

# When the Tax Machine Cometh: Who Benefits from Automation?

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# How do employers respond to automation shocks?

Forbes

LEADERSHIP > CAREERS

## AI And Automation: Threats And Opportunities For White-Collar Professionals

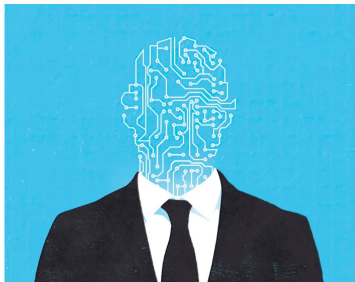
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### The Jobs That Will Fall First As AI Takes Over The Workplace

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Apr 25, 2025, 09:16am EDT

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ROBOTS  
**Robots and automation are going white collar — but they're not here to steal your job just yet**

By [Pedro Nicolaci da Costa](#)

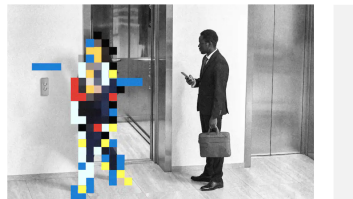
The Washington Post  
Democracy Dies in Darkness

## Americans worry AI is coming for these jobs

A Pew Research survey shows that Americans and experts agree on some jobs they think will be most affected by artificial intelligence.

April 8, 2025

4 min [🔍](#) [🗨️](#) [📄](#) [📑](#)



### Main Question

How do employers respond when their beliefs about workforce automation potential are exogenously shifted?

- ▶ Do they revise expectations about revenues, profits, costs, or wages?
- ▶ Do they plan to change hiring, firing, or skill investments?
- ▶ Do they anticipate task transformation or only job displacement?

Do they share the benefits of automation?

## The Setting: Tax Consulting and Auditing

- ▶ White-collar, high-skill industries **exposed to generative AI**
- ▶ Structured and repetitive tasks ideal for automation (e.g., tax filing, payroll)
- ▶ Use official registry to target **entire population** of tax firms in Germany
- ▶ Granular occupational categories (5-digits KldB 2010, V. 2020):
  - ▶ reduce bias from occupation-task misalignment
  - ▶ heterogeneity across skill levels

## Contribution to the Literature

- ▶ **Automation and labor markets in white-collar settings**
  - ▶ Extends beyond blue-collar automation to high-skill, professional occupations (e.g., Acemoglu and Restrepo (2020); Dauth et al. (2021))
  - ▶ Shows that generative AI (GenAI) enhances efficiency without immediate labor displacement
- ▶ **Employer responses to automation**
  - ▶ Shifts the focus from ex-post worker-level outcomes to anticipatory firm behavior (e.g., Bessen et al. (2025); Acemoglu et al. (2022))

**Key novelty:** Employer-centered experiment about granular expertise levels in white collar labor market

## Contribution to the Literature

### ▶ **Information interventions and belief updating**

- ▶ Uses a randomized information treatment to isolate belief-updating effects on employment and investment expectations (e.g., Altmann et al. (2018); Belot et al. (2022); Lergertporer et al. (2023))
- ▶ Documents systematic belief updating, particularly about lower-skilled
- ▶ Shows how updated beliefs translate into revised revenue and cost expectations

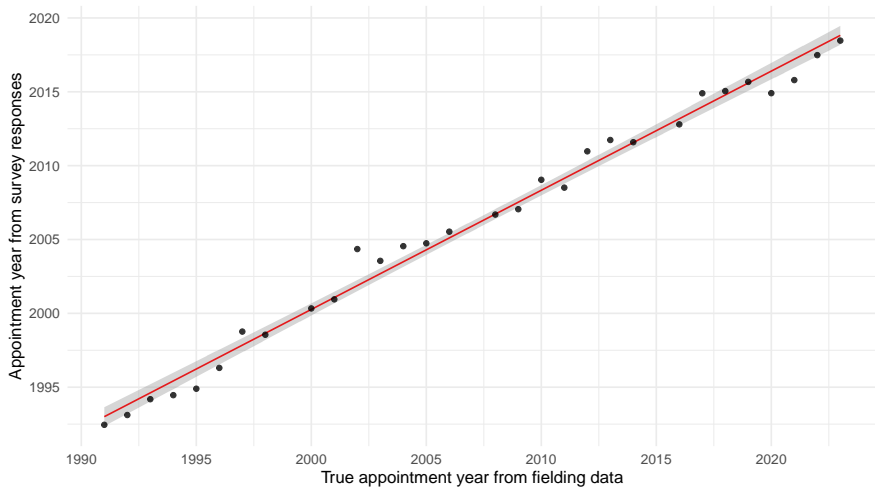
**Key novelty:** Employer-centered experiment about granular expertise levels in white collar labor market

# Data and Survey Design

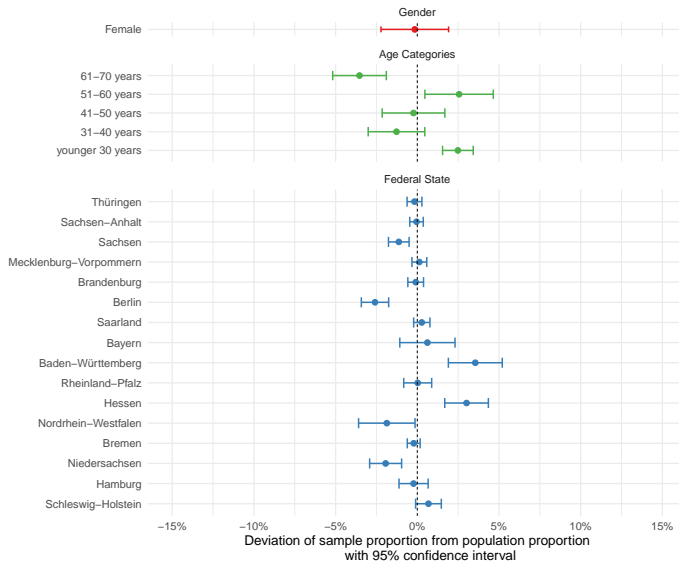
## Data and Survey Design

- ▶ Based on German Business Panel survey of tax advisors
- ▶ Fielded from Nov 2024 to Jan 2025
- ▶ Targeting almost 90,000 licensed professionals
- ▶ Uses official registry: **mandatory, complete coverage** of all firms
- ▶ Freiberufler not covered in standard datasets → unique sample
- ▶ Online survey, optimized for all device types
- ▶ **Final sample: 1,229 firms**

# Appointment Year in Survey and Register



# Composition of Sample vs. Tax Advisor Register



# The information experiment

## Experimental Design

- ▶ Credibility: Chamber of Tax Advisors
- ▶ Elicited prior beliefs on automatability of 4 specific tax occupations
- ▶ Random assignment to info about:
  - ▶ nothing (**Control**),
  - ▶ automation rate of **Lower-Skilled, Higher-Skilled, Combined**
- ▶ Information treatment based on IAB Job-Futuromat
- ▶ Post-treatment: updated beliefs, plus expectations on employment, wages, revenue, costs
- ▶ Also measured perceived automation potential of tasks and importance of **new tasks** (e.g., legal tech, prompt engineering), continued education, and likelihood to switch jobs

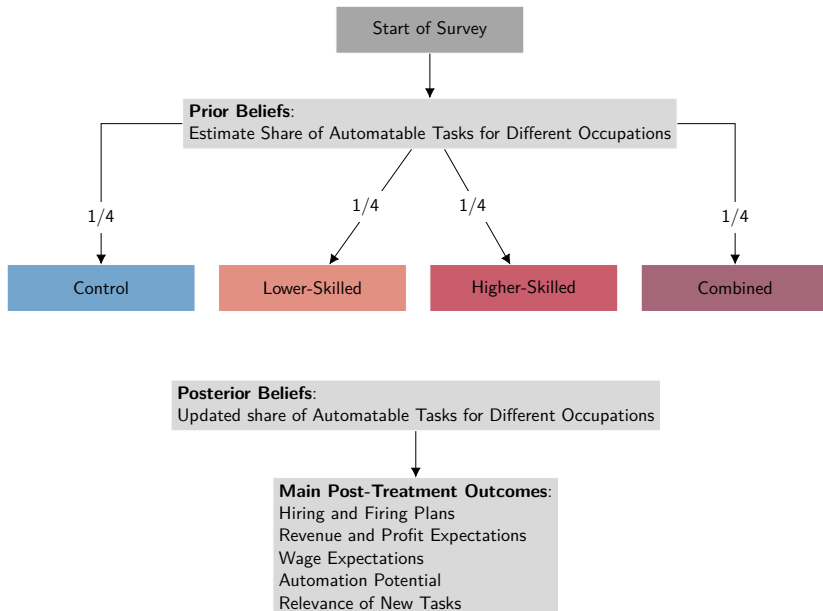
## Expertise and Automation Potential

### Classification of Occupations (KldB 2010, Version 2020) with IAB Job-Futuromat Automation Potential

| Code  | German Title            | English Translation     | Tasks                                                                                                        | Automation Potential |
|-------|-------------------------|-------------------------|--------------------------------------------------------------------------------------------------------------|----------------------|
| 72302 | Steuerfachangestellte/r | Tax clerk               | Prepares tax returns,<br>manages accounting records,<br>assists with payroll and financial reporting         | 100%                 |
| 72303 | Steuerfachwirt/in       | Certified tax assistant | Supervises tax clerks,<br>prepares complex tax returns,<br>provides tax advice,<br>assists tax advisors      | 80%                  |
| 72304 | Steuerberater/in        | Tax advisor             | Offers tax planning and consultancy,<br>represents clients before tax authorities,<br>ensures tax compliance | 62%                  |
| 72244 | Wirtschaftsprüfer/in    | Auditor                 | Examines financial statements,<br>ensures regulatory compliance,<br>identifies financial discrepancies       | 57%                  |

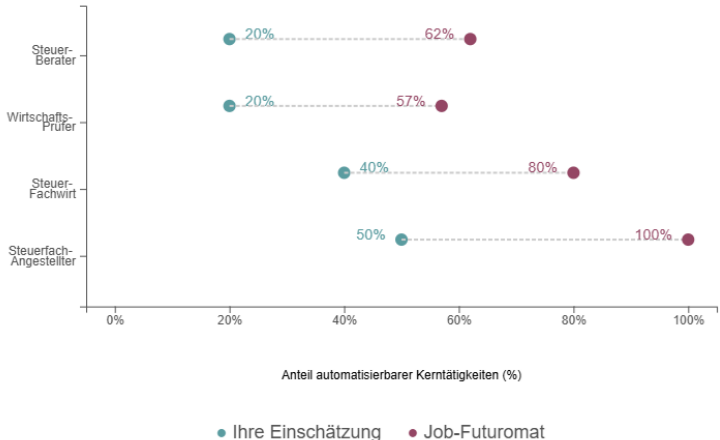
- ▶ Lower-skilled roles show **extreme automation exposure**
- ▶ Even higher-skilled roles like auditors are not immune

# Experimental Design



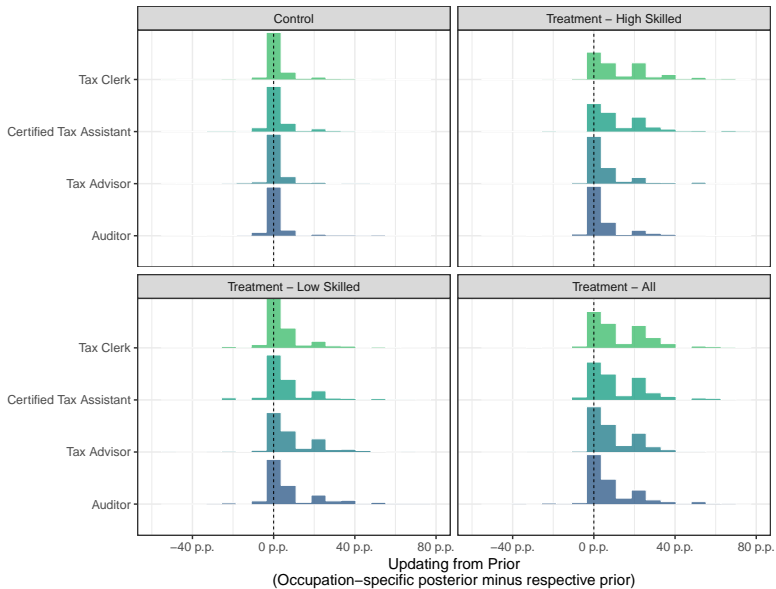
## Example Screenshot of the Information Treatment

Hier sehen Sie Ihre Antworten zur Automatisierungsquote sowie die Einschätzungen des Instituts für Arbeits- und Berufsforschung (IAB).

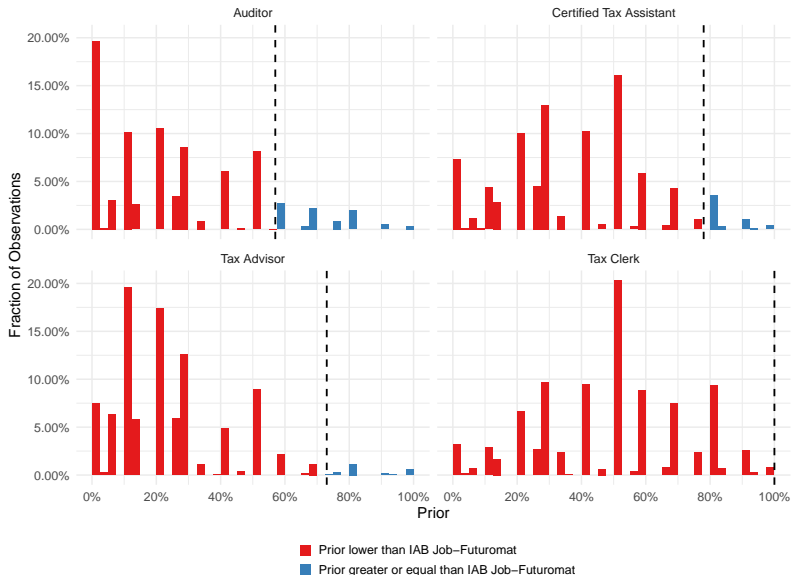


**Quelle:** Die Automatisierungsquoten des IAB stammen aus dem Job Futuromat 2024.

# Belief Updating by Occupation and Treatment Arm



# Prior Automation Beliefs About Tax Expertise Levels



# Empirical Framework

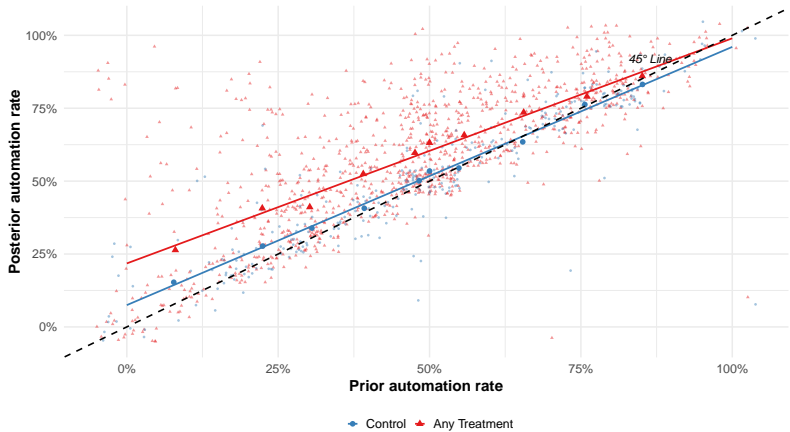
## Bayesian Learning Framework for Belief Updating

- ▶ Belief updating process as a Bayesian learning framework
- ▶ Agents combine prior beliefs with new information to form posteriors (e.g. Coibion et al., 2025):

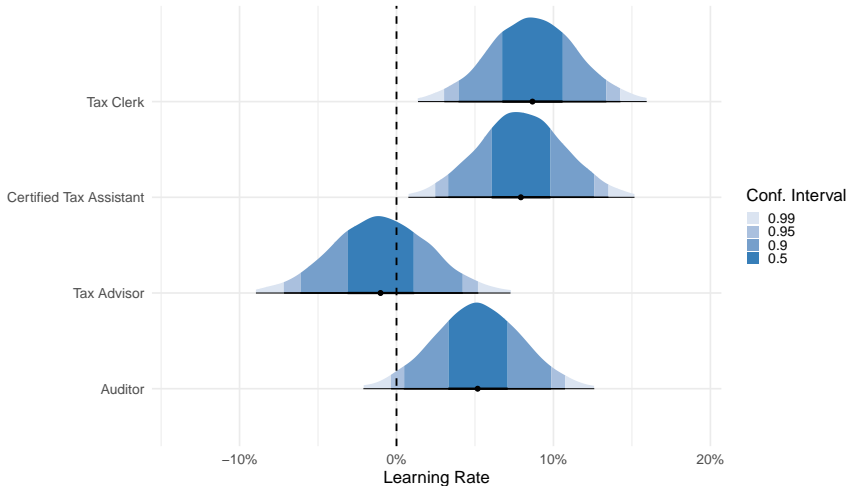
$$\text{posterior}_{io} = \alpha_o + \beta_o \cdot \text{prior}_{io} + \sum_j \delta_{oj} \cdot D_{ij} + \sum_j \gamma_{oj} \cdot (D_{ij} \times \text{prior}_{io}) + \varepsilon_{io}, \quad (1)$$

- ▶  $\text{posterior}_i$ : updated belief about the share of automatable tasks for respondent  $i$
- ▶  $\text{prior}_i$ : initial estimate before receiving information
- ▶  $\text{treated}_i$ : binary indicator for treatment assignment
- ▶  $\delta$ : direct effect of information on belief updating
- ▶  $\gamma$ : interaction term capturing how strong priors moderate belief updating

# Update of Prior Beliefs



# Updating Rates For Beliefs About Expertise Levels



## IV Estimation Framework

We estimate the effect of updated automation beliefs on firm outcomes using a 2SLS approach:

### First Stage:

$$\text{posterior}_{io} = \alpha_o + \beta_o \cdot \text{prior}_{io} + \sum_j \delta_{oj} \cdot D_{ij} + \sum_j \gamma_{oj} \cdot (D_{ij} \times \text{prior}_{io}) + \varepsilon_{io}, \quad (2)$$

### Second Stage:

$$Y_i = \beta_0 + \sum_o \beta_{o1} \hat{z}_{io} + \mathbf{X}'_i \gamma + \eta_i, \quad (3)$$

$$\sum_{o=1}^4 \hat{\beta}_{o1} \cdot \overline{\text{Updating}}_{o, \text{Treatment-Combined}} \quad (4)$$

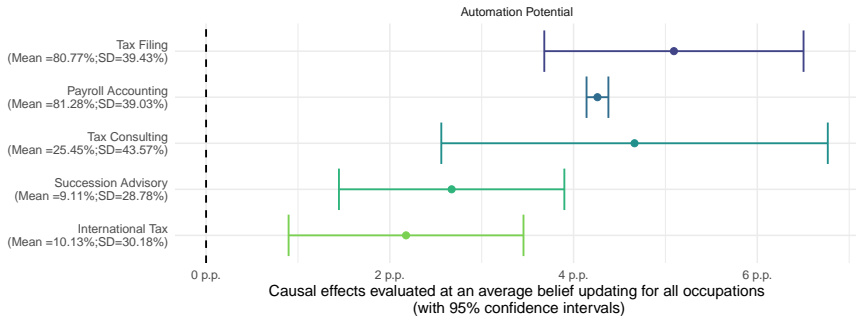
### Instruments:

Randomized treatment assignment and interaction with prior beliefs.

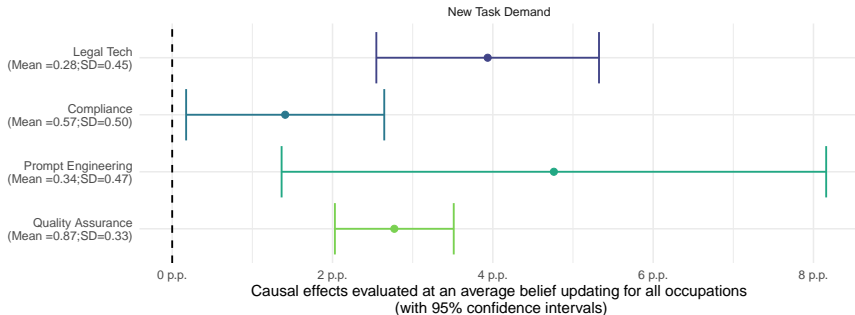
**Outcomes:** Firing, Hiring, Revenue, Profit, Costs, Wages, Training, AI adoption, ...

# Automation, Tasks, and Attitudes

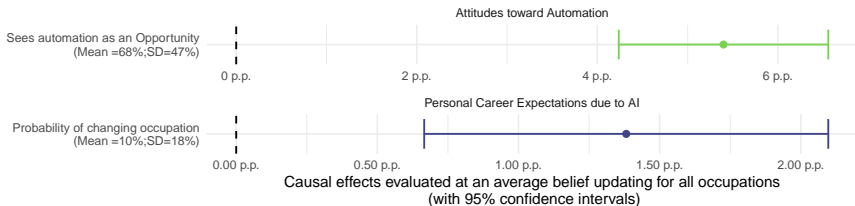
# Information Effect on Automation Potential



# Information Effect on New Tasks

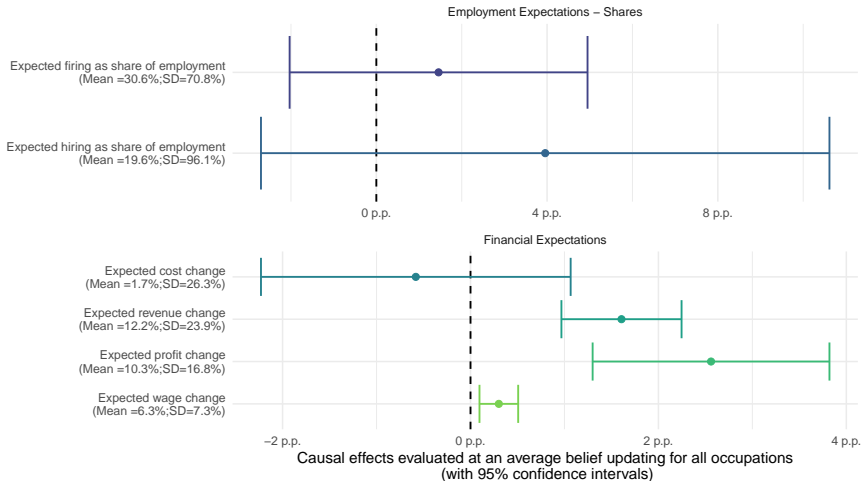


# Information Effect on Attitudes toward Automation

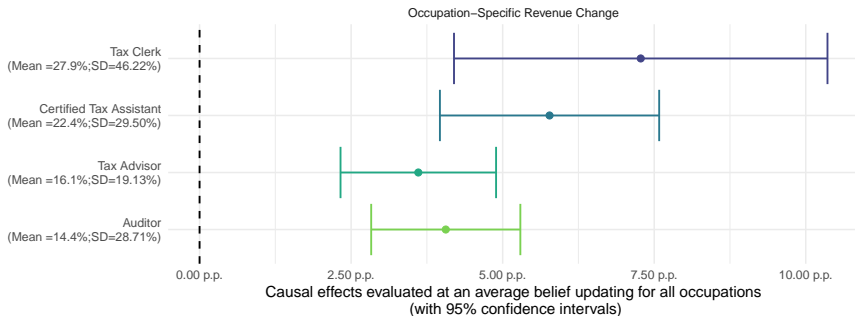


Employment, Revenue, Wages,  
Training

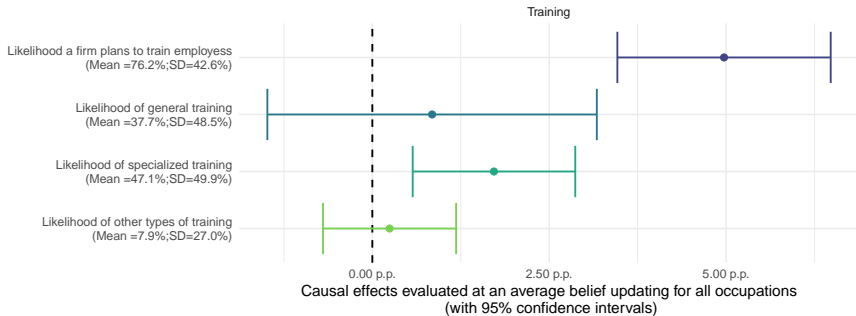
# Information Effect on Employment Expectations



# Information Effect on Occupation-Specific Revenue Change

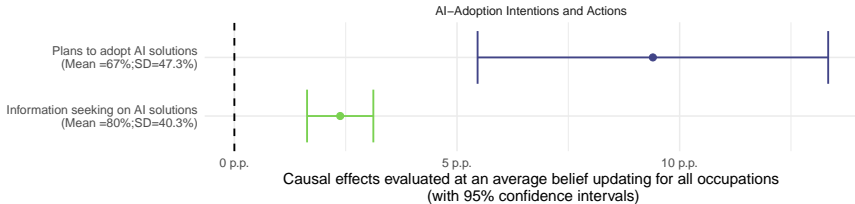


# Information Effect on Training



# Intentions and Actions

# Information Effect on AI-Adoption Intentions and Actions



## Intentions and Actions

- ▶ **Plans to adopt AI solutions:**

Rise by 9.4 p.p. from baseline 66.5%  $\Rightarrow$  +14% relative increase

- ▶ **Information search choices** about AI solutions:

+2.4 p.p. effect (baseline already high at 80%), consistent with ceiling effect

- ▶ **Validation of hiring intentions:**

Matched survey plans with German Federal Employment Agency job ads

- ▶ All firms with job postings had reported corresponding plans
- ▶ Occupation-level match (tax advisors, clerks, certified assistants)
- ▶ Some postings combined multiple occupations

- ▶ **Overall:** Stated survey intentions translate into observable actions in AI adoption and hiring

Robustness

## Robustness

- ▶ **Balancing:** Covariates and priors balances across treatments
- ▶ **Reduced form vs. 2SLS:** Very similar magnitudes at the average belief update; identical signs for all main outcomes (hiring, firing, revenue, profits, wages)
- ▶ **Belief aggregation:**  
Mean shift vs. dispersion (SD) yield the same qualitative patterns
- ▶ **Sample restrictions:**  
Excluding large firms ( $> 150$  employees or  $> 10m$  revenue) leaves results unchanged
- ▶ **Outcome definitions:**  
Shares vs. levels; winsorization at tails; extensive vs. intensive margins  $\rightarrow$  stable estimates
- ▶ **Limited Effect Heterogeneity:**  
Very limited heterogeneity in estimates by age, gender, and familiarity with AI technologies.

## Conclusions

- ▶ Firms systematically update automation beliefs in response to expert information
- ▶ These shifts shape expectations for **revenue, profits, costs** and somewhat **wages**, but **not employment**
- ▶ Belief updates are strongest for **low-skilled roles** and highly automatable tasks
- ▶ Firms expect **new tasks** to emerge rather than job destruction
- ▶ Answer to: why are there still so many jobs?

## Conclusions

- ▶ Key implication: Employers see automation as complementing productivity of workers
- ▶ But: Employers do not share the extra profits from automation with employees

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