Investments in Human Capital in the Age of AI

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Roadmap

Past Technological Change

- Before AI (LLMs): mostly **automation** of "routine" tasks.

  Acemoglu and Autor (2011)

- **Highly educated** workers have been **complementary**.

  Autor (2019)

- Stronger **incentives** to enroll in **tertiary education**.

AI is Different

- **AI** performs (also) "non-routine" tasks (coding, analysis).
- **Ambiguous impact** on demand for **college workers**:

  → Displacement vs complementarity.

- **Not all human capital is the same:**

  → Some training paths face **automation risks**.

  → Others are more likely to be **augmented**.

  → **Uncertainty** not equally distributed.

AI Literature

(Most of) **Macro literature** focuses on **labor demand effects**:

- Which occupations/tasks are most exposed to AI? Eloundou et al. (2024), Massenkoff and McCrory (2026), Tomlinson et al. (2025)
- Long run effects of AI. Restrepo (2025), Ide and Talamàs (2025)
- Displacement vs complementarity. Autor and Thompson (2025), Gans and Goldfarb (2026)

What about **workers' adaptation**?

- Althoff and Reichardt (2026): model of occupational choice.
- **This paper**: focus on **training choice**.

This Paper

I use a task-based model and US data to answer:

1. **How do individuals adjust human capital investments** in response to AI?

2. Quantifying the impact of AI on **employment and expected wages** for each training.

Preview of Results

1. **Expected automation drives reallocation of labor:**
   - Paths exposed to automation lose workers (up to -16%).
   - Safer paths gain workers

     $\rightarrow$ Technical manual jobs (+2.6%), education (+9%)...

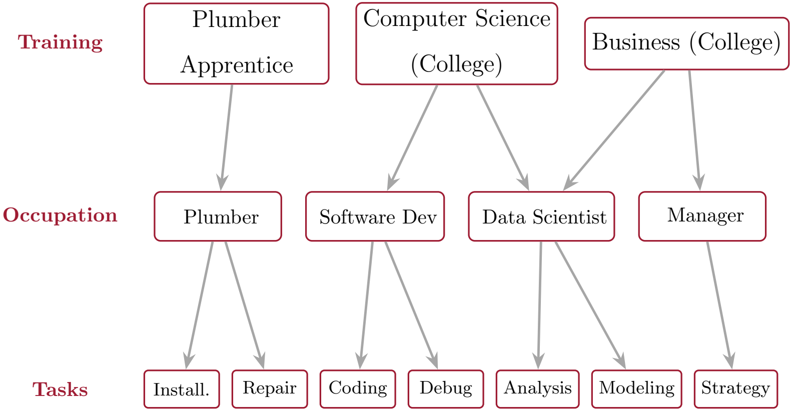
     $\rightarrow$ ... or no training at all (+4%)

2. **Expected wages increase for all training paths (+14%)**
   - Negative impact of AI is offset by labor scarcity.

3. **Uncertainty generates risk premium**
   - Labor scarcity due to risk aversion (up to -3.3%).
   - Uncertainty raises wages (up to +2.3%).

Roadmap

Training, Occupations, and Tasks



The Model: Setup

- **2 periods:** Training period and working period.
- **Training period:** agents maximize lifetime utility

$$\max_j \{\beta \mathbb{E}_t [u(\ln w_j)] - C_{ij}\}$$

- C_{ij} is disutility cost of training j for individual i.
- Training choice is irreversible.

  $\rightarrow$ **Working period:** labor force composition is fixed.

Working Period

- Each training j linked with bundle of tasks $\tau \in \mathcal{T}_j$.

- Output per worker for training j

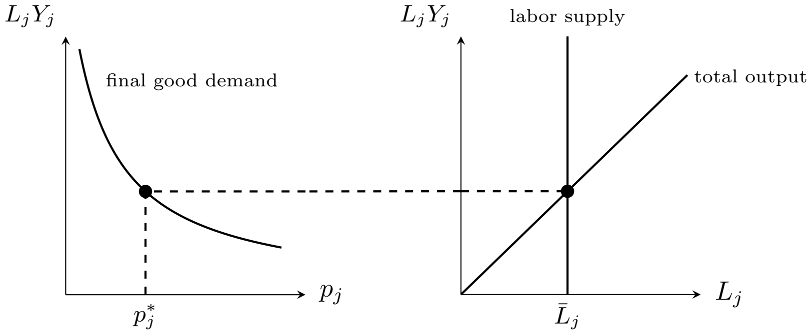
$$Y_j = \left(\sum_{\tau \in \mathcal{T}_j} \underbrace{\theta_{j,\tau}^{\frac{1}{\rho}}}_{\text{task importance}} y_\tau^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}$$

$$y_\tau(l_\tau, k_\tau) = \begin{cases} l_\tau \gamma_\tau & \text{if task is not automatable } (\tau \in \mathcal{N}_j) \\ \phi_\tau k_\tau & \text{if task is automatable } (\tau \in \mathcal{A}_j) \end{cases}$$

- AI **Automation**: set $\mathcal{A}_j$ expands.
- AI **Augmentation**: higher labor productivity $\uparrow \gamma_\tau$

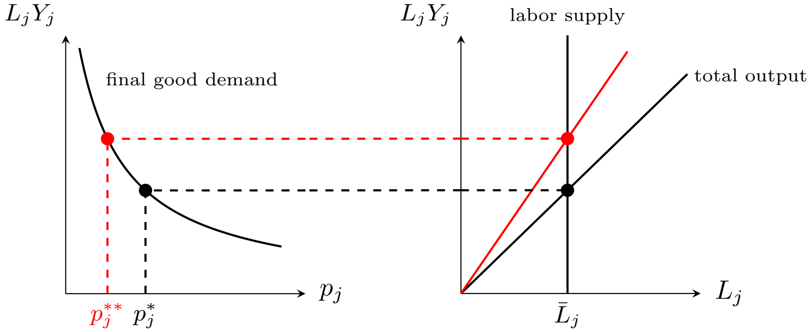
Channels and Mechanisms: Baseline

- Number of workers with training j is fixed at $\bar{L}_j$
- Competitive markets $\implies w_j = p_j Y_j \underbrace{\Gamma_j}_{\text{Labor Share}}$



Channels and Mechanisms: Automation

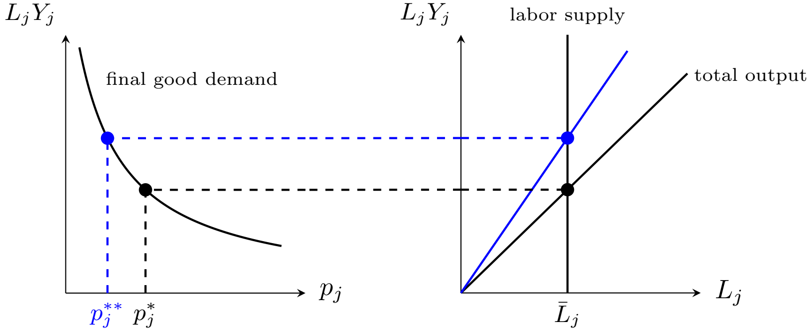
- **Automation**: increase in set of automatable tasks ($\uparrow \mathcal{A}_j$).



Ambiguous impact on wage: $w_j = \downarrow p_j \uparrow Y_j \downarrow \Gamma_j$

Channels and Mechanisms: Augmentation

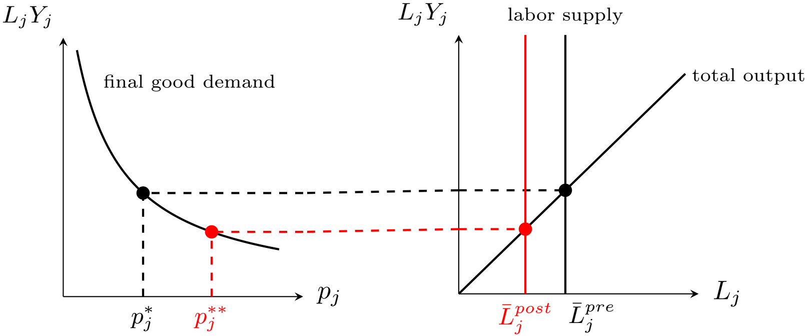
- **Augmentation**: increase in labor productivity ($\uparrow \gamma_\tau$).



Ambiguous impact on wage: $w_j = \downarrow p_j \uparrow Y_j \Gamma_j$

Channels and Mechanisms: Labor Supply Adjustment

- **AI can shift labor supply** for next generation.



Positive impact on wage: $w_j = \uparrow p_j Y_j \Gamma_j$

Training Period

- Agents maximize lifetime utility:

$$\max_{j} \{\beta \mathbb{E}_t \left[u(\ln w_j(\mathcal{A}_j, \gamma_j))\right] - C_{ij}\}$$

- Future automation ($\mathcal{A}_j$) and augmentation (γ_j) are unknown.

- Agents' beliefs:

  $\rightarrow$ Future share of automated tasks: $A_j \sim \mathcal{N}(\mu_{A,j}, \sigma^2_{A,j})$

  $\rightarrow$ Average future augmentation: $\gamma_j \sim \mathcal{N}(\mu_{\gamma,j}, \sigma^2_{\gamma,j})$

Solution: Training Choice

- Using the **Certainty Equivalent Ω_j**

$$\Omega_j = \underbrace{\ln p_j + \frac{\ln \Gamma_j(\mu_{A,j})}{1-\rho} + \frac{\ln\left((1-\mu_{A,j})\mu_{\gamma,j}{}^{\rho-1}\right)}{\rho-1}}_{\mathbb{E}(\ln w_j)} - \underbrace{\frac{\eta-1}{2} Var(\ln w_j)}_{\text{Risk premium}}$$

- Assuming $C^*_{ij} = \underbrace{\bar{C}^*_j}_{\text{average cost}} - \underbrace{\epsilon_{ij}}_{\sim \text{iid Gumbel}(0,\zeta)}$

- The share of labor choosing training j is

$$L^*_j = \frac{\exp\left((\beta\Omega_j - \bar{C}^*_j)/\zeta\right)}{\sum_{h=0}^{J} \exp\left((\beta\Omega_h - \bar{C}^*_h)/\zeta\right)}$$

Roadmap

Task-level AI measures

Three measures at the task level:

- **Automatable**: AI can perform the entire task. Althoff and Reichardt (2026)
- **Augmentable**: increase in labor productivity due to AI (1 = no gains, 1.1 = 10% productivity boost). Althoff and Reichardt (2026)
- **AI penetration**: current AI usage. Massenkoff and McCrory (2026)

  $\rightarrow \in [0,1]$: closer to 1 means more automation.

Classifying tasks: Automation vs Augmentation

Tasks are classified as follows:

- **Already Automated**: automatable + AI penetration ≥ 0.9
- Potentially **Automatable**: automatable + AI penetration < 0.9
- **Currently Augmented**: augmentable + AI penetration > 0
- Potentially **Augmentable**: augmentable + not automatable + + AI penetration $= 0$

Expected Automation and Augmentation

- **Expected Automation**

$$\mu_{A,j} = \underbrace{S_{A,j}^{cur}}_{\text{Already automated tasks}} + p_A \underbrace{S_{A,j}^{pot}}_{\text{Potentially automatable tasks}}$$

- **Expected Augmentation**

$$\mu_{\gamma,j} = \sum_{\tau \in \mathcal{T}_j} \theta_{j,\tau} \left(\underbrace{1 + E[b_\tau](\gamma_\tau - 1)}_{\text{Task Expected Augmentation}} \right)$$

- **Uncertainty** depends on

  → the weighted share of automatable/augmentable tasks.

  → the number of potentially automatable/augmentable tasks.

Automation by Training Path

Baseline results: $p_A = p_\gamma = 0.5$ Alternative scenario

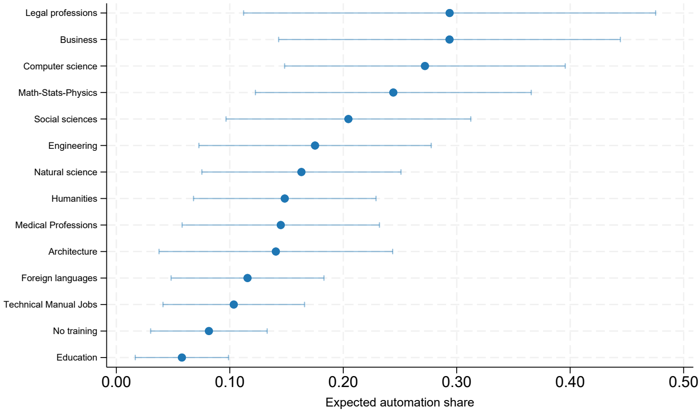


Figure 1: Expected Automation across Training Paths (with 1 sd CI).

Augmentation by Training Path

Alternative scenario

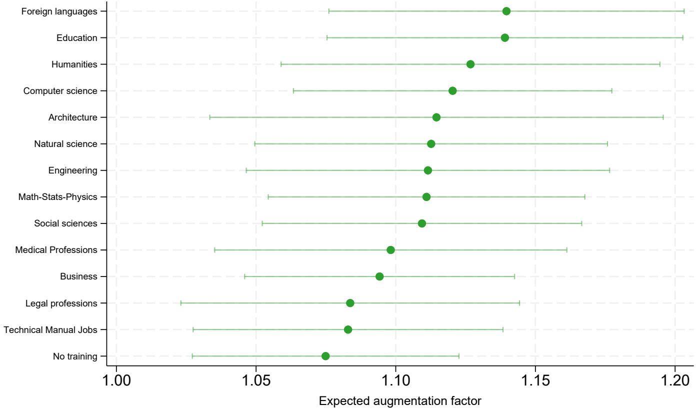


Figure 2: Expected Augmentation across Training Paths (with 1 sd CI).

Roadmap

Data

US data:

- O*NET for task descriptions and importance weights.
- CIP-SOC crosswalk to map training to occupations (and tasks).
- BLS for median wages.
- ACS microdata for labor force composition.

Calibration

- Pre-AI data (2022):

  $\rightarrow$ AI is not yet present ($\mu_{A,j} = \mu_{\gamma,j} = \sigma^2_{\gamma,j} = \sigma^2_{A,j} = 0$)

  $\rightarrow$ $\Omega_j^{pre} = \ln w_j^{2022}$ and $L_j^* = L_j^{2022}$

- Reference category: no training $\implies$ $\bar{C}_0^* = 0$

- $\bar{C}_j^* = \beta(\ln w_j^{2022} - \ln w_0^{2022}) - \zeta\left(\ln L_j^{2022} - \ln L_0^{2022}\right)$

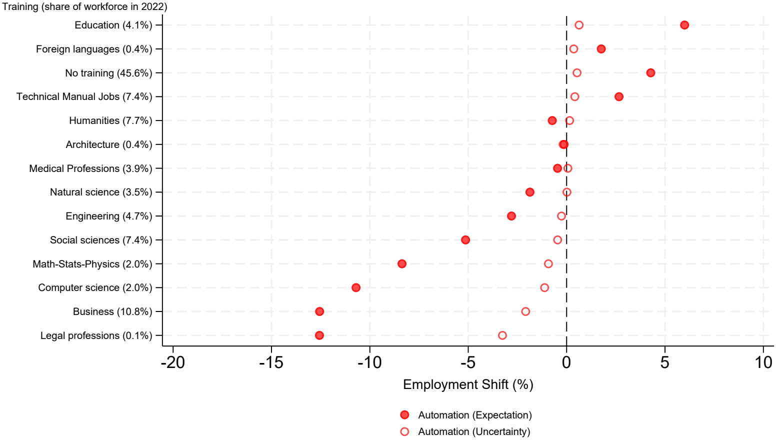
- I follow the literature for other parameters. Other Parameters

Roadmap

AI impact on employment: Automation

Expected Automation: no augmentation and no uncertainty.

Automation Uncertainty: labor reallocation due to risk aversion.



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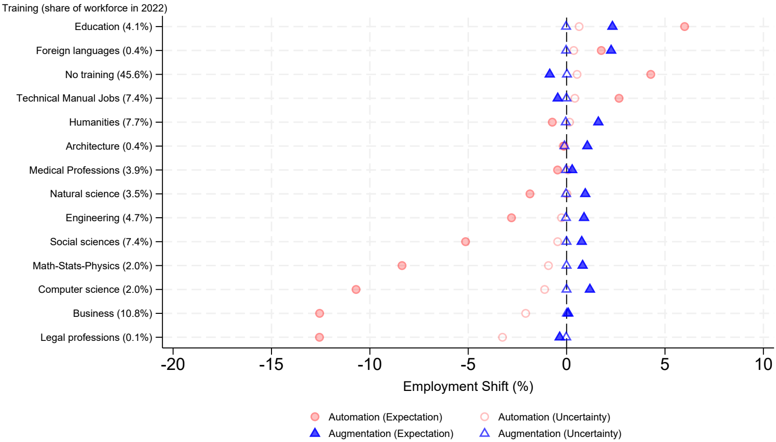
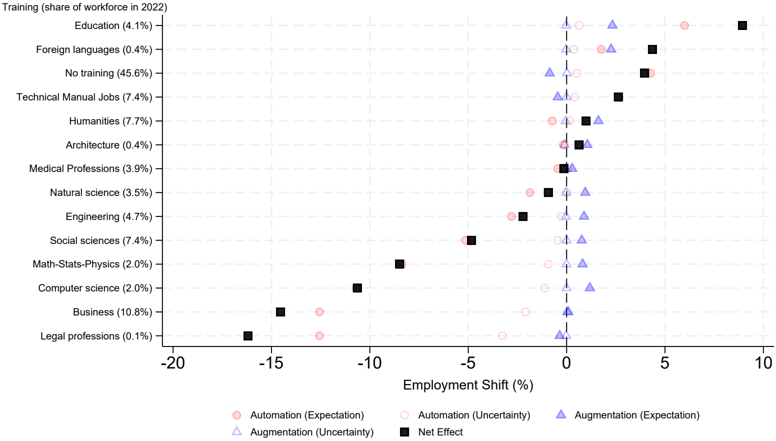


AI impact on employment: Net Effect

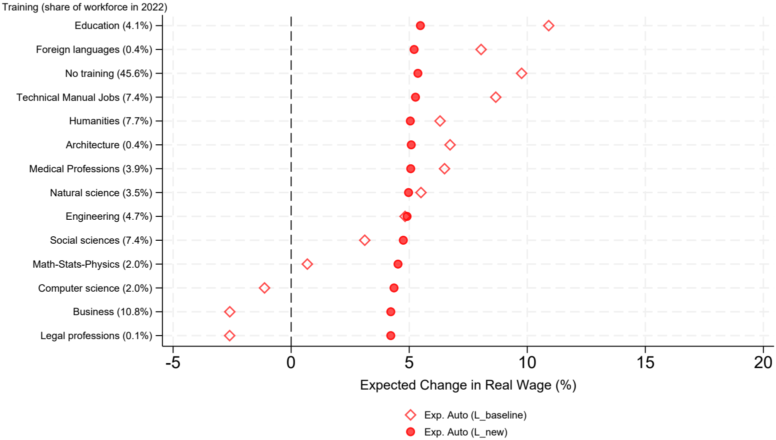
Alternative scenario

Net effect: Final impact on employment.



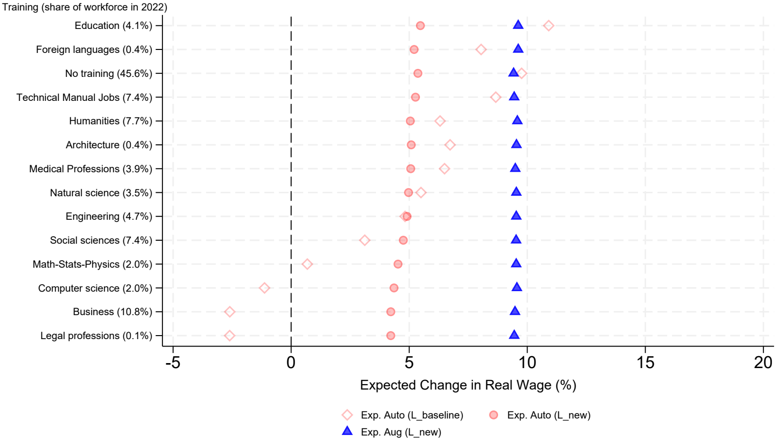
AI impact on expected wages: Automation

Expected Automation: the impact of labor reallocation on wages.



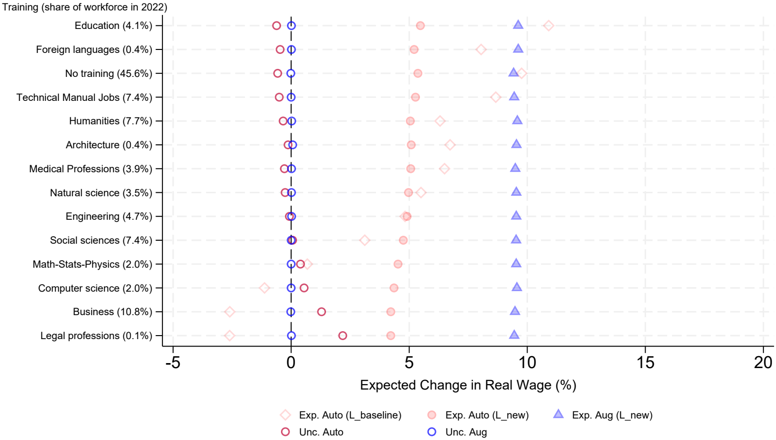
AI impact on expected wages: Augmentation

Expected Augmentation: the impact of augmentation on wages.



AI impact on expected wages: Uncertainty

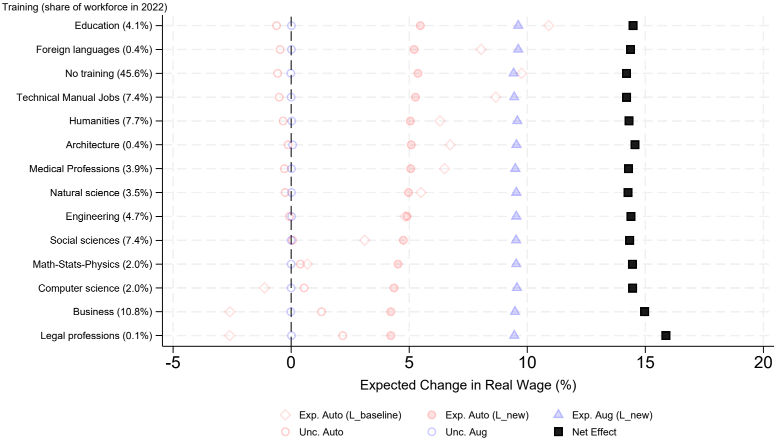
Uncertainty: risk premium due to uncertainty.



AI impact on expected wages: Net Effect

Alternative scenario

Net effect: Final impact on expected wages.



Conclusion

- AI has the potential to shift human capital allocation.
- Most of the labor reallocation is driven by expected automation.
- Labor scarcity offsets the negative impact of AI on wages.
- Expected wages increase for all training paths by 14%.
- Uncertainty generates a risk premium.

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Automation and Augmentation Uncertainty

κ: AI correlation between tasks within training.

$\rightarrow$ $\kappa = 0$: tasks are independent.

$\rightarrow$ $\kappa = 1$: tasks are perfectly correlated.

$$\sigma^2_{A,j} = (1-\kappa) \underbrace{\sum_{\tau \in \mathrm{S}^{pot}_{A,j}} \theta^2_{j,\tau} Var_{A,\tau}}_{\text{Sum of individual variances}} + \kappa \underbrace{\left(\sum_{\tau \in \mathrm{S}^{pot}_{A,j}} \theta_{j,\tau} \sqrt{Var_{A,\tau}} \right)^2}_{\text{Joint Variance}}$$

$$\sigma^2_{\gamma,j} = (1-\kappa) \sum_{\tau \in \mathrm{S}^{pot}_{\gamma,j}} \theta^2_{j,\tau} Var_{\gamma,\tau} + \kappa \left(\sum_{\tau \in \mathrm{S}^{pot}_{\gamma,j}} \theta_{j,\tau} \sqrt{Var_{\gamma,\tau}} \right)^2$$

Automation by Training Path (Alternative)

Back

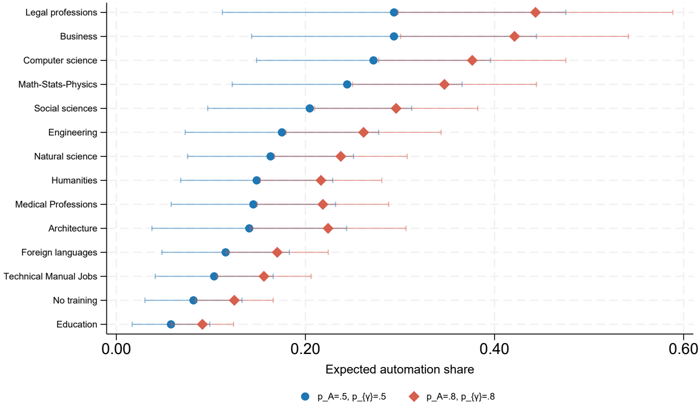


Figure 3: Expected Automation across Training Paths: p = 0.5 vs p = 0.8 (with 1 standard deviation confidence interval).

Augmentation by Training Path (Alternative) Back

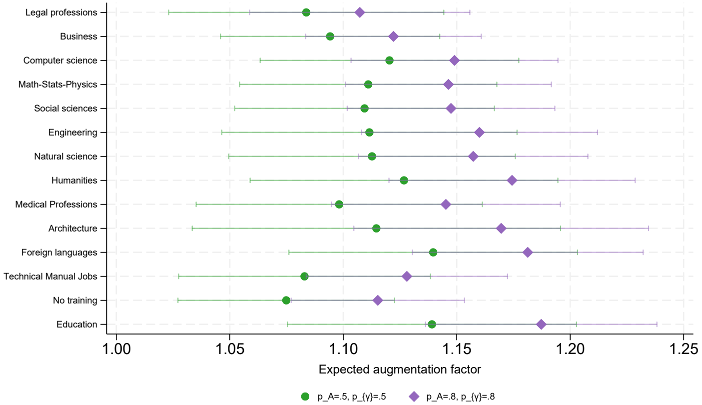


Figure 4: Expected Augmentation across Training Paths: p = 0.5 vs p = 0.8 (with 1 standard deviation confidence interval).

Calibration of Other Parameters

Back

- $\epsilon = 1.57$: elasticity of substitution across training goods.
- $\rho = 0.49$: elasticity of substitution across tasks within training.
- $\beta = 0.813$: discount factor (3% annual discount rate for 7 years).
- $\zeta = 0.053$: scale parameter of the Gumbel distribution.
- $\eta = 5$: relative risk aversion.
- Labor share:

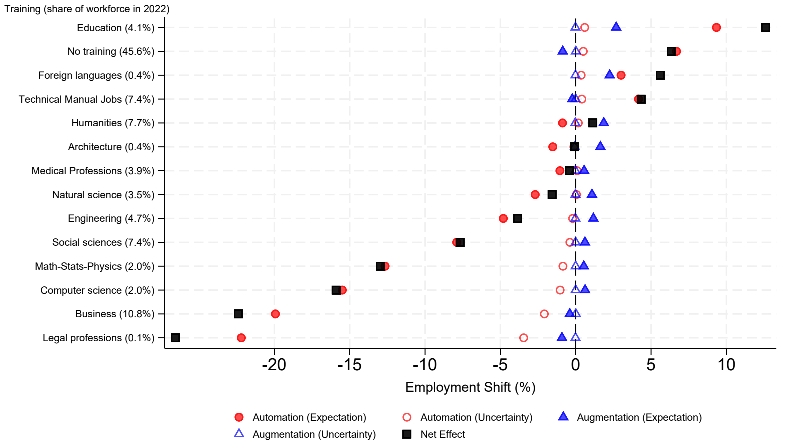
  → $\Gamma_j^{pre} = 1$ before AI.

  → I assume cost savings from automation are 27% ($\chi = 0.73$).

$$\Gamma_j^{post} \approx \frac{\chi^{\rho-1}\left(1-\mu_{A,j}\right)}{\mu_{A,j} + \chi^{\rho-1}\left(1-\mu_{A,j}\right)}$$

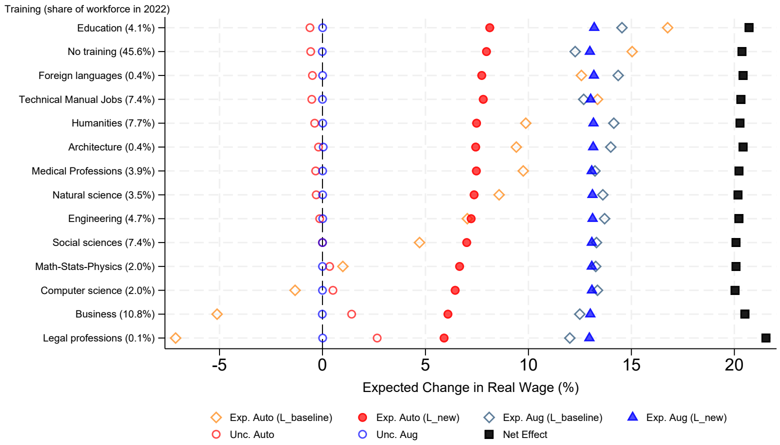
AI impact on employment: Alternative Scenario back

Alternative scenario: $p_A = p_\gamma = 0.8$



AI impact on wages: Alternative Scenario back

Alternative scenario: $p_A = p_\gamma = 0.8$



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