acknowledgment

The Census Bureau has reviewed this data product to ensure appropriate access, use, and disclosure avoidance protection of the confidential source data used to produce this product (Data Management System (DMS) number: P-7503840, Disclosure Review Board (DRB) approval numbers: CBDRB-FY21-POP001-0176, CBDRB-FY22-SEHSD003-006, CBDRB-FY22-SEHSD003-023, CBDRB-FY22-SEHSD003-028, CBDRB-FY23-SEHSD003-064).

APPENDIX SLIDES

Application: AI

Can we use the model parameters to make predictions about the impact of AI?

- AI is a general-purpose technology that can simultaneously complement and substitute worker tasks.

Methodology:

- Use GPT4 to identify current occupation tasks that are potentially complemented or substituted by AI.
- Use GPT4 separately identify tasks for which AI can also be easily implemented by AI (proxy for $-\Delta q(j)$)
- Assume uniform adoption across industries (difficult to forecast).
- Use estimated parameters to back out implied direct effects of AI.
    - Decompose AI exposure into automation, complementary, and skill-displacement components.

Wage Growth Due to AI Exposure by Broad Occupation Category

Occupation	2-digit SOC	Automation	Complementary	Skill Displacement	Total	% of Emp
Management	11	-0.74	4.65	-5.84	-1.93	12.8
Business and Financial	13	-1.51	7.67	-9.63	-3.47	6.57
Computer and Mathematical	15	-1.98	5.82	-7.31	-3.47	4.12
Architecture and Engineering	17	-0.88	3.95	-4.96	-1.89	2.56
Science	19	-0.83	4.24	-5.32	-1.91	1.25
Community and Social Service	21	-0.29	2.52	-3.16	-0.93	1.84
Legal	23	-0.77	3.28	-4.12	-1.61	1.33
Education and Library	25	-0.54	3.89	-4.88	-1.53	6.16
Arts, Entertainment, Media	27	-1.21	3.96	-4.97	-2.22	1.66
Healthcare Practitioners	29	-1.19	3.46	-4.34	-2.08	6.65
Healthcare Support	31	-1.54	4.71	-5.92	-2.74	3.03
Protective Service	33	-2.03	4.63	-5.82	-3.21	2.45
Food Preparation and Serving	35	-4.01	4.28	-5.37	-5.10	3.76
Cleaning and Maintenance	37	-3.17	3.59	-4.50	-4.08	2.77
Personal Care and Service	39	-1.62	2.75	-3.45	-2.32	1.46
Sales and Related	41	-3.79	8.11	-10.20	-5.86	8.59
Office and Administrative	43	-6.92	6.82	-8.57	-8.66	10.6
Farming, Fishing, and Forestry	45	-3.33	3.06	-3.84	-4.11	0.61
Construction and Extraction	47	-0.98	3.13	-3.93	-1.78	4.71
Installation and Repair	49	-1.42	2.73	-3.42	-2.12	3.44
Production	51	-5.47	3.43	-4.31	-6.34	5.85
Transportation	53	-5.58	5.09	-6.38	-6.88	7.73
Overall		-2.74	4.95	-6.22	-4.01	100

Horizon: 5 years

Wage Growth Due to AI Exposure by Broad Occupation Category

Occupation	2-digit SOC	Automation	Complementary	Skill Displacement	Total	% of Emp
Management	11	-0.74	4.65	-5.84	-1.93	12.8
Business and Financial	13	-1.51	7.67	-9.63	-3.47	6.57
Computer and Mathematical	15	-1.98	5.82	-7.31	-3.47	4.12
Architecture and Engineering	17	-0.88	3.95	-4.96	-1.89	2.56
Science	19	-0.83	4.24	-5.32	-1.91	1.25
Community and Social Service	21	-0.29	2.52	-3.16	-0.93	1.84
Legal	23	-0.77	3.28	-4.12	-1.61	1.33
Education and Library	25	-0.54	3.89	-4.88	-1.53	6.16
Arts, Entertainment, Media	27	-1.21	3.96	-4.97	-2.22	1.66
Healthcare Practitioners	29	-1.19	3.46	-4.34	-2.08	6.65
Healthcare Support	31	-1.54	4.71	-5.92	-2.74	3.03
Protective Service	33	-2.03	4.63	-5.82	-3.21	2.45
Food Preparation and Serving	35	-4.01	4.28	-5.37	-5.10	3.76
Cleaning and Maintenance	37	-3.17	3.59	-4.50	-4.08	2.77
Personal Care and Service	39	-1.62	2.75	-3.45	-2.32	1.46
Sales and Related	41	-3.79	8.11	-10.20	-5.86	8.59
Office and Administrative	43	-6.92	6.82	-8.57	-8.66	10.6
Farming, Fishing, and Forestry	45	-3.33	3.06	-3.84	-4.11	0.61
Construction and Extraction	47	-0.98	3.13	-3.93	-1.78	4.71
Installation and Repair	49	-1.42	2.73	-3.42	-2.12	3.44
Production	51	-5.47	3.43	-4.31	-6.34	5.85
Transportation	53	-5.58	5.09	-6.38	-6.88	7.73
Overall		-2.74	4.95	-6.22	-4.01	100

Horizon: 5 years

Wage Growth Due to AI Exposure by Broad Occupation Category

Occupation	2-digit SOC	Automation	Complementary	Skill Displacement	Total	% of Emp
Management	11	-0.74	4.65	-5.84	-1.93	12.8
Business and Financial	13	-1.51	7.67	-9.63	-3.47	6.57
Computer and Mathematical	15	-1.98	5.82	-7.31	-3.47	4.12
Architecture and Engineering	17	-0.88	3.95	-4.96	-1.89	2.56
Science	19	-0.83	4.24	-5.32	-1.91	1.25
Community and Social Service	21	-0.29	2.52	-3.16	-0.93	1.84
Legal	23	-0.77	3.28	-4.12	-1.61	1.33
Education and Library	25	-0.54	3.89	-4.88	-1.53	6.16
Arts, Entertainment, Media	27	-1.21	3.96	-4.97	-2.22	1.66
Healthcare Practitioners	29	-1.19	3.46	-4.34	-2.08	6.65
Healthcare Support	31	-1.54	4.71	-5.92	-2.74	3.03
Protective Service	33	-2.03	4.63	-5.82	-3.21	2.45
Food Preparation and Serving	35	-4.01	4.28	-5.37	-5.10	3.76
Cleaning and Maintenance	37	-3.17	3.59	-4.50	-4.08	2.77
Personal Care and Service	39	-1.62	2.75	-3.45	-2.32	1.46
Sales and Related	41	-3.79	8.11	-10.20	-5.86	8.59
Office and Administrative	43	-6.92	6.82	-8.57	-8.66	10.6
Farming, Fishing, and Forestry	45	-3.33	3.06	-3.84	-4.11	0.61
Construction and Extraction	47	-0.98	3.13	-3.93	-1.78	4.71
Installation and Repair	49	-1.42	2.73	-3.42	-2.12	3.44
Production	51	-5.47	3.43	-4.31	-6.34	5.85
Transportation	53	-5.58	5.09	-6.38	-6.88	7.73
Overall		-2.74	4.95	-6.22	-4.01	100

Horizon: 5 years

Wage Growth Due to AI Exposure by Broad Occupation Category

Occupation	2-digit SOC	Automation	Complementary	Skill Displacement	Total	% of Emp
Management	11	-0.74	4.65	-5.84	-1.93	12.8
Business and Financial	13	-1.51	7.67	-9.63	-3.47	6.57
Computer and Mathematical	15	-1.98	5.82	-7.31	-3.47	4.12
Architecture and Engineering	17	-0.88	3.95	-4.96	-1.89	2.56
Science	19	-0.83	4.24	-5.32	-1.91	1.25
Community and Social Service	21	-0.29	2.52	-3.16	-0.93	1.84
Legal	23	-0.77	3.28	-4.12	-1.61	1.33
Education and Library	25	-0.54	3.89	-4.88	-1.53	6.16
Arts, Entertainment, Media	27	-1.21	3.96	-4.97	-2.22	1.66
Healthcare Practitioners	29	-1.19	3.46	-4.34	-2.08	6.65
Healthcare Support	31	-1.54	4.71	-5.92	-2.74	3.03
Protective Service	33	-2.03	4.63	-5.82	-3.21	2.45
Food Preparation and Serving	35	-4.01	4.28	-5.37	-5.10	3.76
Cleaning and Maintenance	37	-3.17	3.59	-4.50	-4.08	2.77
Personal Care and Service	39	-1.62	2.75	-3.45	-2.32	1.46
Sales and Related	41	-3.79	8.11	-10.20	-5.86	8.59
Office and Administrative	43	-6.92	6.82	-8.57	-8.66	10.6
Farming, Fishing, and Forestry	45	-3.33	3.06	-3.84	-4.11	0.61
Construction and Extraction	47	-0.98	3.13	-3.93	-1.78	4.71
Installation and Repair	49	-1.42	2.73	-3.42	-2.12	3.44
Production	51	-5.47	3.43	-4.31	-6.34	5.85
Transportation	53	-5.58	5.09	-6.38	-6.88	7.73
Overall		-2.74	4.95	-6.22	-4.01	100

Horizon: 5 years

Production

Aggregate output is a CES combination of many industries:

$$\bar{Y} = \left(\int_k Y(k)^{\frac{\chi-1}{\chi}} dk \right)^{\frac{\chi}{\chi-1}},$$

Industry output is a function of many tasks indexed by j:

$$Y = \left(\sum_{i=1}^{J} y(j)^{\frac{\psi-1}{\psi}} \right)^{\frac{\psi}{\psi-1}},$$

$$y(j) = \left((1-\gamma_j)k(j)^{\frac{\nu_j-1}{\nu_j}} + \gamma_j l(j)^{\frac{\nu_j-1}{\nu_j}} \right)^{\frac{\nu_j}{\nu_j-1}},$$

Tasks j can be **routine** ($j \in J_R$) or **non-routine** ($j \in J_N$)

- If routine, $\nu_j = \nu_R > 1$, if non-routine, $\nu_j = \nu_N < 1$.
- Alternative interpretation: R = low skill and N = high skill

Back

Technology

Two periods: before/after technology shock.

Technology shock = fall in the price of task-specific capital:

$$\Delta \log q(j) = -\varepsilon(j)$$

Technology

Two periods: before/after technology shock.

Technology shock = fall in the price of task-specific capital:

$$\Delta \log q(j) = -\varepsilon(j)$$

Interpretation:

- Technology improvements in $i \in J_R$: labor-saving (automation)
  - Capital $k(j)$ and routine labor $l(j)$ are substitutes
  - Wage in task i falls if $\nu_R > \psi$

Technology

Two periods: before/after technology shock.

Technology shock = fall in the price of task-specific capital:

$$\Delta \log q(j) = -\varepsilon(j)$$

Interpretation:

- Technology improvements in $i \in J_R$: labor-saving (automation)
  - Capital $k(j)$ and routine labor $l(j)$ are substitutes
  - Wage in task i falls if $\nu_R > \psi$
- Technology improvements in $i \in J_N$: complementary to labor
  - Capital $k(j)$ and non-routine labor $l(j)$ are complements
  - Wage in task j rises if $\nu_N < \psi$

Using GPT4 to tag R/NR tasks

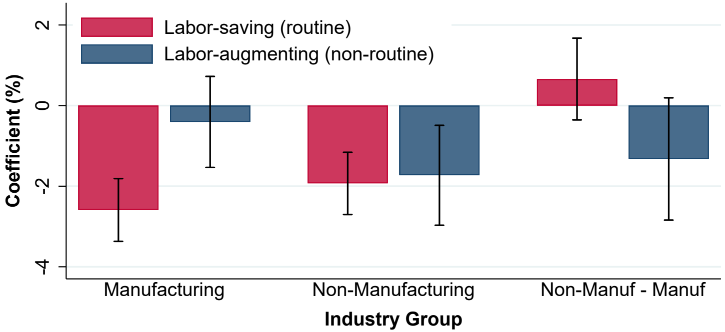
GPT4 prompt:

> *A routine task can be defined as follows: A routine task involves carrying out a limited and well-defined set of work activities, those that can be accomplished by following explicit rules. These tasks require methodical repetition of an unwavering procedure, and they can be exhaustively specified with programmed instructions and performed by machines. Tell me whether the following task is primarily routine, primarily non-routine, or involves a mix of both routine and non-routine tasks; and, explain your reasoning in one sentence.*

GPT4 characterizes 62% as routine tasks, 15% as non-routine and 22% as mixed. We group the latter two into non-routine.

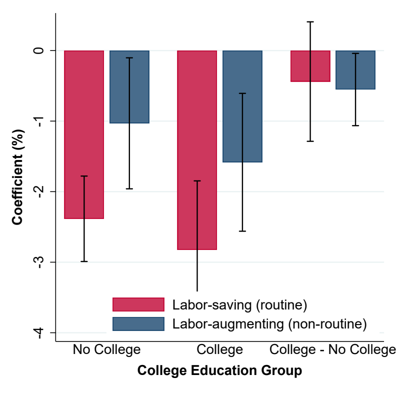
Back

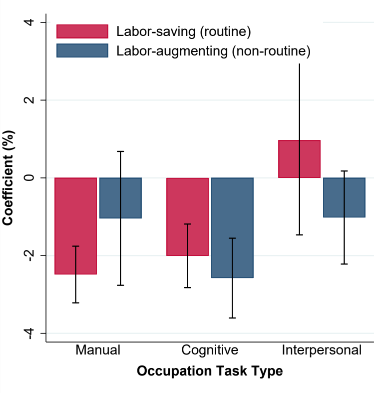
Exposure by Sector



Back

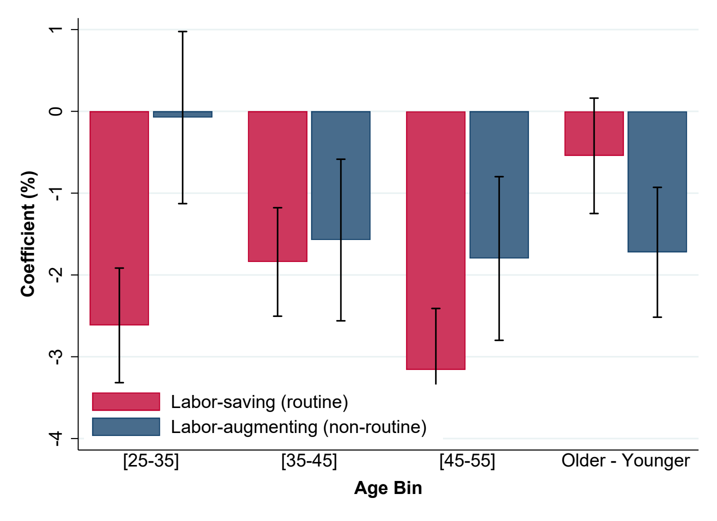
Exposure by Education and Occupation Task Type





Back

Effects Vary with Age



Back

Directed Innovation?

Automation (R)

- Incentive to develop technologies targeting tasks that have become more expensive.
- Prediction: Past wage growth should positively predict automation.

Complementary technologies (NR)

- Incentive to develop complementary technologies targeting jobs that have accumulated more human capital.
- Prediction: Past wage growth should positively predict exposure to complementary technologies.

Back

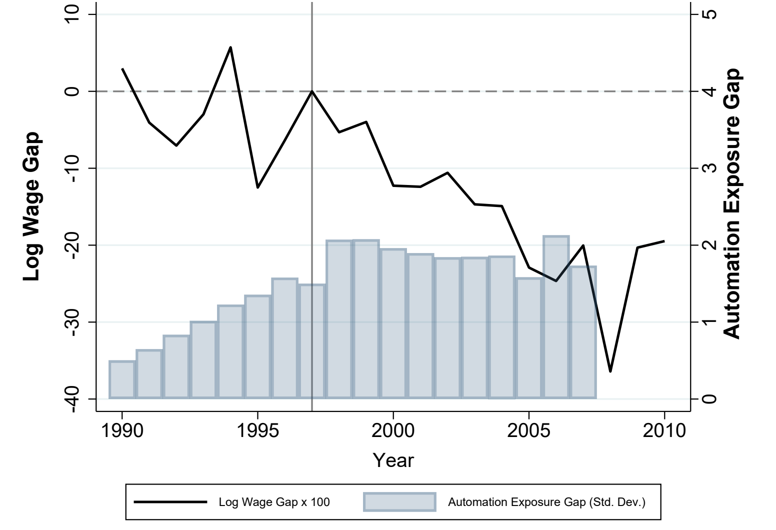
Validation

GPT4 Query	% Agree	
	5 **most** similar OCCs	5 **least** similar OCCs
Distance to Routine Tasks: *"Here is the abstract of a patent: [Patent abstract here]. Here are some tasks: [DOT title here]. Do you think the technology mentioned above can perform some of the tasks mentioned above that were formerly performed by workers? Output yes or no, and your reasoning in one sentence."*	86%	4%
Distance to Non-Routine Tasks: *"Here is the abstract of a patent: [Patent abstract here]. Here are some tasks: [DOT title here]. Do you think the patent mentioned above can increase the productivity of workers when performing some of the tasks mentioned above? Output yes or no, and your reasoning in one sentence."*	83%	10%

Note: Results based on random sample of 10k patents. Back

What happened to order clerks?

Order Clerks compared to Payroll and Timekeeping Clerks



Back

Wage growth and future technology exposure

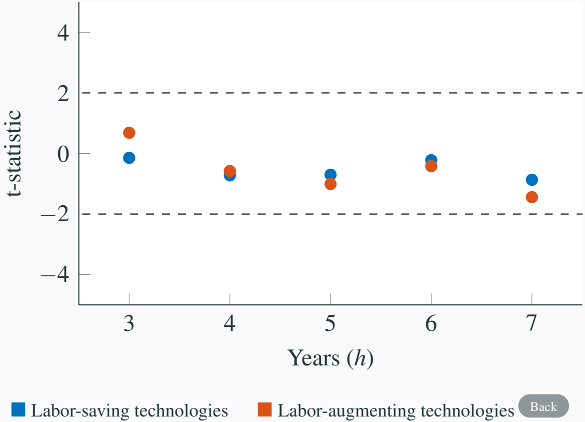
Estimate:

$$\xi_{i,t+5+h} = b\,\Delta w^{i}_{t+5} + c\,\mathbf{Z}_{i,t} + u_{i,t}.$$

Wage growth and future technology exposure

Estimate:

$$\xi_{i,t+5+h} = b\,\Delta w^{i}_{t+5} + c\,\mathbf{Z}_{i,t} + u_{i,t}.$$



Back

Endogenous Adoption?

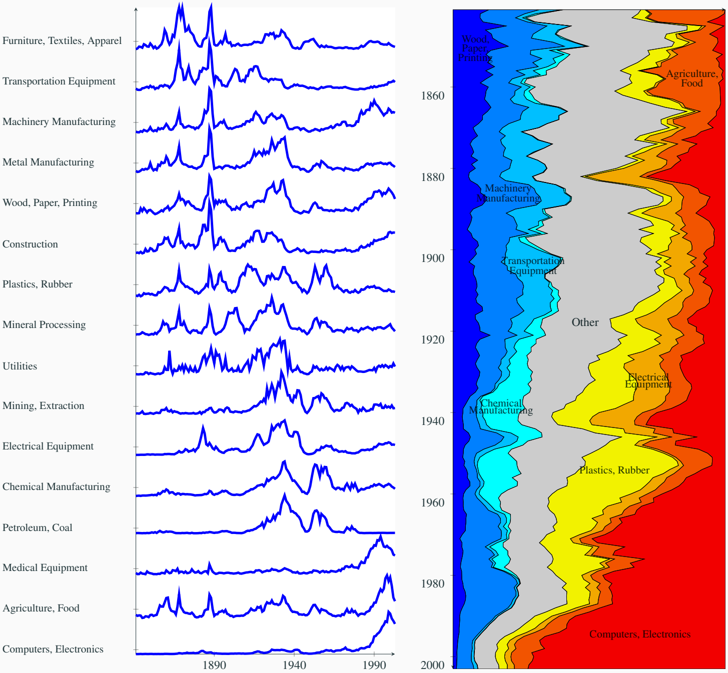
Automation (R)

- Incentive to adopt automation for high-wage tasks.
- However, cost to develop or adopt these technologies may be higher
- Data: automation exposure does not vary by income, effects cancel?

Complementary technologies (NR)

- No incentive to adopt NR for high-wage tasks
- Age/income pattern in impact of NR-technologies unlikely due to endogenous adoption

Back



Furniture, Textiles, Apparel
Transportation Equipment
Machinery Manufacturing
Metal Manufacturing
Wood, Paper, Printing
Construction
Plastics, Rubber
Mineral Processing
Utilities
Mining, Extraction
Electrical Equipment
Chemical Manufacturing
Petroleum, Coal
Medical Equipment
Agriculture, Food
Computers, Electronics
1890
1940
1990
1860
1880
1900
1920
1940
1960
1980
2000
Wood, Paper, Printing
Agriculture, Food
Machinery Manufacturing
Transportation Equipment
Other
Electrical Equipment
Chemical Manufacturing
Plastics, Rubber
Computers, Electronics

Back

Model Estimation

Are our empirical estimates consistent with a common set of parameters?

Model Estimation

Are our empirical estimates consistent with a common set of parameters?

Estimate parameters via GMM: 11 parameters identified by 16 moments + 2 cross-equation restrictions.

Model Estimation

Are our empirical estimates consistent with a common set of parameters?

Estimate parameters via GMM: 11 parameters identified by 16 moments + 2 cross-equation restrictions.

Assumptions:

- **Measurement Error:** Empirical proxies for ξ^R and ξ^N capture true model counterparts up to industry-level measurement error.

Model Estimation

Are our empirical estimates consistent with a common set of parameters?

Estimate parameters via GMM: 11 parameters identified by 16 moments + 2 cross-equation restrictions.

Assumptions:

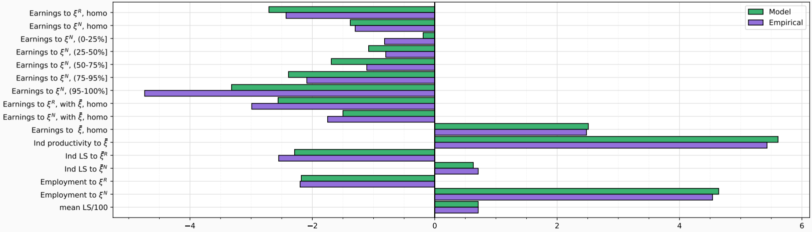
- **Measurement Error:** Empirical proxies for ξ^R and ξ^N capture true model counterparts up to industry-level measurement error.

Identification:

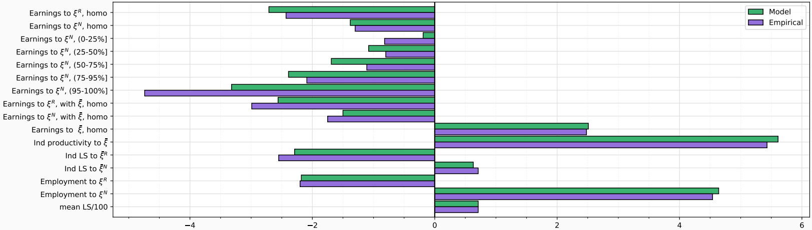
- **Substitution between K and L in Routine Tasks (ν_R):** Worker-level earnings responses (relative to ψ); Industry-level labor share response.
- **Substitution between K and L in Non-Routine Tasks (ν_N):** Worker-level (relative to average displacement β) and occupation-industry responses.
- **Relative Skill displacement (ω):** Gradient of coefficients w.r.t income.

Back

Model Parameters and Fit



Model Parameters and Fit



Parameter	Symbol	Estimate
Elasticity of substitution across tasks	ψ	1.191
Elasticity of substitution across industries	χ	1.910
Elasticity of substitution between capital and labor, routine tasks	ν_R	1.439
Elasticity of substitution between capital and labor, non-routine tasks	ν_N	0.928
Elasticity of labor supply, routine tasks	ζ_R	0.725
Elasticity of labor supply, non-routine tasks	ζ_N	0.871
Mean skill loss for incumbent workers	β	0.052
Capital-labor expenditure ratio, routine tasks	κ_R	0.349
Capital-labor expenditure ratio, non-routine tasks	κ_N	0.452
Skill loss across technology vintages	ω	0.014
Ratio of noise to signal for industry $\bar{\xi}^R$, $\bar{\xi}^N$ and $\bar{\xi}$	γ	1.035

Back

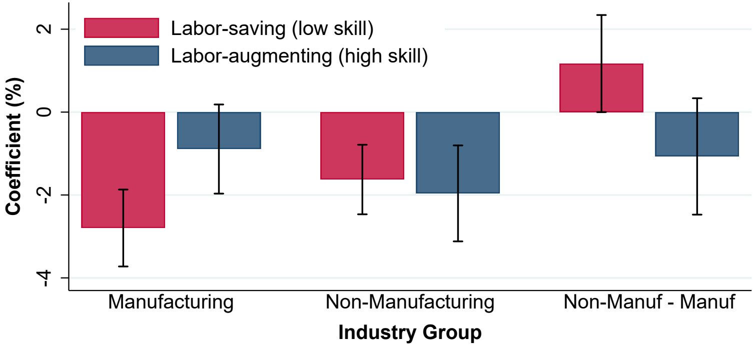
Alternative measure of automation

> *Specific Vocational Preparation is the amount of lapsed time required by a typical worker to learn the techniques, acquire the information, and develop the facility needed for average performance in a specific job-worker situation. Tell me whether attaining proficiency in the below occupation task requires A) an extensive amount (more than 5 years); B) a fair amount (1 to 5 years); C) a moderate amount (3 months to 1 year); or D) very little (less than 3 months) of specific vocational preparation; and, explain your reasoning in one sentence. Output only a tuple: (category A/B/C/D, reasoning) format" + x, x is the sentence task description*

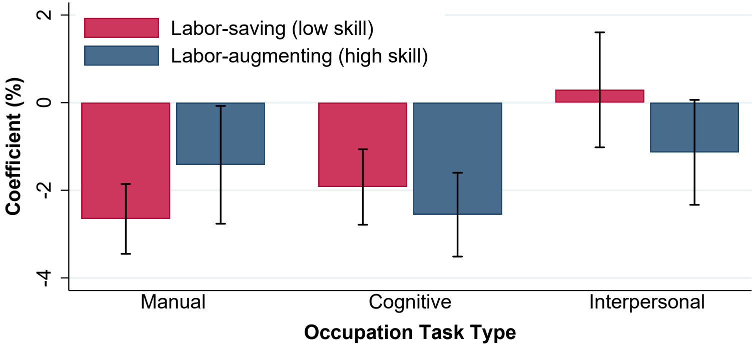
GPT4 labels: D: 61%, C: 25%, B: 13%, A: 0.01%

Label D: low experience, A/B/C as high experience.

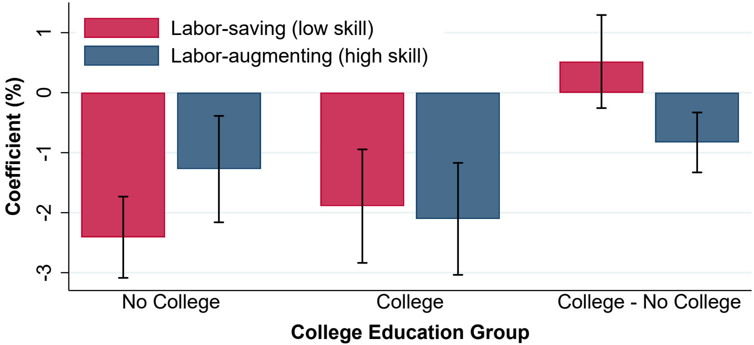
Exposure by Industry



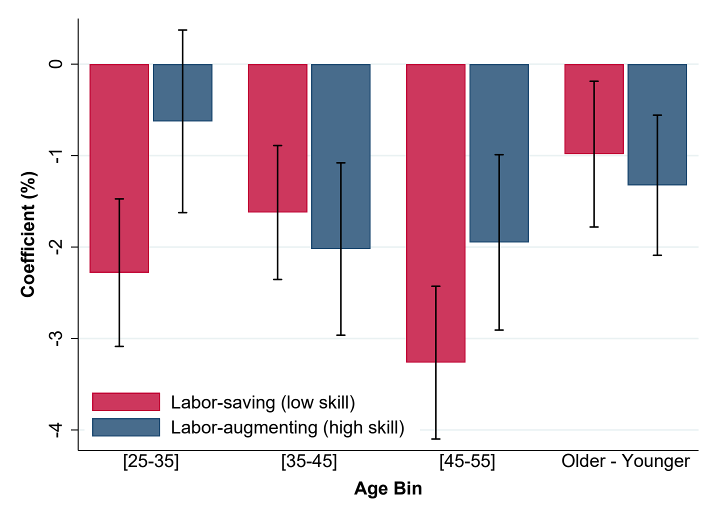
Exposure by Job Type



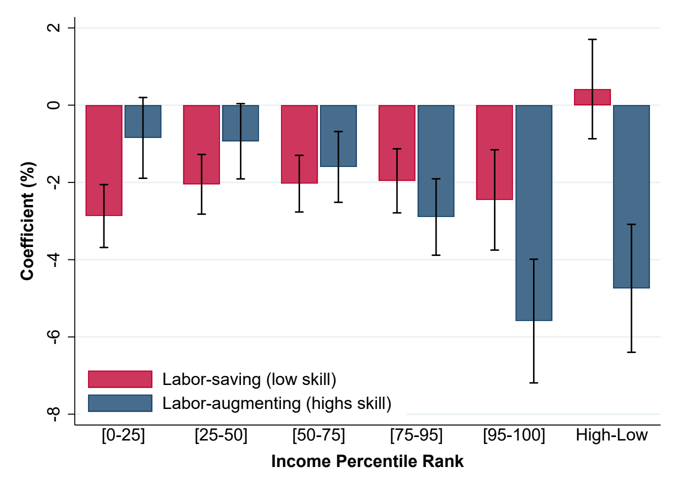
Exposure by Education



Effects Vary with Age

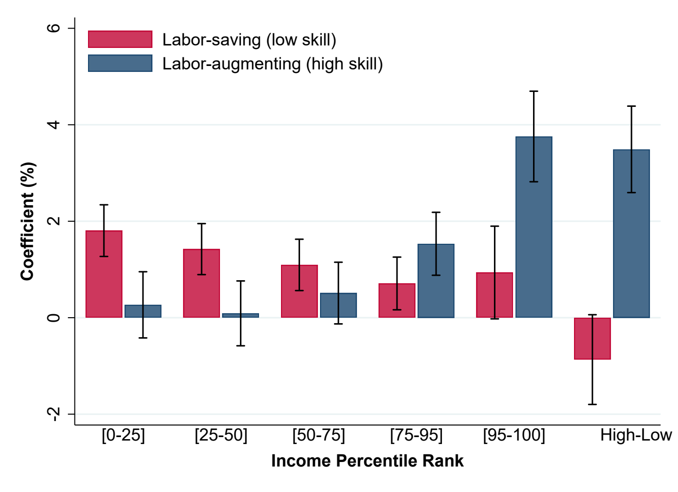


Effects Vary with Worker Income



Prior Income: relative to industry and occupation. Robust to sorting on income residual of age, gender, industry, firm, and union status.

Involuntary Exit



Involuntary Exit: Leave firm within 5 years + income growth below 20th prctile.