Generative AI and Job Displacement - Initial Evidence from EU Online Job Markets

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Abstract

Artificial Intelligence's recent technological breakthroughs, particularly in language models, have sparked concerns about potential labor market disruption. This paper examines the early impact of AI on labor markets by analyzing online job postings across the European Union from 2021 to 2024. Using a difference-in-differences design with continuous treatment and the release of ChatGPT as the event date, I find that occupations with higher AI exposure experience a 13-18% larger decrease in job postings compared to less exposed occupations. This result is robust across four different measures of occupational AI exposure. Additional analysis reveals that job skills most similar to AI capabilities see a 10% reduction in mention frequency within job descriptions, suggesting changes in task composition. However, industry-level analysis shows no significant impact on labor or capital productivity, indicating a scenario of "so-so automation" where AI adoption leads to labor displacement without corresponding productivity gains. The findings suggest that while AI's initial impact on labor demand is measurable, its magnitude remains modest relative to other labor market dynamics. The results are subject to several caveats, including potential violations of parallel trends assumptions and limitations of online job posting data as a proxy for labor demand.

JEL Classification: O33, J24, J23, O31, J31, C55, C81

Keywords: artificial intelligence, labor markets, job automation, online job postings, difference-in-differences

1 Introduction

Generative AI has been one of the most rapidly adopted technologies, with the initial release of ChatGPT gaining more than 300 million users in about two years OpenAI (2025). Since its initial release in November 2022, the field has seen further rapid advancements, including bigger and more powerful foundation models, breakthroughs in image and video generation, and the introduction of additional capabilities for AI agents, including writing computer code, browsing the internet, carrying out multi-step research plans, among others Mollick (2024).

This fast pace of technological progress has naturally sparked many questions regarding AI's potential to automate jobs and disrupt labor markets. According to a survey conducted by Oliver Wyman among fifteen thousand people, about 60% of white-collar workers fear AI automation, with a third of them already seeking new positions to better position themselves against automation threats Forum (2024). A different survey by Mercer finds that a third of CEOs and CFOs surveyed are redesigning their workflows to reduce their dependency on people, while 44% are exploring ways to incorporate AI in their processes mer (2024).

With this high level of public concern and interest, there have been several attempts by experts to estimate AI's projected impact on jobs. Most of these attempts rely on classifying jobs according to their potential for automation and looking at the total number of workers employed in the jobs most susceptible to automation. For example, a report of the World Economic Forum in collaboration with Accenture finds that a quarter of all jobs will experience changes due to generative AI, with the net effect coming out to a decrease of employment by 2% wef (2023). Using similar methods, McKinsey estimates that up to half of all tasks currently performed in the economy may be automated by 2060 mck (2023), while Ernst and Young classify two-thirds of all jobs as "high exposure" Daco and Khan (2023). A separate report by McKinsey estimates that AI will automate about 8

These grim forecasts are often contrasted with the more positive promises of AI adoption. For example, the same McKinsey report cited above also estimates that AI may add up to $4.4 trillion to the global economy by 2060 and boost productivity by 0.6% per annum. Besides the direct effect on productivity, AI may lead to positive job market outcomes by enabling the creation of new business models and products Daco and Khan (2023). The literature on automation, as discussed at length below, generally focuses on three main effects when it comes to labor impact: job displacement, labor augmentation, and new task creation Acemoglu and Restrepo (2019). The balance between these effects is not clear a priori for any given new technology, but Autor et al. (2024) demonstrates that over the past two centuries new task creation has generally outpaced direct automation, with the effect especially pronounced when examining product innovations rather than process automation Hall (2011).

Despite the large-scale social implications and the plethora of long-term forecasts of AI's impact on jobs, relatively little has been done to study the currently existing evidence of AI-induced automation. This paper aims to address this gap by exploiting a large dataset of online job opening listings across the EU compiled by CEDEFOP Cedefop (2021). Combining this data source with four distinct AI exposure scores enables the examination of relative dynamics of occupations highly exposed to AI compared to those with little to no exposure. Specifically, this study employs a difference-in-difference style design with a continuous treatment (the AI exposure scores) using the release of ChatGPT (November 29, 2022) as the event date. This approach, combined with country and industry-level fixed effects, allows for a more robust identification of causal effects.

The current paper, similar to most others in this literature, is based on the task-based model of job automation, originally proposed by Zeira (1998). In this framework, economic output is produced by combining the outputs of multiple tasks, some of which can only be completed by labor, while others can be performed by capital. Automation is modeled as an increase in the proportion of tasks that can be produced using capital. As shown in the Model section below, this has an immediate displacement effect on labor, but could potentially result in increased employment if the productivity improvements due to automation are large enough. In any case, the model implies that we would expect to see changes in the set of tasks performed by labor in exposed occupations.

CEDEFOP's data classifies job openings according to ESCO European Commission, Directorate-General for Employment, Social Affairs and Inclusion (2019), and additionally breaks down job descriptions in terms of required skills and competences. The granularity of the data allows not only examination of whether occupations highly exposed to AI experience relative decline in labor demand, but also analysis of whether within a given occupation, skills that are more likely to be performed by new AI models are mentioned in job postings less often. Indeed, this is exactly what the empirical section of this paper shows, with jobs at the highest levels of AI exposure experiencing 13-18% decrease in the number of online job adverts relative to occupations with low exposure levels. Similarly, job skills and competences that are highly similar to novel AI capabilities are mentioned 3-5% less often in job descriptions. Both results are statistically significant.

In order to assess the impact of AI on productivity, this paper first constructs industry-level AI exposure scores, and then uses these scores in a model of labor productivity, using productivity data from Eurostat European Commission (2025c). The approach adopted is analogous to the difference-in-differences method used to model job adverts; however, the explanatory power of the model is hindered by relatively worse data availability. None of the measures of AI exposure result in significant coefficient estimates, indicating that AI's early impact on productivity is too small to be measured in the data.

Taken together, these results point toward the outcome that Acemoglu and Restrepo call "lackluster automation." In this scenario, new technologies are just barely more productive than human labor - enough for firms to shift production to capital, but not enough to create widespread productivity effects that counteract the disemployment effects. Although these conclusions are troubling, they should be taken with considerations of the limitations in the data and methods employed and the fact that the elapsed period since the advent of generative AI may be too short to draw overarching conclusions. Nevertheless, the results presented below underscore the importance of continuous monitoring of labor market outcomes for occupations at risk of automation.

This paper proceeds as follows: section two presents a short overview of related literature; section three lays out the conceptual theoretical framework for studying AI automation; section four goes over the sources of data used; section five explains the empirical estimation strategy; section six presents the results, and section seven discusses the implications and limitations of the study.

2 Related Literature

As mentioned in the introduction, most efforts to understand AI's impact on labor demand are grounded in the task-based family of growth models, first proposed in Zeira (1998). This framework has been successfully used to study job automation in previous waves of technological disruption, for example in the context of industrial robots by Acemoglu and Restrepo (2020). The defining feature of these models is viewing the total output in the economy as a (typically CES) aggregate of individual tasks' output. Those tasks in turn are either performed by labor or by capital, depending on the technological possibilities and the relative task-specific productivity of the two factors.

This family of models has seen a number of extensions, some of which are specifically tailored toward studying AI-induced automation. These include a series of works by Autor, Acemoglu and Restrepo such as Autor et al. (2003) and Acemoglu and Restrepo (2019). All of these models focus on the interplay between automation-caused labor displacement and the potential reinstatement due to the introduction of novel tasks in the economy (think, for example, of the disappearance of switchboard operators and the introduction of remote customer support as telecommunication technology improved in the 20th century). A comprehensive overview of this line of models is given in Acemoglu et al. (2024). The effect of technology on labor in these models is generally ambiguous, as the direct effect of automation can be counterbalanced by increases in productivity that raise aggregate output by a sufficiently large amount, such that the increased labor demand in non-automated tasks overcompensates for the reduced demand in automated tasks.

A separate, but related strand of work deals with AI's potential tendency to cause the sectors that are most affected by it to shrink in terms of their total share of output. This occurs when goods in the economy are gross complements. In this case, rapid improvements in productivity shift more and more of the demand to non-automated sectors, as the economy is increasingly constrained by a few hard-to-do tasks. Notable recent works in this line of research include Aghion et al. (2019) and Jones and Liu (2024), the latter of which also endogenizes the innovation process to show that a balanced growth path with constant labor shares can be achieved in the task-based framework from microfoundations. Regardless of the general countervailing forces to labor displacement due to capital dilution emphasized in these papers, they also share the prediction of shrinking labor demand in tasks directly impacted by automation.

The structure of these task-based models naturally raises the question of which tasks are most likely to be automated due to AI. Recently, a number of papers have attempted to tackle this question by developing occupation-level measures of AI susceptibility. These "exposure scores" typically try to look at the tasks and skills that characterize each occupation and map those to AI capabilities to arrive at a relative measure of how easy or hard it would be for AI-powered algorithms to perform these tasks.

The pioneering work in this direction was done by Brynjolfsson and Mitchell (2017) and Brynjolfsson et al. (2018). In these works, a "suitability for machine learning" metric is developed for several thousand work-related activities taken from the ONET database. The metric is based on crowd-sourced questionnaires and is then aggregated to the occupation level based on the preponderance of each activity in the occupation-level descriptions in ONET.

Following a similar approach, Felten et al. (2018) develop a dataset of hand-labeled exposure scores for 70 representative occupations by consulting machine learning experts. Next, using occupational characteristics from O*NET, they train a machine learning model on the measure, which they in turn use to estimate the exposure scores for a total of 702 additional occupations. Felten et al. (2023) is another study along similar lines, but it adopts an objective measure of AI progress in the form of benchmark measures of AI capabilities developed by the Electronic Frontier Foundation. They then link these capabilities to occupational abilities and aggregate the scores up to the occupation level.

More recently, Webb (2022) employs large-scale text analysis to study AI-related patents and compares the verb-noun pairs found in the patent descriptions to verb-noun pairs in job-specific tasks from O*NET, allowing him to construct an AI-susceptibility measure based on patented AI innovations. Similarly, Demirev (2024) analyzes a corpus of corporate press releases regarding AI product launches and uses vector similarity to link the capabilities of the newly released AI products to job skills taken from the ESCO classification of occupational skills and competences. Finally, Eloundou et al. (2023) applies a more unconventional approach by directly feeding occupation descriptions to a frontier large language model and asking the model itself to rate each occupation relative to the likelihood it gets automated.

Despite the array of different approaches, all these scores lead to similar conclusions, with occupations requiring routine generation or analysis of text, creation of documentation, writing code, or frequent communication being most exposed to AI disruption. This is in general contrast to previous waves of automation that tended to target lower-skill manual work Acemoglu and Johnson (2023). It is worth noting that ”exposure to AI” doesn't always equate to ”susceptible to AI automation,” as several of the approaches above cannot generally distinguish between automation-enhancing technological advances and productivity-enhancing ones.

Nevertheless, these scores, coupled with direct data on labor demand by occupation, can serve to test whether occupations more exposed to AI exhibit a reduction in employment. This is exactly what this paper tries to do, leveraging the indices developed by Felten et al. (2018), Webb (2022), Eloundou et al. (2023), and Demirev (2024), which are made publicly available by their respective authors.

As outlined in the introduction, the existence of these exposure measures, combined with task-based models of growth, has allowed for rough estimates of the mid- to long-term impacts of AI. These range from the largely optimistic forecast of McKinsey for $6.1to7.9$ trillion of additional value added to the economy mck (2023), to the much more reserved calculations of Acemoglu for a 0.71% increase in total factor productivity spread over the next ten years Acemoglu (2024).

However, attempts to empirically estimate the initial impacts of generative AI on jobs and productivity are sparser. One such paper is a recent report by the OECD, which uses several heterogeneous sources of data on UK firms for 2019 Calvino et al. (2022). By combining patent filings, website announcements, and job posting data, the authors identify firms that are AI adopters.

They then compare those firms to similar companies that are not adopting AI and find that they tend to be more productive on average (without claiming to show a causal link). Regarding labor market outcomes, the study only shows that, perhaps unsurprisingly, AI adopters tend to increase their hiring of AI-related talent.

In a similar vein, a new working paper out of Carnegie Mellon University examines data from the US Patent and Trademark Office to identify AI-adopting firms Alderucci et al. (2019). The authors then link those firms to micro firm-level data to examine their performance. Using an event-study design, they find that AI adopters exhibit 25% faster employment growth and 40% faster revenue growth. Additionally, higher AI adoption was associated with higher per-worker productivity and an increase in inter-firm wage inequality.

Albanesi et al. (2023) use the indices of Felten Felten et al. (2023) and Webb Webb (2022) and combine them with occupation data for the EU using the Labor Force Survey (EU-LFS) over the period 2011-2019. To do so, they first use a crosswalk to convert the Felten and Webb data, which is originally in terms of the US O*NET classification, to the international ISCO classification used in the EU-LFS (an approach that is also adopted below). They find that highly exposed occupations increase their relative share of the population mix over the observed period. Specifically, moving up one quartile in terms of relative AI exposure was associated with between 3.1% and 6.6% higher sector-occupation employment share.

Using a different approach, Gazzani and Natoli (2024) create an aggregate time series of AI innovation intensity using patent data to study its effect on macroeconomic indicators. They find that increases in AI innovation intensity are associated with higher industrial production and a reduction in consumer prices. They also find, on aggregate, an increase in the demand for workers, suggesting that productivity effects outpace displacement effects. In terms of labor income, the authors show evidence that AI innovation intensification is linked to increases in the wealth share of the top decile of workers coupled with a decline in the wealth share of the bottom half, suggesting that AI-powered innovations may be contributing to wealth inequality.

While the papers above show a generally positive outlook in terms of AI's impact on employment, other studies have found more conflicting evidence. Acemoglu et al. (2022) use data on almost all job vacancies posted online in the United States over the period 2010-2018. They find that firms with occupational mixes more heavily skewed toward AI-exposed occupations increase the hiring of professionals directly working on AI, while simultaneously decreasing the hiring in all other occupations (while also exhibiting greater changes in the job requirements for non-AI workers). This behavior is consistent with a view of automating some of the tasks previously performed by labor (and hiring specialists to implement the AI that does so). At the same time, the authors fail to find a noticeable effect beyond the firm level, suggesting a more localized impact.

Huang (2024), on the other hand, is able to show aggregate disemployment effects at the commuting zone level in the US. A regional AI exposure score is constructed using per-industry survey data on AI adoption. This measure is then regressed on the commuting zone's employment-to-population ratio. To avoid simultaneity bias and endogeneity issues, the author uses an instrumental variable approach based on the occupational structure of a given commuting zone and AI adoption statistics from the EU. The results show that a one standard deviation increase in AI exposure is associated with a nearly 1 percentage point decrease in the employment ratio. The data used in this paper covers the period 2010-2021.

In related work, Bonfiglioli et al. (2024) largely replicate the above findings. This paper again looks at commuting zone level data and uses a similar shift-share instrument estimation strategy and employment data for 2000-2020. However, it derives a different measure of regional AI exposure by leveraging O*NET's category of "Hot Technologies" and assigning a higher exposure score to commuting zones with faster growth in that category. The resulting estimates show an average effect over a zero-exposure counterfactual of a 0.6 percentage point reduction in employment.

Taken together, the studies mentioned above show a conflicting array of evidence regarding the effects of AI on employment. The applicability of the findings to future developments in artificial intelligence is further restricted because almost all of them cover periods ending before the release of modern language models in 2022. Insofar as LLMs pose a paradigm shift in machine learning, it is far from certain whether their effects on labor will be similar to prior waves of AI.

Both data and peer-reviewed studies for the period after the release of GPT-3.5 are hard to find, but an August 2024 business survey conducted by the New York Federal Reserve gives some indications about the spread and initial effects of generative AI Abel et al. (2024). Among the surveyed firms, 25% of service companies and 16% of manufacturing companies reported using some form of AI over the previous six months, with generative AI accounting for about 80% of that usage. Five percent of service companies reported hiring new workers to accommodate the technology, while 10% had laid off workers due to AI. About 50% of the firms have plans to retrain part of their workforce to better handle the new technology. Overall, this survey points to a noticeable negative, though not dramatic, effect on employment of current-generation AI systems.

By focusing on recent data in the time window 2021-2024, this paper aims to build on the existing literature by providing an early estimation of the impact of LLM-powered AI systems on the labor market.

3 Conceptual Framework

The theoretical framework used for this paper is a straightforward application of the model in Acemoglu et al. (2022). Consider an economy consisting of S different sectors, where the output for each sector $s \in S$ is given by:

$$\ln y_s = \ln A_s + \int_{T_s} \alpha(x) \ln y_s(x) dx \tag{1}$$

where $T_s \subseteq T$ is the set of tasks that need to be performed to produce the final good output in sector s (T being the set of all tasks in the economy). Final output in the sector is a weighted average of individual task outputs, with the weights given by $\alpha(x) \geq 0$, $\int_{T_s} \alpha(x) dx = 1$. A_s is a sector-specific productivity factor.

Output in each sector is produced by a per-sector representative firm, facing downward-sloping demand for its final good and obtaining production factors on a perfectly competitive factor market.

Task-level output is produced using labor and AI-powered algorithms, combined via a constant elasticity of substitution production function:

$$y_s(x) = [(\gamma_l(x)l_s(x))^{\frac{\sigma-1}{\sigma}} + (\gamma_a a_s(x))^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{2}$$

Here $\gamma_l(x)$ and $\gamma_a(x)$ are labor productivity and AI productivity for some task x, respectively. The elasticity of substitution is assumed to be unity (i.e., σ tends to infinity), so that labor and AI are perfect substitutes when adjusted for productivity. This means that in equilibrium, a cost-optimizing firm will use either only labor or only AI when producing the output of a given task, depending on which one delivers higher productivity per cost unit.

An (economically meaningful) automation-inducing advance in the capabilities of Artificial Intelligence in this framework is interpreted as an increase in $\gamma_a(x)$ for some tasks $x \in T^a \subseteq T$, such that firms are induced to switch from labor to AI when producing the output of those tasks.

It is worth pausing here to observe that labor augmentation is just one possible channel through which technological advancements can affect output in this family of models. Namely, using the notation above and following Acemoglu et al. (2024), we distinguish between:

- *Labor Displacement*, i.e., relative increase in $\gamma_a(x)$ against $\gamma_l(x)$ such that previously manual tasks are now more efficiently produced by algorithms.

- *Labor Reinstatement* due to the introduction of new manual tasks, which would manifest in an increase in the size of the set T_s.

- *Capital Deepening* or the increase in $\gamma_a(x)$ for tasks x that are already produced by capital.

- *Labor Augmentation* due to an increase in the productivity of labor for labor tasks, i.e., a rise of $\gamma_l(x)$.

This paper focuses on the automation or displacement channel. However, it is worth noting that the other three channels all have a positive effect on wages and labor demand, mostly acting through a rise in the overall productivity of the economy. Even displacement itself can lead to a positive effect on labor demand once general equilibrium effects are taken into account, if the overall increase in productivity due to automation is large enough, as demand for labor in non-automated tasks will increase.

Going back to the partial equilibrium model considered in this paper, we can then define a sector's exposure to advances in Artificial Intelligence over tasks in T^a as the share of the sector's labor force employed in producing tasks that are about to be automated. Specifically:

$$exposureAI_s = \frac{\int_{x \in T^A \cap T_s} l_s(x)dx}{\int_{x \in T_s} l_s(x)dx} \tag{3}$$

As shown in the Appendix (and more thoroughly derived in Acemoglu et al. (2022)), firms respond to advances in AI by changing their demand for labor in proportion to each sector's exposure to AI. Specifically, assuming that the initial share of AI in the economy is small, an economically meaningful improvement in $\gamma_a(x)$ for some tasks T^A induces:

$$d \ln l_s = (-1 + (\epsilon_s \rho_s - 1)\pi_s) \times exposureAI_s \tag{4}$$

Here $\epsilon_s > 1$ is the demand elasticity of the final product of sector s; $\rho_s > 0$ is the pass-through rate of the firms in s, i.e., the sensitivity of their final price to reductions in cost; and $\pi_s \geq 0$ is the average cost reduction resulting from switching from labor to AI for tasks in T^A.

While theory clearly predicts that labor demand will be affected by AI exposure, the sign of the correlation remains ambiguous. If $(\epsilon_s \rho_s - 1)\pi_s < 1$, increased use of AI reduces sector employment, while in the opposite case it expands it. This means that AI can lead to more workers being employed in an industry if both a) the quantity demanded for the sector's output expands (by a combination of a price decrease resulting from the lower costs and an elastic enough demand function) and b) cost reductions are sufficiently high. Otherwise, the displacement effect dominates and employment is reduced.

4 Data

In order to empirically assess the theoretical predictions laid out above, three main sources of data are needed: 1) data on AI exposure by occupation, 2) data on labor demand by occupation, and 3) data on labor productivity.

AI occupational exposure has received relatively strong research interest recently, and several datasets are made publicly available by their authors. Coupled with data on the sectoral occupational employment mix, we can derive a per-sector exposure measure. Productivity data are part of the standard national accounts data and are typically available at the sector level. Finally, data on labor demand by occupation is generally hard to come by, but we can leverage high-frequency and high-availability data on online job postings to serve as a proxy.

The following subsections cover each data source in detail.

4.1 Data on AI Exposure

In order to estimate a version of equation 4, we need a measure of occupation-level exposure to AI. I rely on four separate studies using different methods to get a comprehensive measurement - Felten et al. (2018), Webb (2022), Eloundou et al. (2023), and Demirev (2024). Each of these approaches utilizes a different methodology to measure exposure as detailed below. To ensure that the findings of this paper are not contingent on using a specific measure of exposure, all results below are reported for each of the four indices as an independent variable.

These specific exposure measures were chosen because the final result datasets of all four papers are made publicly available by their respective authors. Some of them have been used by other empirical studies of AI's impact on jobs, such as Albanesi et al. (2023) and Acemoglu (2024).

The exposure data of Felten et al. (2018) is made available via GitHub[1]. Their measure of "AI Occupational Exposure (AIOE)" is constructed by linking 52 human job-relevant abilities taken from the ONET database to 10 AI applications tracked by the Electronic Frontier Foundation. These applications include image recognition, visual question answering, reading comprehension, language modeling, translation, speech recognition, and various game-playing capabilities. The authors then use a crowd-sourced matrix of links between the occupational abilities and AI applications, as well as forecasts on the expected progress of each AI ability to construct a per-ability measure of AI exposure. The aggregation to an occupation level is then carried out by using the importance of each ability for a given occupation as per ONET. In subsequent work Felten et al. (2023), the same authors refined their exposure index to better correspond to occupational exposure due to large language models by only considering the occupation abilities links with the "language modeling" application. However, since the two measures are highly correlated (correlation coefficient of 0.97), and since the next-token prediction approach inherent to language modeling can (and is) also be applied to other AI applications, such as visual reasoning, reading comprehension, and translation, in this paper I use the more general AIOE measure.

The data for the exposure measure of Webb (2022) is taken from the author's website[2]. This measure relies on patent data to link AI capabilities to job-relevant human abilities. The patent data is taken from Google Patents Public Data. Each patent's title and description is then processed to extract verb-noun pairs describing the invention. These verb-noun pairs are then compared to 964 task descriptions from the O*NET database (after first being further processed based on a dictionary of hierarchical word definitions). The task-level measure is then aggregated to the occupation level.

The exposure index developed by Eloundou et al. (2023) is available through the paper's repository[3]. This OpenAI-authored study uses GPT-4 directly to determine how much each occupation is at risk of AI automation. Task descriptions are passed directly to the large language model, with the custom-created prompt instructing the AI to opine on how likely the task is to be done by AI in the near future. The study distinguishes between tasks that are exposed to current-generation AI systems directly (defined as ones where a system like GPT-4 can improve performance by 50% or more), and tasks where additional systems and processes need to be built around the LLM to achieve significant performance improvement. The paper finds that about one-fifth of all occupations may see at least half of their tasks significantly impacted by AI. Notably, this is the only one of the exposure studies that can claim to distinguish "automation" effects directly, rather than the more general "exposure" effects that capture both substitution and complementarity. In this paper, I use the "beta" index from Eloundou et al. (2023) which combines direct and indirect exposure.

[1]https://github.com/AIOE-Data/AIOE

[2]https://www.notion.so/michaelwebb/Data-for-The-Impact-of-Artificial-Intelligence-on-the-Labor-Market-3b52b281505a48b8be107d11d8d0c363

[3]https://github.com/openai/GPTs-are-GPTs/

Finally, Demirev (2024) takes a different approach by using press release data on new products using AI scraped from a popular news aggregator. They then employ text embedding techniques to find the cosine similarity between the AI capabilities claimed by those products and job-relevant skills. Similar to Eloundou et al. (2023), this paper also uses GPT-4 as part of the text analysis process, but only for summarizing the press releases and putting them in a format that can more easily be compared to the occupational skills. The data from this paper is also available on GitHub. Unlike the other studies cited above, this paper uses the European Skills, Competences, Qualifications and Occupations (ESCO) database of occupations European Commission, Directorate-General for Employment, Social Affairs and Inclusion (2019), instead of the American O*NET.

Since the job market demand data and industry occupation mix data used in this paper (and detailed below) are from the European Union, all measures of occupational AI exposure needed to be converted from the O*NET classification of occupations to the International Standard Classification of Occupations (ISCO) used across the EU Office (2012). This was accomplished via a crosswalk provided by ESCO European Commission, Directorate-General for Employment, Social Affairs and Inclusion (2019). ISCO is a hierarchical classification of occupations with five levels of increasing specificity. To match the granularity of the job demand data, the intermediate 3-level ISCO classification was used throughout.

The four measures of AI exposure used here capture different aspects of the overlap between AI capabilities and job skills. While Felten et al. (2018) is rooted ultimately in core scientific advances as measured in projected improvements in AI application benchmarks, Webb (2022) and Demirev (2024) focus on marketable innovations by examining patents and product releases, respectively. Eloundou et al. (2023) is unique in directly using language models to evaluate their own automation potential and is perhaps the most forward-looking of the four. Webb (2022) and Demirev (2024) were primarily developed after the widespread release of powerful language models, while Felten et al. (2018) received an update Felten et al. (2023) to account for the rapid pace of progress in the area. Despite the different approaches, the four indices are highly correlated with each other, as shown in 6, with Eloundou et al. and Felten et al. having $r = 0.86$, and both of them having a correlation coefficient close to 0.75 with the index of Demirev. A notable exception is Webb's index, which shows no correlation with Felten et al. and Eloundou et al., and only a modest correlation with Demirev. This might indicate that Webb's approach is capturing a different aspect of AI susceptibility, or that part of what the other indices are measuring is captured by Webb's complementary "exposure to software" index, which is outside the scope of the current paper. Overall, the four studies represent a comprehensive and up-to-date picture of the degree to which AI capabilities overlap with the skills required to perform the most relevant job tasks for each occupation.

4.2 Job Adverts Data

The data on online job vacancies used to examine AI's early impact on labor demand is taken from the Skills Online Vacancy Analysis Tool for Europe (Skills OVATE) Cedefop (2021), developed jointly by the European Centre for the Development of Vocational Training (CEDEFOP) and Eurostat Cedefop (2019). The dataset contains information about more than 100 million job vacancies published on online job boards across the European Union (and the UK). Both public employment services and private job boards are included in the set of portals monitored by CEDEFOP.

The Skills OVATE provides an occupation label for each job vacancy according to the ISCO/ESCO classification system, as well as a breakdown of the skills mentioned in the job description. The skills are also classified using the ESCO system, which includes a hierarchical taxonomy of job skills, competences, and knowledge. The data is further broken down by country, region (NUTS2 classification), and industry (NACE-R2). The data is updated quarterly, with each release including information for the previous twelve months.

For the purposes of this paper, the Skills OVATE dataset was collected by downloading the publicly available interactive dashboard representing each quarterly release and extracting the underlying tables. The period covered spans Q4 of 2021 to Q2 of 2024. The main tables used are "Countries and Occupations," which includes the number of job vacancies for a given occupation (at the 2-digit ESCO level) over the last 12 months for each country, as well as "Occupation skills across occupations," which includes the number of times a given ESCO third-level skill was mentioned for each ESCO 3-digit occupation by country. The scripts used to collect the public dashboards, extract the underlying tables from each Tableau file, and process the data are available in the project repository[4].

The data is analyzed below on the country level, excluding data points on the EU-27/28 aggregate level. This approach was taken to include country-level fixed effects to control for regional labor market dynamics. The level-3 ESCO hierarchy was used for both skills and occupations, as that is the most granular level of data availability.

Using the number of online job adverts by occupation as the main dependent variable of the analysis presents both advantages and drawbacks. The main advantage is that the data is close to real-time and of considerably high volume, allowing us to examine the most recent trends and developments. The wide geographical coverage and the uniformity of the definitions of skills and occupations applied by CEDEFOP is another considerable advantage, allowing for an EU-wide analysis. The main drawback of this source of data, on the other hand, is that online job openings are only a proxy of real labor demand. Some firms may keep open positions even if not actively recruiting, while entire sectors and occupations that rely on more traditional recruiting channels may be underrepresented in the data. Approaches to overcome these challenges are addressed below.

4.3 Productivity Data

The study also uses industry-level output per unit of input data to try to estimate AI's early impact on productivity. Specifically, Eurostat's annual national accounts series is used (nama10). This data source includes data on output and factor usage across EU members at an annual frequency.

[4]

Its availability and publishing date varies by country, with this study using data for 2021, 2022, and 2023, which was the latest available full year at the time of the analysis European Commission (2025c).

Labor productivity was measured by the "Real labour productivity by hour worked" variable (RLPR-HW) European Commission (2025b). A measure of capital productivity was also used - "Gross value added per unit of net fixed assets" (GVA-NCS) European Commission (2025a). Both variables are provided as 2015-based indices. The data is broken down by country and by industry using the 15 top-level NACE revision 2 categories Eurostat (2008).

To derive the per-industry AI exposure metric described below, additional data was needed on the number of employed people by ESCO occupation in each NACE industry. This was again collected from CEDEFOP, this time using their "Skills Intelligence" online reporting tools European Centre for the Development of Vocational Training (2024). This tool includes an estimate of the by-industry breakdown of employment for each level-2 ESCO occupation. This dataset is available on the country level but only at a fixed time period.

5 Methods

The main empirical quantity this paper aims to estimate is the effect of higher exposure to AI (as measured by one of the four exposure metrics) on the labor demand for a given occupation (as measured by the number of job postings published online and tracked by CEDEFOP).

To achieve this, I adopt a difference-in-differences style approach, where the event date is taken to be the release of ChatGPT - the first widely available and capable large language model. By adopting a set of typical parallel-trends assumptions (discussed in detail below), this approach allows for an estimation of average treatment effect on the treated (ATT) style parameters, with high-exposure occupations serving effectively as the treatment group, and low-exposure occupations as the control group, used as counterfactual outcomes.

Besides the effect of AI exposure on labor demand, a number of secondary outcomes are also assessed below. These include:

- The effect of AI skill-level exposure on the relative frequency of within-occupation mentions of a particular skill
- The effects of industry-level AI exposure on industry capital and labor productivity
- The effects of AI exposure on the relative composition of job skills mentioned as requirements in job postings for a given occupation

As far as AI has a measurable impact on job market outcomes, we would expect to see a significant coefficient in the models of number of job listings. This would be either negative, if substitution/automation effects dominate, or positive, if task complementarities are prevalent. Similarly, the coefficient of AI exposure on models of skill-level mention frequency should be negative if AI is indeed used to automate the tasks associated with those skills. The effect on measured productivity is expected to be positive (if it's large enough to measure). Finally, one would expect more exposed occupations to exhibit a higher degree of change in the skills required from job applicants if AI is causing firms to reorganize their labor force.

5.1 Estimation

5.1.1 Occupational labor demand

The number of online job adverts for occupation i in period t and country c is modeled as a function of time, country, and period fixed effects, as well as of AI Exposure for occupation i (X_i^{AI}). All exposure metrics are standardized to cover the 0 to 1 range, with 0 being the lowest exposure score and 1 being the highest. This is done to facilitate comparisons of coefficients from specifications with different independent variables.

AI exposure only enters the model after period $t = 0$, which is taken to be the quarter containing the release date of ChatGPT - November 30th, 2022. This is captured by the indicator variable $\mathbf{I}$.

$$\log y_{i,c}^t = \gamma_t + \alpha_c + \eta_i + \delta^{TWFE} X_i^{AI} \times \mathbf{I}(t > 0) + \varepsilon_{i,c}^t \tag{5}$$

Denoting the effect of AI exposure as δ^{TWFE} and collecting unobserved influences in ε, we get the standard two-way fixed effects (TWFE) formulation in 5. Technically, this includes three separate fixed effects instead of two. An alternative formulation could have combined country-level and occupation-level variables in one common fixed effect dummy, but this approach risks obscuring important variations in between-country labor market dynamics. Nevertheless, the term two-way fixed effects is still used since it is standard in the literature.

The properties of these types of models, known as two-way fixed effects with continuous treatment, are studied extensively in Callaway et al. (2024). They show that under certain assumptions, δ^{TWFE} from 5 can be viewed as an average of causal parameters when estimated with OLS. Specifically, those assumptions are:

- Data consisting of tuples $y_{i,c}^0, y_{i,c}^1.., y_{i,c}^t, X^{AI}ii$ which are i.i.d across occupations and countries
- $X^{AI}i$ takes a number of real values between $dmin$ and d_{max}
- Potential outcomes do not depend on the treatment X^{AI} before the treatment time $t = 0$ (no anticipation)
- $\log y_{i,c}^t(0) - \log y_{i,c}^0(0) = K_c^t$, i.e., counterfactual per-period changes in y would be identical and constant across occupations and countries if all occupations had zero AI exposure

If all these assumptions are met, δ^{TWFE} can be viewed as an average of treatment-effects-on-the-treated type parameters. Specifically, if we denote $y_{i,c}^t(d)$ as the potential outcome equivalent of $y_{i,c}^t$, i.e., the hypothetical number of online job adverts for occupation i in country c at time t if that occupation had exposure $X^{AI} = d$, we have:

$$ATT(d|X^{AI}i) = E[y^ti, c(d) - y^0_{i,c}(0)|X^{AI} = X^{AI}_i] \tag{6}$$

$ATT(d|X^{AI}_i)$ is the average treatment effect for occupations with observed exposure levels X^{AI} had they experienced exposure levels d against the counterfactual where the same occupations had no exposure to AI ($X^{AI} = 0$). Callaway et al. (2024) show that δ^{TWFE} can be decomposed as:

$$\delta^{TWFE} = \int_0^1 w(l)ATT(X^{AI}_i|X^{AI}_i)dl \tag{7}$$

where w are weights depending on the relative frequency of each exposure group and the integration is over all possible values of X^{AI} in the data (in our case exposure is normalized to span the interval from 0 to 1). Essentially, the regression estimate from TWFE is a weighted average of level average treatment effects for each occupation[5].

The fact that the weights in the causal-parameter decomposition of TWFE could be negative makes the resulting coefficient hard to interpret. To address this, we can consider a model of the (log) differences in the average number of job postings in the periods before (PRE) and after (POST) the release of GPT. Taking period differences removes time-invariant fixed effects, while taking logs allows us to treat proportional increases and decreases in the number of job postings for a given occupation as equidistant positive or negative deviations from 0. If $\bar{y}^Tc, t$ is the average of y^tc, t across periods $T \in PRE, POST$ and defining $\Delta\bar{y}c, i = \log\bar{y}^{POST}c, i - \log\bar{y}^{POST}_{c,i}$, the model to be estimated becomes:

$$\Delta\log\bar{y}c, i = \delta_0 + \xi_c + \delta X_i + \varepsilon c, i \tag{8}$$

where we also allow for country-level fixed effects (ξ_c) in the difference form, which could be thought of as an interaction between period and country fixed effects in the simple form $\xi_c = (\gamma_{POST} - \gamma_{PRE})\alpha_c$.

The formulation in 8 is the main empirical specification used below (once for each separate exposure measure) for the main outcome of interest - the number of online job adverts. Results for the TWFE specification are also reported and presented in full in the appendix.

As an additional specification, I also fit a model where the exposure metric is discretized into ten discrete bins. Each decile is treated as a separate dummy variable. This relaxes the assumption of linear relationship between average treatment effects and AI exposure, allowing us to capture more intricate relationships. The dummy-variable approach is a consistent estimator of within-decile ATT[6] Callaway et al. (2024).

Let $\mathbf{I}^j_i = \mathbf{I}(X_{j-1} < X^{AI}i < X_j)$ be an indicator denoting the membership of observation i in decile j, where $Xj - 1$ and X_j denote the lower and upper bound of the decile's span respectively.

[5] The same paper demonstrates another decomposition of the TWFE estimator that does not have weights but requires much stronger assumptions that preclude treatment effect heterogeneity.

[6] Callaway et al. (2024) propose a splines-based method for truly continuous treatment effects that could in principle be applied here, but discretization was chosen for simplicity and ease of interpretation

Then, we have the following functional form:

$$\Delta \log \bar{y}c, i = \delta_0 + \xi_c + \sum j = 2^{10} \delta_j \mathbf{I}_i^j + \varepsilon_{c,i} \tag{9}$$

Here the lowest decile, containing the least exposed occupations, is left out as a reference group and absorbed in the intercept δ_0. An event-study specification is also estimated and reported in the results section to study the potential time-variability of the effects of AI exposure on job listings. The event study also serves as a test of the existence of pre-trends, which in turn might be indicative of a violation of the parallel trends assumption:

$$\log y_{i,c}^t = \gamma_t + \alpha_c + \eta_i + \delta^t X^{AI} i \times \mathbf{I}(t) + \varepsilon^t i, c \tag{10}$$

The event-study design returns a set of coefficients δ^t for all periods t. If prior to $t = 0$ the trends are parallel across occupations, we will expect the corresponding coefficients to not be significantly different from zero.

5.1.2 Skill Demand

An analogous approach is adopted when modeling the demand for individual skills. The only difference is that now there is an additional fixed effect at the occupation level, to isolate changes of skill demand within an occupation against changes in the mix of occupations demanded.

Denoting the number of times a specific ESCO level-3 skill k is mentioned in job listings for occupation i in country c and period t as $z_{c,i,k}$, the relative change specification becomes:

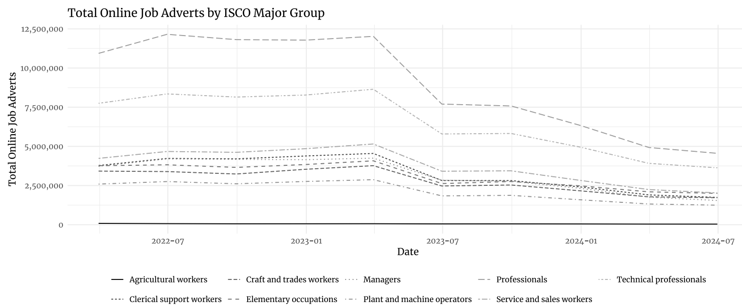
$$\Delta \log \bar{z}c, i, k = \delta_0 + \xi_c + \psi_i + \delta_j X k + \varepsilon_{c,i} \tag{11}$$

The main difference for the skill demand model is the independent variables - only Demirev (2024) reports exposure scores at the ESCO skill level, and therefore only this index was used for skill-level models (denoted X_k above). This inherently limits the conclusions, since any shortcomings of the index will carry over to the estimated coefficients. Besides this log-linear specification, I also estimate a version of the model where the exposure scores are discretized into deciles and the indicator variable for belonging to each decile is included as a dummy variable, similar to the occupation-level model 9. Analogous TWFE and event-study specifications (again with the additional occupation fixed effects) are also estimated and reported in the appendix.

5.1.3 Productivity

The estimation strategy for the effects of AI exposure on capital and labor productivity is similar; however, the industry-level AI exposure index first has to be constructed. I do this by taking an average of the occupation-level indices (using ESCO 2-digit level) weighted by the number of employees of this occupation employed in the industry. For industry j we would have:

Figure 1: Time Series of Total Online Job Adverts



$$S_j^{AI} = \sum_{i \in O} X_i^{AI} w_i^j \tag{12}$$

where w_i^j is the number of employees of occupation i in industry j. The two-way fixed effects specification would then take the form:

$$\log A_F = \gamma_t + \alpha_c + \eta_s + \delta^{TWFE} S_j^{AI} \times \mathbf{I}(t > t_0) \tag{13}$$

where A_F is measured factor productivity for labor or capital $F \in K, L$, and η_s are per-industry fixed effect dummies. Unlike the online job postings data, which is available quarterly with a rolling 12-month index, the national accounts data used for productivity measurement is available annually, so γ_t are year dummies instead of quarter dummies. As before, α_c are country dummies.

5.2 Limitations

6 Results

6.1 Occupational Labor Demand

To provide general context for the results from estimating the main empirical equations described in the preceding section, 1 presents the total number of online job listings collected by CEDEFOP for each period by ESCO level-1 occupation. The data for each quarter contains observations for the preceding twelve months, so the time series should be interpreted as a rolling window total across countries. The release of ChatGPT (the "event" time for the difference-in-differences design) is marked by a vertical line.

As shown, the total number of posted listings declines dramatically over the observation period. At the beginning of the sample, there are a total of 40.2 million online job adverts, covering the twelve months prior to March 31st, 2022. By the end of the sample period in June 2024, there are only 18.5 million - a more than two-fold reduction. This decline is relatively even across top-level occupations, with the relative reduction ranging between 2.40 for Managers and 1.88 for Elementary workers.

This overall drastic decrease in the number of job listings can be attributed to macroeconomic conditions from mid to late 2022 onward, with the ECB's deposit facility rate rising from 0% in July 2022 to 4% in September 2023. This development directionally matches findings from the US, where BLS data shows a comparable decline in job openings over the same period from 12.2 million to 7.2 million of Labor Statistics (2025). Job vacancy data tracked by Eurostat also shows a marked decline in the same period, with a decrease in the vacancy rate from 3.4% to 2.4% Eurostat (2024). In terms of relative magnitudes, these figures represent a decline of 1.7 and 1.4 times the initial number of vacancies, somewhat short of the two-fold decrease in the online job adverts data.

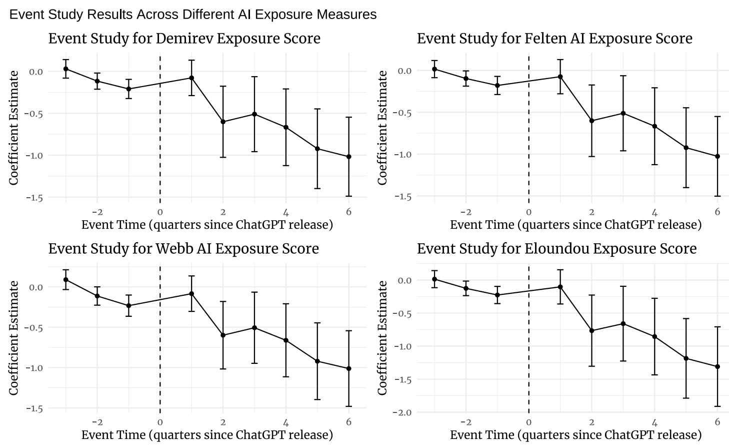
One possible explanation for this is that online job adverts don't necessarily track openings one-to-one. Cedefop (2019) notes the existence of 'ghost listings' used to test the market or to gather contacts of potential applicants for future openings. Comparing the CEDEFOP data to other aggregators of online listings, we see that online adverts show more drastic movements compared to employment or vacancy data. For example, the Help Wanted Online (HWOL) index provided by The Conference Board and tracking US online job markets shows a reduction of one-third from mid-2022 to the end of 2024 The Conference Board (2024). Similarly, the Internet Vacancy Index (IVI) provided by Jobs and Skills Australia shows a similar reduction from 305 thousand listings in June 2022 to 214 thousand in December 2024 - again close to one-third Jobs and Skills Australia (2024). Still, these figures fall short of the reduction in CEDEFOP's database, raising the possibility of a change in the data composition or methodology during the sample period. There was no public information for such a change, but if it did indeed take place, it may affect the results and conclusions in this paper insofar as the changes were not uniform across occupations.

Keeping those caveats about the data in mind, 4 presents descriptive statistics of the number of job postings in the periods before and after the release of ChatGPT (averaged over quarters and across countries) for individual level-3 occupations. The occupations that had the highest decrease in the number of listings include blue-collar professions such as Machine operators, Fishery workers, and Crop producers, but also knowledge workers, such as Software developers, database professionals, and life science professionals. On the other hand, occupations such as Traditional medicine workers, forestry workers, and ship crewmen saw an increase in the number of online job postings. Finally, professions such as Librarians, Primary and University teachers, and Electrical equipment installers had a more robust number of job adverts across the two periods and saw little to no change.

5 rounds up the descriptive statistics by showing the Pearson correlation coefficients between log change in number of online job adverts ($\log(y^{POST}i, c - y^{PRE}i, c)$ in the notation developed above) and each of the four measures of AI exposure. The plots show that all exposure metrics correlate negatively with the relative log change, with coefficients ranging between -0.08 for Eloundou et al. (2023) to -0.044 for Demirev (2024). While these correlation magnitudes are relatively small, all of them are significant at the 5

Going beyond the descriptive statistics, 2 presents the results of estimating the event-study specification 10 for each of the four occupational exposure metrics. The graphs show significant

Figure 2: Event Study of ChatGPT's introduction against number of OJA



negative coefficients for all periods after the event date, with the coefficients growing in absolute magnitude with each successive period. The coefficients in the pre-event period, while much closer to zero, are still significant for at least one period for each of the exposure indices. This indicates the possible existence of pre-trends in online job listings between occupations. The exact numerical values are presented in 6.

With that caveat in mind, 1 presents the results from estimating the log-linear relative change model with country fixed effects from 8. This is the main empirical result of this study. The dependent variable is the log of the ratio of the average number of job listings per period in the periods after and after the release of ChatGPT. The independent variable in each of the four models is one of the four exposure metrics. Country fixed effects are included and standard errors are clustered at the country level. From an initial dataset of 3,270 country-occupation pairs, all observations with fewer than 20 job adverts in either the pre or post periods were excluded. The final dataset thus includes 2,814 country-occupation pairs.

Each column of 1 represents a different measure of occupational AI exposure. All estimates are negative and significant at the 1% level, ranging in magnitude from -0.138 to -0.193. This means that an increase in AI exposure from the lowest to the highest possible level (0 to 1) results in between 12.9% and 17.6% (one minus the exponents of the regression coefficients) decrease in the number of online job adverts relative to the baseline period.

3 illustrates the estimate for the Eloundou exposure metric. It shows the partial correlation plot derived by regressing both the dependent variables (log of the ratio of job listings before and after the event date) and the independent variable (any of the four AI exposure metrics) and plotting the residuals of the two regressions against each other. Each dot is an individual country-occupation pair, while crosses represent occupation averages. Similar plots for the remaining exposure metrics are broadly similar and are presented in the appendix 7.

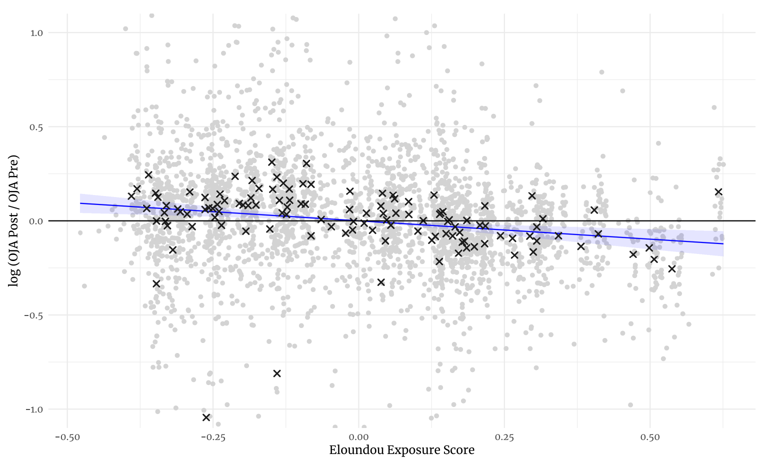
It should be noted that despite the significant coefficient on the AI exposure variable, the model produces a weak overall fit to the data across the exposure metrics, with a within-country R-squared

Table 1: Impact of AI Exposure on Online Job Ads

	(1)	(2)	(3)	(4)
Demirev Exposure	-0.186***			
	(0.056)			
Felten AI Exposure		-0.138***		
		(0.047)		
Webb AI Exposure			-0.174***	
			(0.035)	
Eloundou Exposure				-0.193***
				(0.054)
Observations	2,814	2,814	2,805	2,814
R^2 (within)	0.013	0.013	0.013	0.018
Adjusted R^2	0.480	0.479	0.480	0.482
Country FE	Yes	Yes	Yes	Yes

Standard errors clustered at country level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

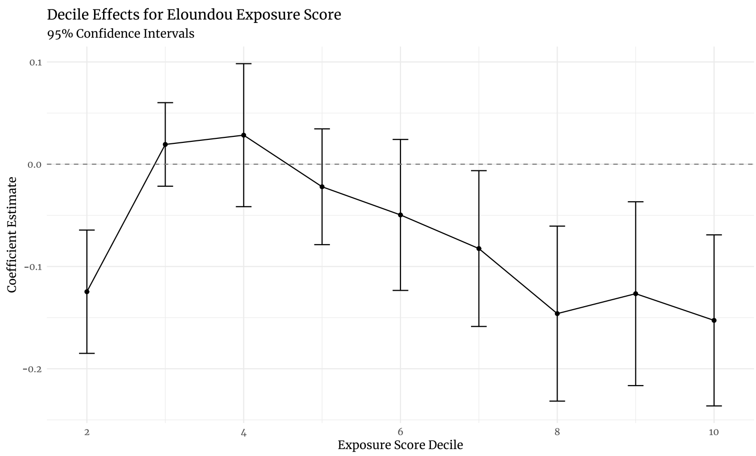
Figure 3: Decile Model of AI Exposure and OJA



ranging between 0.013 and 0.018. The total R-squared of the models is noticeably larger - close to 0.5 for all specifications - indicating that between-country differences are a much greater source of variation. Overall, this means that while the association between AI exposure and online labor demand is strong enough to be picked up in the data, it accounts for relatively little in the overall variation in job postings. This is visible both in 1 and in 7, where despite occupation averages being close to the regression line, individual country-occupation pairs exhibit large variation above and below it.

7 hints at a possible non-linear relationship between AI exposure and the change in job adverts. To examine this, I fit a model where the exposure metrics are binned in deciles and a separate dummy is included for each decile (specification 9). The results of this model are plotted in 4 for the Eloundou exposure metric (and in the appendix as 8 for the other exposure metrics. Additionally,

Figure 4: AI Exposure and Change in Online Job Postings



the appendix contains the estimates in tabular form as 7). The estimates of this specification show that for measures of Demirev and Webb, the lowest 30% of occupations in terms of exposure show little to no change in the number of job postings, while the effect for the remaining occupations is relatively similar. Felten's and Eloundou's measures, on the other hand, show an increasing effect of AI exposure on the number of job adverts for higher deciles, a notable exception being the lowest exposure decile, which also has an associated strongly negative coefficient.

Before moving on to examining skill-level demand, 8 in the Appendix presents the results of estimating the TWFE specification (5). The results are broadly in line with the ones presented above, with all four AI exposure regression coefficients being negative and significant.

6.2 Skill Demand

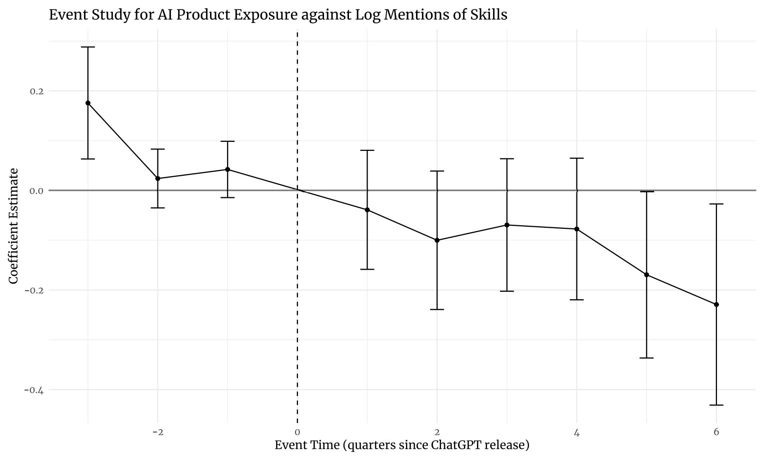
Analogously to occupation-level exposure to AI, the data from Demirev (2024) includes a measure of skill-level exposure. This is derived by calculating the cosine similarity between the string describing the job skill in the ESCO database and strings describing the capabilities of new AI products derived by the author from corporate press releases. The paper provides exposure scores on individual ESCO skills. To use this data together with other ESCO data, I aggregated the measure up to the ESCO level-3 data using simple averaging. The most exposed and least exposed level-3 skills are presented in 9[7].

Since the data on online job adverts provided by CEDEFOP also includes a breakdown of skill mentions across adverts by occupation type, we can estimate the model of skill demand specified in 11. The results are presented in 2. The dependent variable is the difference in the log of the number of times a given skill was mentioned in periods before and after the introduction of ChatGPT. The independent variable is the skill exposure measure, while fixed effects for country and occupation are also included. The associated event study is shown in 5.

The event study clearly shows that the point estimates of the coefficient of the interaction

[7]This exposure metric is standardized to have mean 0 and standard deviation of 1

Figure 5: AI Skill Exposure and Change in Skill Mentions



between the exposure variable and the time dummy become progressively more negative in the later periods after the event date. However, only the last period is associated with a significant negative coefficient. Additionally, the interaction between the first observed period dummy and the exposure variable also has a significant coefficient (although positive). These results indicate a potential violation of the parallel trends assumption, meaning that the results may not have a valid causal interpretation.

Table 2: Impact of AI Exposure on Skill Demand

Dependent variable:	Δ log(Skill Mentions)
AI Product Exposure	-0.025**
	(0.011)
Observations	75,864
R^2 (within)	0.001
Adjusted R^2	0.095
Occupation FE	Yes
Country FE	Yes

Note: Δ represents the change from pre to post-ChatGPT period

The estimate of the coefficient from 11 is -0.025 with a p-value of 0.024. This means that an increase of 1 standard deviation in skill AI exposure is associated with a modestly lower ratio of post-GPT to pre-GPT skill mentions of roughly 2.5%. Since the model includes occupation fixed effects, this is a change in within-occupational skill demand, net of the change in the composition of occupations in the dataset. The data spans roughly four standard deviations of the exposure variable (-2.44 to 1.5), so going from the least exposed skill to the most exposed skill corresponds to roughly 10% lower number of mentions in the post period.

6.3 Productivity

As described in the methods and data section, productivity data is available from Eurostat on the NACE Revision 2 Industry level (and not on the occupation level). In order to derive an exposure score for each industry, I leverage data from CEDEFOP about the number of people employed in each industry by occupation. The resulting industry exposure scores are presented in 3. There are four separate scores, corresponding to the four individual exposure measures that can be used at the occupation level.

There are some differences between the four measures, but generally, knowledge-intensive industries such as ICT, Finance, Education, and Professional Services have the highest exposure scores. On the other hand, industries relying more on manual labor and physical object manipulation, such as Agriculture, Waste treatment, Construction, and Accommodation tend to have lower exposure scores. Notably, the industry scores derived from Webb (2022) seem to be somewhat distinct from the others, with Agriculture and Mining scoring highly while Education has the lowest exposure score.

Table 3: AI Exposure Scores by Industry

Code	Industry	AI Product Exposure	Felten Score	Webb Score	Eloundou Beta
J	ICT services	0.771	0.886	0.717	0.779
K	Finance & insurance	0.667	0.931	0.491	0.682
M	Professional services	0.640	0.857	0.610	0.599
P	Education	0.630	0.793	0.084	0.442
D	Energy supply services	0.601	0.625	0.791	0.438
O	Public sector & defence	0.570	0.541	0.416	0.319
Q	Health & social care	0.560	0.729	0.480	0.546
G	Wholesale & retail trade	0.434	0.574	0.253	0.434
C	Manufacturing	0.407	0.385	0.657	0.255
R	Arts & recreation	0.401	0.528	0.326	0.317
H	Transport & storage	0.379	0.360	0.604	0.276
B	Mining & quarrying	0.330	0.230	0.723	0.133
F	Construction	0.306	0.198	0.580	0.136
N	Administrative services	0.302	0.328	0.398	0.222
I	Accommodation & food	0.292	0.373	0.205	0.194
E	Water and waste treatment	0.247	0.252	0.557	0.173
A	Agriculture & fishing	0.207	0.163	0.836	0.169

Note: Industries are ordered by AI Product Exposure score
All scores are scaled between 0 and 1

Taking this data, together with the capital and labor productivity measures described in the data section, I estimate versions of the TWFE specification 12, as well as a version of the "delta specification" 8 with country fixed effects. The results are presented in 10 and 11 in the appendix. None of the estimated coefficients is statistically significant. This supports a claim that AI is yet to have any noticeable impact on industry-level productivity.

It should be noted, however, that the productivity data is by its nature more limited relative to the online job adverts data. It is only available at the yearly level and is released with some lag, meaning that the time series terminates 9 months earlier than the OJA dataset. Considering that the occupation-level event studies show the largest negative coefficients for 2024, this may mean that it is simply too early to notice any effects. The data is also available on a generally less granular level (a total of only 17 industries, compared to the 122 ISCO level-3 occupations), which may conceal some variation in vertical AI applications.

7 Conclusion

The advent of Large Language Models poses serious questions about labor market resilience and job automation. This paper proposes a way to measure the initial impacts of this new wave of Artificial Intelligence on labor demand, occupational task composition, and productivity. The approach is enabled by a range of recently developed AI exposure metrics, as well as a detailed database of online job adverts across the EU from 2021 to 2024.

The main empirical result of this paper is an application of a difference-in-differences style approach to examine the number of job postings before and after the release of ChatGPT. Four different occupational AI exposure scores are used and treated as a continuous treatment. The resulting estimates are significant and negative, indicating that the most exposed occupations exhibit about 15% higher relative decrease in job postings compared to the least exposed occupations. The result is robust across the four exposure metrics.

There is evidence that the impact on labor demand does not increase linearly with AI exposure but is instead concentrated in the most exposed occupations. This follows from estimating a model where the exposure metrics are discretized into deciles. The effect is also uneven across time, with the associated event studies showing an increase in absolute magnitude toward the end of the sample period. This can be interpreted as either companies needing time to implement the new technology, or AI's displacement capabilities increasing with newer models released over this time frame.

This main result should be interpreted with several caveats in mind. First, the proportion of variance explained by the exposure variables within fixed effects groups is rather small, suggesting that AI automation is far from the main driving factor for recent occupational labor demand dynamics. Second, despite the pseudo-experimental approach, we cannot rule out omitted variable bias influencing the results. For example, any factor that could affect both occupational AI exposure and occupational resilience to interest rate changes may lead to spurious estimates. The event studies further cast doubts on the assumptions of parallel trends across exposure groups, as some of the pre-event coefficients are significant. Finally, the data on online job adverts itself presents a partial view of the labor market and its dynamics.

Two secondary results concern the change in skill composition across occupations and changes in labor and capital productivity. Changes in the skills associated with each occupation may be indicative of a change in the task mix of the occupation. Using a measure of the similarity between job skills and AI capabilities, I employ a similar difference-in-differences approach with continuous treatment. The results show that even within occupations, skills that are more similar to AI capabilities are mentioned less often in job adverts after the release of ChatGPT, with the most exposed skills exhibiting 10% fewer mentions relative to the least exposed ones. Similar caveats apply as with the main result, as despite the significant coefficient estimate, the overall contribution of the exposure metric to the model fit is quite small.

To measure potential effects of AI adoption on productivity, I utilize industry-level data on capital and labor productivity from Eurostat and develop industry exposure scores based on the occupation exposure scores and data on the occupational mix within each industry. None of the estimated productivity models returns a significant coefficient on AI exposure, indicating no measurable effect on industry productivity. This interpretation also comes with caveats, however, since the productivity data is of lower granularity and lower frequency compared to the job postings data.

The significant negative estimates on the number of job adverts, coupled with the non-significant estimates on labor and capital productivity, point toward the "so-so automation" scenario outlined by Acemoglu et al. (2022). In this theoretical outcome, AI does enough to outpace and replace parts of human labor, but the resulting gains in cost and efficiency are insufficient to raise output enough to offset the disemployment effects. The main counteracting force against automation in Acemoglu and Restrepo's framework, however, remains the creation of new tasks. Whether or not AI has had any impact on the rate of creation of such tasks remains outside the scope of this paper. However, the finding that skills that have highest overlap with AI capability show some decrease in their frequency of mentions in job adverts provides some circumstantial evidence for task re-composition.

Overall, the results presented in this paper point toward a small yet measurable negative effect of AI adoption on hiring decisions. The modest magnitude of the estimates may seem reassuring for the overall prospects of labor in exposed occupations; however, it is worth remembering that these are only the initial effects as businesses are starting to adapt to the new technology. As AI continues to advance both in terms of foundational model capabilities as well as more focused applications, monitoring labor market outcomes should remain an important task for policymakers and researchers concerned with job automation.

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A Additional Plots and Tables

Figure 6: Correlation between Indices of AI Exposure

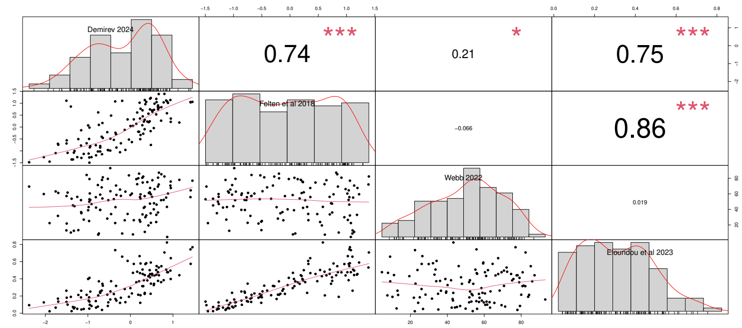

Figure 7: AI Exposure and Change in Online Job Postings

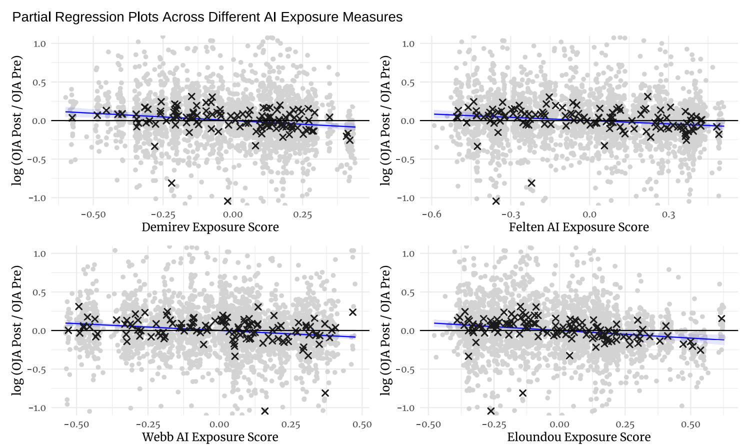

Table 4: Changes in Online Job Listings by Occupation

Occupation	Change
Panel A: Largest Decreases (¿25% decline)	
Textile & leather machine operators	0.349
Fishery workers & hunters	0.435
Mining plant operators	0.596
Street vendors & market sales	0.616
Life science technicians	0.629
Mixed crop & animal producers	0.633
Software developers	0.671
Database & network professionals	0.706
Life science professionals	0.726
Sales & marketing professionals	0.727
Panel B: Minimal Change (±5%)	
Machinery mechanics	0.980
Mining & construction supervisors	0.981
Electronics installers	0.982
Truck & bus drivers	0.985
Personal care workers	0.989
Painters & cleaners	0.991
Food machine operators	0.994
Cleaners & helpers	0.996
Electrical equipment installers	0.999
Librarians & archivists	1.000
Primary school teachers	1.000
University teachers	1.000
Metal processing operators	1.010
Clerical support workers	1.030
Panel C: Largest Increases (¿10% growth)	
Locomotive drivers	1.100
Other health professionals	1.110
Child care workers	1.120
Vehicle cleaners	1.130
Veterinary technicians	1.140
Hairdressers & beauticians	1.150
Street vendors (non-food)	1.150
Ship deck crews	1.180
Traditional medicine professionals	1.190
Forestry workers	1.280
Traditional medicine associates	1.440

Note: Values represent geometric mean of post/pre-ChatGPT job listings across countries. Values below 1 indicate decline, above 1 indicate growth.

Table 5: Raw Correlations between AI Exposure Measures and Changes in Job Listings

AI Exposure Measure	Correlation	95% CI	p-value
AI Product Exposure	-0.044**	[-0.079, -0.010]	0.011
Felten Score	-0.068***	[-0.102, -0.033]	$<$0.001
Webb Score	-0.071***	[-0.106, -0.037]	$<$0.001
Eloundou Beta	-0.079***	[-0.113, -0.045]	$<$0.001

*** p<0.01, ** p<0.05, * p<0.1

Note: Correlations with $\Delta \log$(Job Listings)

N = 3,241-3,269 occupation-country pairs

Table 6: Event Study: Impact of AI Exposure on Online Job Ads

Quarter	AI Product Exposure	Felten AI Exposure	Webb AI Exposure	Eloundou Beta
2022 Q1	0.030	0.016	0.090	0.014
	(0.056)	(0.052)	(0.063)	(0.066)
2022 Q2	-0.117**	-0.097**	-0.112*	-0.126**
	(0.049)	(0.047)	(0.058)	(0.056)
2022 Q3	-0.210***	-0.180***	-0.232***	-0.227***
	(0.058)	(0.055)	(0.067)	(0.067)
2023 Q1	-0.078	-0.075	-0.084	-0.103
	(0.108)	(0.104)	(0.112)	(0.132)
2023 Q2	-0.601***	-0.601***	-0.599***	-0.766***
	(0.216)	(0.218)	(0.213)	(0.275)
2023 Q3	-0.511**	-0.512**	-0.506**	-0.660**
	(0.228)	(0.229)	(0.225)	(0.289)
2023 Q4	-0.667***	-0.667***	-0.662***	-0.856***
	(0.233)	(0.234)	(0.231)	(0.296)
2024 Q1	-0.923***	-0.924***	-0.921***	-1.190***
	(0.242)	(0.244)	(0.243)	(0.308)
2024 Q2	-1.020***	-1.030***	-1.010***	-1.310***
	(0.240)	(0.243)	(0.239)	(0.307)
Country FE	Yes	Yes	Yes	Yes
Occupation FE	Yes	Yes	Yes	Yes

Standard errors clustered at country-occupation level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Decile Analysis: Impact of AI Exposure on Online Job Ads

Decile	AI Product Exposure	Felten AI Exposure	Webb AI Exposure	Eloundou Beta
2nd	-0.032	-0.099**	0.002	-0.125***
	(0.029)	(0.039)	(0.021)	(0.031)
3rd	-0.012	0.005	0.000	0.019
	(0.021)	(0.025)	(0.033)	(0.021)
4th	0.016	0.006	-0.005	0.028
	(0.024)	(0.031)	(0.029)	(0.036)
5th	-0.135***	-0.009	0.067*	-0.022
	(0.031)	(0.034)	(0.036)	(0.029)
6th	-0.092*	-0.058	-0.122**	-0.050
	(0.035)	(0.052)	(0.037)	(0.038)
7th	-0.059	-0.056	-0.031	-0.082*
	(0.037)	(0.046)	(0.027)	(0.039)
8th	-0.072*	-0.097*	-0.156***	-0.146**
	(0.031)	(0.041)	(0.033)	(0.044)
9th	-0.092**	-0.162**	-0.121***	-0.127*
	(0.031)	(0.051)	(0.028)	(0.046)
10th	-0.149***	-0.118*	-0.086*	-0.153**
	(0.039)	(0.051)	(0.038)	(0.043)
Observations	2,817	2,814	2,805	2,814
R^2 (within)	0.022	0.025	0.037	0.035
Adjusted R^2	0.483	0.484	0.490	0.489
Country FE	Yes	Yes	Yes	Yes

Standard errors clustered at country level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: First decile is the reference category

Table 8: Impact of AI Exposure on Online Job Ads: Two-Way Fixed Effects Estimates

	(1)	(2)	(3)	(4)
AI Product Exposure × Post	-0.179			
	(0.119)			
Felten AI Exposure × Post		-0.191*		
		(0.099)		
Webb AI Exposure × Post			-0.147**	
			(0.057)	
Eloundou Beta × Post				-0.245**
				(0.111)
Observations	34,546	34,488	34,274	34,488
R^2 (within)	0.0003	0.0005	0.0002	0.0006
Adjusted R^2	0.842	0.842	0.844	0.842
Occupation FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Standard errors clustered at country-occupation level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Dependent variable is log(Online Job Ads)

Figure 8: AI Exposure and Change in Online Job Postings

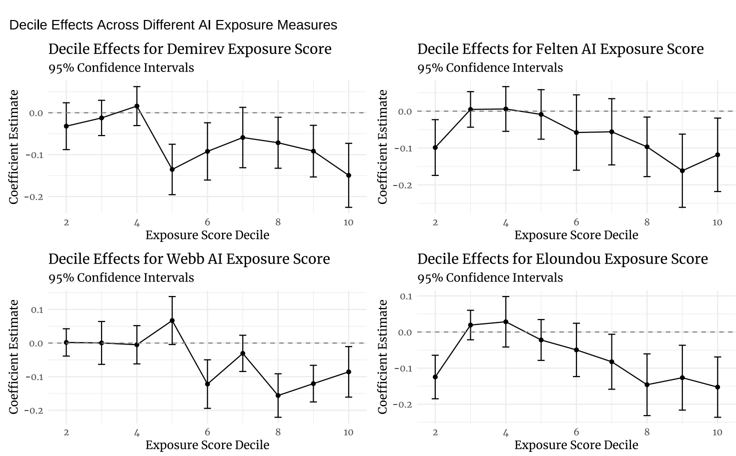

Table 9: Most and Least AI-Exposed Skills

Skill	AI Exposure	Δ log(Mentions)
Panel A: Most AI-Exposed Skills		
Designing ICT systems or applications	1.50	-0.585
Protecting privacy and personal data	1.48	-0.305
Assisting people to access services	1.47	-0.120
Information skills	1.45	-0.566
Working with computers	1.41	-0.698
Providing information and support	1.38	-0.266
Using digital tools for collaboration	1.35	-0.386
Developing health programmes	1.35	-0.313
Programming computer systems	1.27	-0.455
Developing solutions	1.23	-0.433
Panel B: Least AI-Exposed Skills		
Shaping materials to create products	-2.45	-0.147
Cutting materials and drilling holes	-2.43	-0.301
Installing roofing	-2.37	-0.484
Washing and maintaining textiles	-2.28	-0.269
Smoothing surfaces	-2.08	-0.296
Cleaning tools and equipment	-1.88	-0.226
Driving heavy vehicles	-1.82	-0.338
Operating metal processing machinery	-1.78	-0.587
Operating mixing machinery	-1.76	-0.583
Applying protective coatings	-1.72	-0.297

Note: AI Exposure scores are standardized (mean 0, SD 1)

Δ log(Mentions) represents change from pre to post-ChatGPT period

Table 10: Impact of AI Exposure on Industry Productivity: Two-Way Fixed Effects Estimates

	Dependent variable:	
	Labor Productivity	Capital Productivity
	(1)	(2)
Panel A: AI Product Exposure		
Exposure × Post	-0.083	-0.052
	(0.055)	(0.091)
Panel B: Felten Score		
Exposure × Post	-0.027	-0.027
	(0.022)	(0.063)
Panel C: Webb Score		
Exposure × Post	-0.099	-0.122
	(0.080)	(0.147)
Panel D: Eloundou Beta		
Exposure × Post	-0.035	-0.072
	(0.031)	(0.108)
Observations	990	237
Industry FE	Yes	Yes
Country FE	Yes	Yes
Year FE	Yes	Yes

Standard errors clustered at country-industry level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Dependent variables are in logs

Table 11: Impact of AI Exposure on Industry Productivity: Pre-Post Changes

	Dependent variable: $\Delta \log(\text{Productivity})$	
	Labor	Capital
	(1)	(2)
Panel A: AI Product Exposure		
AI Exposure	-0.070	-0.012
	(0.044)	(0.098)
Panel B: Felten Score		
AI Exposure	-0.018	0.028
	(0.022)	(0.069)
Panel C: Webb Score		
AI Exposure	-0.107	-0.141
	(0.064)	(0.129)
Panel D: Eloundou Beta		
AI Exposure	-0.022	-0.009
	(0.033)	(0.099)
Observations	330	79
Country FE	Yes	Yes
R^2 (within)	0.001-0.029	0.000-0.061

Standard errors clustered at country-industry level in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Note: Δ represents the change from pre to post-ChatGPT period