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

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Little is known about the firm-level effects of AI adoption on labor demand. Recent work has focused on estimating causal effects of AI adoption at the individual employee level *within* the firm (e.g., Brynjolfsson et al., 2023; Noy and Zhang, 2023; Toner-Rodgers, 2024), documenting positive effects of AI on worker-level productivity. Instead, in this paper we use comprehensive measures of AI adoption to document the relationship between AI and employment at the firm level.

Using French firm-level data on AI adoption between 2018 and 2020,[1] we establish four results. First, we document that AI adopting firms are larger, more productive, more skill-intensive, and primarily concentrated in IT and scientific activities.

Second, using difference-in-differences, we show that AI adoption is positively associated with an increase in total firm-level employment and sales. This finding is consistent with the idea that AI adoption induces productivity gains allowing the firm to expand its scope and raise its labor demand. The productivity effect appears to be stronger than potential displacement effects, whereby AI takes over the tasks of certain workers, reducing labor demand (Acemoglu and Restrepo 2018).[2]

Third, we find positive labor demand responses even for occupations that were classified in recent work as likely to be displaced by AI (Pizzinelli et al. 2023, Gmyrek et al. 2023, and Bergeaud 2024), suggesting that the productivity effect outweighs the displacement effect even for these occupations.

Fourth, we show that certain uses of AI (e.g., for ICT security) lead to positive employment growth, while other uses (e.g., administrative processes) have small negative effects. We thus

[1] Our focus in this paper is thus on early development of AI, and we do not cover generative AI.

[2] Our finding is consistent with the firm-level analysis of Babina et al. (2024), who measure AI investments using employee resumes and document a positive relationship between AI investment, employment, and sales. While their measure of AI investment is directly linked to labor demand (via resumes), our analysis complements theirs with a direct measure of all AI investments. See Acemoglu et al. (2022) and Bonfiglioli et al. (2023) for analyses at the commuting zone levels.

find that heterogeneous labor demand effects appear to be primarily governed by different uses of AI, rather than by inherent characteristics of occupations.

In what follows, we present in turn the data, the results on AI adoption, the average labor demand response, and the heterogeneous effects shaped by different uses of AI. The final section concludes.

I. Data

We use French firm-level data between 2014 and 2023, combining datasets on the measurement of AI, employment, and balance sheet records.

Firm-level AI adoption is measured between 2017 and 2020 in the "Information and Communication Technologies in business" survey from Insee (2021). The survey provides detailed information on AI adoption, categorized across seven types of uses: marketing or sales; production processes; administration processes; management of enterprises; logistics; ICT security; HR management or recruiting.

The employment and balance sheet information datasets are standard (see, e.g., Aghion et al., 2024 for more detail). We use the French matched employer-employee dataset ("BTS") from Insee (2022), which covers all private sector firms from 2014 to 2022. To measure firm sales, we use the industrial and commercial profits database ("BIC-IS") from French Ministry of Finance (2023), which covers all private sector firms from 2014 to 2023.

II. Which Firms Adopt AI?

	Adopters	Non adopters
Employment (FTE)	869	496
Sales (k€)	342,896	156,882
Labor Productivity (k€ per worker)	93	80
Capital Intensity (k€ per worker)	228	202
Labor share in Value Added	0.64	0.74
Low skilled workers (share)	0.17	0.26
High skilled workers (share)	0.29	0.22
Engineers (share)	0.14	0.09
Export share	0.23	0.11
Age (Years)	21	20

TABLE 1. CHARACTERISTICS OF FIRMS ADOPTING AI

Note: This table presents the 2017 characteristics of firms that adopted AI between 2018 and 2020, compared to those that did not.

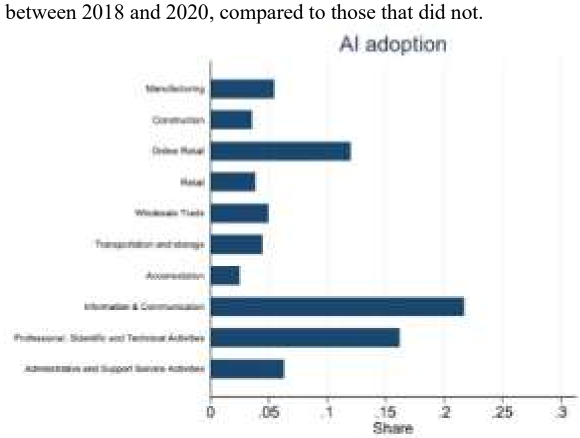

FIGURE 1. AI ADOPTION ACROSS SECTORS

Note: This figure reports the share of firms that use AI in 2020 across industry sectors in France.

Table 1 describes the characteristics of firms that adopt AI, compared to the characteristics of non-adopters. AI adopters are much larger – almost twice bigger by total employment, and more than twice larger by sales –, their labor productivity is 16 % higher, their labor share in value added is 10pp lower, they are slightly more capital intensive and more skill intensive – with a share of engineers 60% higher than non-adopters –, they are much more likely to export and are slightly older. Figure 1 shows that rates of adoption vary across sectors, with more adoption in IT, scientific activities, and online retail. Overall, these patterns show that AI adoption is highly uneven, which in turn will shape the distributional effects of AI as workers will be unevenly exposed to AI depending on the firms they work for.

III. Average Labor Demand Response

We now use a difference-in-differences design to estimate the response of labor demand to AI adoption. We work with a balanced panel of firms between 2014 and 2022, focusing on firms that had not yet adopted AI by 2017. This sample includes 232 firms that adopted AI between 2017 and 2020, and 636 that did not adopt AI. The specification is:

(1) $y_{it} = \sum_k \delta_k Adopt_i + \mu_i + \lambda_{st} + \epsilon_{it}$,

where y_{it} denotes the firm-level outcome (log employment or sales), $Adopt_i$ is an indicator that equals 1 if the firm adopts AI, δ_k are year dummies, μ_i firm fixed effects, and λ_{st} 1-digit "industry by year" fixed effects.

Equation (1) allows for an analysis of pre-trends. A lack of pre-trends is reassuring and restricts the potential set of confounders to contemporaneous demand or supply shocks.[3]

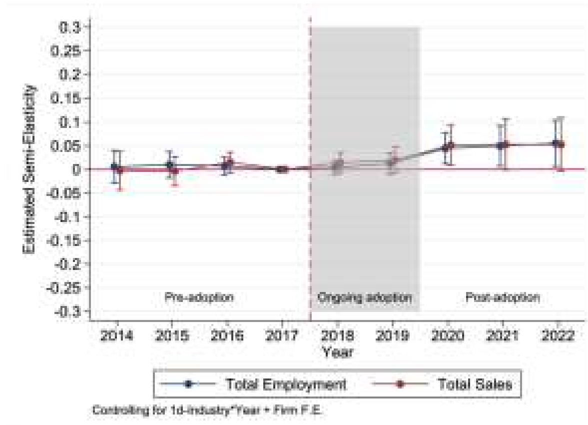

FIGURE 2. THE RESPONSE OF FIRM EMPLOYMENT AND SALES TO AI

Note: This figure documents the response of firm-level employment and sales to AI adoption, using specification (1). Standard errors are clustered by firms. Since information on AI adoption is available only for two years, 2017 and 2020, the gray area represents the time period during which firms in the treatment group adopt AI.

Figure 2 report the response of employment and sales to AI adoption. There are no pre-trends and we see a marked increase in both employment and sales after the adoption event. The semi-elasticities are about 0.05 for both employment and sales after a few years

Thus, the results suggest that AI adoption leads to an increase in productivity and hence

[3] Studying investment in automation technologies rather than AI, Aghion et al. (2024) validate a similar event study methodology with a complementary research design, a shift-share instrument variable (SSIV) approach. The SSIV estimates are similar in magnitudes to the event study estimates, which motivate our assumption that, in the context of AI investment, there are also no contemporaneous shocks confounding the firm-level event studies.

to higher sales and an increase in labor demand. However, the labor demand response could be heterogeneous, which we investigate next.

IV. Heterogeneous Effects and the Role of Different Uses of AI

The canonical approach to predict the heterogeneous effects of technologies is based on an analysis of an occupation's tasks that could be performed by a new technology (e.g., Autor et al. 2003, Webb 2020). We apply this approach to our sample, leveraging the AI exposure matrix across occupations built by Bergeaud (2024).[4]

We focus on the set of occupations where the effect of adoption of AI is expected to be most negative according to the AI exposure matrix. These occupations include, for instance, accountants, telemarketers, and secretaries.[5]

Figure 3 reports the result: for these occupations "at a high risk of displacement", employment actually *increases* in firms that adopt AI, like in the full sample of occupations.[6] This finding suggests that the productivity effect outweighs the displacement effect even for the occupations that are thought to be most at risk.[7]

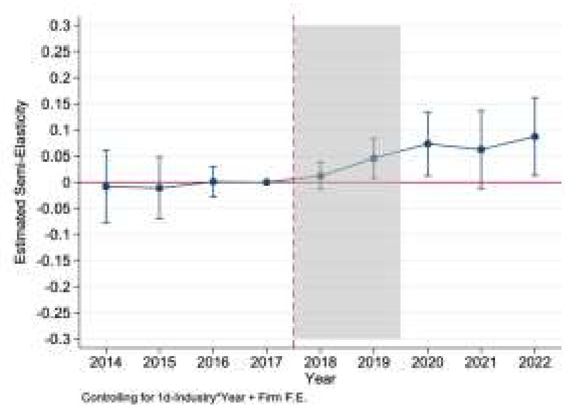

FIGURE 3. THE RESPONSE OF FIRM EMPLOYMENT TO AI ADOPTION, OCCUPATIONS WITH HIGH EXPOSURE AND HIGH SUBSTITUTABILITY

Note: This figure documents the response of firm-level employment to AI adoption, using specification (1), considering only employment in occupations that are classified as highly exposed to AI and highly substitutable with AI according to the methodology of Bergeaud (2024), Pizzinelli et al. (2023) and Gmyrek et al. (2023). Standard errors are clustered by firms.

[4] Bergeaud (2024) applies to the French economy the methodology of Pizzinelli et al. 2023 and Gmyrek et al. 2023. The matrix combines two measures of AI exposure computed separately for each occupation. First, "overall exposure to AI" is calculated as a weighted-average of task-level AI, where the weights reflect the importance of each task in the occupation. This measure captures whether an occupation is exposed to AI but does not predict whether AI is likely to act as a substitute or complement for labor. The second measure addressed this limitation by calculating the "share of tasks likely to be replaced by AI". This measure aims to capture the potential for substitution with AI, based on the likelihood that key activities can be assigned to AI without human supervision and based on the level of education and training required to perform an occupation.

[5] At the firm level, an average of 19% of occupations are highly exposed and classified as substitutable with AI.

[6] The Online Appendix presents results for "low-exposed" occupations and "highly exposed and complementary with AI" occupations, along with estimate of changes in the employment shares of these occupations (which are small).

[7] This result is reminiscent of paradigmatic cases of technologies substituting for workers that in fact raise labor demand. For instance, Bessen (2015) analyzes automated teller machines and shows they led to an increase in the demand for bank tellers, because the ATM allowed banks to operate branch offices at lower cost and thus to open many more branches.

As an alternative to occupation characteristics, we examine whether different uses of AI may shape the labor demand response. Across the seven AI usage types measured in the survey, we find significant heterogeneity.

Retaining the focus on the "at risk" occupations, Figure 4 analyze the employment responses separately for two types of AI adoption, for ICT security or administrative processes. It shows a positive response of employment when AI is adopted for ICT security and a weak negative response of employment when AI adoption focuses on administrative processes. To save space, the Online Appendix reports the heterogeneity analysis for the other types of AI uses and for the full sample of occupations, reporting additional heterogeneity patterns.

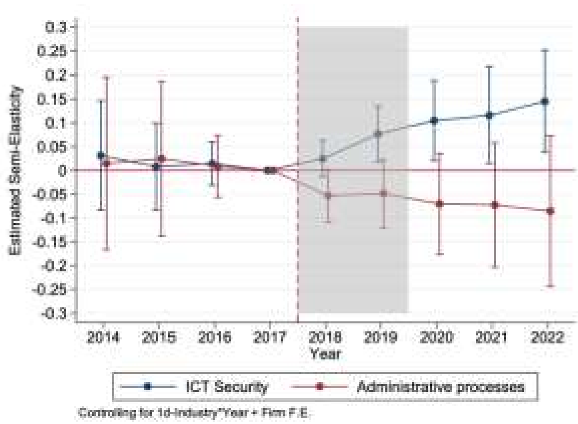

FIGURE 5. THE RESPONSE OF FIRM EMPLOYMENT TO AI ADOPTION FOR ICT SECURITY AND ADMINISTRATIVE PROCESSES

Note: This figure documents the response of firm-level employment to AI adoption for ICT security and administrative processes, using specification (1), considering only employment in occupations that are classified as highly exposed to AI and highly substitutable with AI. Standard errors are clustered by firms.

Overall, these results suggest that the distributional effects of AI are nuanced and depend on the specific AI uses, rather than on inherent characteristics of the occupation. In sum, specific AI uses are likely to govern the relative strength of the productivity and displacement effects.

V. Conclusion

Combining a survey of AI adoption with administrative data from France, we document the characteristics of firms that adopt AI and estimate its impact on labor demand. AI adopters are a highly selected set of firms, which are much larger and more productive than non-adopters. Furthermore, our difference-in-differences estimates indicate that, on average, labor demand increases after AI adoption, in line with recent firm-level studies of the labor demand effects of automation at firm level (e.g., Acemoglu et al. (2020), Aghion et al. (2024), Dixon et al. (2021), Domini et al. (2021), Humlum (2021), Koch et al. (2021)). Finally, we found that the labor demand effects of AI can be heterogeneous but that the heterogeneity is primarily tied to different uses of AI rather than to inherent characteristics of the tasks performed across occupations.

Together, our findings point to at least two fruitful directions for future research. First, much more remains to be learned about market-level dynamics. Firms that adopt AI may displace those that do not and estimating the magnitude of these business stealing effects is an important task for future research. Indeed, the main risk for workers is likely to be displacement by workers at other firms using AI, rather than being replaced by AI directly within the firm. Second, our results suggest that larger and more productive firms should be the great winners of the AI revolution, as they are much more likely to adopt AI. To avoid increased market concentration and entrenched market power, it appears important to encourage AI adoption by smaller firms going forward – which in turn can be achieved through a combination of competition policy, financial liberalization, training programs, and suitable industrial policy to ease firms' and workers' access to data and computing power (Aghion and Bunel, 2024). This approach could be beneficial both for aggregate innovation dynamics and from the point of view of inequality, by allowing workers in smaller firms to also benefit from AI.

REFERENCES

Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo. 2022. "Artificial Intelligence and Jobs: Evidence from Online Vacancies", *Journal of Labor Economics*.

Acemoglu, Daron, Claire Lelarge, and Pascual Restrepo. 2020. "Competing with robots: Firm-level evidence from France." *AEA Papers and Proceedings* Vol. 110, 383–88.

Acemoglu, Daron, and Pascual Restrepo. 2018. "The race between man and machine: Implications of technology for growth, factor shares, and employment.", *American Economic Review*, *108* (6).

Aghion, Philippe, Céline Antonin, Simon Bunel, and Xavier Jaravel. 2024. "Modern Manufacturing Capital, Labor Demand, and Product Market Dynamics: Evidence from France." Working paper.

Aghion, Philippe, and Simon Bunel. 2024. « AI and Growth: Where Do We Stand? », mimeo College de France

Autor, David, Frank Levy, Richard Murnane, "The Skill Content of Recent Technological Change: An Empirical Exploration", *Quarterly Journal of Economics*, 118 (4).

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson. 2024. « Artificial Intelligence, Firm Growth, and Product Innovation », *Journal of Financial Economics,* 151: 103745.

Bessen, James. 2015. *Learning by doing*. Yale University Press.

Bergeaud, Antonin, 2024. « Exposition à l'intelligence artificielle générative et emploi

: une application à la classification socio-professionnelle française », *Document de travail.*

Bonfiglioli, Alessandra, Rosario Crinò, Gino Gancia and Ioannis Papadakis. 2024. "Artificial Intelligence and Jobs: Evidence from US Commuting Zones", *CEPR Discussion Paper 18495.*

Brynjolfsson, Erik, Danielle Li, and Lindsey Raymond. 2023. « Generative AI at Work », NBER Working paper.

Brynjolfsson, Erik, and Andrew McAfee. 2014. *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. WW Norton & Company.

Dixon, Jay, Bryan Hong, and Lynn Wu. 2021. "The Robot Revolution: Managerial and Employment Consequences for Firms", *Management Science* 67 (9).

Domini, Giacomo, Marco Grazzi, Daniele Moschella, and Tania Treibich. 2021. "Threats and opportunities in the digital era: Automation spikes and employment dynamics." *Research Policy* 50 (7).

French Ministry of Finance. 2023. *Industrial and commercial profits - all schemes database (BIC-IS).* 2014-2023. doi: 10.34724/CASD.342.5475.V2

Gmyrek, Pawel, Janine Berg and David Bescond. 2023. "Generative AI and Jobs: A global analysis of potential effects on job quantity and quality", ILO Working Paper.

Humlum, Anders. 2021. "Robot Adoption and Labor Market Dynamics." Working paper.

Insee. 2022. *All employees databases - job position data database (BTS-Postes).* 2014-2022. doi: 10.34724/CASD.21.5278.V2

Insee. 2021. *Information and Communication Technologies usage in enterprises.* doi: 10.34724/CASD.49.4545.V1

Koch, Michael, Ilya Manuylov, and Marcel Smolka. 2021. "Robots and Firms." *The Economic Journal* 131 (638), 2553–2584.

Noy, Shakked, and Withney Zhang. 2023. « Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence », *Science* 381 (6654).

Pizzinelli, Carlo, Augustus Panton, Marina Mendes Tavares, Mauro Cazzaniga, Longji Li. 2023. « Labor Market Exposure to AI: Cross-country Differences and Distributional Implications », IMF Working paper.

Toner-Rodgers, Aidan. 2024. "Artificial Intelligence, Scientific Discovery, and Product Innovation", Working paper

Webb, Michael. 2020. "The Impact of Artificial Intelligence on the Labor Market", Working paper