How Different Uses of Al Shape Labor Demand: Evidence from France

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Motivation

- Literature on employment exposure to Al
 - Large range of estimates
- Literature on individual-level effects of AI
 - ▶ Positive effects on the productivity of low-skilled workers, high-skilled workers and researchers
- However, limited evidence exists on firm-level effects based on direct measures of AI adoption to date
 - \longrightarrow This paper examines the relationship between AI adoption and employment at the firm level, while documenting heterogeneity across occupations

This paper

- Documents the characteristics of firms that adopt AI
 - Larger, more productive, and skill-intensive firms, primarily concentrated in the IT and scientific activities sectors
- Firm-level Al adoption is positively associated with increases in employment and sales
 - lacktriangle Diff-in-diff approach: **Semi-elasticities** ~ 0.05 for both employment and sales
- Heterogeneous effects by occupation seem to partially validate the substitution/exposure matrices (Pizzinelli et al., 2023; Gmyrek et al., 2023)
 - Neutral effect on low-exposed occupations
 - ▶ Positive effects for highly exposed occupations, whether complementary or substitutable
- A missing dimension in prior research is the heterogeneity by type of usage
 - Within highly exposed occupations, certain usages (e.g., production processes or ICT security) are associated with positive employment growth, while others (e.g., administrative processes) are linked to slightly negative effects.

This paper - Limitations

- Diff-in-diff approach has inherent limitations, particularly the potential presence of correlated demand or supply shocks
 - Previous research on the effects of modern manufacturing capital and automation technologies (Aghion et al., 2024) indicates that a diff-in-diff approach with industry fixed effects produces results similar to those obtained using a Shift-Share IV approach
- The adoption of AI technologies between 2018 and 2020 focuses on "first-generation AI" and, in particular, does not include generative AI

Literature

- Effect of AI on employment in the US:
 - ▶ Babina et al. (2024): (+) at both firm and industry levels, combining worker resumes and job postings
 - Acemoglu et al. (2022): (≈ 0) at the commuting zones level, using Al-related job vacancies
 - ▶ Bonfiglioli et al. (2023): (-) at the commuting zones level, focusing on Al-related occupations defined via specialized software use
- Employment exposure to AI in advanced economies based on task/abilities exposure:
 - ▶ 19.9% (Eloundou et al., 2023), 60% (Pizzinelli et al., 2023), and 18.5% (Gmyrek et al., 2023)
 - ▶ Albanesi et al. (2023): increase in the employment shares of Al-exposed occupations across Europe
- Staggered introduction of an AI tool (within firm effects):
 - Positive effects on the productivity of both low-skilled (Brynjolfsson et al., 2023) and high-skilled (Noy & Zhang, 2023) workers
 - ▶ Positive impact on researcher productivity (Toner-Rodgers, 2024)

Outline

- Data
- 2 Who are the adopters?
- Average effects
- 4 Heterogeneous effects

Data

- French firm-level data between 2014 and 2023
- Firm-level AI adoption in 2017 and 2020
 - ► Information and Communication Technologies in business (ICT) survey in France
 - Detailed information on AI adoption, categorized by 7 types of usage
 - * Marketing or sales, production processes, administration processes, management of enterprises, logistics, ICT security, HR management or recruiting
- Employment
 - ▶ French matched employer-employee data (DADS) covering all firm in private sector from 2014 to 2022
 - ▶ Detailed information on employment: number of hours, occupation, etc.
- Balance sheet information
 - Industrial and commercial profits (BIC-RN) database covering all firm in private sector from 2014 to 2023
 - Detailed information on economic activities: industry, sales, capital, etc.

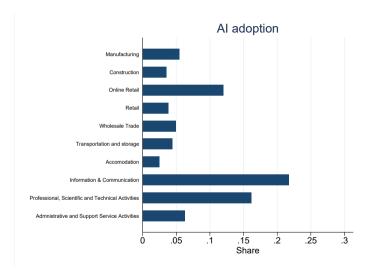
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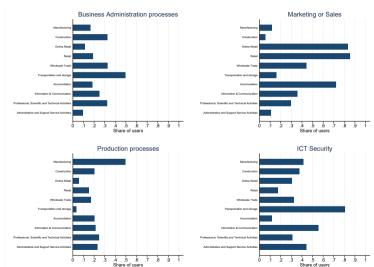
Firm characteristics

	Adopters	Non adopters
Employment	108	35
Sales (k€)	40,676	9,783
Labor Productivity (k€ per worker)	83	69
Capital Intensity (k€ per worker)	76	88
Low skilled workers (share)	0.13	0.26
High skilled workers (share)	0.33	0.16
Engineers (share)	0.18	0.06
Export share	0.13	0.05
Age (Years)	21	22

Sectoral composition



Type of usage



Al usage focused on core business activities:

- "Marketing and Sales" primarily used in Retail
- "Production processes" primarily used in Manufacturing
- Limited usage of AI for "Business Administration Processes"

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Al & Employment - Theory

- Al-induced automation and labor in a task-based framework: Tradeoff displacement vs. productivity (Zeira 1998, Acemoglu-Restrepo 2019)
 - Automation is labor-displacing at task level: Employment \(\sqrt{} \)
 - ▶ But could induce productivity gains, lower prices, higher demand, resulting in higher employment and the need for implementing new tasks: Employment

Empirical Approach

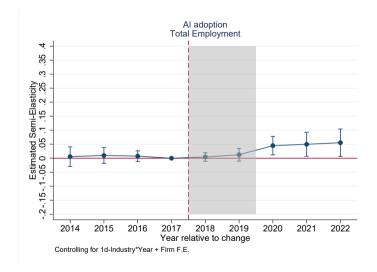
- Balanced panel across all years from 2014 to 2022, focusing on firms that had not yet adopted Al by 2017:
 - 232 firms adopted AI between 2017 and 2020
 - ▶ 636 firms did not adopt AI

$$log\ Y_{it} = lpha + \sum_{t=y_0}^{y_n} \delta_t A dopt_{i,t-2017} + \mu_i + \lambda_{st} + \varepsilon_{it}$$

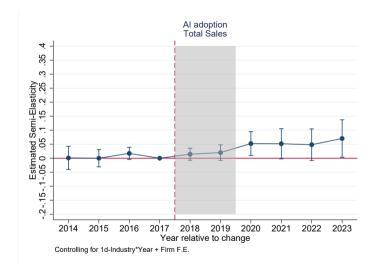
with:

- Outcome Yit
- Adoption event Adopti,t-2017
- Firm F.E. μ_i
- Industry-year F.E. λ_{st}

Al adoption - Employment



Al adoption - Sales



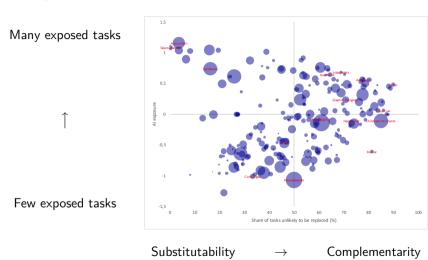
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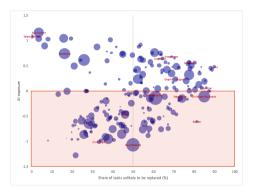
Exposure of Occupations to Al

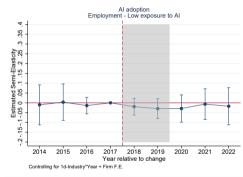
- Is the positive relationship between Al adoption and employment heterogeneous across different occupations?
- This builds on an influential line of work following Webb (2020), among others:
 - Leverages the overlap between job task descriptions and the text of patents to construct a measure of task exposure to various technologies, including AI.
- Job exposure matrix to Al adapted for France by Bergeaud (2024). For each occupation:
 - Overall exposure to AI: Calculated following Gmyrek et al. (2023) as the weighted average of task-level exposure, where the weights reflect the importance of each task within an occupation
 - Share of tasks unlikely to be replaced by AI: Based on Gmyrek et al. (2023) and Pizzinelli et al. (2023), using:
 - * Work contexts: The likelihood that key activities can be assigned to AI without human supervision.
 - * Job zones: The level of education and training required to perform an occupation.

Heterogeneity by occupation?



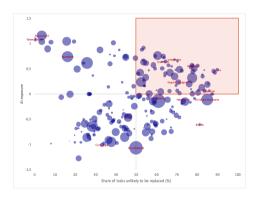
Low exposed occupations

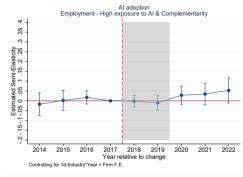




No effect

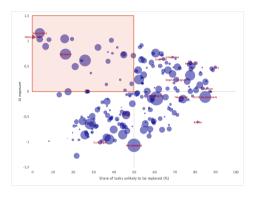
Highly exposed & Complementary occupations

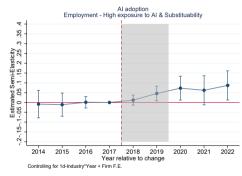




Slightly positive effect

Highly exposed & Substituable occupations





• Positive effect (!)

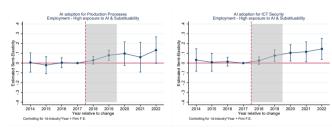
Heterogeneity by occupation

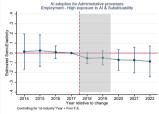
- Heterogeneous effects seem to validate the relevance of the substitution/exposure matrix
- But how can we explain the positive impact on jobs that are, at first glance, negatively exposed to Al?
- Analysis of heterogeneity by type of usage:
 - Marketing or sales
 - Production processes
 - Administration processes
 - Management of enterprises
 - Logistics
 - ICT security
 - HR management or recruiting

Highly exposed & Substituable occupations - By usage



- The overall positive effect breaks down into:
 - A positive effect when AI is used for production processes or ICT security
 - A slightly negative effect when Al is used for administration processes

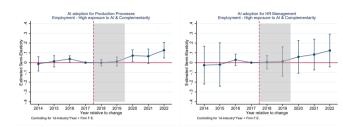


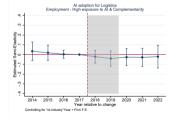


Highly exposed & Complementary occupations - By usage



- The overall positive effect breaks down into:
 - A positive effect when AI is used for production processes or HR management
 - No effect when AI is used for logistics

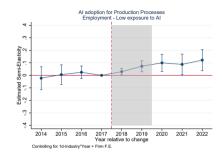


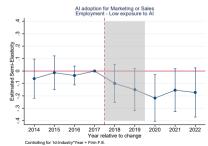


Low exposed occupations - By usage



- For low-exposed occupations, the overall null effect actually breaks down into:
 - A positive effect when AI is used for production processes
 - A negative effect when AI is used for marketing and sales



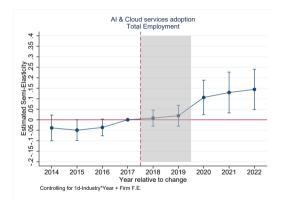


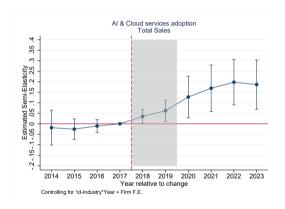
Conclusion

- Firm-level Al adoption is positively associated with increases in employment and sales
- Heterogeneous effects by occupation seem to partially validate the substitution/exposure matrices
- However, a missing dimension in prior research is the heterogeneity by type of usage

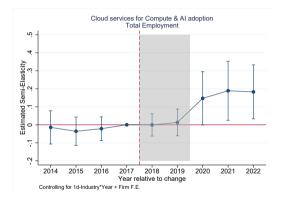
Thank you!

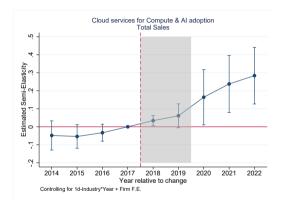
AI & Cloud adoption



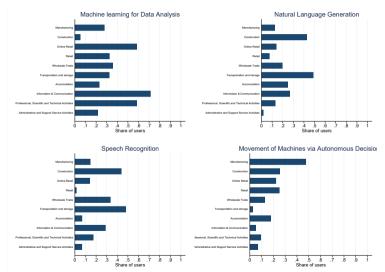


Al & Cloud for compute adoption





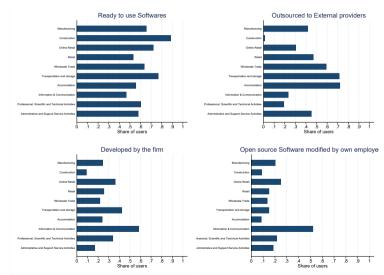
Type of AI technology



Heterogeneous usage of AI technology, related to its final purpose:

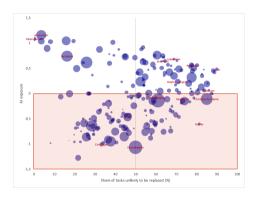
- "Machine learning for data analysis" primarily in the online retail and IT sectors
- "Movement of machines through autonomous decisions" primarily in the manufacturing sector

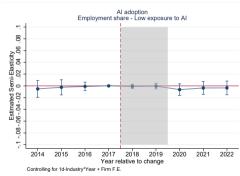
How firms acquired the technology?



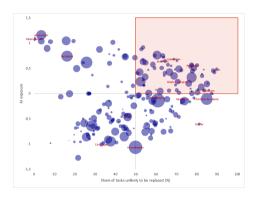
- Most firms have adopted Al by using ready-to-use software solutions.
- Internal development, particularly through the adaptation of open-source software, is specific to the IT sector.

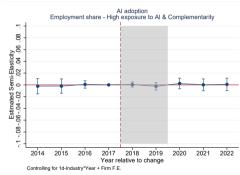
Low exposed occupations - Employment Share



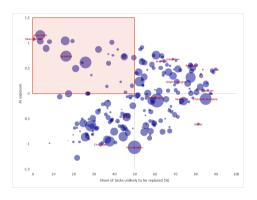


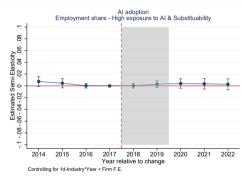
Highly exposed & Complementary occupations - Employment Share



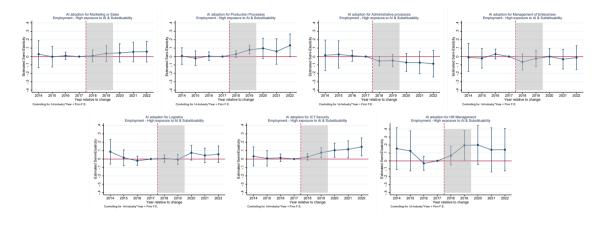


Highly exposed & Substituable occupations - Employment Share

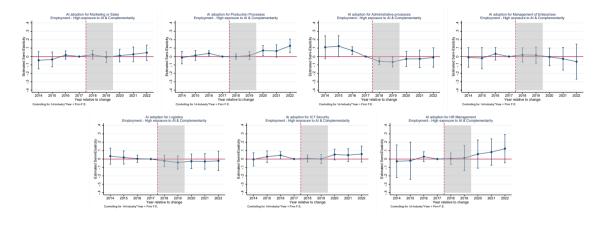




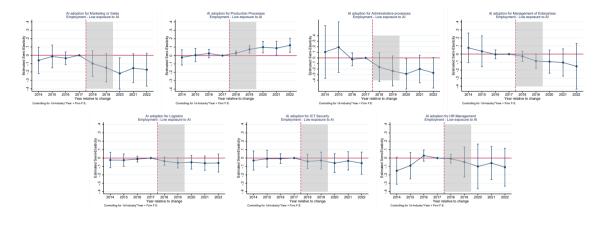
Highly exposed & Substituable occupations - By usage



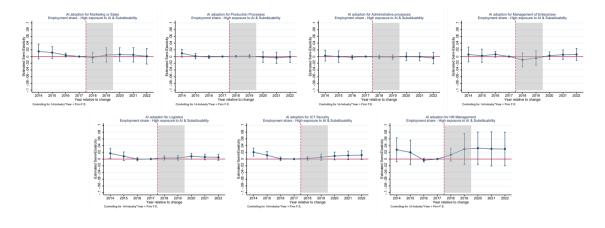
Highly exposed & Complementary occupations - By usage



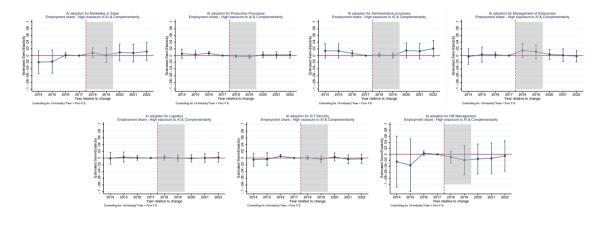
Low exposed occupations - By usage



Highly exposed & Substituable occupations - Employment Share



Highly exposed & Complementary occupations - Employment Share



Low exposed occupations - Employment Share

