

# AI's Dual Impact on Labor Markets: Automation, Augmentation, and Human Capital

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## **Abstract**

This paper examines whether AI's dual effects on labor markets—automation and augmentation—operate through distinct human capital channels. Using Microsoft's "Working with AI" telemetry data matched to O\*NET occupations and BLS employment statistics (N=107,901 observations), I test whether automation primarily substitutes for codified knowledge (formal education) while augmentation complements tacit knowledge (on-the-job experience). Preliminary results suggest education strongly predicts both automation and augmentation exposure, with surprising patterns for experience-based knowledge.

*JEL Classification:* J24, J31, O33

*Keywords:* Artificial intelligence, automation, augmentation, human capital, labor markets

# 1 Introduction

Artificial intelligence is rapidly transforming labor markets, but unlike previous technological revolutions, AI has dual effects: it can automate tasks (substituting for labor) and augment tasks (enhancing productivity). Understanding which effect dominates—and for which workers—is crucial for predicting AI’s impact on employment and inequality.

This paper addresses two questions. First, do AI’s automation and augmentation effects operate through distinct channels? Specifically, does automation primarily substitute for codified knowledge (formal education), while augmentation complements tacit knowledge (on-the-job experience)? Second, can these mechanisms explain recent evidence that AI disproportionately displaces young workers while leaving senior workers unaffected?

Using Microsoft’s “Working with AI” telemetry data matched to O\*NET occupations and BLS employment statistics, I construct occupation-level measures that separately identify AI’s capacity to automate (AAS) versus augment (AGS) labor. I test whether these operate through different human capital channels by regressing AI exposure on measures of codified knowledge ( $K_c$ , from education) and tacit knowledge ( $K_t$ , from experience).

The results reveal strong education gradients: a one-standard-deviation increase in  $K_c$  predicts 42.5 points higher automation exposure and 1.3 points higher augmentation (both  $p < 0.001$ ). Surprisingly, experience also predicts higher automation (8.4,  $p < 0.001$ ) but lower augmentation (-0.27,  $p < 0.001$ ). These patterns suggest that modern workplace experience may involve more routinized tasks than traditional craft skills, making it susceptible to automation, while AI augmentation tools are designed for educated-intensive workflows.

I embed these mechanisms in a lifecycle model combining Ben-Porath human capital accumulation with Acemoglu-Restrepo task-based production. AI shocks shift the relative rental rates of codified versus tacit knowledge, generating heterogeneous impacts across occupations and age groups. Young workers with high  $K_c$  but low  $K_t$  face automation risk, while senior workers with both knowledge types are shielded—consistent with recent empirical evidence.

This paper makes three contributions. First, it provides the first empirical decomposition of AI’s dual effects using occupation-level telemetry data. Second, it validates a knowledge-specific mechanism linking AI exposure to human capital composition. Third, it develops a structural framework that can rationalize observed age-employment gradients from AI adoption.

The paper proceeds as follows. Section 2 reviews related literature. Section 5 presents the theoretical framework. Section 3 describes data construction. Section 4 presents the bridge regressions testing the AI-knowledge hypothesis. Section 6 discusses structural estimation. Section 7 presents results. Section 8 concludes.

## 2 Literature Review

This paper contributes to three literatures on task-based models, AI exposure measurement, and human capital theory.

**Task-Based Models.** The task-based approach (Autor et al., 2003; Acemoglu and Autor, 2011) analyzes how technology affects specific job tasks rather than broad skill categories. Acemoglu and Restrepo (2019) formally distinguish automation (task substitution) from task creation, showing automation reduces labor demand while task creation increases it. My framework extends this by adding augmentation—where AI enhances productivity in existing tasks rather than substituting or creating them.

**AI Exposure Measurement.** Felten et al. (2021) link AI capabilities to O\*NET tasks using expert assessments. Webb (2020) measure exposure from patent text similarity. Brynjolfsson et al. (2023) construct GPT exposure indices. Brynjolfsson et al. (2025) document 13% employment declines for young workers in high-AI occupations post-ChatGPT. I use Microsoft Copilot telemetry providing direct observation of automation versus augmentation rather than predicted exposure.

**Human Capital.** Ben-Porath (1967) develops the lifecycle model where workers allocate time between work and human capital investment. Huggett et al. (2011) embed this in general equilibrium. I distinguish codified knowledge (education) from tacit knowledge (experience), allowing differential AI impacts on each type—connecting to skill obsolescence literature (Violante, 2002) but focusing on AI’s dual effects.

## 3 Data

I construct AI exposure measures at the occupation level by combining three data sources: Microsoft’s “Working with AI” telemetry data, O\*NET occupational characteristics, and BLS employment statistics.

### 3.1 Microsoft “Working with AI” Dataset

Tomlinson et al. (2025) provide anonymized telemetry from Microsoft Bing Copilot, mapping 332 Intermediate Work Activities (IWAs) to AI capabilities. For each IWA, the dataset includes:

- **share\_ai:** Frequency of AI usage (0-1 scale), capturing how often workers use AI tools for the activity
- **completion\_ai:** AI’s ability to complete the task autonomously (0-1 scale)

- **impact\_scope\_ai**: Breadth of task impact within workflow (0-1 scale)

I construct two measures:

- **Automation (AAS)**:  $\text{completion\_ai} \times \text{impact\_scope\_ai}$  for activities where  $\text{share\_ai} \geq 0.0005$ . This captures AI’s potential to fully replace human labor in high-impact tasks.
- **Augmentation (AGS)**:  $\text{share\_ai}$ , measuring AI usage frequency as a complementary productivity tool.

### 3.2 O\*NET Occupational Characteristics

O\*NET version 28.0 (2024) provides comprehensive data on 957 six-digit SOC occupations. I use two primary components:

**Intermediate Work Activities (IWAs)**: O\*NET’s taxonomy of 332 generalized work activities serves as the crosswalk between Microsoft’s AI data and occupations. Each occupation has importance ratings (1-5 scale) for relevant IWAs, which I use as weights to aggregate AI scores from the IWA level to occupations:

$$\text{AI Score}_{\text{occ}} = \sum_{\text{IWA}} \frac{w_{\text{IWA}}}{\sum w_{\text{IWA}}} \cdot \text{AI Score}_{\text{IWA}}$$

**Human Capital Measures**: From O\*NET’s Education, Training, and Experience (ETE) data:

- **Codified Knowledge ( $K_c$ )**: “Required Level of Education” mapped to years (high school = 12, associate’s = 14, bachelor’s = 16, master’s = 18, doctorate = 20), averaged across occupational respondents and standardized to mean 0, SD 1.
- **Tacit Knowledge ( $K_t$ )**: Composite index combining (i) “Related Work Experience Required” (months), (ii) “On-the-Job Training” duration (categorical, converted to months), and (iii) “On-Site/In-Plant Training” requirements. Standardized to mean 0, SD 1.

The correlation between  $K_c$  and  $K_t$  is 0.394, indicating they capture distinct dimensions of occupational human capital. High- $K_c$  occupations include Physicians (20 years education), Software Developers (16), and Accountants (16). High- $K_t$  occupations include Construction Managers, Electricians, and Police Officers.

### 3.3 BLS Occupational Employment Statistics

The BLS OES database provides annual employment and wage data by occupation, industry, and metropolitan area for 1988-2024. I use the most recent available year (2023) to match with contemporary AI exposure measures. Key variables include:

- Employment counts at occupation  $\times$  6-digit NAICS industry  $\times$  metropolitan area level
- Mean and median wages (annual and hourly)
- Geographic coverage: National, state, and 12 large metropolitan statistical areas

### 3.4 Sample Construction

Merging Microsoft AI scores (874 occupations), O\*NET human capital measures (957 occupations), and BLS employment data yields 107,901 observations at the occupation  $\times$  area  $\times$  industry level:

- 738 unique occupations (matched across all three sources)
- 13 geographic areas (national + 12 metro areas)
- 444 industries (6-digit NAICS)

AAS (automation) ranges from 0 to 465 (mean = 92, SD = 100), while AGS (augmentation) ranges from 0 to 22 (mean = 4.1, SD = 4.2). Education ( $K_e$ ) and experience ( $K_t$ ) are standardized by construction.

## 4 Bridge Regressions: Testing the AI-Knowledge Hypothesis

This section presents reduced-form evidence testing whether AI’s dual effects—automation (AAS) and augmentation (AGS)—operate through distinct human capital channels. These “bridge regressions” establish the empirical foundation for our structural model by validating that AI shocks differentially affect occupations based on their knowledge composition.

### 4.1 Empirical Strategy

We estimate occupation-level regressions:

$$\text{AAS}_{ijk} = \alpha_0 + \alpha_1 K_{c,i} + \alpha_2 K_{t,i} + \lambda_j + \delta_k + \varepsilon_{ijk} \quad (1)$$

$$\text{AGS}_{ijk} = \gamma_0 + \gamma_1 K_{c,i} + \gamma_2 K_{t,i} + \lambda_j + \delta_k + \nu_{ijk} \quad (2)$$

where  $i$  indexes occupations,  $j$  indexes industries (6-digit NAICS),  $k$  indexes geographic areas (metropolitan areas), AAS and AGS are automation and augmentation scores from Microsoft’s “Working with AI” dataset (Tomlinson et al., 2025),  $K_c$  and  $K_t$  are standardized human capital measures from O\*NET, and  $\lambda_j$ ,  $\delta_k$  are industry and area fixed effects.

### Hypotheses (from research design):

- **H1 (Automation):**  $\alpha_1 > 0$  (targets codified knowledge),  $\alpha_2 < 0$  (tacit provides shield)
- **H2 (Augmentation):**  $\gamma_1 > 0$ ,  $\gamma_2 > 0$  (complements both knowledge types)

We run three specifications: (1) baseline without controls, (2) adding industry and area fixed effects (443 industries, 12 areas), and (3) adding annual mean wage control. Data are described in Section 3.

## 4.2 Results

**Automation (Table 1):** Column (1) shows baseline OLS:  $K_c = 38.6^{***}$  ( $p < 0.001$ ), strongly confirming H1’s prediction that automation targets educated workers. However,  $K_t = 9.9^{***}$  enters *positively*, contradicting the hypothesis that experience shields against automation. This relationship is robust: adding industry/area FE (col 2) yields  $K_c = 42.0^{***}$ ,  $K_t = 8.5^{***}$ , and the full specification with wage controls (col 3) gives  $K_c = 42.5^{***}$ ,  $K_t = 8.4^{***}$ . R-squared increases from 0.133 to 0.163.

**Augmentation (Table 2):** The results present a stronger puzzle. While  $K_c$  positively predicts augmentation ( $1.10^{***}$ ,  $p < 0.001$ ),  $K_t$  enters *negatively* ( $-0.36^{***}$ ,  $p < 0.001$ ), directly contradicting H2. This is robust across specifications: with FE,  $K_c = 1.13^{***}$ ,  $K_t = -0.40^{***}$ ; full specification  $K_c = 1.30^{***}$ ,  $K_t = -0.27^{***}$ . R-squared reaches 0.060.

## 4.3 Interpretation and Implications

**Key Finding:** AI exposure is strongly mediated by human capital composition, with education ( $K_c$ ) playing a dominant role in *both* automation and augmentation. This validates the central mechanism of our structural model.

**Unexpected Results:** The positive  $K_t$  for automation and negative  $K_t$  for augmentation contradict initial hypotheses but suggest important refinements:

Table 1: Automation (AAS) and Human Capital: Three Specifications

|                    | <i>Dependent variable: Automation (AAS)</i> |                      |                      |
|--------------------|---------------------------------------------|----------------------|----------------------|
|                    | Baseline                                    | + Fixed Effects      | + Wage               |
|                    | (1)                                         | (2)                  | (3)                  |
| Constant           | 82.515***<br>(0.289)                        | 55.815***<br>(3.136) | 60.330***<br>(3.227) |
| $K_c$ (Education)  | 38.649***<br>(0.392)                        | 41.041***<br>(0.401) | 42.501***<br>(0.471) |
| $K_t$ (Experience) | 9.865***<br>(0.323)                         | 7.266***<br>(0.327)  | 8.354***<br>(0.375)  |
| Wage (\$1000s)     |                                             |                      | -0.000***<br>(0.000) |
| Industry FE        | No                                          | Yes                  | Yes                  |
| Area FE            | No                                          | Yes                  | Yes                  |
| Observations       | 107,901                                     | 107,901              | 107,901              |
| $R^2$              | 0.133                                       | 0.163                | 0.163                |
| Adjusted $R^2$     | 0.133                                       | 0.159                | 0.159                |

Notes: Standard errors in parentheses.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Industry FE: 443 industries (6-digit NAICS). Area FE: 12 metropolitan areas.

Table 2: Augmentation (AGS) and Human Capital: Three Specifications

|                    | <i>Dependent variable: Augmentation (AGS)</i> |                        |                      |
|--------------------|-----------------------------------------------|------------------------|----------------------|
|                    | Baseline<br>(1)                               | + Fixed Effects<br>(2) | + Wage<br>(3)        |
| Constant           | 3.088***<br>(0.013)                           | 2.210***<br>(0.137)    | 2.725***<br>(0.141)  |
| $K_c$ (Education)  | 1.096***<br>(0.017)                           | 1.131***<br>(0.018)    | 1.298***<br>(0.021)  |
| $K_t$ (Experience) | -0.355***<br>(0.014)                          | -0.395***<br>(0.014)   | -0.271***<br>(0.016) |
| Wage (\$1000s)     |                                               |                        | -0.000***<br>(0.000) |
| Industry FE        | No                                            | Yes                    | Yes                  |
| Area FE            | No                                            | Yes                    | Yes                  |
| Observations       | 107,901                                       | 107,901                | 107,901              |
| $R^2$              | 0.037                                         | 0.058                  | 0.060                |
| Adjusted $R^2$     | 0.037                                         | 0.054                  | 0.056                |

Notes: Standard errors in parentheses.

\*p<0.1; \*\*p<0.05; \*\*\*p<0.01.

Industry FE: 443 industries (6-digit NAICS). Area FE: 12 metropolitan areas.

1. **Modern experience may be codifiable:** Unlike traditional craft skills, modern “experience” (e.g., software patterns, business processes) may involve learnable routines susceptible to automation.
2. **Augmentation tool design:** Microsoft Copilot may be optimized for workflows common in educated-intensive occupations (coding, writing, analysis) rather than experience-based tasks.
3. **Adoption barriers:** Older/experienced workers may face higher costs adopting augmentation tools, or tools may complement recent formal training more than on-the-job experience.

**Economic Magnitudes:** Moving from 25th to 75th percentile of  $K_c$  ( $\approx 1.3$  SD) associates with a 55-point AAS increase (1.2 SD of automation exposure) and 1.7-point AGS increase (0.5 SD).

**Structural Model Implications:** These findings motivate our Ben-Porath-Acemoglu-Restrepo framework where AI shocks differentially affect  $R_c$  and  $R_t$ . The unexpected signs suggest richer modeling: perhaps distinguishing codifiable vs. non-codifiable experience, or skill-biased adoption of augmentation. The core mechanism—knowledge-specific AI impacts—remains validated, with education effects consistent and economically large across all specifications.

## 5 Theoretical Framework

We develop an overlapping generations model integrating Acemoglu-Restrepo task-based production with Ben-Porath human capital accumulation. The framework endogenizes equilibrium rental rates for codified knowledge ( $K_c$ ) and tacit knowledge ( $K_t$ ), allowing us to trace how AI shocks differentially affect workers by age.

### 5.1 Production: Task-Based Framework

Firms produce final output  $Y$  by aggregating a continuum of tasks  $i \in [0, 1]$ :

$$Y = \left( \int_0^1 y(i)^{\frac{\sigma-1}{\sigma}} di \right)^{\frac{\sigma}{\sigma-1}} \quad (3)$$

where  $\sigma$  is the elasticity of substitution between tasks. Tasks are allocated across three production technologies based on thresholds  $I_K$  and  $I_L$ :

$$y(i) = \begin{cases} A_K \cdot k(i) & \text{if } i \in [0, I_K] \text{ (Automated tasks)} \\ A_c \cdot K_c(i) & \text{if } i \in (I_K, I_L] \text{ (Codified tasks)} \\ A_t \cdot K_t(i) & \text{if } i \in (I_L, 1] \text{ (Tacit tasks)} \end{cases} \quad (4)$$

where  $k(i)$ ,  $K_c(i)$ , and  $K_t(i)$  are input allocations to task  $i$ , and  $(A_K, A_c, A_t)$  are productivities. Capital  $k$  substitutes for routine tasks, codified knowledge  $K_c$  performs tasks requiring formal education, and tacit knowledge  $K_t$  performs tasks requiring experience.

**Equilibrium Rental Rates:** Competitive profit maximization implies zero profits in each task segment. The unit cost of producing  $y(i)$  equals the output price (normalized to 1). This yields first-order conditions that pin down equilibrium rental rates:

$$R_c = R_c(K_c, K_t; A_c, A_t, I_K, I_L, \sigma) \quad (5)$$

$$R_t = R_t(K_c, K_t; A_c, A_t, I_K, I_L, \sigma) \quad (6)$$

The rental rates depend on aggregate human capital supplies  $(K_c, K_t)$  (derived from summing individual  $h_c$  and  $h_{t,j}$  across agents), task productivities, task allocation thresholds, and the elasticity of substitution. Key properties: (i)  $\partial R_c / \partial K_c < 0$  and  $\partial R_t / \partial K_t < 0$  (diminishing returns), (ii)  $\partial R_c / \partial I_K < 0$  and  $\partial R_t / \partial I_L < 0$  (automation reduces demand).

## 5.2 Human Capital Accumulation

Agents live  $J$  periods (ages 22-65). Each enters with fixed codified knowledge  $h_c$  (from education) and minimum tacit knowledge  $h_{t,1}$ . At age  $j$ , agents choose time allocation  $s_j \in [0, 1]$  for skill investment versus work  $l_j = 1 - s_j$ . They maximize expected lifetime utility:

$$V_j(h_{t,j}) = \max_{s_j \in [0,1]} \{u(c_j) + \beta \mathbb{E}[V_{j+1}(h_{t,j+1})]\} \quad (7)$$

subject to:

**Income and Consumption:** Agents are hand-to-mouth (no financial savings), consuming all labor income:

$$c_j = \text{Income}_j = \underbrace{(R_c \cdot h_c + R_t \cdot h_{t,j})}_{\text{Human capital rental}} \cdot \underbrace{(1 - s_j)}_{\text{Work time}} \quad (8)$$

**Tacit Knowledge Accumulation (Ben-Porath):**

$$h_{t,j+1} = (1 - \delta)h_{t,j} + A(h_c \cdot s_j)^\alpha \quad (9)$$

where  $\delta \in (0, 1)$  is depreciation,  $A > 0$  is learning productivity, and  $\alpha \in (0, 1)$  captures diminishing returns. Crucially, codified knowledge  $h_c$  serves as input to tacit learning—education enables experience accumulation. This implies higher-educated workers accumulate tacit skills faster.

**Optimal Policy:** The agent’s optimal investment policy  $s_j^*(h_{t,j}; R_c, R_t)$  balances current income loss from time spent learning against future income gains from higher  $h_{t,j+1}$ . The solution exhibits standard lifecycle patterns:  $s_j$  decreases with age as remaining working years shrink and  $h_{t,j}$  rises.

**Life-Cycle Dynamics:** Young workers (low  $h_{t,j}$ ) earn primarily from  $R_c \cdot h_c$ , invest heavily ( $s_j$  high) to build tacit skills. Senior workers (high  $h_{t,j}$ ) earn from both  $R_c \cdot h_c$  and  $R_t \cdot h_{t,j}$ , reduce investment ( $s_j \rightarrow 0$ ). This generates endogenous age-heterogeneous exposure to shocks affecting  $R_c$  versus  $R_t$ .

### 5.3 AI Shocks: Automation and Augmentation

We model AI as shifting task allocation and productivities, guided by our empirical findings (Section 4):

**Automation (AAS):** The positive coefficients on both  $K_c$  and  $K_t$  suggest automation targets formal procedures *and* routinized experience. We model this as rightward shifts in both thresholds:  $I_K \rightarrow I'_K$  (automating codified tasks) and  $I_L \rightarrow I'_L$  (automating routine tacit tasks). This shrinks demand for both skill types:

$$\Delta R_c^{AAS} < 0, \quad \Delta R_t^{AAS} < 0 \quad (10)$$

**Augmentation (AGS):** The positive  $K_c$  coefficient and negative  $K_t$  coefficient indicate augmentation tools (e.g., Microsoft Copilot) are designed for educated workers, not experience-intensive occupations. We model this as a productivity boost to codified tasks:  $A_c \rightarrow A'_c > A_c$ . This raises codified knowledge returns:

$$\Delta R_c^{AGS} > 0, \quad \Delta R_t^{AGS} = 0 \quad (11)$$

**Net Effect:** The total AI shock combines automation and augmentation:

$$\Delta R_c = \Delta R_c^{AAS} + \Delta R_c^{AGS} \quad (12)$$

$$\Delta R_t = \Delta R_t^{AAS} \quad (13)$$

For young workers (income  $\approx R_c \cdot h_c$ ), the net effect depends on whether augmentation’s positive impact dominates automation’s negative impact on  $R_c$ . For senior workers (income

$\approx R_c \cdot h_c + R_t \cdot h_{t,j}$ ), they face additional downward pressure from  $\Delta R_t < 0$ , but their diversified human capital provides partial insurance.

## 5.4 Connection to Empirical Evidence

This framework directly rationalizes Brynjolfsson et al. (2025)' finding that young workers face 13% employment declines post-ChatGPT while senior workers are unaffected.

**Age-Heterogeneous Wage Effects:** Consider the income change for workers at different lifecycle stages:

- **Young workers** ( $j$  small,  $h_{t,j} \approx h_{t,1}$ ): Income  $\approx R_c \cdot h_c$ . The wage shock is:

$$\Delta \text{Income}_{\text{young}} \approx h_c \cdot \Delta R_c = h_c \cdot (\Delta R_c^{\text{AAS}} + \Delta R_c^{\text{AGS}}) \quad (14)$$

The net effect is theoretically ambiguous: automation pushes  $R_c$  down, augmentation pushes it up.

- **Senior workers** ( $j$  large,  $h_{t,j} \gg h_{t,1}$ ): Income  $\approx R_c \cdot h_c + R_t \cdot h_{t,j}$ . The wage shock is:

$$\Delta \text{Income}_{\text{senior}} \approx h_c \cdot \Delta R_c + h_{t,j} \cdot \Delta R_t = h_c \cdot (\Delta R_c^{\text{AAS}} + \Delta R_c^{\text{AGS}}) + h_{t,j} \cdot \Delta R_t^{\text{AAS}} \quad (15)$$

The  $R_t$  component unambiguously falls ( $\Delta R_t^{\text{AAS}} < 0$ ), but their diversified human capital ( $h_c, h_{t,j}$ ) provides partial insurance.

**Employment Effects via Wage Rigidity:** Introducing a wage floor  $\underline{R}_c$  (e.g., from institutional rigidities, efficiency wages, or search frictions) generates the BCC employment pattern:

1. If the AI shock yields  $R_c^* < \underline{R}_c$  (i.e., the equilibrium  $R_c$  from equations 5 is below the floor), the observed wage remains at  $\underline{R}_c$ .
2. Firms cannot cut young workers' wages, so they adjust on the **extensive margin**: reduce hiring of new young workers. This manifests as employment declines concentrated among entrants and early-career workers.
3. Senior workers' total compensation ( $R_c \cdot h_c + R_t \cdot h_{t,j}$ ) may remain above their reservation wage even with  $\Delta R_t < 0$ , so they remain employed. Additionally, if  $R_t$  adjusts more flexibly (less institutional rigidity for experience premia), senior workers' wages can partially adjust without employment losses.
4. **Empirical prediction:** The model predicts  $\frac{d(\text{Employment})}{d(\text{Age})} > 0$  post-shock—exactly the "canaries in the coal mine" gradient observed in the data.

**Investment Response:** Forward-looking young workers anticipate lower future  $R_t$  (due to  $\Delta R_t^{AAS} < 0$ ). This reduces the return to tacit skill accumulation, leading them to:

- Reduce investment  $s_j$  (work more now, learn less)
- Switch to higher- $h_c$  occupations where augmentation benefits dominate
- Exit labor force or shift to less-automatable sectors

This amplifies current income losses and can trigger occupational reallocation, consistent with the large employment effects observed for young workers despite modest estimated wage effects in aggregate studies.

## 6 Structural Estimation

*[To be developed: Simulated Method of Moments estimation strategy, calibration targets, identification.]*

## 7 Results

*[To be developed: Counterfactual simulations, welfare analysis, age-heterogeneous impacts.]*

## 8 Conclusion

This paper provides empirical evidence that AI’s dual effects—automation and augmentation—operate through distinct human capital channels. Education strongly predicts both types of AI exposure, while experience shows unexpected patterns: positive correlation with automation but negative with augmentation. These findings validate a mechanism where AI shocks differentially affect returns to codified versus tacit knowledge, with implications for understanding age-heterogeneous employment effects and designing effective retraining policies.

Future work will complete the structural model estimation and quantify welfare effects across different worker types.

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