# From Code to Cash: The Impact of AI on Wages

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Work. Transform? Repeat!
Tagung des DFG-Schwerpunktprogramms 2267

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# Motivation

1. **Growing public interest, esp. since Chat GPT!**
2. **Rapidly growing technology!**
   - Share of German firms adopting AI increased from 6% to 13% between 2019-23 (Rammer 2022; Noyer et al. 2023).
3. **Changing skill requirements?**
   - Changing skill demand has implications for productivity, wages (Brynjolfsson, Li, and Raymond 2023; Gilardi, Alizadeh, and Kubli 2023; Noy and Zhang 2023)
4. **Different LM effects than previous technologies?**
   - High-skilled workers possibly more exposed (Webb 2020; Fossen and Sorgner 2022)

# This Paper

1. **Demand for AI skills among German firms**
   - Stylized facts on the diffusion of AI in Germany
     - Novel online job vacancy data (OJV) with original text data
2. **Worker-level analysis of wage effects of AI**
   - Are there AI-induced wage effects?
     - OLS (IV): AI Skill Demand $\uparrow$ 10% $\Rightarrow$ Wages 0% - $\uparrow$ 0.8% (2%)
   - What are the key Mechanisms?
     - 85% of AI-induced wage effects due to (i) Employer quality, (ii) Socioeconomics, and (iii) Occupational characteristics
     - Wage gains rising with skill level
     - Primary beneficiaries: Younger workers w/ college degree
     - Occupational Mobility $\uparrow$, LM concentration $\downarrow$

# Contributions

1. **Labor market impact of AI**
   - \+ Diffusion of AI skills (in GER) between 2017-21
     - Alekseeva et al. 2021; Babina et al. 2021; Tambe 2021; Acemoglu et al. 2022
   - \+ Analysis at detailed Occ-LMR-Year level
     - Industries/ Occupations: (Webb 2020; Albanesi et al. 2023; Eloundou et al. 2023; Felten, Raj, and Seamans 2023)
     - Local LM: (Bessen, Cockburn, and Hunt 2021; Gathmann and Grimm 2022)
     - Firms: (Rammer 2022; Arntz et al. 2023; Copestake et al. 2023; Peede and Stops 2023)
2. **Worker-level effects of digital technologies**
   - \+ Decompose wage effects of rising AI skill demand
     - (Genz, Janser, and Lehmer 2019; Genz et al. 2021; Fossen and Sorgner 2022)
   - \+ Causal analysis, Highlight key mechanisms

# Data

## 1 Online Job Vacancy (OJV) Data

- Cooperation with private IT-company (OJV Data Provider)
- Scrape OJV webpages, save OJV, merge with company registry
  - We receive: Information on firms, OJV source, and OJV text

**NLP steps in-house**:

- Data cleaning/ preprocessing (Gentzkow, Kelly, and Taddy 2019)
- Classification of occupations (KldB 2010, 5-digit)
- Keyword list comprising AI skills

$\Longrightarrow$ **Final product: 8.3 million vacancies, 232k firms**

- 2017/01 - 2021/12 Details, External Validity

## 2 Labor Market Data

- SIAB, 2017-2021
- BHP, 2017-2021

# Data: OJV - Identification of AI skills

- Extensive keyword list ($N = 237$)
  - Enrich existing keyword lists, e.g., (Büchel and Mertens 2021), using Chat GPT 4.0 and Manual annotation (1k vacancies)

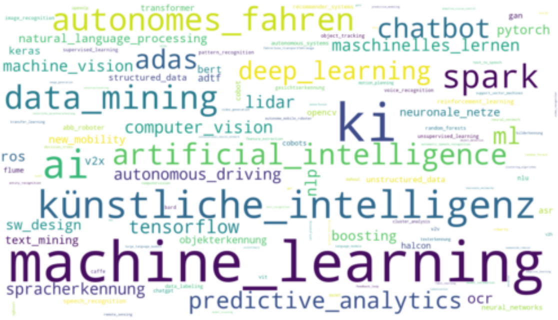



Figure 1: Word cloud of AI skills - Baseline

# Fact #1: Share of AI vacancies has increased over time

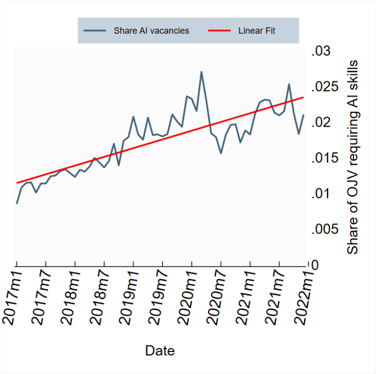
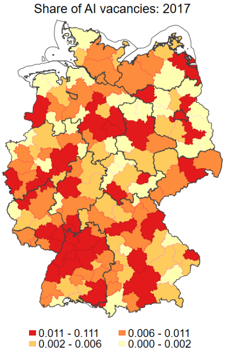



Figure 2: Trends in AI Demand, 2017/01 - 2021/12

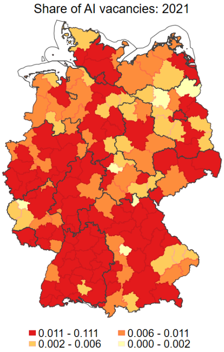
NOTE. —Vacancies are defined as an "AI vacancy" if a job posting contains at least one AI-related skill in a given month.

- 16% YoY growth from 2017/1 - 2021/12 Context

# Fact #2: AI skills have diffused broadly across LMRs




(a) AI demand: 2017

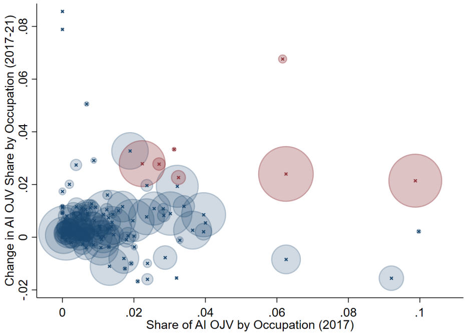



(b) AI demand: 2021

NOTE. —Local labor markets are assigned into four classes of task intensity. Each class corresponds to quartiles as of 2017 where lowest quartile implies lowest AI demand (yellow) and highest quartile implies hightest AI demand (red). Gathmann & Grimm (2022)

Figure 3: Demand for AI skills in Germany across local labor markets, 2017-01 - 2021-12

# Fact #3: AI skill demand concentrated in few occupations




NOTE. —The X-axis displays the share of OJV with AI demand ("AI Vacancies") for 140 3-d occupations as of 2017. The Y-axis displays the change in AI Vacancies between 2017 - 2021 for each occupation.

Figure 4: Dynamics in occupational demand for AI skills

1. Computer Science
2. Mathematics/Statistics
3. Software Development and Programming
4. Social Sciences
5. Media, Documentation & Info. Services
6. IT-System Analysis/Sales
7. Insurance/Fin. Services

Definition | Early Adopters & Late Bloomers | Emloyment Shares

# Wage Regressions

$$lnw_{ilot} = \beta_1 \mathbf{AI}_{lot} + \beta_2 X_{it} + \beta_3 \psi_l + \beta_4 \omega_o + \beta_6 \theta_t + \epsilon_{ilt} \qquad (1)$$

- $w_{ilot}$: log daily wage of worker $i$
- $\mathbf{AI}_{lot}$: Demand for AI skills in occupation $o$ in labor market region $l$ (*144 times 141 = 20,304 local labor markets*)
- $\psi_l$, $\omega_o$,$\theta_t$: LMR FE, Occupational FE (3d), Year FE
- $X_{it}$: Worker-level controls
  - Socioeconomic characteristics
    - Age, Education, Gender, Nationality
  - Work
    - Labor Market, Occupational, Firm Tenure
  - Firm
    - Employer size and industry (WZ08, 2d)
  - Firm Quality (establishment level)
    - AKM effects

# Identification

- Problem: Endogeneity of AI skill demand
  - Depends on adoption of AI technologies, which are not random

$\Longrightarrow$ IV: **Leave-one-out-mean (LOOM)** demand for AI skills (outside of LMR or state)

  - Leverage differential Occupation-LMR level exposure to firms' national hiring practices

$$LOOM_{lot} = \sum_{l \neq l'} AI_{lot} \tag{2}$$

- **Identifying assumption**: Firms' national skill requirements orthogonal to local conditions

Intuition, Details

# Wage Regressions: OLS & IV Results

Table 1: Wage regressions (AI Exposure: Occupation-LMR-level)

| | Dependent Variable: Log Wages | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **IV**: AI Share (Occ-LMR) | 1.10*** | 0.73*** | 0.01 | 0.16** |
| | (0.21) | (0.18) | (0.12) | (0.06) |
| **OLS**: AI Share (Occ-LMR) | 1.43*** | 1.30*** | 0.07 | 0.07*** |
| | (0.19) | (0.15) | (0.05) | (0.01) |
| Socio, Year FE, Work, Firm | ✓ | ✓ | ✓ | ✓ |
| LMR FE | | ✓ | ✓ | ✓ |
| Occupation FE | | | ✓ | ✓ |
| Worker FE | | | | ✓ |
| AI Share (Occ-LMR) Mean | 0.012 | | | |
| Fstat (1st stage) | 1,590.9 | 1,045.1 | 947.6 | 856.4 |
| Observations | 2,239,937 | 2,239,937 | 2,239,937 | 2,239,937 |
| R-squared (IV) | 0.30 | 0.12 | 0.10 | 0.22 |

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls start from model (2) and include establishment size and industry (WZ08, 2-digit). Firm quality, LMR FE, Occupation FE, and Panel FE are introduced in models (3) and (4) respectively, indicating a progression in the complexity of the model.

- **IV**: 10% AI Share ↑ ⇒ Wage **0%** - ↑ **2%**
- **OLS**: 10% AI Share ↑ ⇒ Wage **0%** - ↑ **0.8%**

# Which variation matters?

$\Longrightarrow$ Perform Gelbach Decomposition (Gelbach 2016)

1. Estimate Base model

$$lnw_{ilot} = \beta_1^{Base} AI_{lot} + \epsilon_{ilot} \tag{3}$$

2. Estimate Full model

$$lnw_{ilot} = \beta_1^{Full} AI_{lot} + \beta_2 X_{it} + \beta_3 \delta_j + \beta_4 \psi_l + \beta_5 \omega_o + \beta_6 \theta_t + \epsilon_{ilot} \tag{4}$$

$\Longrightarrow \beta_1^{Full} \neq \beta_1^{Base}$

3. Estimate auxiliary wage regressions and decompose wage gap
   - How much $\Delta\beta_1$ when $\beta_1^{Base} \Rightarrow \beta_1^{Full}$ attributed to each X?
   - Scale unique contributions with impact on wages

# Decomposition Results

Table 2: Gelbach Decomposition (AI Exposure: Occupation-LMR-level)

| | Dependent Variable: Log Wages | |
|---|---|---|
| AI Share Decomp. | (Absolute) | (Relative) |
| Occup FE | 1.78*** | 0.36 |
| Socioeconomics | 1.38*** | 0.28 |
| Firm Quality (AKM) | 1.04*** | 0.21 |
| Firm | 0.59*** | 0.12 |
| LMR FE | 0.30*** | 0.06 |
| Year FE | 0.03*** | 0.01 |
| Work | -0.14** | -0.03 |
| Total | 4.98*** | 100 % |

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and industry (WZ08, 2-digit). Firm quality is proxied the avg. wage in workers' establishment.

– 85% of AI-induced wage effects due to **firm quality**, **socioeconomic** characteristics & **occupational characteristics**

# Mechanisms

1. **Occupational Heterogeneity**
   - Positive wage effects associated with task complexity ▸ Skill levels
   - Higher outside option value of occupations raise wages ▸ OOOI
2. **LM Competition**
   - Workers in less concentrated markets benefit more from rising AI demand ▸ HHI (OJV) ▸ HHI (AI OJV)
3. **Mobility**
   - Wage effects pronounced among occupationally mobile workers
   - Regional mobility less important ▸ Mobility
4. **Worker Heterogeneity**
   - Primary beneficiaries: Younger workers w/ college degree ▸ Age ▸ Education ▸ Gender
5. **Firm Quality**
   - Medium-Q firms pay higher wages for AI skills ▸ Productivity

# Robustness/ Work in Progress

- **Work in Progress/ Future Outlook**
  - Validation of IV
  - Alternative IV strategies
- **Robustness/ Extended Results**
  - Alternative AI measures
    - AI applications vs methods
    - Intensity-based measure (AI skill intensity)
  - AI skills vs Digital skills
  - Extension of Gelbach Decomposition to accomodate IV
  - Different clustering
  - More flexible FE specifications (LMR-time, occupation-time, ...)

# Conclusions

- **Analysis of AI-induced wage effects**
  - AI Skill Demand $\uparrow \Rightarrow$ Wages $\uparrow$ 0.8 - 2.0%
  - 85% of AI-induced wage effects due to (i) Employer Quality, (ii) Socioeconomic, and (iii) Occupational characteristics
- **Policy Implications**
  - Targeted Skill Development $\Rightarrow$ Education Curricula, Training
  - Labor shortages $\Rightarrow$ Support Job Mobility, More Competition
- **Future Research**
  - Matching: Skill Demand + Skill Supply
  - LM Competition: AI and Imperfect LMs
  - Employer quality: Firm-level adoption (Linked EE)

# Literature: AI diffusion in Germany

- (Worker-level) Survey Data
  - 20% —if asked directly (Giering et al. 2021)
  - 45% —if asked indirectly (ibid.)
- (Firm-level) Survey Data
  - 4.0 Technologies
    - 22% as of 2016 (Genz et al. 2021)
  - AI adoption
    - 5.8% as of 2019 (Rammer 2022)
    - 10.1 - 11.0% as of 2021 (ibid.)
- OJV Data
  - 1% of all OJV postings mention AI skills (BGT.2022)

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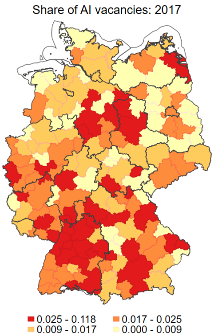
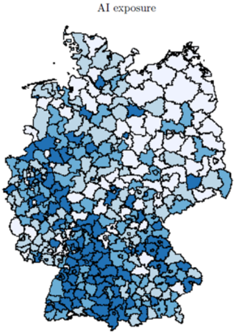
# Identification: Spatial variation of AI exposure




(a) AI demand based on OJV: 2017




(b) AI exposure based on patents: 2018

NOTE. —Panel (b) is taken from Gathmann & Grimm (2022, Fig. 3, p. 28) and defines local AI exposure based on a combination of number of patents and local industry mix.

Figure 5: OJV-and Patent-based exposure to AI in Germany, 2017-18

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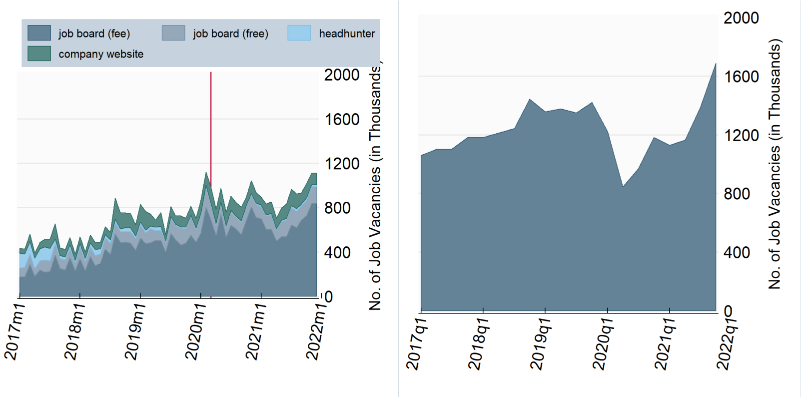
# Data: OJV - Validity over time




(a) OJV data, by source (Inflow)

(b) IAB Vacancy Panel (Stock)

Figure 6: Number of Online Job Vacancies over Time, 2017-01 - 2021-12

# Data: OJV - Validity by industries

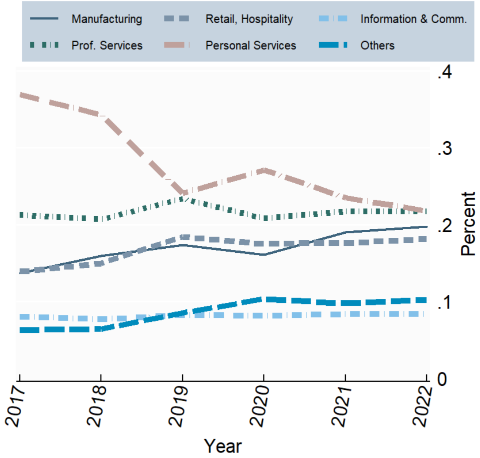
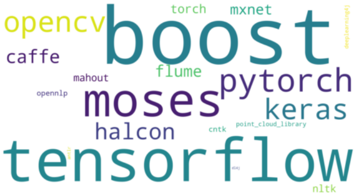



Figure 7: Industry Composition of Online Job Vacancies year, 2017 - 2021

# Word Cloud: AI Tools Skills




NOTE. ——**AI tools summarize tools and software packages commonly deployed.**

Figure 8: Word cloud of AI tools

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# Summary Statistics: AI Postings

Table 3: Summary Statistics: Postings with and without AI skill demand

| | AI OJV | Non-AI OJV | Difference |
|---|---|---|---|
| Firm: Age | 22.07 | 21.69 | -0.39*** |
| Firm: Avg. No. Job Postings per Month | 2.82 | 2.20 | -0.62*** |
| Firm: Workforce size | 9,027 | 2,834 | -6,193*** |
| Firm: Revenue | 381,939 | 200,819 | -181,120*** |
| Share of OJV w/ AI skills: TOOLS | 0.01 | 0.00 | -0.01*** |
| Share of OJV w/ AI skills: METHODS | 0.05 | 0.00 | -0.05*** |
| Share of OJV w/ AI skills: APPLICATIONS | 0.06 | 0.00 | -0.06*** |
| Share of OJV requiring NRA tasks | 0.71 | 0.63 | -0.07*** |
| Share of OJV requiring NRI tasks | 0.84 | 0.82 | -0.02*** |
| Share of OJV requiring RC tasks | 0.50 | 0.46 | -0.04*** |
| Share of OJV requiring RM tasks | 0.39 | 0.37 | -0.02*** |
| Share of OJV requiring NRM tasks | 0.44 | 0.41 | -0.03*** |
| Observations | 2,210,584 | 7,480,354 | 9,690,938 |

*Note:* Standard errors in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

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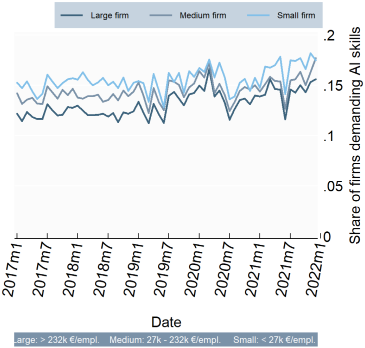
# Fact #4: Demand for AI skills by Revenue/Employee

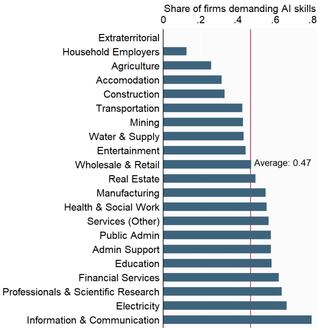



NOTE. —Small firms are defined as those at or below the 25th percentile of the firm revenue/employee distribution. Old firms "AI firms" are defined as those at or above the 75th percentile of the firm revenue/employee distribution. Medium firms are defined as those above the 25th and below the 75th percentile of the firm revenue/employee distribution.

Figure 9: Share of German firms posting AI skills in online job vacancies, 2017 - 2021 —by revenue per employee

- Advantage of large firms vanishes once accounting for revenue/employee ▸ Return

# Fact #5: Demand for AI skills varies by industry




NOTE. —Industries are defined at the 1-digit level. The industry share of firms demanding AI skills is based on the share of firms within each industry that demanded at least one AI skill at any point between 2017 - 2021/21.

Figure 10: Share of German firms posting AI skills in online job vacancies, 2017 - 2021 —by industry

- But: Wide variation in demand for AI skills across industries (up to 60 pp.) More stylized facts Firm-level regressions

# Fact #6: Share of AI firms has increased over time


(a) AI firms

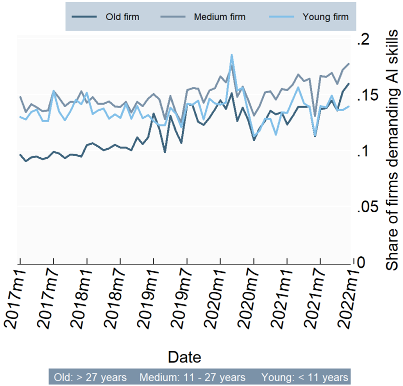
(b) AI firms

NOTE. —Firms are defined as an "AI firm" if they have at least one AI-related skill in a job posting in a given month. Both panels are based on a definition of AI skills comprising skills regarding tools, applications, and methods.

Figure 11: Trends in AI Demand, 2017/01 - 2021/12

- 4.4% YoY growth from 2017/1 - 2021/12 Context

# Fact #7: Younger firms demand more AI skills

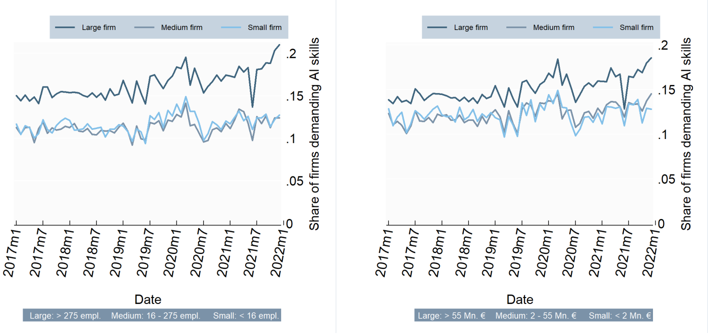



NOTE. —Young firms are defined as those at or below the 25th percentile of the firm age distribution. Old firms "AI firms" are defined as those at or above the 75th percentile of the firm age distribution. Medium firms are defined as those above the 25th and below the 75th percentile of the firm age distribution.

Figure 12: Share of German firms posting AI skills in online job vacancies, 2017 - 2021 —by firm age

- But: Older firms have caught up in recent years

# Fact #8: Large firms demand more AI skills




(a) By workforce (b) By revenue

NOTE. —Small firms are defined as those at or below the 25th percentile of the firm size distribution. Large firms are defined as those at or above the 75th percentile of the firm size distribution. Medium firms are defined as those above the 25th and below the 75th percentile of the firm size distribution.

Figure 13: Share of German firms posting AI skills in online job vacancies, 2017 - 2021 —by firm size

- Novel insight: Dominance of large firms more pronounced wrt workforce rather than revenue ▸ Return

# AI Tiers: Definition

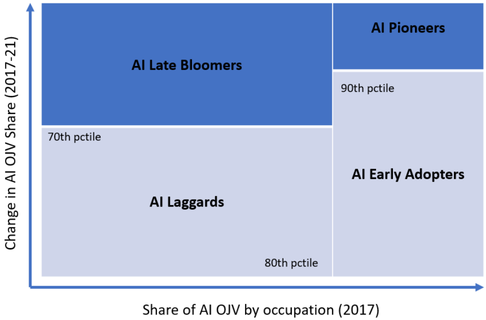



Figure 14: Illustration of AI Tiers

NOTE. —AI PIONEERS are defined as occupations whose (i) share of AI OJV in 2017 ranked $\geq p80$ and (ii) change in the share of AI OJV ranked in $\geq\geq p90$. For AI EARLY ADOPTERS: (i) share of AI OJV in 2017 ranked $\geq p80$, but (ii) change in the share of AI OJV ranked $< p80$. For AI LATE BLOOMERS: (i) share of AI OJV in 2017 ranked $< p80$, but (ii) change in the share of AI OJV ranked $\geq p75$. For AI LAGGARDS: (i) share of AI OJV in 2017 ranked $< p80$, and also (ii) change in the share of AI OJV ranked $< p70$.

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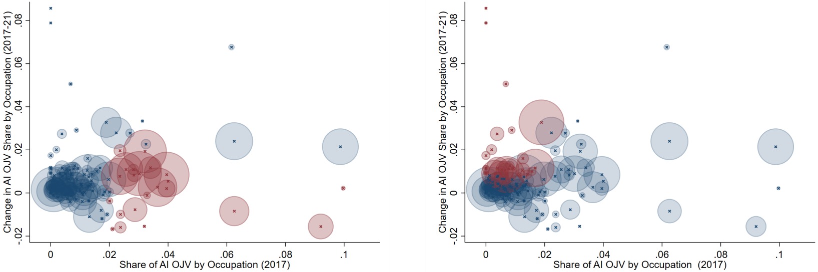
# AI Occupations: Early Adopters & Late Bloomers




(a) AI Early Adopter

(b) AI Late Bloomers

NOTE. —The X-axis displays the share of OJV with AI demand ("AI Vacancies") for 140 3-d occupations as of 2017.

The Y-axis displays the change in AI Vacancies between 2017 - 2021 for each occupation.

Figure 15: Dynamics in occupational demand for AI skills (Early Adopters and Late Bloomers

Return

# Worker flows between AI Groups

Table 4: Origin Occupations of AI Pioneers (Top 3)

| Destination Occupation | Origin Occup. | Share Unique Transitions (in %) |
|---|---|---|
| Computer Science (KLdB: 431) | IT-Network Eng./Coord./Admin. (433) | 19.6 |
| | Software Development And Programming (434) | 17.5 |
| | Business Organisation And Strategy (713) | 17.1 |
| | Electrical Engineering (263) | 16.0 |
| | IT-System Analysis/Sales (432) | 11.5 |
| Mathematics and Statistics (411) | Business Organisation And Strategy (713) | 29.4 |
| | Office Clerks And Secretaries (714) | 22.5 |
| | Insurance And Financial Services (721) | 22.5 |
| | Teachers & Researchers (Uni) (843) | 16.5 |
| | Technical Research And Development (271) | 1.8 |
| Software Development and Programming (434) | IT-System Analysis/Sales (432) | 44.2 |
| | Computer Science (431) | 20.8 |
| | Technical Research And Development (271) | 9.2 |
| | Business Organisation And Strategy (713) | 7.1 |
| | IT-Network Eng./Coord./Admin. (433) | 5.6 |

NOTE. —Destination occupations represent the AI Pioneers. Origin occupation represent occupations from which workers most frequently originate from when switching to an AI Pioneer.

$\Longrightarrow$ Worker flows into AI Pioneers concentrated in 3 - 5 occupations

$\Longrightarrow$ Who's primarily attracted by AI Pioneer Jobs?

- IT, Business Mgmt., Electrical Engineering/ Technical R&D

Return

# Worker flows in AI Tiers

Table 5: Origin Occupations of AI Pioneers (Top 4-5)

| Destination Occupation | Origin Occupation | Share Unique Transitions (in %) |
|---|---|---|
| Social Sciences (913) | Education & Social Work (831) | 91.6 |
| | Office Clerks And Secretaries (714) | 2.7 |
| | Business Organisation And Strategy (713) | 1.8 |
| | Teachers & Researchers (Uni) (843) | 0.8 |
| | Teachers (General Educ.) (841) | 0.5 |
| Media, Documentation & Info. Services (733) | Office Clerks And Secretaries (714) | 49.3 (714) |
| | Public Administration (732) | 15.9 |
| | Nursing & EMS (813) | 9.2 |
| | Business Organisation And Strategy (713) | 5.7 |
| | Doctors' Receptionists and Assistants (811) | 5.0 |

NOTE. —Destination occupations represent the AI Pioneers. Origin occupation represent occupations from which workers most frequently originate from when switching to an AI Pioneer.

Return

# Worker flows in AI Tiers

Table 6: Origin Occupations of AI Pioneers (Top 6-7)

| Destination Occupation | Origin Occupation | Share Unique Transitions (in %) |
|---|---|---|
| IT-System Analysis/Sales (432) | Business Organisation And Strategy (713) | 32.6 |
| | Computer Science (431) | 16.4 |
| | Software Development And Programming (434) | 13.1 |
| | IT-Network Eng./Coord./Admin. (433) | 12.1 |
| | Electrical Engineering (263) | 9.2 |
| Insurance And Financial Services (721) | Business Organisation And Strategy (713) | 39.1 |
| | Office Clerks And Secretaries (714) | 29.1 |
| | Accounting/Controlling And Auditing (722) | 8.7 |
| | Purchasing And Sales (611) | 8.4 |
| | Advertising And Marketing (921) | 4.8 |

NOTE. —Destination occupations represent the AI Pioneers. Origin occupation represent occupations from which workers most frequently originate from when switching to an AI Pioneer.

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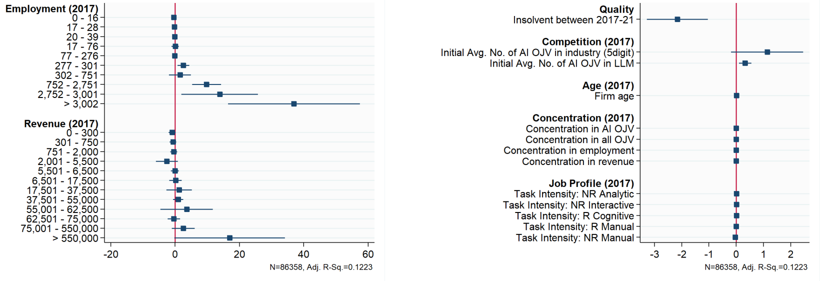
# Firm-level Analysis: OLS

$$
\begin{aligned}
\Delta AI_{ijl}^{(t+n)-t} =& \beta_1 Size_{ijl}^{2017} + \beta_2 Age_{ijl}^{2017} + \beta_3 Qual_{ijl} \\
& + \beta_4 Comp_{ijl}^{2017} + \beta_5 Conc_{ijl}^{2017} + \beta_6 Profile_{ijl}^{t} \\
& + \gamma X_l^{2017} + \gamma Ind_j + \epsilon_{ijl}
\end{aligned} \tag{5}
$$

- $AI_{ijl}^{(t+n)-t}$ = change of AI postings for firm $i$
- $Size_{ijl}^{2017}$ = firm's employment and revenue
- $Age_{ijl}^{2017}$ = firm age
- $Qual_{ijl}$ = dummy for insolvency between 2017 and 2021
- $Comp_{ijl}^{2017}$ = baseline competition at regional/industry level
- $Conc_{ijl}^{2017}$ = concentration measure (HHI index)
- $Profile_{ijl}^{t}$ = firm's task requirement in the year of 1st appearance
- $X_l^{2017}$ & $Ind_j$: regional controls and industry FE at 3-digit level

# Firm-level Analysis: OLS




NOTE. —Point estimates are displayed with a 95% Confidence Interval.

Figure 16: Firm-level regressions of the change in AI vacancies, 2017-2021

Return

# Top 10 Occupations by OOOI

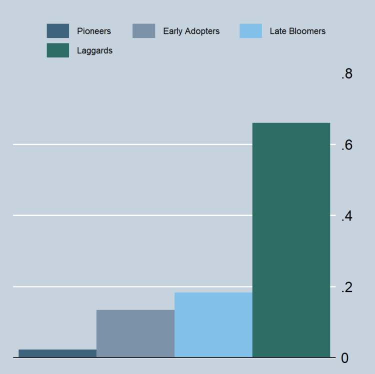
Table 7: OOOI and AI Share by Occupation (Top 10 by OOOI)

| Occupation | OOOI | OJV AI Share |
|---|---|---|
| Aircraft Pilots | 2.29 | 11% |
| **Software Development and Programming** | 1.40 | 12% |
| **IT-System Analysis/Sales** | 1.25 | 6% |
| **Insurance and Financial Services** | 1.06 | 5% |
| IT-Network Eng./Coord./Admin. | 1.03 | 7% |
| **Computer Science** | 0.93 | 16% |
| Editorial Work/Journalism | 0.88 | 8% |
| Accounting/Controlling And Auditing | 0.66 | 3% |
| Public Relations | 0.66 | 4% |
| Technical R&D | 0.65 | 15% |

NOTE. —This table provides the OOOI and share of vacancies with AI demand for the 10 occupations with the highest values for OOOI. The OOOI is standardized with mean zero and standard deviation one. The average OJV AI share for the full sample is 4%. The correlation between OOOI and the OJV AI Share is 0.29.

Return

# Employment Shares of AI Tiers




NOTE. —AI PIONEERS are defined as occupations whose (i) share of AI OJV in 2017 ranked $\geq p80$ and (ii) change in the share of AI OJV ranked in $\geq > p90$. For AI EARLY ADOPTERS: (i) share of AI OJV in 2017 ranked $\geq p80$, but (ii) change in the share of AI OJV ranked $< p80$. For AI LATE BLOOMERS: (i) share of AI OJV in 2017 ranked $< p80$, but (ii) change in the share of AI OJV ranked $\geq p75$. For AI LAGGARDS: (i) share of AI OJV in 2017 ranked $< p80$, and also (ii) change in the share of AI OJV ranked $< p70$.

Figure 17: Employment Share of AI Occupational Tiers

Return

# Matching Results: Variation at LMR-level (coarse, unweighted)

Table 8: Wage Regressions (unweighted)

| | Dependent Variable: log wages | | | | |
|---|---|---|---|---|---|
| | (Full) | (Pioneers) | (Early Adopters) | (Late Bloomers) | (Laggards) |
| AI Region (Treated) | 0.011 | 0.028* | 0.002 | 0.022** | 0.009 |
| | (0.007) | (0.014) | (0.006) | (0.009) | (0.006) |
| Socio, Work, Firm Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| 1d Occupation FE | ✓ | ✓ | ✓ | ✓ | |
| AI Share (LMR) | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 |
| Observations | 2,617,063 | 63,765 | 502,783 | 354,067 | 1,696,448 |
| R-squared | 0.56 | 0.49 | 0.53 | 0.58 | 0.51 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and avg. wage in establishment.

return

# IV: Details Intuition

- **Intuition**
  - AI adoption pronounced among large firms (Rammer 2022) Desc
  - Large firms operate across many labor markets (Rossi-Hansberg, Sarte, and Trachter 2020)
  - LMRs differentially exposed to different large firms, but broadly similar to frontier technologies (Azar et al. 2020)

Return

# Matching Results: Variation at LMR-level (granular, unweighted

Table 9: Wage Regressions (unweighted)

| | Dependent Variable: log wages | | | | |
|---|---|---|---|---|---|
| | (Full) | (Pioneers) | (Early Adopters) | (Late Bloomers) | (Laggards) |
| AI Share (Region) | 0.093 | 0.159 | 0.075 | 0.267** | 0.066 |
| | (0.084) | (0.223) | (0.093) | (0.121) | (0.071) |
| Socio, Work, Firm Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| 1d Occupation FE | ✓ | ✓ | ✓ | ✓ | |
| Observations | 2,617,063 | 63,765 | 502,783 | 354,067 | 1,696,448 |
| R-squared | 0.56 | 0.49 | 0.53 | 0.58 | 0.51 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and avg. wage in establishment.

return

# Matching Results: Variation at Occup.-LMR-level (unweighted

Table 10: Wage Regressions (unweighted)

| | Dependent Variable: log wages | | | | |
|---|---|---|---|---|---|
| | (Full) | (Pioneers) | (Early Adopters) | (Late Bloomers) | (Laggards) |
| AI Share (Occ × LMR) | 0.387*** | -0.149*** | 0.038 | 0.072 | 0.344*** |
| | (0.070) | (0.070) | (0.050) | (0.051) | (0.088) |
| Socio, Work, Firm Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| 1d Occupation FE | ✓ | ✓ | ✓ | ✓ | |
| AI Share (LMR) | 0.02 | 0.02 | 0.02 | 0.02 | 0.02 |
| Observations | 2,239,971 | 60,824 | 472,676 | 299,044 | 1,407,427 |
| R-squared | 0.56 | 0.48 | 0.53 | 0.58 | 0.50 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and avg. wage in establishment.

return

# Decomposition of AI employment dynamics

$$\Delta N_{t,t-1}^{AI} = inflows - outflows \tag{6}$$

$$inflows = N_{t-1,t}^{notAI,AI} + N_{t-1,t}^{NLF,AI} + N_t^{\cdot,AI} \tag{7}$$

$$outflows = N_{t-1,t}^{AI,notAI} + N_{t-1,t}^{AI,NLF} \tag{8}$$

- $N_t^{AI}$: employment in AI occupations in year $t$
- $N_{t-1,t}^{notAI,AI}$: movers from a non-AI to an AI occupation
- $N_{t-1,t}^{NLF,AI}$: entrants into AI occupation from unemployment/inactivity
- $N_t^{\cdot,AI}$: new labour market entrants in AI occupations

# Worker flows between AI Groups

Table 11: AI Origin and Destionation Groups

| Destination AI Group | Origin Group | Origin Group (in %) |
|---|---|---|
| **Pioneers** | **Pioneers** | 28 |
| | Early Adopters | 33 |
| | Late Bloomers | 22 |
| | Laggards | 18 |
| **Early Adopters** | Pioneers | 5 |
| | **Early Adopters** | 28 |
| | Late Bloomers | 17 |
| | Laggards | 49 |
| **Late Bloomers** | Pioneers | 5 |
| | Early Adopters | 28 |
| | **Late Bloomers** | 12 |
| | Laggards | 54 |
| **Laggards** | Pioneers | 1 |
| | Early Adopters | 20 |
| | Late Bloomers | 12 |
| | **Laggards** | 68 |

NOTE. —Destination AI Groups represent occupations to which workers transition to. Origin Groups represent the categories from which workers most frequently originate from when transitioning to a different AI group.

$\Longrightarrow$ Pioneers stick with one another, yet, AI Jobs accessible

1-3 4-5 6-7

# What determines transitions into occupations?

- **Outside-Occupation Option Idx** (OOOI) (Schubert, Stansbury, and Taska 2023)

$$oooi_{o,l,t} = \underbrace{\sum_{o \neq d}^{N_{occ}} \pi_{d \Rightarrow o}}_{\text{Worker Flows}} \times \underbrace{\frac{s_{d,l,t}}{s_{d,t}}}_{\text{Employment Shares}} \times \underbrace{\bar{w_{d,l,t}}}_{\text{Average Wages}} \qquad (9)$$

- **LM Concentration**: HHI (Herfindahl–Hirschman index)

$$hhi_{o,l,t} = \sum_{i=1}^{N_{firm}} \left( \frac{v_{i,o,l,t}}{\sum_{i=1}^{N_{firm}} v_{i,o,l,t}} \right)^2 \qquad (10)$$

Top 10 OOOI Occupations

# OOOI: Logit Regressions

$$P(OC=1) = \beta_1 OOOI_{ol,t-1} + \beta_2 HHI_{ol,t-1} + \beta_3 X_{it} + \beta_4 \delta_j + \beta_5 \psi_l + \beta_6 \theta_t + \epsilon_{ilt} \quad (11)$$

- $P(OC=1)$: Dummy $=1$ if worker $i$ changed occupation
- $X_{it}$, $\delta_j$, $\psi_l$, $\theta_t$: Controls, Industry FE (1d), state FE, Year FE

Table 12: Logit of Occupational change on lagged OOOI, by AI Tiers

| | Dependent Variable: Indicator for occupational change | | | | |
|---|---|---|---|---|---|
| | All | Pioneers | Early Adopter | Late Bloomer | Laggards |
| OOOI (t-1) | -0.027 | -0.071 | -0.079 | -0.086 | -0.004 |
| | (0.048) | (0.073) | (0.062) | (0.055) | (0.052) |
| HHI (t-1) | 0.035 | 2.064*** | 2.198*** | 0.530*** | -0.391*** |
| | (0.087) | (0.943) | (0.382) | (0.154) | (0.131) |
| Socio, Work, Firm Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 1,494,705 | 38,147 | 325,398 | 195,373 | 935,787 |
| Pseudo R-squared | 0.19 | 0.19 | 0.17 | 0.20 | 0.22 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and avg. wage in establishment.

- 0.15 $\uparrow$ HHI $\Rightarrow$ Mobility $\uparrow$ 8-30% (AI) & $\downarrow$ 6% (Laggard)

# OOOI: Wage Regressions

$$lnw_{ilot} = \beta_1 OOOI_{olt} + \beta_2 HHI_{olt} + \beta_3 X_{it} + \beta_4 \delta_j + \beta_5 \psi_l + \beta_6 \theta_t + \epsilon_{ilt} \quad (12)$$

Table 13: Wage regressions on OOOI, by AI Tiers

| | Dependent Variable: Log Wages | | | | |
|---|---|---|---|---|---|
| | All | Pioneers | Early Adopter | Late Bloomer | Laggards |
| OOOI | 0.019*** | 0.014*** | 0.015*** | 0.010*** | 0.027*** |
| | (0.002) | (0.002) | (0.003) | (0.002) | (0.003) |
| HHI | -0.098*** | 0.095*** | -0.029 | -0.049** | -0.042*** |
| | (0.014) | (0.033) | (0.022) | (0.023) | (0.011) |
| Socio, Work, Firm Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Observations | 1,848,398 | 46,138 | 403,623 | 239,105 | 1,159,532 |
| R-squared | 0.57 | 0.47 | 0.53 | 0.58 | 0.51 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and avg. wage in establishment.

- 1 SD $\uparrow$ OOOI $\Rightarrow$ Daily Wage $\uparrow$ 1 -3%
- 0.15 $\uparrow$ HHI $\Rightarrow$ Wage $\uparrow$ 2% (Pioneers) & $\downarrow$ 1% (Others)

# Matching Procedure

- Treatment: LLM in Top Quartile of AI demand in 2017
- 2-stage matching procedure(Hethey-Maier and Schmieder 2013; Blien, Dauth, and Roth 2021; Arntz, Ivanov, and Pohlan 2022)
  1. Exact matching: Year × Occupation (1-digit)
  2. Coarsened & Propensity Score (PS) matching (NNM)
     - Coarsened: Socioeconomic characteristics
     - PS: Urbanity, work, firm

$$lnw_{ilot} = \beta_1 + \beta_2 AI_{lot} + \beta_3 X_{it} + \epsilon_{ilt} \tag{13}$$

– $lnw_{ilot}$: log daily wage of worker $i$ in LLM $l$ in occupation $o$ at time $t$

– $AI_{lot}$: Share of AI OJV (Occupation ×)-LRM-level

– $X_{it}$: Controls

# Covariate Balancing

Table 14: Covariate table matching

| | Treated Workers | | Control Workers | |
|---|---|---|---|---|
| | mean | sd | mean | sd |
| Women | 0.43 | 0.50 | 0.42 | 0.49 |
| Men | 0.57 | 0.50 | 0.58 | 0.49 |
| No vocational training | 0.07 | 0.26 | 0.07 | 0.26 |
| Vocational training | 0.67 | 0.47 | 0.69 | 0.46 |
| University degree | 0.25 | 0.43 | 0.24 | 0.43 |
| Age | 43.22 | 11.74 | 43.46 | 11.72 |
| Foreign | 0.15 | 0.36 | 0.11 | 0.32 |
| Work experience | 6246.45 | 3940.52 | 6296.35 | 3943.34 |
| Tenure at firm | 3041.11 | 3131.13 | 3031.62 | 3119.70 |
| Tenure | 2740.72 | 2954.88 | 2739.74 | 2928.92 |
| Establishment size | 1.35 | 0.97 | 1.35 | 0.97 |
| Wage firm (mean) | 131.10 | 59.87 | 128.13 | 53.85 |
| Agglomerated Areas | 0.56 | 0.50 | 0.60 | 0.49 |
| Urbanized Areas | 0.36 | 0.48 | 0.32 | 0.47 |
| Rural Areas | 0.07 | 0.25 | 0.08 | 0.27 |
| Observations | 658.564 | | 320.425 | |

# Matching Results: Variation at LMR-level (coarse)

Table 15: Wage Regressions (PS weighted)

| | Dependent Variable: log wages | | | | |
|---|---|---|---|---|---|
| | Full | Pioneers | Early Adopters | Late Bloomers | Laggards |
| AI Region (Treated) | -0.005 | -0.009 | -0.017* | 0.025** | -0.000 |
| | (0.007) | (0.016) | (0.009) | (0.012) | (0.009) |
| Socio, Work, Firm Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| 1d Occupation FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| AI Share (LMR) | 0.025 | 0.025 | 0.025 | 0.025 | 0.025 |
| Observations | 768,406 | 25,439 | 186,813 | 106,796 | 449,358 |
| R-squared | 0.57 | 0.46 | 0.54 | 0.56 | 0.52 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and avg. wage in establishment.

- AI OJV Share $\uparrow \Rightarrow$ Daily Wage —

unweighted

# Matching Results: Variation at LMR-level (granular)

Table 16: Wage Regressions (PS weighted)

| | Dependent Variable: log wages | | | | |
|---|---|---|---|---|---|
| | Full | Pioneers | Early Adopters | Late Bloomers | Laggards |
| AI Share (Region) | -0.128 | -0.565* | -0.039 | -0.023 | -0.167* |
| | (0.096) | (0.294) | (0.124) | (0.194) | (0.096) |
| Socio, Work, Firm Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| 1d Occupation FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| AI Share Mean (LMR) | 0.025 | | | | |
| Observations | 768,406 | 25,439 | 186,813 | 106,796 | 449,358 |
| R-squared | 0.57 | 0.46 | 0.54 | 0.57 | 0.52 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and avg. wage in establishment.

– AI OJV Share ↑ ⇒ Daily Wage —

unweighted

# Matching Results: Variation at Occup.-LMR-level

Table 17: Wage Regressions (PS weighted)

| | Dependent Variable: log wages | | | | |
|---|---|---|---|---|---|
| | Full | Pioneers | Early Adopters | Late Bloomers | Laggards |
| AI Share (Occup $\times$ LMR) | 0.296*** | -0.314*** | -0.027 | 0.009 | 0.251*** |
| | (0.080) | (0.093) | (0.537) | (0.127) | (0.083) |
| Socio, Work, Firm Controls | ✓ | ✓ | ✓ | ✓ | ✓ |
| State FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| 1d Occupation FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| AI Share Mean (Occ $\times$LMR) | 0.02 | | | | |
| Observations | 768,406 | 25,439 | 186,813 | 106,796 | 449,358 |
| R-squared | 0.57 | 0.46 | 0.54 | 0.56 | 0.52 |

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and avg. wage in establishment.

– 10% ↑ AI OJV Share ⇒ Daily Wage ↑ 6%

unweighted

# Mechanism I: Occupational Heterogeneity AI Groups

Table 18: Wage Regressions by AI Groups (AI Exposure: Occupation-LMR-level)

| Dep. Var.: Log Wages | (1) |
|---|---|
| AI Share | 0.53*** |
| | (0.08) |
| Late Bloomers | 0.11*** |
| | (0.02) |
| Late Bloomers × AI Share | -0.44*** |
| | (0.07) |
| Early Adopters | 0.10*** |
| | (0.02) |
| Early Adopters × AI Share | -0.57*** |
| | (0.09) |
| Pioneers | 0.13*** |
| | (0.03) |
| Pioneers × AI Share | -0.87*** |
| | (0.16) |
| AI Share Laggards (mean) | 0.001 |
| AI Share Late Bloomers (mean) | 0.022 |
| AI Share Early Adopters (mean) | 0.044 |
| AI Share Pioneers (mean) | 0.075 |
| Observations | 2,239,971 |
| R-squared | 0.57 |

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —All specifications comprise socioeconomic, work, firm, and productivity controls, as well as year and LMR FE.

Return

# OOOI

- **Outside-Occupation Option Idx** (OOOI) (Schubert, Stansbury, and Taska 2023)

$$oooi_{o,l,t} = \underbrace{\sum_{o \neq d}^{N_{occ}} \pi_{d \Rightarrow o}}_{\text{Worker Flows}} \times \underbrace{\frac{s_{d,l,t}}{s_{d,t}}}_{\text{Employment Shares}} \times \underbrace{\bar{w_{d,l,t}}}_{\text{Average Wages}} \quad (14)$$

  - $\pi_{o \Rightarrow p}$: switching prob. from origin to destination occupation
  - $\frac{s_{dlt}}{s_{dt}}$: relative employment share of $d$ in (home) LMR
  - $\bar{w_{dkt}}$: avg. local wage in occupation d

# Wage Regressions: Results

Table 19: Wage regressions (AI Exposure: LMR-level)

| | Dependent Variable: Log Daily Wage | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| AI Share (LMR) | 4.71*** | 2.96*** | 2.67*** | 2.44*** | 1.68*** | 1.13*** | 0.07*** |
| | (0.86) | (0.68) | (0.66) | (0.64) | (0.48) | (0.27) | (0.02) |
| Year FE | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Occupation FE | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Socio | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Work | | | | ✓ | ✓ | ✓ | ✓ |
| Firm | | | | | ✓ | ✓ | ✓ |
| Firm Quality | | | | | | ✓ | ✓ |
| Panel FE | | | | | | | ✓ |
| AI Share (Reg) Mean | | | | 0.015 | | | |
| Observations | 2,617,063 | 2,617,063 | 2,617,063 | 2,617,063 | 2,617,063 | 2,617,063 | 2,617,063 |
| R-squared | 0.01 | 0.32 | 0.43 | 0.49 | 0.54 | 0.60 | 0.11 |

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and industry (WZ08, 2-digit). Firm quality is the avg. wage in workers' establishment.

– 10% AI Share ↑ ⇒ Wage ↑ **1.1%**

▸ Occ-LMR-level

# Wage Regressions: Results

Table 20: Wage regressions (AI Exposure: Occupation-level)

| | Dependent Variable: Log Daily Wage | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| AI Share (Occ) | 11.80** | 11.25** | 6.65* | 6.40* | 4.21* | 3.81* | 0.50*** |
| | (2.47) | (2.57) | (2.10) | (1.91) | (1.40) | (1.20) | (0.04) |
| Year FE | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| LMR FE | | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Socio | | | ✓ | ✓ | ✓ | ✓ | ✓ |
| Work | | | | ✓ | ✓ | ✓ | ✓ |
| Firm | | | | | ✓ | ✓ | ✓ |
| Firm Quality | | | | | | ✓ | ✓ |
| Panel FE | | | | | | | ✓ |
| AI Share (Occ) Mean | | | | 0.011 | | | |
| Observations | 2,617,063 | 2,617,063 | 2,617,063 | 2,617,063 | 2,617,063 | 2,617,063 | 2,617,063 |
| R-squared | 0.10 | 0.13 | 0.34 | 0.41 | 0.49 | 0.57 | 0.10 |

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and industry (WZ08, 2-digit). Firm quality is the avg. wage in workers' establishment.

– 10% AI Share $\uparrow \Rightarrow$ Wage $\uparrow$ **5.5%**

Occ-LMR-level

# Mechanism I: Occupational Heterogeneity OOOI

Table 21: Wage Regressions by OOOI (AI Exposure: Occupation-LMR-level)

| Dep. Var.: Log Wages | (1) | (2) |
|---|---|---|
| AI Share | -0.09 | 0.05** |
| | (0.05) | (0.02) |
| Medium OOOI | 0.00 | 0.01* |
| | (0.00) | (0.00) |
| Medium OOOI × AI Share | 0.11 | -0.00 |
| | (0.08) | (0.02) |
| High OOOI | 0.01* | -0.00 |
| | (0.00) | (0.01) |
| High OOOI × AI Share | 0.41** | 0.12*** |
| | (0.13) | (0.03) |
| AI Share low OOOI | 0.018 | |
| AI Share medium OOOI | 0.018 | |
| AI Share high OOOI | 0.022 | |
| LMR FE | ✓ | ✓ |
| Occupation FE | ✓ | ✓ |
| Panel FE | | ✓ |
| Observations | 2,239,971 | 2,239,971 |
| R-squared | 0.57 | 0.62 |

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —All specifications comprise socioeconomic, work, firm, and productivity controls, and year FE.

– **High OOOI**: 10% AI Share ↑ ⇒ Wage ↑ **3%**

▸ Return

# Mechanism II: Mobility

Table 22: FE Wage regressions Mobility (AI Exposure: Occupation-LMR-level)

| | Dependent Variable: Log Wages | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Same Lmr & Occ | | Same Lmr & Diff Occ | | Diff Lmr & Same Occ | | Diff Lmr & Occ | |
| AI Share (Occ-LMR) | 0.03*** | 0.02** | 0.09*** | 0.00** | 0.00 | 0.03 | 0.10*** | -0.0 |
| | (5.4) | (3.8) | (5.2) | (0.3) | (0.4) | (1.2) | (4.2) | (-0.1) |
| AI Share (Occ-LMR) Mean | | | | 0.02 | | | | |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| LMR FE | ✓ | | ✓ | | ✓ | | ✓ | |
| Occupation FE | | ✓ | | ✓ | | ✓ | | ✓ |
| Observations | 1,650,743 | 1,650,743 | 288,787 | 288,787 | 125,196 | 125,196 | 175,245 | 175,245 |

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —All specifications incldue socioeconomic, work, and firm quality controls. Socioeconomic controls include age, citizenship, education, and gender. Work controls include LM experience, establishment tenure, and job tenure. Firm controls include establishment size and industry (WZ08, 2-digit). Firm quality is the avg. wage in workers' establishment.

- **Same LMR & Diff Occ**: 10% AI Share $\uparrow \Rightarrow$ Wage $\uparrow$ **1.8%**
- **Diff LMR & Occ**: 10% AI Share $\uparrow \Rightarrow$ Wage $\uparrow$ **2%**

Return

# HHI

- **LM Concentration**: HHI (Herfindahl–Hirschman index)

$$hhi_{o,l,t} = \sum_{i=1}^{N_{firm}} \left( \frac{v_{i,o,l,t}}{\sum_{i=1}^{N_{firm}} v_{i,o,l,t}} \right)^2 \tag{15}$$

# Mechanism III: Labour Market Concentration

Table 23: Wage Regressions by OJV HHI (AI Exposure: Occupation-LMR-level)

| Dep. Var.: Log Wages | (1) | (2) |
|---|---|---|
| AI Share | 0.15 | 0.10** |
| | (0.08) | (0.02) |
| OJV HHI | -0.01 | 0.01 |
| | (0.01) | (0.00) |
| OJV HHI × AI Share | -0.48 | -0.16* |
| | (0.36) | (0.07) |
| AI Share (Occ-LMR) Mean | 0.02 | |
| LMR FE | ✓ | ✓ |
| Occupation FE | ✓ | ✓ |
| Panel FE | | ✓ |
| Observations | 2,239,971 | 2,239,971 |
| R-squared | 0.57 | 0.62 |

robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —All specifications comprise socioeconomic, work, firm, and productivity controls, and year FE.

– For avg. AI Share: 10% ↑ HHI ⇒ Wage ↓ **0.4%**

Return

# Mechanism III: AI Market Concentration

Table 24: Wage Regressions by AI HHI (AI Exposure: Occupation-LMR-level)

| Dep. Var.: Log Wages | (1) | (2) |
|---|---|---|
| AI Share | 0.39** | 0.18*** |
| | (0.12) | (0.03) |
| OJV HHI AI | -0.01** | -0.01* |
| | (0.00) | (0.00) |
| OJV HHI AI × AI Share | -0.48** | -0.16*** |
| | (0.17) | (0.04) |
| AI Share (Occ-LMR) Mean | 0.02 | |
| LMR FE | ✓ | ✓ |
| Occupation FE | ✓ | ✓ |
| Panel FE | | ✓ |
| Observations | 2,239,971 | 2,239,971 |
| R-squared | 0.57 | 0.62 |

robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —All specifications comprise socioeconomic, work, firm, and productivity controls, and year FE.

– For avg. AI Share: 10% ↑ HHI ⇒ Wage ↓ **0.35%**

Return

# Mechanism IV: Worker differences - Education

Table 25: Wage Regressions by Education (AI Exposure: Occupation-LMR-level)

| Dep. Var.: Log Wages | (1) | (2) |
|---|---|---|
| AI Share | -0.16 | 0.03 |
| | (0.15) | (0.04) |
| Vocational Training | 0.06*** | 0.12*** |
| | (0.00) | (0.00) |
| Voc. Training × AI Share | 0.06 | -0.03 |
| | (0.16) | (0.05) |
| Tertiary Education | 0.37** | 0.25*** |
| | (0.01) | (0.01) |
| Tertiary Education × AI Share | 0.52** | 0.19*** |
| | (0.17) | (0.05) |
| AI Share no Voc. Training | 0.015 | |
| AI Share Voc. Training | 0.018 | |
| AI Share Tertiary Education | 0.030 | |
| LMR FE | ✓ | ✓ |
| Occupation FE | ✓ | ✓ |
| Panel FE | | ✓ |
| Observations | 2,239,971 | 2,239,971 |
| R-squared | 0.56 | 0.6 |

robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —All specifications comprise socioeconomic, work, firm, and productivity controls, and year FE.

– **Tertiary**: 10% AI Share ↑ ⇒ Wage ↑ **6%**

Return

# Mechanism IV: Worker differences - Skill

Table 26: Wage Regressions by Worker Skill level (AI Exposure: Occupation-LMR-level)

| Dep. Var.: Log Wages | (1) | (2) |
|---|---|---|
| AI Share | 0.36*** | -0.05 |
| | (0.09) | (0.03) |
| Skilled | 0.12*** | 0.03*** |
| | (0.00) | (0.00) |
| Skilled × AI Share | 0.47*** | 0.09* |
| | (0.10) | (0.04) |
| Specialist | 0.28*** | 0.07*** |
| | (0.00) | (0.00) |
| Specialist × AI Share | 0.59*** | 0.13** |
| | (0.13) | (0.04) |
| Expert | 0.43*** | 0.09*** |
| | (0.00) | (0.00) |
| Expert × AI Share | 0.29* | 0.20*** |
| | (0.13) | (0.05) |
| AI Share Unskilled Workers | 0.005 | |
| AI Share Skilled Workers | 0.010 | |
| AI Share Specialist Workers | 0.020 | |
| AI Share Expert Workers | 0.022 | |
| LMR FE | ✓ | ✓ |
| Occupation FE | ✓ | ✓ |
| Panel FE | | ✓ |
| Observations | 2,239,971 | 2,239,971 |
| R-squared | 0.63 | 0.65 |

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

- **Skilled**: 10% AI Share ↑ ⇒ Wage ↑ **1%**
- **Special.**: 10% AI Share ↑ ⇒ Wage ↑ **2.6%**
- **Expert**: 10% AI Share ↑ ⇒ Wage ↑ **4.4%**

▸ Return

# Mechanism IV: Worker differences - Age

Table 27: Wage Regressions by Age (AI Exposure: Occupation-LMR-level)

| Dep. Var.: Log Wages | (1) | (2) |
|---|---|---|
| AI Share | -1.32*** | 0.39*** |
| | (0.28) | (0.03) |
| Prime Age Workers (30-49) | 0.05*** | 0.05*** |
| | (0.00) | (0.00) |
| Prime Age Workers × AI Share | 1.37*** | -0.18*** |
| | (0.28) | (0.03) |
| Older Workers (50-65) | -0.02*** | 0.04*** |
| | (0.01) | (0.00) |
| Older Workers × AI Share | 2.30*** | -0.71*** |
| | (0.40) | (0.03) |
| AI Share Young Workers | 0.013 | |
| AI Share Prime-age Workers | 0.014 | |
| AI Share Older Workers | 0.012 | |
| LMR FE | ✓ | ✓ |
| Occupation FE | ✓ | ✓ |
| Panel FE | | ✓ |
| Observations | 2,239,971 | 2,239,971 |
| R-squared | 0.57 | 0.62 |

robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —All specifications comprise socioeconomic, work, firm, and productivity controls, and year FE.

- **Young (Prime-Age)**: 10% ↑ ⇒ Wage ↑ **5.1% (2.9%)**
- **Older**: 10% AI Share ↑ ⇒ Wage ↓ **3.8%**

Return

# Mechanism IV: Worker differences - Gender

Table 28: Wage Regressions by Gender (AI Exposure: Occupation-LMR-level)

| Dep. Var.: Log Wages | (1) | (2) |
|---|---|---|
| AI Share | -0.32*** | 0.11*** |
| | (0.08) | (0.02) |
| Men | 0.18*** | |
| | (0.1) | |
| Men $\times$ AI Share | 0.57*** | -0.04 |
| | (0.10) | (0.03) |
| AI Share Women | 0.012 | |
| AI Share Men | 0.013 | |
| LMR FE | ✓ | ✓ |
| Occupation FE | ✓ | ✓ |
| Panel FE | | ✓ |
| Observations | 2,239,971 | 2,239,971 |
| R-squared | 0.57 | 0.62 |

robust standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —All specifications comprise socioeconomic, work, firm, and productivity controls, and year FE.

- **Men**: 10% AI Share $\uparrow \Rightarrow$ Wage $\uparrow$ **1.4%**
- **Women**: 10% AI Share $\uparrow \Rightarrow$ Wage $\uparrow$ **1.3%**

Return

# Mechanism V: Firm productivity differences

Table 29: Wage Regressions by Firm Quality (AI Exposure: Occupation-LMR-level)

| Dep. Var.: Log Wages | (1) | (2) |
|---|---|---|
| AI Share | -0.08 | 0.05** |
| | (0.07) | (0.02) |
| Medium-Quality Firm | 0.23*** | 0.16*** |
| | (0.00) | (0.00) |
| Medium-Quality Firm × AI Share | 0.19* | 0.05* |
| | (0.08) | (0.03) |
| High-Quality Firm | 0.42*** | 0.29*** |
| | (0.01) | (0.00) |
| High-Quality Firm × AI Share | 0.31** | -0.03 |
| | (0.12) | (0.03) |
| AI Share LQ Firm | 0.008 | |
| AI Share MQ Firm | 0.013 | |
| AI Share HQ Firm | 0.017 | |
| LMR FE | ✓ | ✓ |
| Occupation FE | ✓ | ✓ |
| Panel FE | | ✓ |
| Observations | 2,239,971 | 2,239,971 |
| R-squared | 0.54 | 0.59 |

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

NOTE. —All specifications comprise socioeconomic, work, firm, and productivity controls, and year FE. The mean AI exposure for a medium-quality firms is 0.018 and for a high-quality firm 0.03.

- **HQ Firm**: 10% AI Share ↑ ⇒ Wage ↑ **0.9%**
- **MQ Firm**: 10% AI Share ↑ ⇒ Wage ↑ **1.3%**

Return