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

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Big Picture

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This paper: Construct time-varying measure of workers' broad exposure to technological change based on their occupation and industry, and examine the effects of exposure on labor earnings.

What we do

1. Using textual analysis of patent data and occupation task descriptions, directly measure whether a given technology improvement is a complement or substitute to a given occupation.

2. Link to individual worker earnings using administrative tax data.

3. Interpret coefficient estimates using both individual and aggregate data through the lens of a structural model.

4. Use model to speculate on the impact of AI on worker earnings and employment.

What we find

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2. Complementary technology improvements:
   - ▶ Small negative average effects on incumbent individual workers.
   - ▶ Positive effects on aggregate employment and wages.
   - ▶ Significant heterogeneity: older and most highly paid workers experiencing largest earnings declines.
   - ▶ Patterns consistent with skill displacement of incumbents.

Outline

Model

Production

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

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6

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

- If routine, $v_j = v_R > 1$, if non-routine, $v_j = v_N < 1$.
- Alternative interpretation: R = low skill and N = high skill

Technology

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$$\Delta \log q(j) = -\varepsilon(j) \qquad \forall j \in J_R \cup J_N$$

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- 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 $\nu_N < \psi$

Labor Supply

Continuum of measure I workers supply task-j specific labor:

$$L(j) = \int_0^I l(i,j)di$$

$l(i,j)$ is efficiency units of labor supplied by worker j in task i.

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Assumptions:

1. Set of tasks J partitioned into occupations J_o (can include both R or N).

2. Each worker associated with a single occupation $o(i)$

3. Each worker has same skill in all tasks: $l(i,j) = \bar{l}(i) \ \forall j \in J_{o(i)}$

4. Upward-sloping total labor supply for task j:

$$\Delta \log L(j) = \bar{\zeta} + \zeta_j \Delta \log w(j),$$

   via extensive margin (new workers)

Individual Skill Displacement

Following technological shock

$$\Delta \log l(i,j) = \begin{cases} -\beta I[i \in J_N]\varepsilon(j) + u_{i,j} - \log l(i,j) & \text{w/ prob. } I[i \in J_N]\,\omega\varepsilon(j) \\ -\beta I[i \in J_N]\varepsilon(j) & \text{otherwise} \end{cases},$$

Interpretation:

- Using a complementary technology requires a level of skill that is specific to the vintage of the technology.

- Allow for mean-reversion in skills ($u_{i,j} - \log l(i,j)$) and average skill loss (β)

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

Wage Earnings Growth for Incumbent Workers

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

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

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

Outline

Steps

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. Classification of each task 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

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

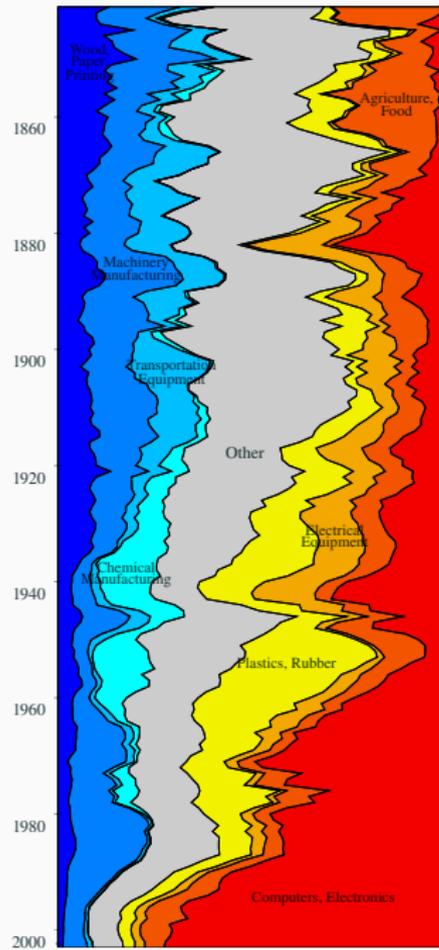- Breakthroughs: patents in the top 10 percent of the unconditional distribution of impact/novelty

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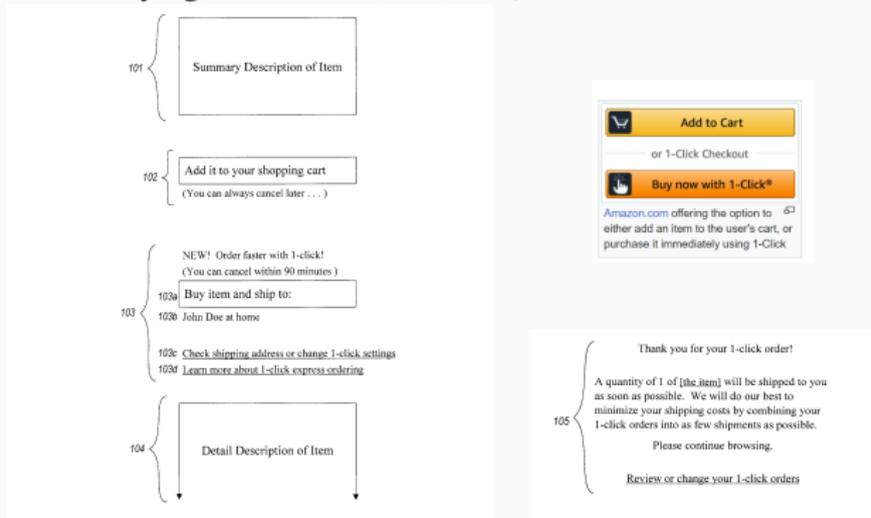
"The server system receives purchaser information including identification of the purchaser, payment information, and shipment information from the client system. The server system then assigns a client identifier to the client system and associates the assigned client identifier with the received purchaser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

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

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.

Routine vs Non-Routine Tasks
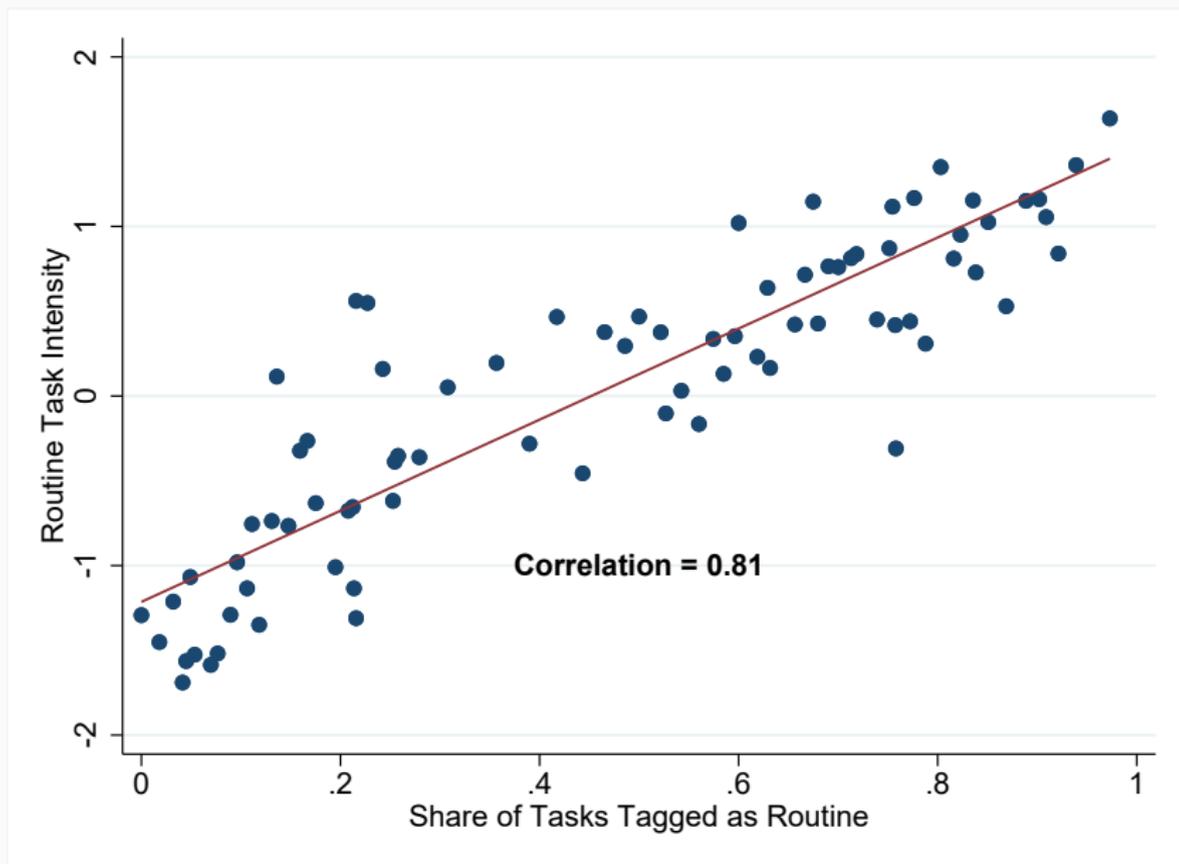
Computer Programmers (SOC Code 151131)

- Prepares detailed workflow chart and diagram to illustrate sequence of steps that program must follow and to describe input, output, and logical operations involved.
- 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.
- 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.

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Validation with Routine-Task Intensity

Correlation = 0.81

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

Occupation Task Description

"**Method for Training a Neural Network**" (US Patent 5,806,053): more related to computer programmers' non-routine tasks

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Patent Text	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.
- Assists, designers, 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

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.
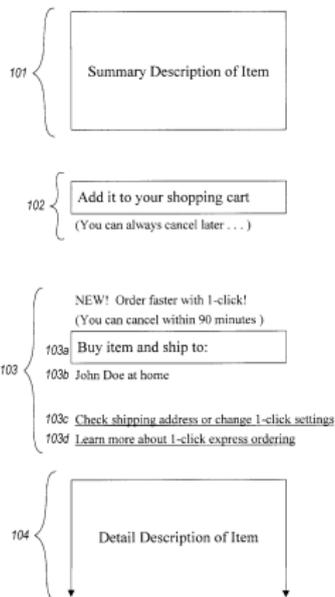
Most similar routine task occupation:
Order clerks.

Example 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."
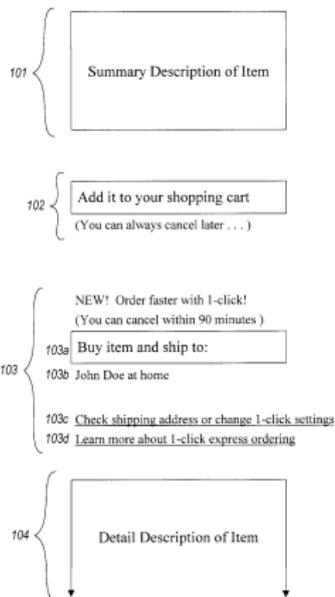
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One-click patent early part of the e-commerce wave of the late 1990s

What happened?

Order Clerks compared to Payroll and Timekeeping Clerks

Technology Exposure
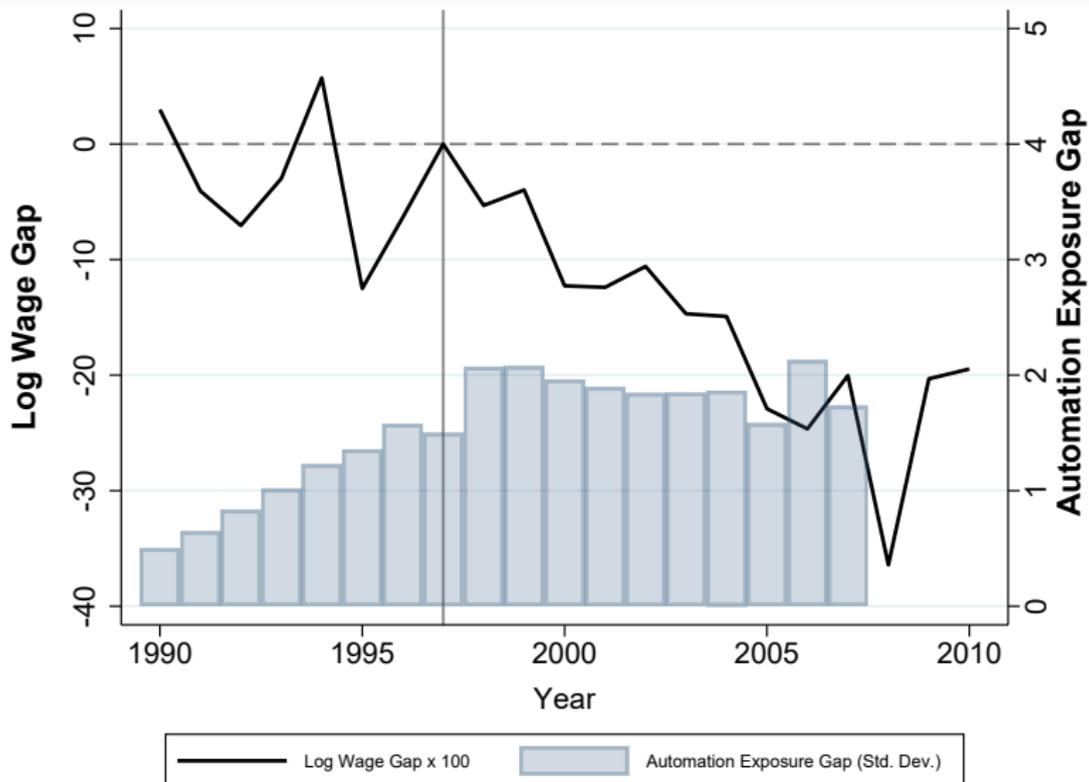
Empirical measure:

$$\xi^j(k,o,t) = \theta^j(o) \log \left(1 + \sum_{b \in \mathcal{B}_{k,t}} \tilde{\rho}^j(o,b) \right), \qquad j \in \{R, N\}$$

Notes:

- Measure depends on sum of breakthroughs, weighted by the distance $\rho^j(o,b)$ between each breakthrough technology b and the R or N tasks performed by o.

- Measure varies across industry, occupation and time: firms in different industries patent different technologies that are related to different occupations at different points in time.

- Allows us to have industry $\times$ year and occupation $\times$ year FEs in our empirical specifications.

Which occupations are most exposed?

Occupation Mean Technology Exposure, Relative to Population
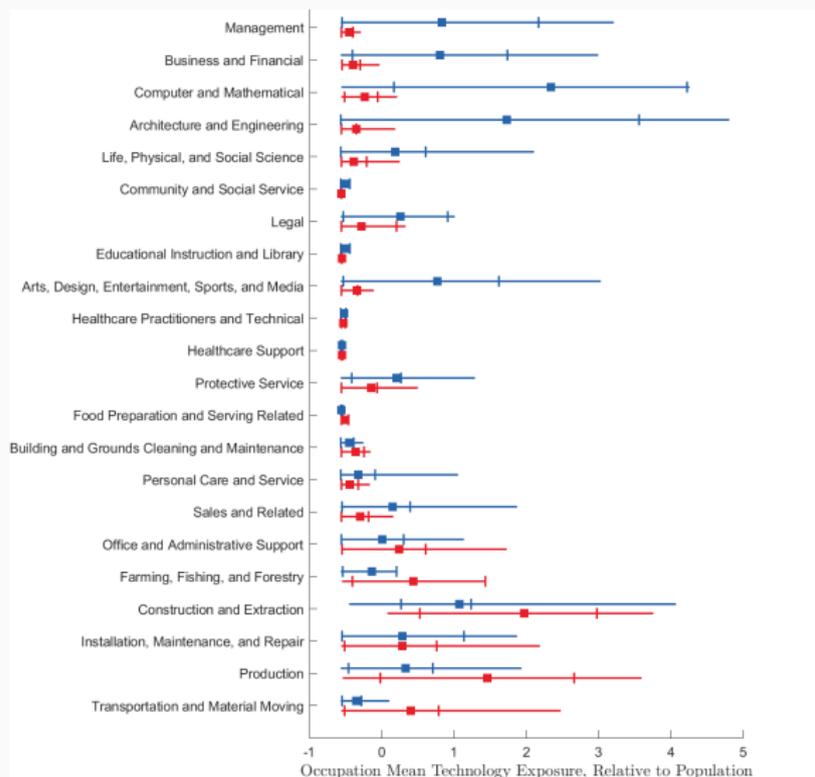
■ Labor-Saving ■ Labor-Augmenting

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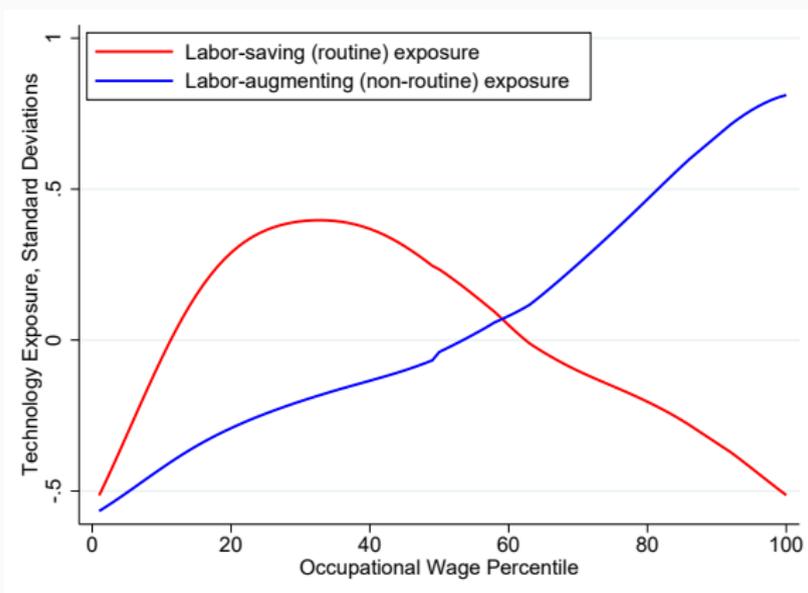
- Labor-saving innovations primarily affect occupations in the middle of the skill distribution ('polarization')
- Labor-augmenting innovations primarily affect high-skill occupations ('skill-bias')

Outline

Impact of innovation on individual workers

Track individual workers over time using a panel of individuals in the CPS linked with administrative tax data (DER).

Calculate growth in age-adjusted (cumulative) W2 earnings

$$\Delta w_{t+h}^i \equiv w_{t+1,t+h}^i - w_{t-2,t}^i$$

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).

Homogeneous Marginal Effects by Horizon
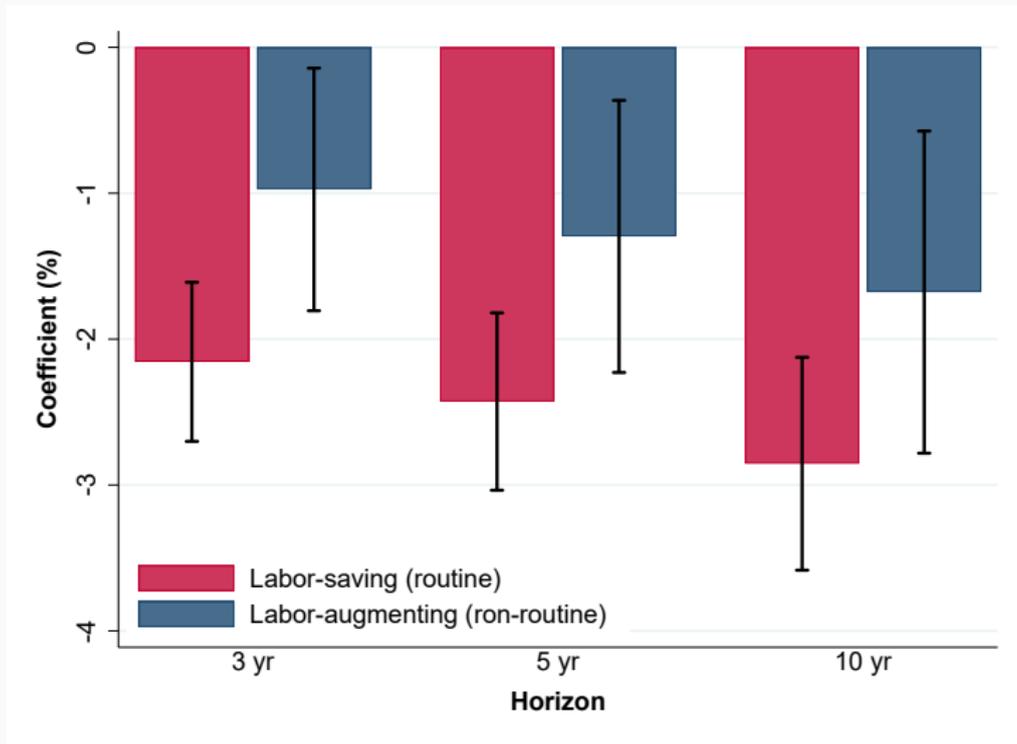
Magnitudes: Moving from 50th to 90th percentile of tech exposure.

Exposure by Industry
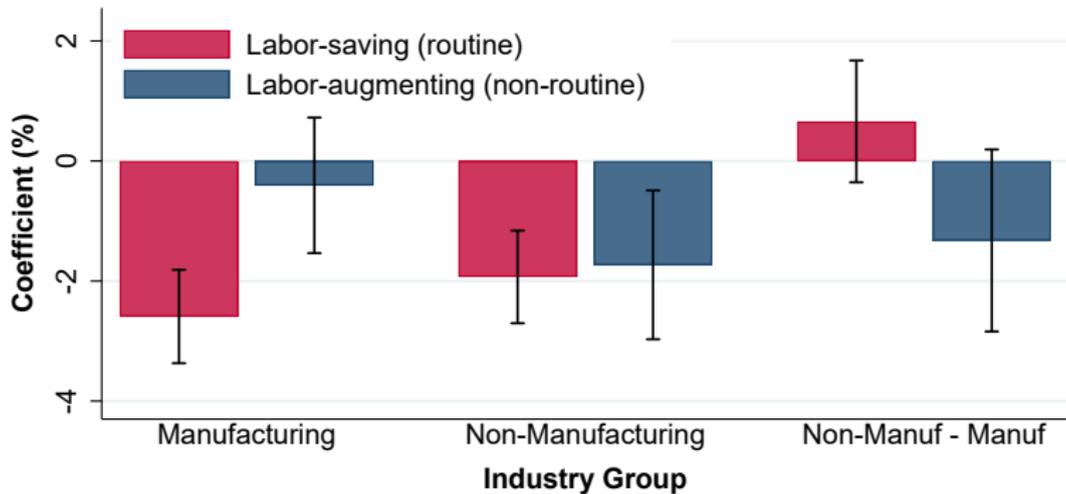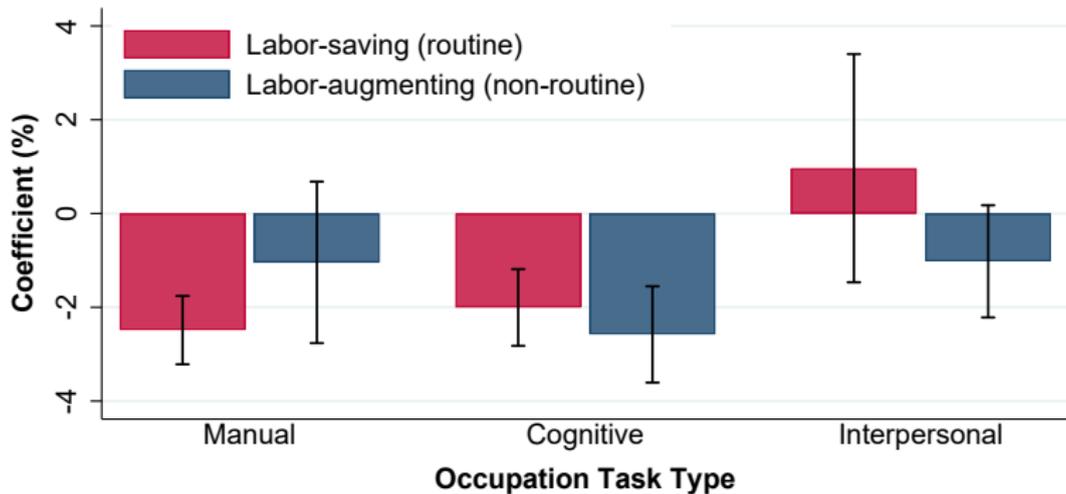
Exposure by Education
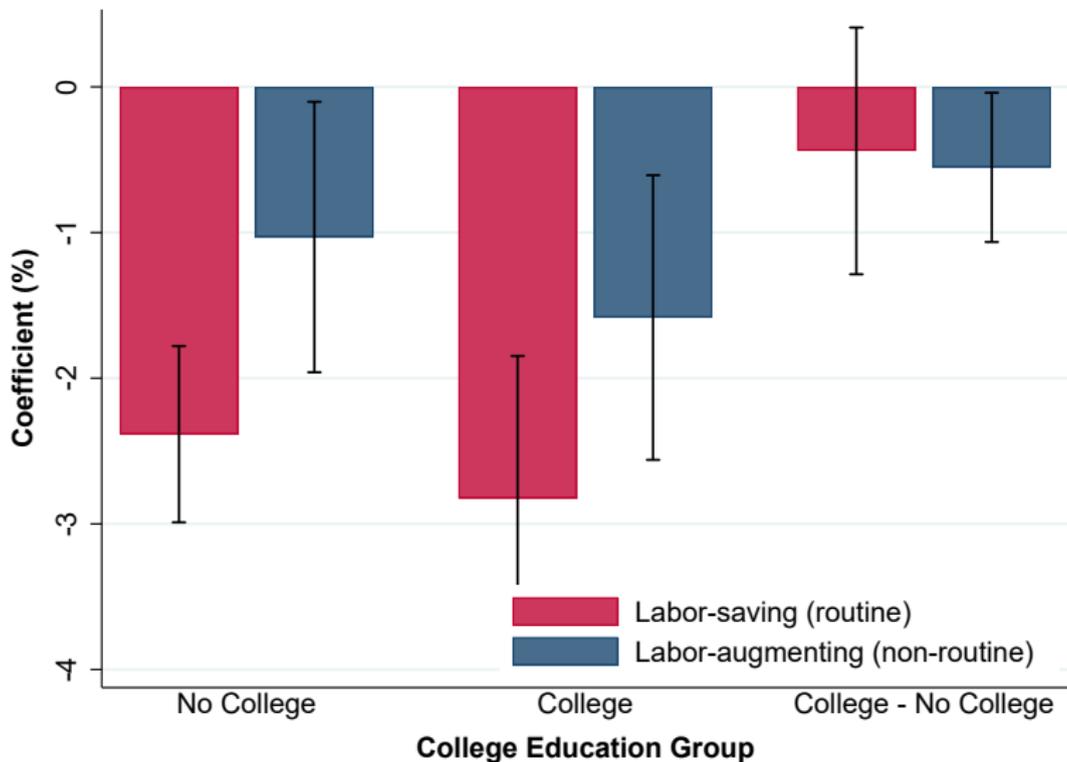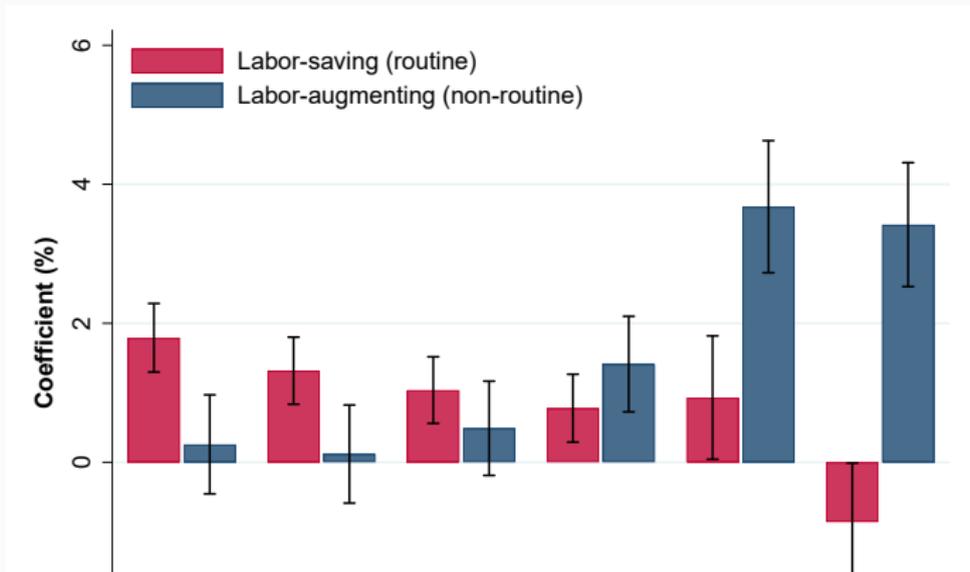
Effects Vary with Age
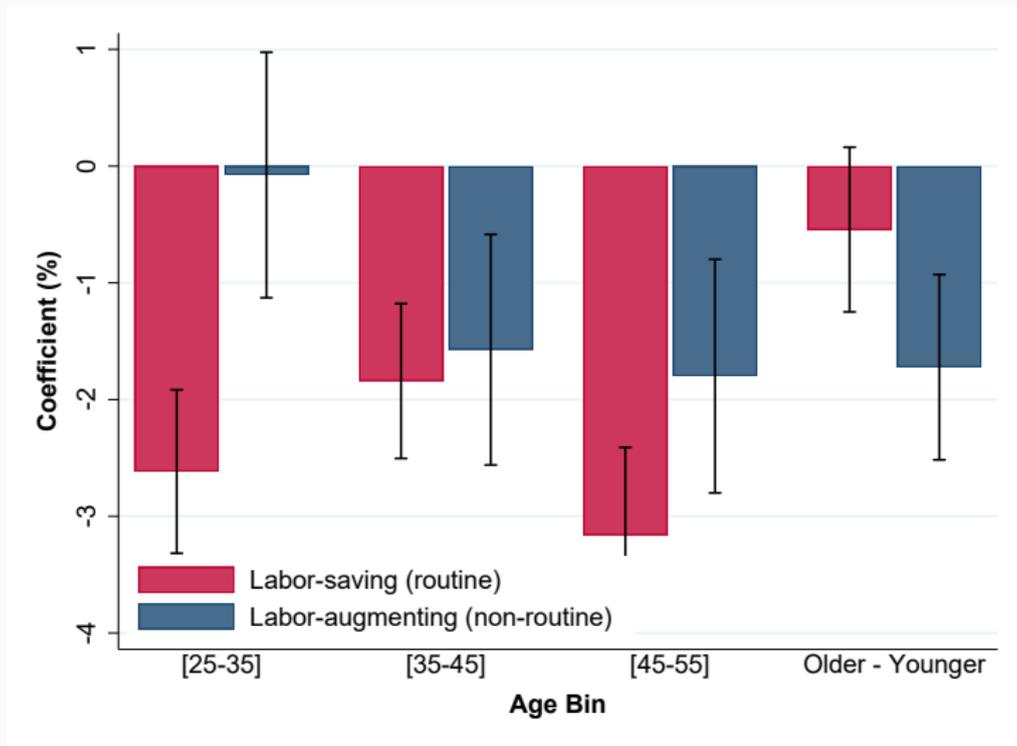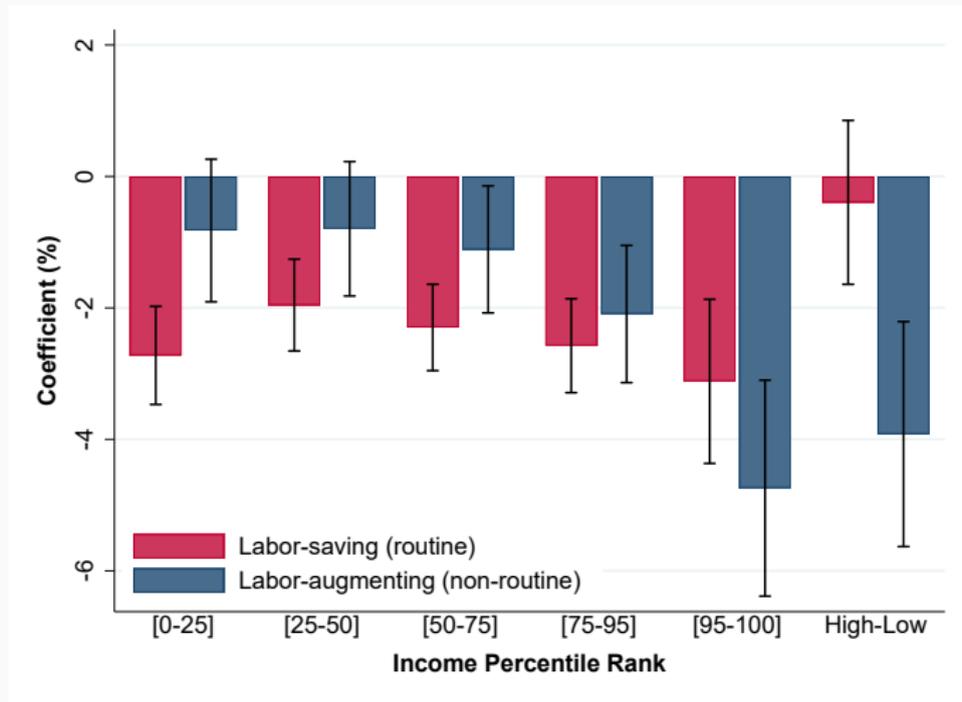
Effects Vary with Worker Income

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

Likelihood of Job Loss

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

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.
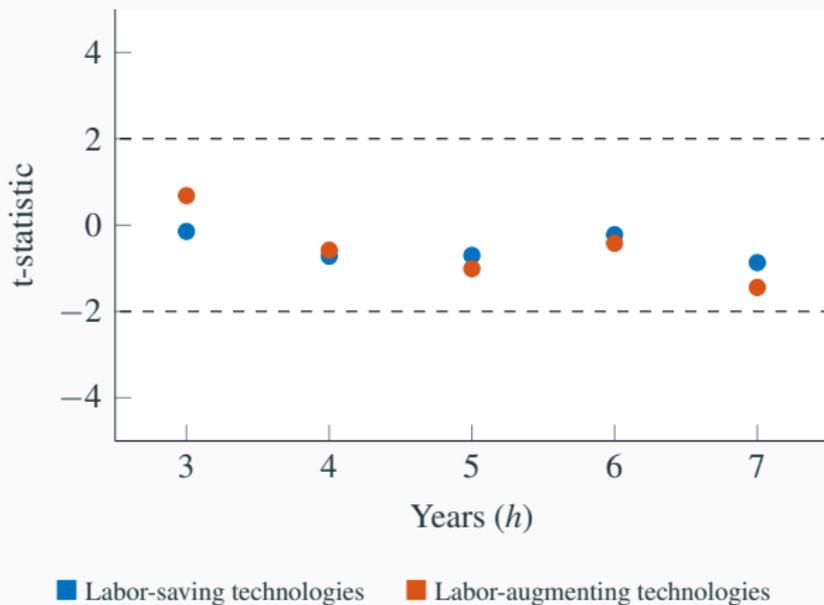
Wage growth and future technology exposure

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:

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

■ Labor-saving technologies   ■ Labor-augmenting technologies

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

Outline

Aggregate Outcomes

Summary so far:

- Automation uniformly lowers earnings of individual workers, regardless of industry, job type, or skill level.
- Complementary technologies have small negative average effects, but significant heterogeneity by skill.

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Next: Individual vs Aggregate Outcomes

1. Aggregate wage and employment dynamics can be very different than individual workers due to new entry and composition effects.
2. Technology improvements can increase productivity, and therefore increase labor demand, which may increase wages for all workers.

Industry-level outcomes

	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)
Observations	2,700	2,700	2,700	2,700

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Observations	2,700	2,700	2,700	2,700

- Both types of technology improvements increase productivity.
- However, they have opposite implications for labor share.

Occupation-Industry Level Aggregate Outcomes

	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)
Observations	65,500	65,500	65,500

Occupation-Industry Level Aggregate Outcomes

	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)
Observations	65,500	65,500	65,500

- Automation lowers labor demand.

- Complementary technologies increase labor demand.
  - ▶ Incumbents lose in favor of new entrants.

Productivity Spillovers

- So far, we have ignored productivity spillovers to wage earnings (they are absorbed by industry $\times$ year FEs).
- Increase in industry productivity increases labor demand for all workers (assuming $\chi - \psi > 0$).
- Effect on wage earnings is proportional to productivity growth $\Delta \log X$, which depends on industry-level average of $\bar{\xi} \equiv \xi^R + \xi^N$.
- To be able to estimate them, we move to 2-digit industry $\times$ year FEs.

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Empirical Estimates:

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

Outline

Estimating Model

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

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Identification:

- **Substitution between K and L in Routine Tasks (ν_R):** Worker-level responses (relative to ψ); 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.
- **Skill displacement** (ω)**:** Gradient of coefficients w.r.t income.

Model Parameters and Fit
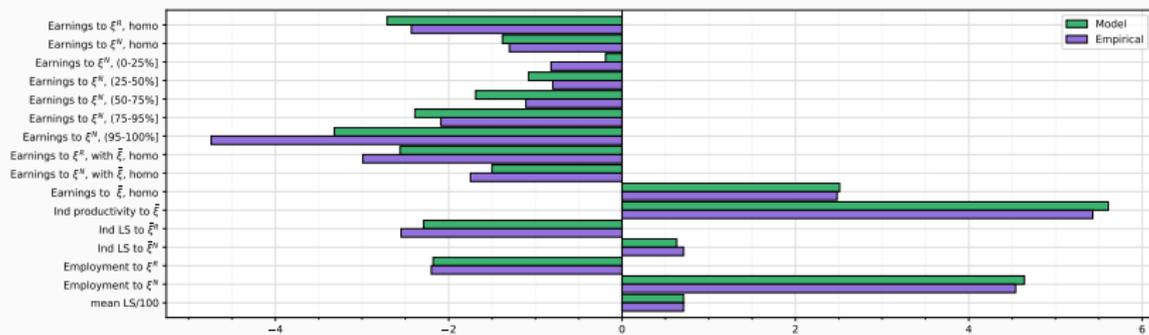
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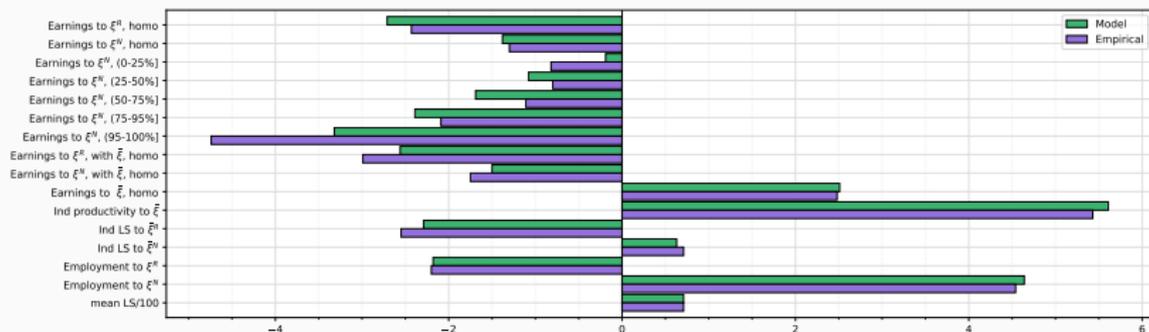
Parameter	Symbol	Estimate
Elasticity of substitution across tasks	ψ	1.191
Elasticity of substitution across industries	χ	1.910
Elasticity of substitution between capital and labor, routine tasks	ν_R	1.439
Elasticity of substitution between capital and labor, non-routine tasks	ν_N	0.928
Elasticity of 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

Outline

Application: AI

Can we use the model 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

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Horizon: 5 years

Conclusion

- Direct, time-varying measure of exposure to labor-saving and complementary technologies

- Automation has large, pervasive, and persistent effect on earnings of individual workers

- Complementary effect modest on average, but significant heterogeneity suggests role for skill displacement

- Application of model to AI suggests AI automates office admin jobs and production; exposes sales, admin, and business professionals to skill displacement

APPENDIX SLIDES

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.
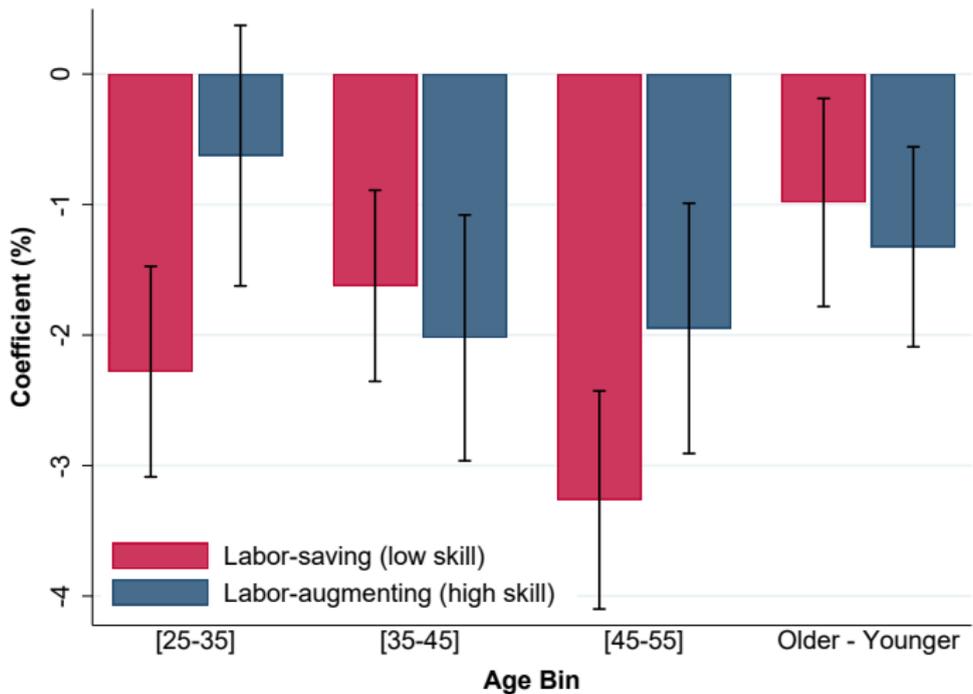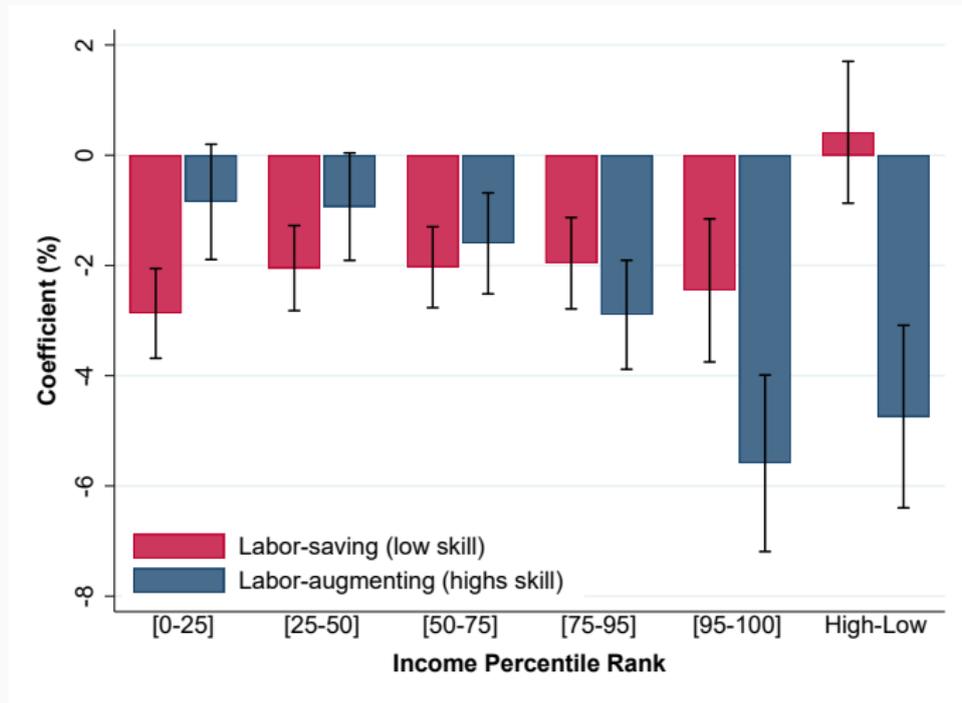
Exposure by Industry
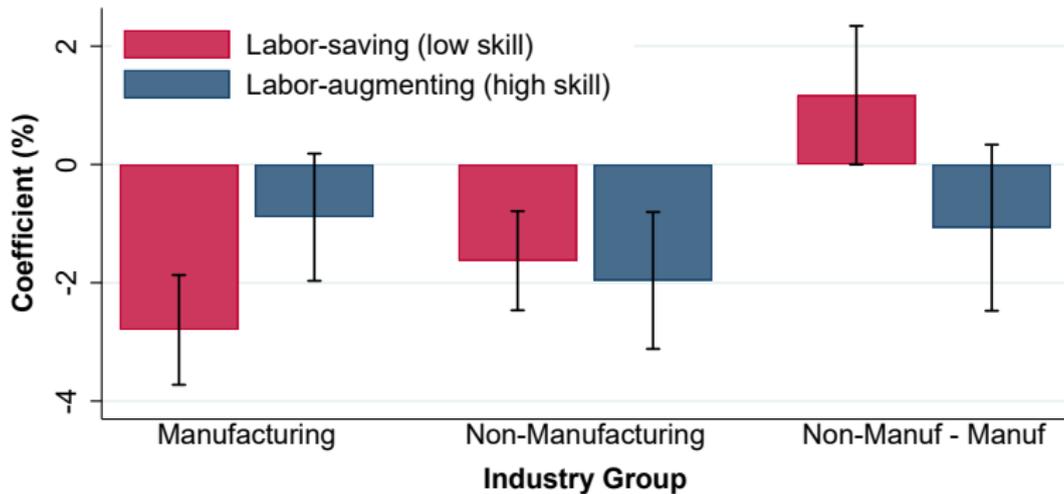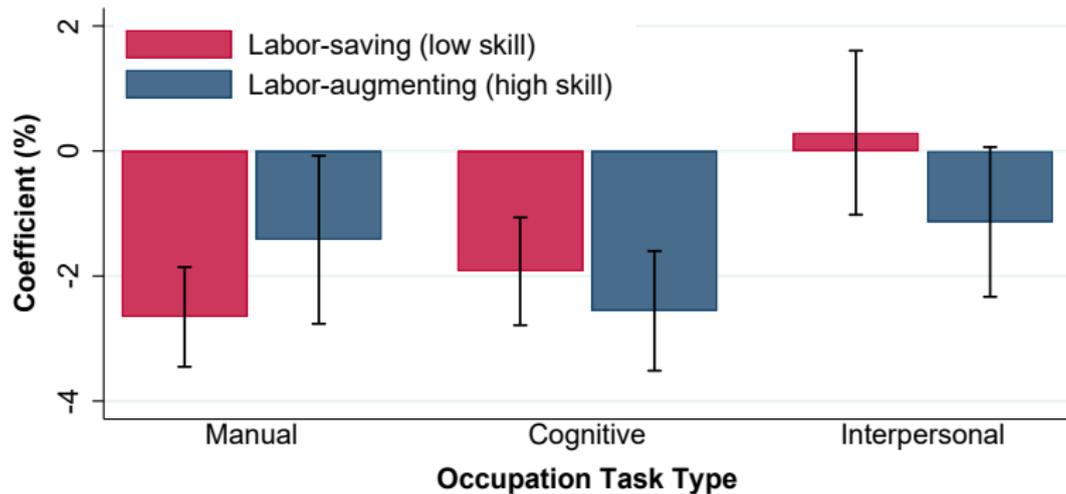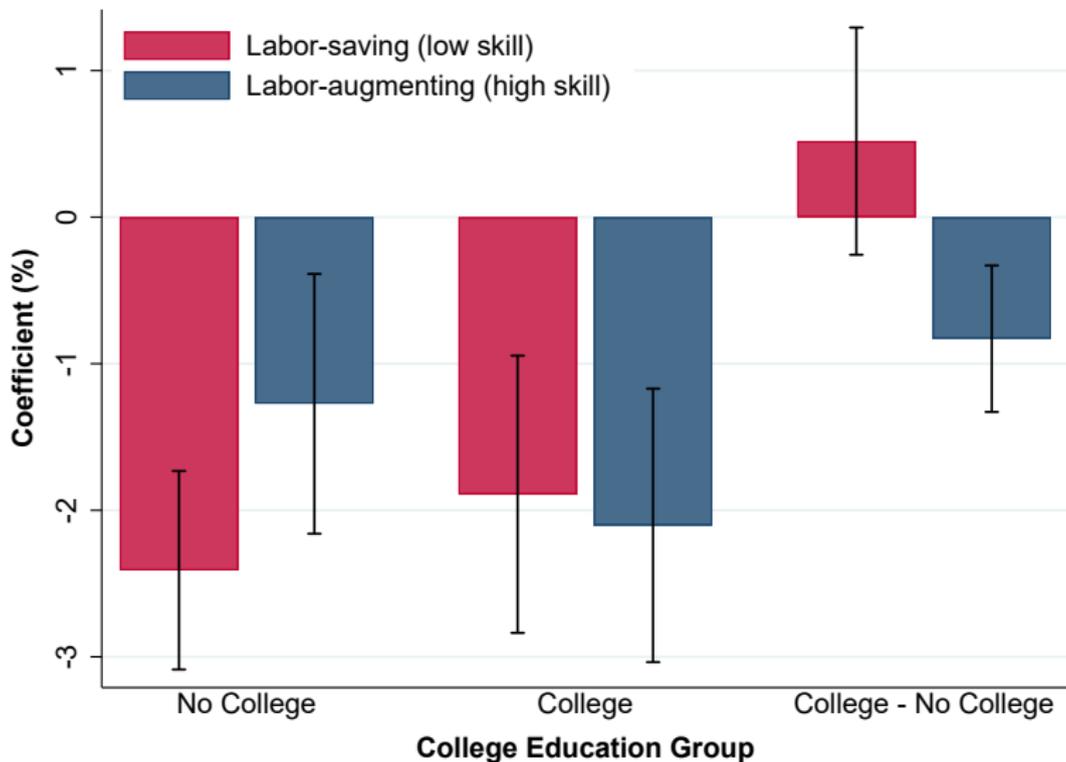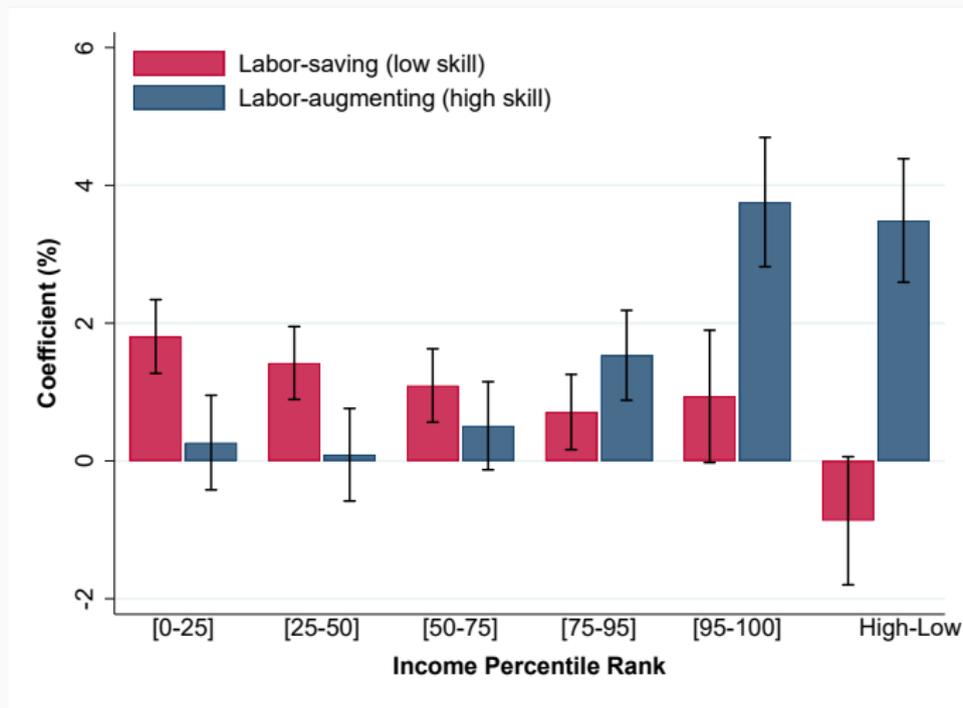
Effects Vary with Age

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.

Comparison to the Literature

1. Routine Task Intensity (RTI) (Autor, 2013; Autor and Dorn, 2013)

   - ▶ RTI measures the *potential* for automation, and is a time-invariant occupation characteristic.
   - ▶ Our measure captures actual technological developments that could automate tasks and is therefore dynamic.

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 × year fixed effects in our worker level analysis.