The Diffusion of Artificial Intelligence: Implications for Wages and Employment

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Definition of Artificial Intelligence (AI)

- "An AI system is a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI systems are designed to operate with varying levels of autonomy." (OECD 2022)

$\Longrightarrow$ The ability to learn with varying levels of autonomy distinguishes AI systems from earlier digital technologies

(Abrardi, Cambini, and Rondi 2022)

Motivation

(a) Singularity? (b) Substitutability? (c) Complementarity? (d) Fear?

Sources. —Panel (a): The Economist May 9th 2015, Panel (b): The Economist June 25th 2016, Panel (c): The Economist Jun 9th 2022, Panel (d): The Economist April 22nd 2023.

Figure 1: Promises & Perils of AI, The Economist: 2015 - 2022

- Growing (public) interest, esp. since inception of Chat GPT
- General purpose technology (Brynjolfsson, Mitchell, and Rock 2018) vs "*so-so* technology" (Acemoglu and Restrepo 2019)

Motivation

AI adoption still rare: $\Rightarrow$ Why should we care (already)?

1. **Rapidly growing technology!**
   - Share of German firms adopting AI nearly doubled between 2019-21 from 5.8% to 11.0% (Rammer 2022), reaching 13.3% in 2023 (Schaller et al. 2023).
2. **Changing skill requirements?**
   - Implications for productivity, wages (Brynjolfsson, Li, and Raymond 2023; Gilardi, Alizadeh, and Kubli 2023; Noy and Whitney 2023)
   - Displacement vs reinstatement effects (Acemoglu and Restrepo 2019)
3. **Different labor market effects than previous (automation) technologies?**
   - High-skilled workers (Webb 2020; Fossen and Sorgner 2022)

This Paper

1. **Analysis of demand for AI skills among German firms**
   - Stylized facts on the diffusion of AI in Germany
     - Novel online job vacancy data (OJV) comprising original text data

2. **Worker-level analysis of LM effects of AI**
   - *What are the Pioneering AI Jobs? Who's attracted by them?*
     - Transition Matrix $\Rightarrow$ "AI Bubble"
     - Logit & Wage Regressions s.t. Outside Options (OO)
     - **1 SD $\uparrow$ OO $\Rightarrow$ Mobility $\uparrow$ 5 - 8% & Wages $\uparrow$ 3.3 - 5.8%**
   - *Do workers most exposed to AI experience positive wage effects compared to observationally equivalent workers?*
     - 2-stage Matching Procedure
     - **LM Region (LMR)-level AI Demand $\uparrow$ $\Rightarrow$ Wages —**
     - **(Occ. $\times$ LMR)-level $\uparrow$ 10% $\Rightarrow$ Wages $\uparrow$ 4%**

Contributions

1. **AI Demand in Online Job Vacancies (OJV)**
   - Diffusion of AI skills (in GER) between 2017-21.
   - Identify "AI Pioneers"
     - Alekseeva et al. 2021; Babina et al. 2021; Tambe 2021; Acemoglu et al. 2022
2. **Labor market impact of AI**
   - AI exposure at Occupation-LMR-year level derived from OJV and its implications for employment & wages.
     - Industries/ Occupations: (Webb 2020; Felten, Raj, and Seamans 2021; Albanesi et al. 2023; Eloundou et al. 2023; Felten, Raj, and Seamans 2023)
     - Local Labor Market: (Bessen, Cockburn, and Hunt 2021; Gathmann and Grimm 2022)
     - Firms/ Establishments: (Rammer 2022; Arntz et al. 2023; Copestake et al. 2023; Peede and Stops 2023)
3. **Worker-level effects of digital technologies**
   - LM Transitions & Outside Options
     - (Danieli and Caldwell 2022; Schubert, Stansbury, and Taska 2023)
   - Wages: Matching of observationally equivalent workers
     - (Genz, Janser, and Lehmer 2019; Genz et al. 2021; Fossen and Sorgner 2022)

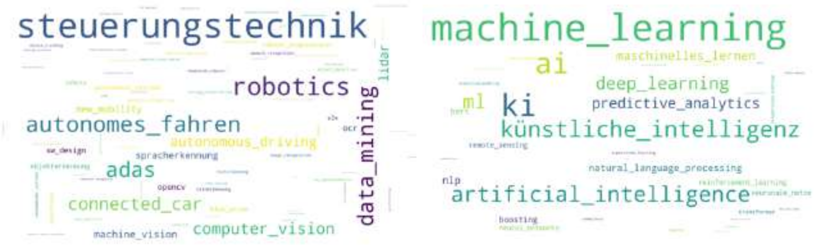
Data: OJV - Data-generating process

- 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) and linkages
  - Classification of occupations (KldB 2010, 3-digit)
  - Sample Selection (*"HR-Sample"*)
  - Keyword list comprising AI skills
- **Final product**
  - 20 million vacancies (2017/01 - 2021/12)
  - 230k firms & 7.5 million firm-month-kldb-lmr observations
    - Firms' # of (job-specific!) postings for each LLM and month
    - Total # of AI skills & "AI postings" demanded in each cell

External Validity

Data: OJV - Identification of AI skills

- Extensive keyword list ($N = 237$)
  - Enrich existing keyword lists, e.g., (Bessen, Cockburn, and Hunt 2021; Büchel and Mertens 2021; Lightcast 2023), using (i) Chat GPT 4.0 and (ii) Manual annotation (1k vacancies)



(a) AI Applications

(b) AI Methods

NOTE. —AI applications comprise specific domains in which AI skills are applied to. AI methods comprise methods and algorithms commonly deployed.

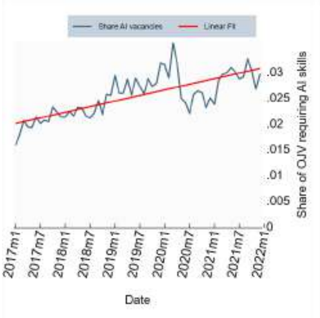
Figure 2: Breakdown of AI skills

AI Tools Summary Statistics

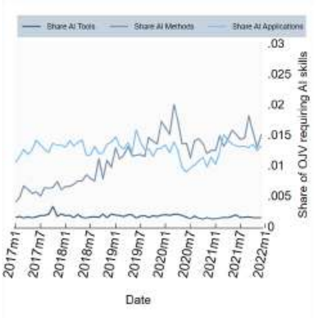
Data: Labor Market Data

- Sample of Integrated Labour Market Biographies (SIAB v7521)
  - 2 % sample drawn from the Integrated Employment Biographies
  - 2017 - 2021
  - Employment, Wages, Skill composition, Socio-demographic composition (Age, citizenship, gender)
- Establishment History Panel (BHP)
  - All establishments in Germany covered by the IAB Employment History
  - 2017 - 2021
  - Employment, Industry, Location of work

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



(a) AI vacancies: Baseline



(b) AI vacancies: Breakdown

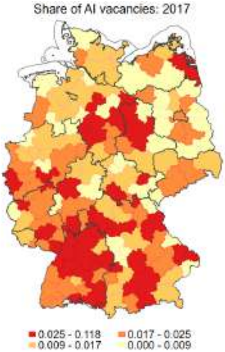
NOTE. —Vacancies are defined as an "AI vacancy" if a job posting contains at least one AI-related skill in a given month.

Figure 3: Trends in AI Demand, 2017/01 - 2021/12

- 7.6% YoY growth from 2017/1 - 2021/12

Context

Fact #2: Demand for AI skills has diffused across most regions



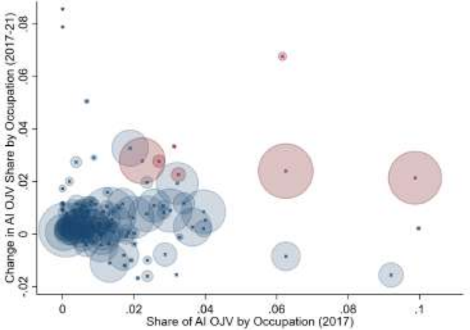
(a) AI demand: 2017

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

Fact #3: "AI Pioneers" separated themselves



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 5: 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

Worker flows into AI Pioneers

Table 1: 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

4-5 6-7

AI Pioneers & Outside Options

What determines transitions into AI Pioneers?

- Outside-Occupation Option Index (OOOI), following Schubert, Stansbury, and Taska 2023

$$OOOI_{olt} = \underbrace{\sum_{o \neq d}^{N_{occ}} \pi_{d \Rightarrow o}}_{\text{Worker Flows}} \times \underbrace{\frac{s_{dlt}}{s_{dt}}}_{\text{Employment Shares}} \times \underbrace{\bar{w_{dkt}}}_{\text{Average Wages}} \quad (1)$$

  – $\pi_{o \Rightarrow p}$: unique transitions from origin occupation o (current to destination occupation d
  – $\frac{s_{dlt}}{s_{dt}}$: relative employment share of d in (home) LMR l relative to national avg.
  – $\bar{w_{dkt}}$: Avg. wage in destination occupations

Top 10 OOOI Occupations

OOOI: Logit Regressions

$$P(OC = 1) = \beta_1 + \beta_2 OOOI_{ol,t-1} + \beta_3 X_{it} + \beta_4 \delta_j + \beta_5 \psi_l + \beta_6 \theta_t + \epsilon_{ilt} \quad (2)$$

- $P(OC = 1)$: Dummy = 1 if worker i changed occupation
- X_{it}, δ_j, ψ_l, θ_t: Controls, Industry FE (2d), LLM FE, Year FE

Table 2: 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)	0.084***	0.072***	0.078***	0.070***	0.051***
	(0.002)	(0.011)	(0.004)	(0.006)	(0.004)
Socio, Work, Firm Controls	✓	✓	✓	✓	✓
LLM FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Observations	2,141,099	52,121	415,152	289,297	1,384,428
Pseudo R-squared	0.20	0.20	0.17	0.20	0.23

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 ↑ OOOI ⇒ Mobility ↑ 5 - 8%

OOOI: Wage Regressions

$$lnw_{ilot} = \beta_1 + \beta_2 OOOI_{olt} + \beta_3 X_{it} + \beta_4 \delta_j + \beta_5 \psi_l + \beta_6 \theta_t + \epsilon_{ilt} \quad (3)$$

Table 3: Wage regressions on OOOI, by AI Tiers

	Dependent Variable: Log Wages				
	All	Pioneers	Early Adopter	Late Bloomer	Laggards
OOOI	0.041***	0.037***	0.058***	0.033***	0.033***
	(0.011)	(0.004)	(0.008)	(0.011)	(0.010)
Socio, Work, Firm Controls	✓	✓	✓	✓	✓
LLM FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Industry FE	✓	✓	✓	✓	✓
Observations	2,357,038	53,321	466,524	300,525	1,536,668
R-squared	0.56	0.47	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.

– 1 SD ↑ OOOI ⇒ Daily Wage ↑ 3.3 - 5.8%

Matching Procedure

- Treatment: LLM in Top Quintile 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

$$lnw_{ilot} = \beta_1 + \beta_2 AI_{lot} + \beta_3 X_{it} + \epsilon_{ilt} \tag{4}$$

– 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 4: 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 5: Wage Regressions (PS weighted): AI Top Region Dummy

	Dependent Variable: log wages			
	(1)	(2)	(3)	(4)
AI Region (Treated)	0.001	0.007	-0.002	-0.002
	(0.009)	(0.009)	(0.008)	(0.004)
Interaction 2018	-0.009*	-0.009*	-0.009*	-0.009*
	(0.005)	(0.005)	(0.005)	(0.001)
Interaction 2019	-0.002	-0.002	-0.003	-0.002
	(0.005)	(0.005)	(0.005)	(0.005)
Interaction 2020	0.001	0.002	0.002***	0.002
	(0.007)	(0.007)	(0.007)	(0.007)
Interaction 2021	-0.008	-0.007	-0.008***	-0.007
	(0.007)	(0.006)	(0.002)	(0.006)
Socio, Work, Firm Controls	✓	✓	✓	✓
State FE		✓	✓	✓
1d Occupation FE			✓	
3d Occupation FE				✓
Observations	943,186	943,186	943,186	943,186
R-squared	0.55	0.56	0.56	0.57

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 LMR-level (granular)

Table 6: Wage Regressions (PS weighted): AI Share by LMR

	Dependent Variable: log wages			
	(1)	(2)	(3)	(4)
AI Share (LMR)	0.010	0.035	-0.073	-0.071
	(0.132)	(0.128)	(0.113)	(0.110)
Interaction 2018	-0.137	-0.156	-0.136	-0.141
	(0.111)	(0.110)	(0.096)	(0.094)
Interaction 2019	0.023	0.016	0.037	0.040
	(0.113)	(0.109)	(0.108)	(0.103)
Interaction 2020	0.297	0.303	0.152	0.164
	(0.216)	(0.216)	(0.179)	(0.179)
Interaction 2021	0.014	0.057	-0.060	-0.027
	(0.211)	(0.202)	(0.183)	(0.182)
Socio, Work, Firm Controls	✓	✓	✓	✓
State FE		✓	✓	✓
1d Occupation FE			✓	
3d Occupation FE				✓
Observations	943,186	943,186	943,186	943,186
R-squared	0.55	0.56	0.56	0.57

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 7: Wage Regressions (PS weighted): AI Share by Occupation and LMR

	Dependent Variable: log wages			
	(1)	(2)	(3)	(4)
AI Share (Occ x LMR)	0.106***	0.097***	0.108***	0.095***
	(0.039)	(0.032)	(0.041)	(0.033)
Interaction 2018	0.070	0.020	0.064	0.015
	(0.048)	(0.045)	(0.048)	(0.044)
Interaction 2019	0.116***	0.064	0.116***	0.064
	(0.054)	(0.050)	(0.052)	(0.047)
Interaction 2020	0.280***	0.190**	0.271***	0.181**
	(0.077)	(0.075)	(0.074)	(0.072)
Interaction 2021	0.162*	0.091	0.169**	0.096
	(0.082)	(0.074)	(0.080)	(0.072)
Socio, Work, Firm Controls	✓	✓	✓	✓
State FE		✓	✓	✓
1d Occupation FE			✓	
3d Occupation FE				✓
AI Share (Mean)	0.04	0.04	0.04	0.04
Observations	696,748	696,748	696,748	696,748
R-squared	0.55	0.56	0.55	0.56

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 ↑ 4%

▸ unweighted

Robustness/ Work in Progress

- Work in Progress/ Future Outlook
  - Non-binary treatment
  - Wage effects for switchers vs non-switchers
  - Role of regional mobility
  - IV approach to address endogeneity
- Robustness/ Extended Results
  - LM Transitions for Early Adopters and Late Bloomers
  - Alternative Specifications for OOOI
  - Alternative matching procedures
  - Treatment via alternative AI measures

Conclusions

- Demand AI skills ↑ 7.6% YoY (GER, 2017-21) — But: concentrated in few occupations (AI Pioneers)
- **LM effects**
  - Outside Options ↑ ⇒ Occupational Mobility ↑ & Wages ↑ strongest for occupations with high demand for AI skills
  - AI Demand ↑ ⇒ Wages ↑ —But: only when accounting for regional *and* occupational variation
- **Policy Implications**
  - Labor shortages & Limited Outside Options for workers outside of "AI Bubble"
  - Accessibility ⇒ Education Curricula, Further Training
- **Future Research**
  - Skill transferability (Gathmann and Schönberg 2010; Peede and Stops 2023)
  - AI and Imperfect LMs
    - Competing for Talent (Di Addario et al. 2023), Monopsony Power (Bachmann, Demir, and Frings 2021), Worker Beliefs (Jäger et al. 2021)

Thanks for your attention!

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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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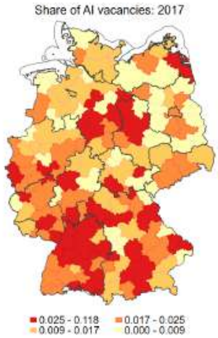
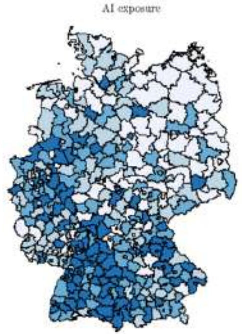
Identification: Spatial variation of AI exposure



(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 6: OJV-and Patent-based exposure to AI in Germany, 2017-18

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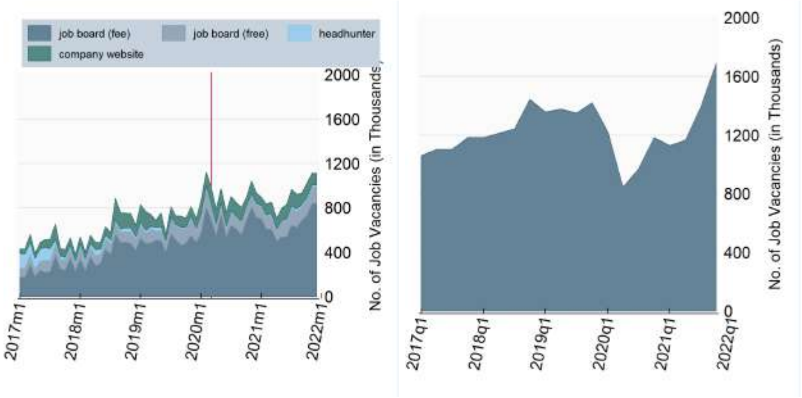
Data: OJV - Validity over time



(a) OJV data, by source (Inflow)

(b) IAB Vacancy Panel (Stock)

Figure 7: Number of Online Job Vacancies over Time, 2017-01 - 2021-12

Data: OJV - Validity by industries

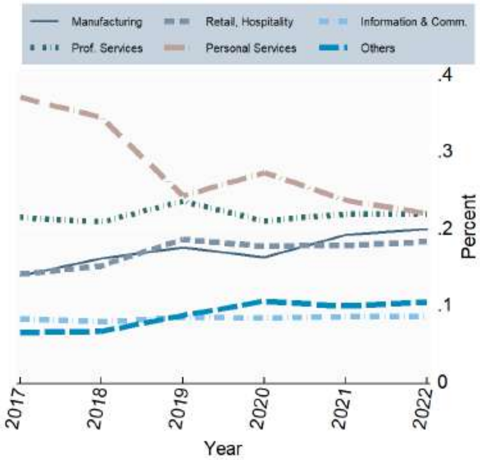


Figure 8: Industry Composition of Online Job Vacancies year, 2017 - 2021

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Word Cloud: AI Tools Skills

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

Figure 9: Word cloud of AI tools

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Summary Statistics: AI Postings

Table 8: 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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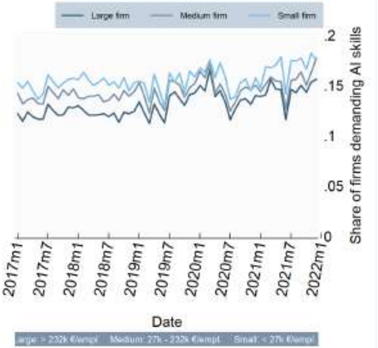
Fact #4: Demand for AI skills by Revenue/Employee

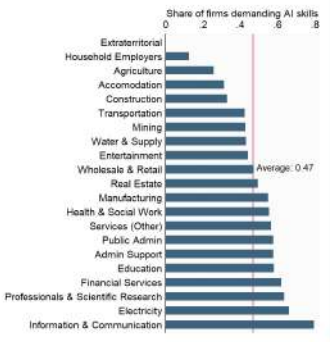


NOTE. —Small firms are defined as those at or below the 25th percentile of the firm revenue/employee distribution. Old firms "AI firms" are defined as those at or above the 75th percentile of the firm revenue/employee distribution. Medium firms are defined as those above the 25th and below the 75th percentile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

Figure 10: 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

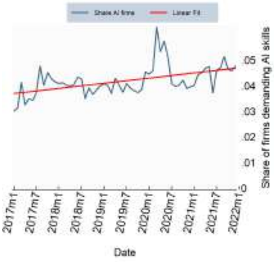


NOTE. —Industries are defined at the 1-digit level. The industry share of firms demanding AI skills is based on the share of firms within each industry that demanded at least one AI skill at any point between 2017 - 2021/21.

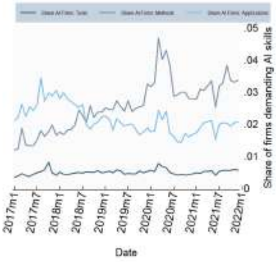
Figure 11: Share of German firms posting AI skills in online job vacancies, 2017 - 2021 —by industry

- 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



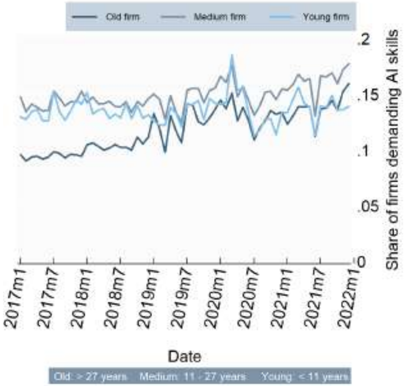
(b) AI firms

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 12: 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

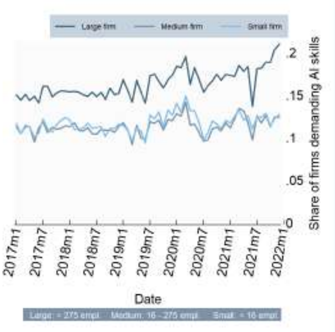


NOTE. —Young firms are defined as those at or below the 25th percentile of the firm age distribution. Old firms "AI firms" are defined as those at or above the 75th percentile of the firm age distribution. Medium firms are defined as those above the 25th and below the 75th percentile of the firm age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

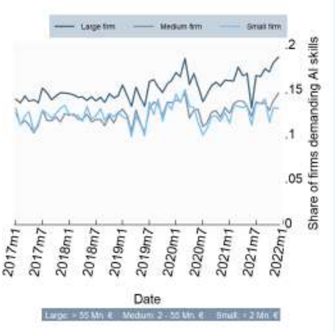
Figure 13: Share of German firms posting AI skills in online job vacancies, 2017 - 2021 —by firm age

- 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 14: 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

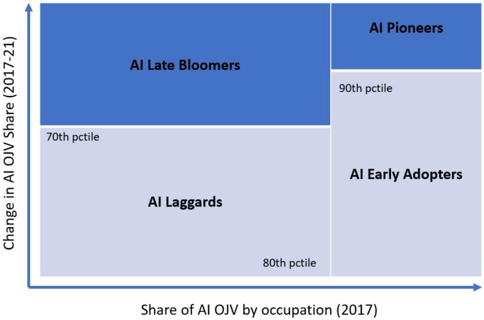
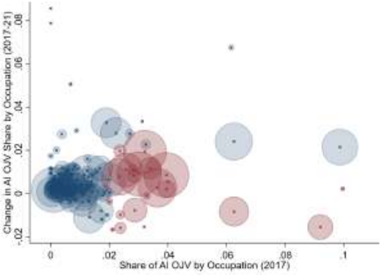


Figure 15: Illustration of AI Tiers

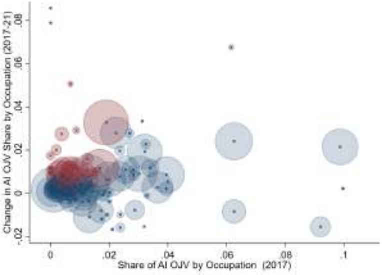
NOTE. —AI PIONEERS are defined as occupations whose (i) share of AI OJV in 2017 ranked $\geq p80$ and (ii) change in the share of AI OJV ranked in $\geq\geq p90$. For AI EARLY ADOPTERS: (i) share of AI OJV in 2017 ranked $\geq p80$, but (ii) change in the share of AI OJV ranked $< p80$. For AI LATE BLOOMERS: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

Return

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

Return

Worker flows in AI Tiers

Table 9: 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 10: 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.

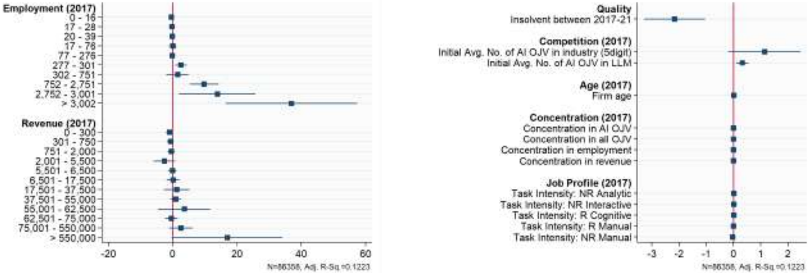
▸ Return

Firm-level Analysis: OLS

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

- $AI_{ijl}^{(t+n)-t}$ = 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 17: Firm-level regressions of the change in AI vacancies, 2017-2021

Return

rwi

Top 10 Occupations by OOOI

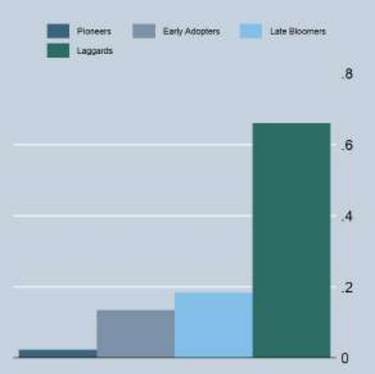
Table 11: OOOI and AI Share by Occupation (Top 10 by OOOI)

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 18: Employment Share of AI Occupational Tiers

Return

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

Table 12: Wage Regressions (unweighted): AI Top Region Dummy

	Dependent Variable: log wages			
	(1)	(2)	(3)	(4)
AI Region (Treated)	0.012	0.013*	0.013*	0.014**
	(0.007)	(0.007)	(0.007)	(0.007)
Interaction 2018	-0.002**	-0.002**	-0.002*	-0.004
	(0.001)	(0.001)	(0.001)	(0.001)
Interaction 2019	-0.001	-0.001	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Interaction 2020	-0.006***	-0.006***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.002)	(0.002)
Interaction 2021	-0.007***	-0.007***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)
Socio, Work, Firm Controls	✓	✓	✓	✓
State FE		✓	✓	✓
1d Occupation FE			✓	
3d Occupation FE				✓
Observations	2,617,063	2,617,063	2,617,063	2,617,063
R-squared	0.55	0.56	0.55	0.56

Standard errors in parentheses

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

NOTE. —TBD.

return

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

Table 13: Wage Regressions (unweighted): AI Share by LMR

	Dependent Variable: log wages			
	(1)	(2)	(3)	(4)
AI Share (LMR)	0.199	0.246*	0.198***	0.216***
	(0.142)	(0.136)	(0.093)	(0.091)
Interaction 2018	-0.159*	-0.182**	-0.171**	-0.182
	(0.075)	(0.072)	(0.069)	(0.070)
Interaction 2019	-0.068	-0.077	-0.065	-0.061
	(0.075)	(0.072)	(0.057)	(0.056)
Interaction 2020	0.000	-0.022	-0.102	0.109
	(0.103)	(0.094)	(0.068)	(0.069)
Interaction 2021	-0.293*	-0.300*	-0.261***	-0.266***
	(0.149)	(0.162)	(0.090)	(0.097)
Socio, Work, Firm Controls	✓	✓	✓	✓
State FE		✓	✓	✓
1d Occupation FE			✓	
3d Occupation FE				✓
Observations	2,617,063	2,617,063	2,617,063	2,617,063
R-squared	0.55	0.56	0.55	0.56

Standard errors in parentheses

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

NOTE. —TBD.

return

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

Table 14: Wage Regressions (unweighted):AI Share by occupation and LMR

	Dependent Variable: log wages			
	(1)	(2)	(3)	(4)
AI Share (occ x LMR)	0.176***	0.157***	0.177***	0.153***
	(0.045)	(0.035)	(0.047)	(0.034)
Interaction 2018	0.061	0.011	0.057	0.008
	(0.044)	(0.040)	(0.044)	(0.040)
Interaction 2019	0.124***	0.076**	0.125***	0.078**
	(0.043)	(0.035)	(0.043)	(0.033)
Interaction 2020	0.176***	0.084*	0.169***	0.079*
	(0.058)	(0.047)	(0.058)	(0.046)
Interaction 2021	0.084	0.008	0.093*	0.018
	(0.053)	(0.044)	(0.053)	(0.043)
Socio, Work, Firm Controls	✓	✓	✓	✓
State FE		✓	✓	✓
1d Occupation FE			✓	
3d Occupation FE				✓
Observations	1,829,045	1,829,045	1,829,045	1,829,045
R-squared	0.54	0.55	0.54	0.56

Standard errors in parentheses

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

NOTE. —TBD.

return

Decomposition of AI employment dynamics

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

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

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

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