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Abstract

Using data from the French Public Employment Service linked to social security records, we examine the shifts in the supply of and demand for information technology (IT) skills that followed the recent emergence of generative artificial intelligence (GenAI). We show that the large-scale deployment of GenAI tools between late 2022 and late 2023 was followed by a sharp decline in vacancies for IT-specialist jobs and, more broadly, for jobs requiring IT skills. While relative wages remained largely unchanged, jobs requiring IT skills also experienced a substantial increase in applicants per vacancy and a marked decline in hiring. These findings are consistent with a model in which GenAI and natural-language coding boost the productivity not only of expert programmers but also of ordinary software users, particularly the least skilled. Tensions in the labor market are all the more acute because, as the required skill levels decline, various IT-exposed jobs become accessible to a broader pool of candidates.

Keywords: generative AI; labor demand; job postings; skills; wage rigidity.
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I Introduction

In November 2022, the launch of ChatGPT by OpenAI sparked an impressive surge in the adoption of generative artificial intelligence (GenAI) across society and the economy. Like any major technological innovation, GenAI has the potential to profoundly alter the tasks that employees can perform and their productivity, with consequences for employment and wages that are still largely unknown and debated (Cui et al., 2026; Eloundou et al., 2024; Acemoglu et al., 2022). In this article, we draw on French administrative data to examine shifts in the supply and demand for skills—particularly IT skills—that have followed the recent large-scale deployment of GenAI.

GenAI tools can be used for a wide variety of tasks by virtually all categories of workers, regardless of the organizational context, whether or not employers have chosen to invest in their development and implementation (Bick et al., 2026; Challapally et al., 2025). Beyond its general-purpose nature, one of the most distinctive features of GenAI is its ability to understand natural language and enable people who have little or no mastery of formal programming to use sophisticated computing tools ("vibe coding"). GenAI tools do not require detailed, explicit formal instructions. They infer what they need to do from the many examples they have been trained on, enabling them to perform a wide variety of tasks at very high speed, including those that would be most difficult for developers to translate into formal programming language. In the field of office work, it is no longer necessary to be an Excel expert to create complex and relevant tables and charts; all you need is a subscription to Microsoft Copilot, the conversational assistant made available by Microsoft starting in late 2023.

One might speculate that such a development contributes to a significant increase in productivity among those who were initially less tech-savvy, while also changing the appeal of many occupations that were once perceived as reserved for those most comfortable with programming. In this article, we aim to test these hypotheses and assess how the emergence of GenAI is changing the skills required by employers, as well as the number and profile of candidates for available jobs. We draw on a particularly rich French administrative database, as it tracks in near real time the evolution of both sides of the labor market: labor demand (via details of job postings by employers) and labor supply (via detailed information on the applications received by employers and their hiring decisions).

To be more specific, this database tracks, on a date-by-date basis, the job postings received by the French public employment service (FPES, also called *France Travail*), as well as the applications generated by those postings—averaging more than 600,000 new job postings per quarter over the 2021–2025 period we will be focusing on. Regarding job postings, this database provides information on the wages offered and the occupations involved (using a classification of more than 500 items). For each posting, it also details the skills required by employers (using a classification of more than 30,000 items), particularly in the IT field. Regarding the candidates, we know their main socio-demographic characteristics (gender, age, education level). By matching FPES data with social security records, we also know whether and when job postings ultimately result in a hire. To explore longer-term trends, we also use a supplementary database that tracks the evolution of job postings by occupation over a longer period (2016–2025) but does not provide information on applications or required skills.

Based on an analysis of job postings from before 2022 (and the emergence of GenAI), we first show that occupations can be classified into three broad categories based on the importance of computer skills required at the time of hiring. First, there are jobs for which employers never, or almost never, require computer skills (for example, nursing assistant, elevator operator, nature area maintenance worker; etc.). These occupations are assumed to be unaffected by the rise of "vibe coding" and will serve as our control group. Second, there are occupations which generally involve screen-based work and for which employers may require specific IT skills, although this is by no means always the case. Most office jobs fall into this category of IT-exposed occupations (for example secretary, accounting assistant, human resources assistant, etc.). Finally, there are a few occupations that contribute directly to the development and maintenance of IT tools and infrastructure. Software developers represent the most emblematic of these IT-specialist occupations. In this context, a key question is how a technological shift that has made computer programming and office software accessible through natural language has impacted employers' relative demand for these different types of occupations, as well as the skills required to perform them. Another key question is whether these developments have changed the number and profile of candidates applying for these different types of occupations, as well as the profile of those who are ultimately recruited.

By comparing job postings published before and after the fourth quarter of 2022 and the emergence of ChatGPT, we first detect a very significant decline in job postings for IT-specialist occupations. Compared to the control group, the number of job postings for these occupations initially remained stable through late 2023, before beginning a rapid decline. This number is estimated to be, on average, about 20% lower in the period following 2023 than in the preceding period. Around the same time, we also detect a drop in the number of job postings for IT-exposed occupations, albeit less pronounced. These declines in job postings for IT-specialist or IT-exposed occupations did not begin immediately after ChatGPT emerged in the public sphere, but nearly a year later, after the first professional versions of GenAI began to be marketed. It is crucial to have data covering the period after 2023 to detect these trends.

With regard to the skills required by employers, the sharp decline in job postings for IT-specialist occupations coincides with an increase (albeit of modest magnitude) in the proportion of these postings that require skills in the field of artificial intelligence. If we set aside AI skills, the proportion of these postings requiring specific IT skills - and specific programming skills in particular - decreases significantly. This decline is offset by an increase in the proportion requiring public speaking skills. The emergence of GenAI appears to coincide with a shift in the profiles of IT specialists sought after by companies, with communication skills becoming more important and the ability to program in various languages becoming less crucial.

With regard to IT-exposed occupations, the decline in job postings is primarily driven by a significant drop in postings for jobs where the employer explicitly requires specific IT skills. Compared to the control group, the number of such postings is about 40% lower at the beginning of 2025 than at the beginning of 2023. For office jobs, there is a notable decline in postings that explicitly require skills in using office software (such as Excel).

When it comes to the wages offered by employers for the various types of jobs, the picture is different: compared to the control group, the wages offered for IT-exposed occupations remained completely stable throughout the period under consideration, while the wages offered for IT specialists remained stable until the end of 2023 before experiencing a slight decline. The shares of IT-specialist and IT-exposed occupations in job postings have declined significantly in the three years following the ChatGPT shock, but this cannot be interpreted as a response to a rise in relative wages. With a decline in the share of job openings but no increase in relative wages, the trends observed since late 2023 clearly point to the existence of skill-biased technical change that is rendering IT skills less and less critical.

Over the same period, the decline in firm demand for IT-exposed roles or IT specialist positions did not lead to a drop in applications; on the contrary, it was accompanied by an increase in the number of applicants - likely a result of lower skill requirements, particularly regarding programming or software usage. Ultimately, with a sharp decline in the number of job openings and an increase in the number of applicants, labor market pressures have primarily resulted in a significant rise in the number of applicants per job opening. When comparing the beginning of 2025 with the period before the emergence of GenAI, there was an increase of about 50% in the number of applicants per job opening for IT-specialist jobs and 10% increase for IT-exposed jobs.

As a robustness test, we verify that our main findings remain unchanged when using, as an alternative control group, occupations identified as unexposed to GenAI in the task-based literature (as represented by Eloundou et al. (2024)). This result is consistent with the fact that our basic control group (i.e., occupations that never require computer skills at baseline) contains no occupations identified as exposed to GenAI in the task-based literature, while our treatment groups (i.e., occupations requiring the most computer skills at baseline) contain virtually no occupations identified as not exposed to GenAI in that same task-based literature. We also verify that our main results remain unchanged when controlling for the specific effects that generative AI may have had on jobs requiring writing skills. Beyond coding and data manipulation tasks, GenAI tools have significantly boosted worker efficiency in writing tasks; however, these specific efficiency gains do not appear to be the factor implicitly driving the decline of occupations requiring IT skills. Along the same lines, we checked that our results are not driven by a decline in labor demand in the industries that initially had the highest demand for IT skills. Using supplementary data from the Ministry of Labor - which is less detailed but covers a longer period (2015–2025) - we further verified that the decline in job postings for IT-specialist or IT-exposed roles observed after 2023 does not represent a simple return to the pre-2020 pandemic situation: the breaks in trends are just as distinct when using pre-pandemic trends as a benchmark.

Generally speaking, the impact on the labor market of a technological shock as pervasive as the emergence of GenAI depends on a wide range of factors that are difficult to separately identify, starting with those that govern the substitutability of different types of jobs in production processes, or those that capture the dispersion in individual productivity across the jobs offered by employers. In the following, we show that our empirical results are consistent with a simple model in which: (i) The emergence of GenAI has boosted employee productivity in IT-specialist and IT-exposed occupations, while lowering the level of computer skills required to perform these jobs ; (ii) IT specialists and other workers represent two complementary inputs in the production process, whereas within IT-exposed occupations, workers with specific IT skills and those without them are substitutes; (iii) relative hiring wages across different occupations (and for employees within the same occupation) adjust very slowly.

Our article contributes to the long-standing literature exploring the effects of technological change on employment and wages. Many studies have examined whether and how the emergence of robots and computers at the end of the last century contributed to the substitution of highly skilled workers for low-skilled ones within companies (Katz and Murphy, 1992; Autor et al., 2003; Michaels et al., 2014). Computers are particularly effective at performing tasks that can be explicitly defined and translated into a formal programming language. Their emergence has contributed to the decline in demand for employees dedicated to repeating such tasks, in favor of employees (often much more qualified) dedicated to the least repetitive tasks and requiring the most analytical and creative skills. In this paper, we show that the emergence of GenAI has a partially opposite effect, as it leads to a relative decline in IT-specialist occupations, which are often highly skilled, as well as a decline in demand for IT skills across a wide range of occupations where these technologies can be used.

Given their magnitude, the effects we identify on IT-specialist and IT-exposed occupations are also different from those estimated in studies that focused primarily on the first wave of AI technology (Acemoglu et al., 2022; Hampole et al., 2025; Aghion et al., 2025). These technologies appear to have significantly altered the content (in terms of the tasks performed) of certain highly skilled occupations, without, however, having had very significant aggregate effects on employment and wages in these occupations.

Our article also contributes to the rapidly expanding body of literature on the impact of the wave of GenAI technologies that has been sweeping through society and businesses since late 2022. Drawing on randomized experiments, several recent studies have demonstrated the positive impact that access to GenAI tools can have on productivity in occupations as diverse as software developers, customer support agents, grant writers or managers (Brynjolfsson et al., 2025; Dell'Acqua et al., 2026). One of the key findings from this body of research - with which our results are consistent - is that GenAI tends primarily to boost the productivity of those who are initially the least experienced and productive.

Closer to our own work, another line of research explores the effects on firms' demand for labor. Drawing on a task-based framework, Eloundou et al. (2024) develop a measure of the exposure of various occupations to the efficiency gains generated by GenAI. They conclude that the vast majority of occupations are at least partially exposed to such gains. However, they show that exposure is greater for occupations that require programming and writing skills. Drawing on a similar exposure measure, Eisfeldt et al. (2026) conduct an event study centered on the launch date of ChatGPT; they highlight a decline in job postings for the most exposed occupations, particularly where generative AI is likely to substitute for an occupation's core tasks.

We contribute to this body of literature by defining our control and treatment groups not based on the tasks likely associated with different occupations, but rather on the skills actually required by employers to perform those occupations. By doing so, we are able to quantify as directly as possible what we believe to be one of the first-order effects of the emergence of GenAI tools: they enable employees to program and interact with computer tools using natural language, which, one might speculate, makes proficiency in software and computer languages much less essential at all levels of an organization, from engineers to secretaries. Our contribution is to test this hypothesis and describe as precisely as possible whether, when, and how the GenAI shock was followed by a decline in firms' demand for IT skills.

Beyond the effects on firms' demand, our contribution is also to describe how labor supply behavior and wages have adapted to this major technological shift. As Autor and Thompson (2025) and, following them, Hosseini Maasoum and Lichtinger (2026) point out, contemporary technological progress has the potential to change the skills required for different types of jobs and, consequently, the appeal that these different types of jobs may hold for different types of workers. To the best of our knowledge, our study is one of the very first to highlight not only the dampening effect of the post-2023 rise of GenAI on firms' demand for IT skills, but also the consequences on labor supply behavior and hiring processes. While the wages offered remained relatively stable, there was little shift in the distribution of applicants across the major occupational categories, leading to a marked increase in the number of applicants per job opening for the categories with the sharpest decline in job postings. The profile of new hires in the various occupational groups (in terms of age or gender) changed relatively little in the years following the rise in GenAI, although the shock was accompanied by a slight increase in the proportion of people 35 and young hired as IT specialists, which may be a result of the growing demand for new AI skills—whether explicitly or implicitly—on the part of employers.

In the remainder of this article, we will begin by reviewing the major milestones in the recent large-scale adoption of GenAI (Section 2). We will then briefly outline the model of supply and demand for skills, which will serve as the interpretive framework for our empirical analyses (Section 3). We will then present our data (Section 4) before moving on to the estimation of the regression and event study models that form the core of our work (Section 5). Section 6 concludes.

II Context

The launch of the (free) chatGPT chatbot by OpenAI in November 2022 marked the beginning of the widespread adoption of GenAI in the public sphere and the business world. This chatbot uses the GPT-3.5 language model. With this tool, non-programmers discovered they could ask their personal computer to write complex programs for them in a formal language (like Python), simply by describing their needs. Figure 1 shows the volume of Google searches including the term "chatGPT" and confirms its emergence in late 2022. In February 2023, OpenAI launched a paid version, ChatGPT Plus, using the GPT-4 language model, which is much more powerful and reliable than the GPT-3.5 model of the initial free version. This marked the beginning of the AI assistant market and the professional use of GenAI.

In early 2023, the hundreds of millions of users and global success of chatGPT intensified competition among the major players in the sector, and Google launched its own chatbot (Bard, using the PaLM2 language model). Meanwhile, Microsoft strengthened its partnership with OpenAI and began integrating GPT-4 into its suite of tools. In February, the company launched the Bing Chat agent, and then in March, it launched Microsoft 365 Copilot, which allows the use of GPT-4 as an interface with Excel, Word, and PowerPoint. Natural language became a control interface for the most popular office software. This was a key step toward informal programming in many Excel-intensive professions, such as accounting and consulting.

In July 2023, OpenAI launched Code Interpreter (later renamed "Advanced Data Analysis"). A non-programmer chatGPT user could now code in natural language and watch the machine not only write the corresponding script, but also manipulate the files, execute the code, and then analyze the output. Informal programming (or "vibe coding") became truly operational.

In the fall of 2023, Microsoft unified its various agents (Bing Chat, Microsoft 365 Copilot, etc.) under a single banner: Microsoft Copilot, which was integrated into Windows 11 and made accessible to users via the taskbar in early 2024. The AI assistant became a native component of the PC. The volume of Google searches including the term "Copilot" surged in the fall of 2023 (see the contextual figure). At the end of 2023, Google launched Gemini (replacing Bard), a multi-mode conversational agent.

From 2024 onwards, new tools (Cursor AI, Replit AI, Github Copilot, etc.) are emerging that further develop the idea of informally mobilizing the most complex IT programming tools through simple conversations with AI agents. However, the foundations of this paradigm were laid in the preceding months, notably with Code Interpreter and Copilot.

Similar developments are occurring in sectors as diverse as communication, marketing, and design. In most fields, traditional expert systems are eventually incorporating AI, and AI agents are becoming increasingly creative. We are moving from an era of tools designed for experts, where creating a logo, for example, requires significant technical expertise, to an era where a logo and a visual identity can be created using natural language instructions (with tools like Midjourney, Dall-e). No longer is it necessary to know how to draw, nor to master specialized software; natural language becomes the interface (prompt designer).

III Conceptual Framework

In this article, our objective is to assess the impact of the emergence of GenAI not only on occupations most directly involved in the development of digital tools and infrastructure, but also across all occupations (often requiring far fewer IT skills) where the use of computer and office software is possible but much less central. In this section, we begin by making the conceptual framework within which our empirical explorations can be interpreted as explicit as possible.

III.1 Occupations and Production

With regard to firms, we will assume that their operations involve three categories of occupations. The first category includes occupations that contribute directly to the development and maintenance of IT tools and infrastructure (hereafter IT-specialist occupations). By definition, these occupations require advanced computer skills. At each date t, we will denote X_{1t} the corresponding number of jobs. The second type of occupation generally involves screen-based work and may require specific IT skills, although this is not necessarily the case. Most office jobs fall into this category, hereafter IT-exposed occupations. In our database, for the 2021–2022 (baseline) period, approximately one-quarter of job postings for office staff positions (i.e., secretary, human resources assistant, accounting secretary, executive assistant, etc.) explicitly require specific computer skills (such as proficiency in spreadsheet software), but the remaining postings for these same jobs do not require any specific computer skills. By construction, these IT-exposed occupations can be performed by two categories of employees: either employees with some specific IT skills or employees without any specific IT skills. At each date t, we will denote X_{2ut} the number of IT-exposed jobs held by people without specific IT skills and X_{2st} the number of IT-exposed jobs held by people with specific IT skills. Also, we denote $\Phi(\alpha_t X_{2ut}, X_{2st})$ the joint contribution of the two types of employees, where Φ is a production function and where the parameter α_t captures technological shocks specifically affecting the productivity of employees without computer skills, for example the emergence of new GenAI tools. A last category of occupations (hereafter control occupations) includes all those which do not require specific IT skills (e.g., nursing assistant), and we will denote X_{3t} the corresponding number of jobs.

Using these notations, we will assume that firms' output can be written as $F(\beta_t X_{1t}, \Phi(\alpha_t X_{2ut}, X_{2st}), X_{3t})$ where F is a three-input production function and where β_t captures the technological shocks specifically affecting IT-specialist occupations. Denoting $W_t=(w_{1t}, w_{2ut}, w_{2st}, w_{3t})$ as the vector of labor input costs, and $L_t=(X_{1t}, X_{2ut}, X_{2st}, X_{3t})'$, firms are assumed to minimize $W_t' L_t$ subject to $F(\beta_t X_{1t}, \Phi(\alpha_t X_{2ut}, X_{2st}), X_{3t}) \geq y_t$, where y_t represents firms' output constraint at time t. Hereafter, to simplify the discussion, we will assume that the functions F and Φ are CES functions. We denote σ as the elasticity of substitution of F and s as that of Φ. Within this nested-CES framework, we are interested in technological shocks that lead to increases in β_t or α_t. The first-order conditions of firms' optimization problems help to understand the effect of such shocks on firms' labor demand by occupation and skill type.

III.2 Labor Demand

To begin with, it is not difficult to check that the first-order conditions of the firms' program lead to a very standard relationship between the demand for specific IT skills in IT-exposed occupations (as captured by X_{2st}/X_{2ut}) on the one hand, and relative wages and technological changes (as captured by α_t), on the other hand, namely,

$$\ln\left(\frac{X_{2st}}{X_{2ut}}\right) = a_0 - s\ln\left(\frac{w_{2st}}{w_{2ut}}\right) + (1-s)\ln(\alpha_t), \tag{1}$$

where a_0 is an intercept. Assuming that the elasticity of substitution s is relatively strong ($s > 1$), a technological shock leading to $\Delta\alpha_t > 0$ contributes to the decline in X_{2st}/X_{2ut} and in the proportion of workers with software skills among IT-exposed occupations. Incidentally, it is worth noting that, under condition (1), the variable $\phi_t = \Phi(\alpha_t X_{2ut}, X_{2st})/X_{2st}$ can be rewritten as $\Phi(\left(\frac{w_{2st}}{w_{2ut}}\right)^s \alpha_t^s/a_0, 1)$. In the case (which, in practice, will be ours) where w_{2st}/w_{2ut} remains stable over time, ϕ_t represents an alternative measure of technical progress that affects employees without specific computer skills.

First-order conditions also allow us to express the relative demand for IT-specialist jobs (as captured by X_{1t}/X_{3t}) as a (log) linear function of relative wages and technical progress (as captured by β_t), that is

$$\ln\left(\frac{X_{1t}}{X_{3t}}\right) = b_0 - \sigma\ln\left(\frac{w_{1t}}{w_{3t}}\right) + (\sigma-1)\ln(\beta_t), \tag{2}$$

where b_0 is an intercept. If σ is small (as we might assume), a technological shock leading to $\Delta\beta_t > 0$ is a factor contributing to a decline in X_{1t}/X_{3t}.

The first-order conditions finally allow us to express firms' relative demand for employees in IT-exposed occupations with computer skills (as captured by X_{2st}/X_{3t}) once again as a (log) linear function of relative wages and technical progress (as captured here by ϕ_t), that is,

$$\ln\left(\frac{X_{2st}}{X_{3t}}\right) = c_0 - \sigma\ln\left(\frac{w_{2st}}{w_{3t}}\right) + \left(\frac{\sigma}{s} - 1\right)\ln(\phi_t). \tag{3}$$

If σ is smaller than s (i.e., $s > \sigma$, the most likely case), the technological shock will have a negative impact on relative demand X_{2st}/X_{3t}.

Combining conditions (1) and (3), it is also possible to show that the relative demand

X_{2ut}/X_{3t} depends on technical progress through the ratio of α_t^{s-1} to $\phi_t^{(s/\sigma-1)}$. Given a fixed relative wage, the impact of technical progress on the relative demand X_{2ut}/X_{3t} can thus vary greatly depending on the elasticities of substitution. For example, in the specific case where $\sigma < s = 1$, technical progress contributes to a decrease in relative demand X_{2ut}/X_{3t}. Conversely, in the case where $\sigma = s > 1$, it contributes to an increase in this relative demand. In the specific case where $s = \sigma = 1$, technical progress has no independent effect on this margin.

III.3 Labor Supply

Regarding labor supply, we will assume that the utility worker i derives from occupation k at date t can be expressed multiplicatively as $u_{kt}(i) = \pi_{kt}(i)w_{kt}$, where $\pi_{kt}(i)$ can be interpreted as the inverse of the effort cost associated with occupation k at date t for worker i. In line with a long tradition of discrete choice models, we will also assume that the vector $(\pi_{1t}(i), \pi_{2ut}(i), \pi_{2st}(i), \pi_{3t}(i))$ is distributed across workers according to a generalized Fréchet distribution, with the cdf given by $\exp(-G(a_{1t}\pi_{1t}{}^{-\theta}, a_{2t}\pi_{2ut}{}^{-\theta}, a_{2st}\pi_{2st}{}^{-\theta}, a_{3t}\pi_{3t}{}^{-\theta}))$, where G is a correlation function while θ and the a_{kt} are positive parameters.[1] The parameter a_{kt} characterizes the distribution of π_{kt} across workers: the higher a_{kt}, the more this distribution shifts toward higher values and the more attractive occupation k is to a large number of workers at date t. The shape parameter θ characterizes the dispersion of the different relative productivities π_{kt}/π_{lt}. The smaller θ is, the greater this dispersion and the fewer workers there are who can easily switch from one occupation to another. The function G further characterizes the correlation of effort costs across occupations.[2]

In this set-up, assuming that at date t worker i chooses the occupation that maximizes $u_{jt}(i) = \pi_{jt}(i)w_{jt}$ when j takes its value in $\{1, 2u, 2s, 3\}$, the fraction of the working population choosing occupation k is simply given by

$$O_{kt} = \frac{a_{kt}w_{kt}^{\theta}G_k\left(a_{1t}w_{1t}^{\theta}, \ldots, a_{3t}w_{3t}^{\theta}\right)}{G\left(a_{1t}w_{1t}^{\theta}, \ldots, a_{3t}w_{3t}^{\theta}\right)}. \tag{4}$$

where G_k is the partial derivative of G with respect to the k-th argument.[3]

For simplicity's sake, let us further assume $G(x_1, x_{2u}, x_{2s}, x_3) = x_1 + (x_{2u}^{1/1-m} + x_{2s}^{1/1-m})^{1-m} + x_3$ where m in (0,1) is a parameter that captures the proximity of jobs requiring specific IT skills to jobs that do not require such skills. More specifically, this parameter provides a measure of the upper tail dependence between x_{2u} and x_{2s}: the larger m is, the greater the probability that x_{2u} will take on a high value when x_{2s} takes on a high value (and vice versa). With this specification we obtain very simple relationships between O_{2ut}/O_{2st} (and O_{1t}/O_{3t})) and relative

[1]The properties of correlation functions (including homogeneity of degree 1) are reviewed in Lind and Ramondo (2023), as is the derivation of the choice probabilities implied by the maximization of multiplicative utilities when productivities (or effort costs) are distributed according to a generalized Fréchet distribution. See also Hsieh and Olken (2014).

[2]If, for example, $G(x_1, x_{2u}, x_{2s}, x_3) = x_1 + x_{2u} + x_{2s} + x_3$, then the π_{kt} are drawn from independent distributions and there is no correlation between them. Equivalently, we could consider the additive model $v_k(i) = ln(u_k(i)) = ln(\pi_k(i)) + ln(w_k)$, and assume that the $ln(\pi_{kt}(i))$ follow a Gumbel distribution.

[3]McFadden (1978) provides an early version of this result using an additive utility scale (in our case, it would be: $v_k(i) = ln(w_k) + ln(\pi_k(i))$ with $ln(\pi_k(i))$ distributed as a log(Fréchet), namely a Gumbel distribution).

wages[4]:

$$\frac{O_{2ut}}{O_{2st}} = \left(\frac{a_{2ut}}{a_{2st}}\right)^{\frac{1}{1-m}} \left(\frac{w_{2ut}}{w_{2st}}\right)^{\frac{\theta}{1-m}} \text{ and } \frac{O_{1t}}{O_{3t}} = \frac{a_{1t}}{a_{3t}} \left(\frac{w_{1t}}{w_{3t}}\right)^{\theta}. \tag{5}$$

In this setup, labor supply can shift from one type of job to another in response to changes in relative wages; the elasticity is greater the higher the value of θ (and the lower the dispersion of relative effort costs π_{1t}/π_{3t} or π_{2ut}/π_{2st}). With regard to IT-exposed occupations, the elasticity of relative labor supply between jobs that require specific IT skills and jobs that do not is also greater as m increases. Importantly, labor supply can also shift in response to changes in the relative values of the parameters a_{kt} - that is, in response to technological developments that shift the distributions of effort costs specific to different occupations in different directions.

Given the behavior of firms and workers, we can ultimately envisage two broad types of short-term developments in the wake of a technological shock leading to an increase in α_t and β_t, but also maybe in a_{1t} and a_{2ut}, as the IT skills required for IT-specialist and IT-exposed positions decrease. First scenario: wages adjust slowly and can be considered rigid.[5] In such a world, and assuming that $\sigma < 1$, the technological shock under consideration leads to a decline in relative demand X_{1t}/X_{3t} for IT specialists, but may also be accompanied by an increase in relative supply O_{1t}/O_{3t}. In this case, we should primarily observe an increase in the relative number of applicants per posting for IT-specialist jobs. Assuming that $s > 1$ and following the same line of reasoning, we should also observe a decline in X_{2st}/X_{2ut}, again without any mitigating adjustment in relative supply O_{2st}/O_{2ut}, resulting in an increase in the relative number of applicants per posting for IT-exposed jobs requiring IT skills. Under the maintained assumption $s > 1 > \sigma$, we can also expect a decline in X_{2st}/X_{3t} without any adjustment of relative supply.

In the second scenario, wages are not rigid and w_{1t}/w_{3t} adjust so that X_{1t}/X_{3t} and O_{1t}/O_{3t} balance out. To be more specific, assuming once again that $\sigma<1$ and that technological progress exerts downward pressure on X_{1t}/X_{3t} and upward pressure on O_{1t}/O_{3t}, we would expect a sharp decline in w_{1t}/w_{3t}, resulting in a mitigation of the negative impact of the technological shock on the relative demand for IT specialists (as captured by X_{1t}/X_{3t}). Assuming $s > 1$, the model also predicts a rise in the relative wages (w_{2ut}/w_{2st}) of employees without computer skills in IT-exposed occupations, resulting in the mitigation of the impact of the technological shock on X_{2ut}/X_{2st}. Under the maintained assumption that $s > 1 > \sigma$, we should also observe a decline in w_{2st}/w_{3t} which should contribute to mitigating the negative impact of the technological shock on X_{2st}/X_{3t}. However, in all these scenarios, since wages are flexible and relative supply and demand remain in equilibrium, there should be no increasing (or decreasing) imbalance between the number of job postings and the number of candidates, namely no significant increase (or decrease) in the number of applicants per posting.

In the remainder of this article, we draw on administrative data that simultaneously tracks job postings by employers, employee applications, and hires to assess which of the two main scenarios described above appears most likely and to assess the impact that the emergence of

[4]The relationship between the O_{2st}/O_{3t} ratio and relative wages is somewhat less direct, since it is easily verified that it depends both (positively) on w_{2st}/w_{3t} and (negatively) on w_{2ut}/w_{2st}.

[5]Wage rigidity has long been at the heart of debates surrounding the functioning of labor markets (Bewley, 1999; Pissarides, 2009). In a recent contribution using job posting data similar to ours, Hazell and Taska (2025) present new clean evidence suggesting significant rigidity in entry wages, particularly regarding downward adjustments.

GenAI in 2023 may have had on the various dimensions of supply and demand for computer skills.

IV Data and Variables

The econometric analyses presented in the remainder of this article will be conducted using data that track, for each occupation in the French classification system (the 500-item ROME classification) and for each quarter between 2021 and 2025, the number of job postings, the skills required in those postings, the average wages offered, the number of applicants, the number of applicants per job opening, the number of hires ultimately made (within 9 months of the job posting), and the characteristics of the candidates hired. This panel is constructed from an administrative database containing all job postings published on the French public employment service's online platform. The dataset begins in 2021, as information on skill requirements becomes sufficiently reliable and consistently recorded only from the middle of that year onward. Our estimation sample covers 15 quarters, from the fourth quarter of 2021 to the second quarter of 2025, with each observation corresponding to a given occupation in a given quarter.[6] In some specifications, the data is further disaggregated to the occupation-by-industry-by-quarter level in order to account for potentially confounding sectoral developments. This disaggregation uses a 21 item classification of industry (i.e., the French NAF classification). In total, depending on the specification and outcome considered, our baseline estimation samples contain approximately 2,000 to 6,000 occupation-by-quarter observations, while the more disaggregated samples contain approximately 20,000 to 60,000 occupation-by-industry-by-quarter observations. In the remainder of this section, we will discuss in greater detail the information contained in the French Public Employment Service (FPES) database that we used to construct our estimation samples. We also explain how the various treatment and control groups are constructed - groups we subsequently use to specify our difference-in-differences and event-study models.

IV.1 The FPES database

We use a database containing all job postings published each quarter on the job board of the French public employment service (FPES) between 2021 and 2025. Job offers are published on the board either directly by employers, or by the FPES caseworkers when they receive job openings sent directly by employers. The job board has existed since before 2015, however data on skill requirements has been available in a consistent and usable format only since the beginning of 2021.[7]

For each job posting, we know the date it was first published. In the rest of this article, each posting will be counted only once, on the date of its first publication. We also have a list of the skills required by employers. The skills that employers may list are selected from a classification system containing approximately 38,000 entries, organized into 61 skill families. In addition to

[6] For outcomes related to actual hiring, we restrict the analysis to job postings published by the end of 2024, in order to consistently measure, over the entire period (i.e., without right-censoring), the hires made within 9 months of the posting's publication.

[7] Some employers (particularly temporary employment agencies) use Application Programming Interfaces (APIs) to automate the submission of their job postings to the FPES job board. Job postings received via this channel (representing 15% of the total) do not provide consistent information on skill requirements over the entire period 2021-2025 under consideration; consequently, we have excluded them from our working dataset.

these 61 families, there are also approximately 3,600 entries that have not yet been assigned to a specific family by the FPES. On average, employers require 6 basic skills per job posting.

For each job posting, we ultimately know which candidates the employer stated an intention to hire. By matching these data with social security records, we can further determine which of these candidates appear (at least temporarily) in the workforce reported by the employer to the social security authorities within nine months of the posting's publication. Based on this information, we were able to develop a measure of the number of hires actually generated by each job posting. We have information on the gender and age of the people recruited.

IV.2 IT Skills

With regard to the 61 skill families, three relate to information technology. They are titled "programming languages," "software and software packages," and "data and new technologies." The first family encompasses a total of 161 basic skills related to proficiency in computer programming (for example, proficiency in the C++ language, or in Delphi or SQL). The second family encompasses a total of 524 basic skills related to proficiency in software tools (particularly office software, such as Excel). The third family encompasses over 1,000 skills and appears more heterogeneous. It combines skills related to the development and maintenance of IT tools and infrastructure, skills related to software usage, and skills related to data management and analysis.

In the following, we will designate as "IT skills" the approximately 1,700 skills belonging to these three skill families, to which we will add around 200 skills drawn from the set of skills not yet assigned to a family but whose descriptions clearly link them to IT.[8]

Among these "IT skills", some include the terms "AI," "artificial intelligence," "machine learning," "deep learning," and "data science" in their descriptions. We will refer to these specific IT skills as AI skills and use them as indicators to test the hypothesis that demand for AI expertise has risen in the months and years following the emergence of generative AI.

More generally, to describe the detailed evolution of IT skills as precisely as possible, we will distinguish within them three main types of skills: (1) programming skills and skills devoted to the maintenance/development of IT tools and infrastructure (612 basic skills), (2) software usage skills (835 basic skills), and (3) database management and analysis skills (420 basic skills). Broadly speaking, this categorization overlaps with the three-family categorization of the FPES, after reintroducing skills not yet assigned by the FPES and further isolating data management and analysis skills. In Appendix Table B2, we provide, for each of the three major skill categories, a list of the 10 basic skills most frequently required in our sample of job postings.

IV.3 IT-specialist versus IT-exposed Occupations

For each job posting, the database also provides detailed information about the occupation associated with the posting. The occupational classification system used to code this information contains approximately 500 entries (ROME classification).

Some of these occupations focus on the development and maintenance of IT tools and

[8]These 200 skills are the ones that (among the skills not yet assigned) include the keywords "data analysis," "data," "analyse de données", "réseau informatique", "logiciels", "software", "langages informatiques", or "deloppement informatique" in their description.

infrastructure. In the French classification system, these IT-specialist occupations include (i) software developers, (ii) information system managers, (iii) computer system experts, (iv) IT system consultants, and (v) computer operation technicians. In the following, we will refer to these specific occupations as IT-specialist occupations. The complete list of IT-specialist occupations is available in Appendix Table B1. By definition, these occupations require advanced IT skills, but not necessarily AI-related skills.

For each of the other occupations in the classification, it is possible to calculate the proportion of job postings requiring specific IT skills during the 2021–2022 period preceding the emergence of GenAI. For about a quarter of the occupations, this proportion is zero, or almost zero. By their very nature, these occupations are not directly affected by the rise of "vibe coding" and GenAI. Hereinafter, these occupations will constitute our control group. For two other quarters, this proportion is not zero but negligible (5% on average). For the final quarter, this proportion is not negligible (greater than 9%) and amounts to approximately 45% on average. In the following, we will refer to these occupations as IT-exposed occupations.

In Appendix Table B1, we provide detailed lists of the IT-specialist, IT-exposed, and control occupations. Among the top IT-exposed occupations (in terms of the number of job postings) are accountants, sales assistants (those who prepare quotes, process invoices, update customer databases, etc.), secretaries, executive assistants, human resources assistants (those who manage payroll records, track employee absences and sick leave, etc.), accounting secretaries (those who file and archive accounting documents, monitor banking transactions and contracts, etc.). With few exceptions, IT-exposed jobs are office jobs requiring an intermediate level of qualification (high school diploma or vocational qualification). Among the top control occupations are nursing assistants, childcare workers, maintenance workers, warehouse workers.

IV.4 Supplementary Data

The database operated by the FPES is extremely comprehensive and offers a unique perspective on changes in supply and demand by skill and occupation during the 2020s. However, one limitation is that it does not cover the period prior to the 2020s. To supplement this, we will also use data tracking the number of job openings by occupations, which is published quarterly by the Ministry of Labor. This dataset does not contain information on skills, wages, or applications, but allows us to identify—on a quarterly basis—job postings for IT-specialist occupations, IT-exposed occupations (as well as job openings in the control group) over a longer period, from 2016 to 2025. The database on the FPES job ads only reports consistently vacancies since the end of 2015, previous data have been reconstructed from different sources and remains unreliable in the classification of adds by occupations. In order to ensure consistency in the sources, we start the robustness analysis in 2016. The resulting series enables us to test whether the trends in the number of job postings observed after 2022 represent a return to the pre-COVID situation or - as we shall see is the case - genuine breaks in trends.

V Regression Analysis

For each quarter t and each type of occupation i, we will consider three main types of outcomes Y_{it}, namely (1) outcomes characterizing the number and characteristics of job postings for occupation i at time t, (2) outcomes characterizing the number and characteristics of applicants for these job postings, and (3) outcomes characterizing the number and characteristics of actual hires. For each outcome Y_{it}, we will estimate the following event study model.

$$Y_{it} = \mu_i + \lambda_t + \sum_l \theta_l \left(Treat_i \times D_{lt}\right) + \epsilon_{it}. \tag{6}$$

where μ_i represents an occupation fixed effect (defined using the detailed classification with 500 items), λ_t a quarter date fixed effect, and D_{lt} a dummy variable indicating whether $t = l$. Standard errors are clustered at the occupation level and the estimation is weighted by occupation-level job-posting volume measured over the pre-treatment period, so that occupations with the highest pre-treatment number of job postings receive greater weight.[9] The variable $Treat_i$ will indicate, in turn, whether i belongs to the different occupational groups for which employers require the most IT skills during the pre-2023 period, with the control group consisting of occupations for which employers never require IT skills in the pre-2022 period. The reference date in each regression will be $l = 2022 - 3$ (i.e., θ_{2022-3} is set to zero), so that the coefficients θ_l can be interpreted as tracing the evolution of the outcome gap between the treatment group and the control group, with the 2022-3 gap taken as the reference. The profile of estimated θ_l values for the pre-2022 period (i.e., $l < 2022 - 3$) will allow us to test for the existence of confounding factors differentially affecting different occupational categories even before the emergence of GenAI. Conversely, the profile of estimated θ_l values for the post-2022 period (i.e., $l > 2022 - 3$) will allow us to visualize the dynamics of the effects of recent successive waves of generative AI.

To obtain more synthetic estimates (and cover a broader range of outcomes), we will also estimate more parsimonious difference-in-differences models,

$$Y_{it} = \mu_i + \lambda_t + \theta \left(Treat_i \times Post_{2022t}\right) + \epsilon_{it}. \tag{7}$$

where $Post_{2022t}$ is a dummy variable indicating that quarter t is after 2022-4. The θ coefficient captures the change in the gap between the treatment and control groups from before to after the fourth quarter of 2022. As a robustness check, we will also test whether the results obtained with model (7) are robust to the inclusion—as control variables—of a full set of industry effects interacted with the $Post_{2022}$ variable, the question being the extent to which the results are not merely the consequence of sectoral shifts in activity. We will also estimate an augmented version of model (7) by introducing $Treat_i \times Post_{2023t}$ as an additional treatment variable, where $Post_{2023t}$ indicates that quarter t occurs after the last quarter of 2023 (and the release of the professional versions of ChatGPT and Copilot). The augmented model is written as follows,

$$Y_{it} = \mu_i + \lambda_t + \theta_1 \left(Treat_i \times Post_{2022t}\right) + \theta_2 \left(Treat_i \times Post_{2023t}\right) + \epsilon_{it}. \tag{8}$$

In this specification, the coefficient θ_2 associated with $Treat_i \times Post_{2023t}$ captures the change in the gap between the treatment and control groups between the period following the fourth quarter of 2023 and the preceding one-year period. As we will see in the section dedicated to the event study, the gap between the treatment and control groups widens significantly from late

[9] As the IT-specialist treatment group comprises only eight occupations, standard cluster-robust inference may be unreliable (Cameron et al., 2008; MacKinnon and Webb, 2018). For this group, we have run the regressions using Webb (2023) six-point weights and find that the significance levels remain robust.

2023 onwards, following the launch of tools like Microsoft Copilot and Code Interpreter—which are far better suited to "vibe coding" than the initial version of ChatGPT. The augmented model will make it possible to gauge the magnitude of this post-2023 shock.

V.1 Event Study

In this section, we present (in graphical form) the results of event study model (6) applied in turn to variables measuring the (log) number of job postings, the average posted wage, the (log) number of applicants, the average number of applicants per job posting, and the (log) number of actual hires. For each of these variables, we will present two types of figures. The first will show the results of the event study when the treatment group consists of either IT-specialist jobs or IT-exposed jobs. These graphs allow us to visualize the trends of these two occupational groups relative to the control group, before and after the emergence of GenAI. The second type of figure will show the results of the event study when the treatment group consists of IT-exposed occupations, considering separately cases where employers require specific IT skills and cases where they do not. These graphs make it possible to visualize the evolution of the demand for IT skills in IT-exposed jobs. The analyses will be conducted using comprehensive PES data for the 2021–2025 period. A supplementary analysis of the number of job postings for IT-exposed and IT-specialist occupations will also be conducted using data from the Ministry of Labor covering the broader 2016–2025 period.

V.1.1 Job Offers and Posted Wages

Using model (6), Figure 2A shows the quarterly evolution of the job offer gap (in ln) between IT-specialist occupations and control occupations, as well as between IT-exposed occupations and control occupations, with the gap observed in 2022-3 used as a reference. The figure shows that the trends in the number of job offers for the three types of jobs remain parallel from the period prior to 2022 through the end of 2023, at which point a significant decline begins for IT-specialist occupations and, to a lesser extent, for IT-exposed occupations. Compared to the control group, job offers for IT-specialist occupations are about 30% fewer at the beginning of 2025 than at the end of 2022. For IT-exposed jobs, the decrease is more than 10%.

One might wonder whether these declines simply represent a return to the situation that prevailed prior to the 2020–2021 period—a time marked by the COVID-19 pandemic and an unprecedented expansion of remote work. Using longer-term data on job postings by occupation published by the Ministry of Labor, Appendix Figure A1 shows that this is not the case: the decline in job postings for IT-exposed and IT-specialist roles observed between early 2024 and mid-2025 is just as pronounced when using the pre-pandemic period of 2018–2019 as a benchmark as it is when using late 2022 or late 2023. Furthermore, the trend emerging between early 2024 and mid-2025 appears to be continuing into the subsequent quarters.

Using the same control group, Figure 2B further traces the evolution of job postings for IT-exposed jobs, distinguishing between those where employers actually require IT skills and those where employers do not require any IT skills. This graph reveals that the decline in job offers for IT-exposed occupations shown in Figure 2A corresponds primarily to a drop in job postings where employers require IT skills. By contrast, postings that do not require IT skills remain very stable.

Using the same control group again, Figure 3 shows the trend in the share of job postings where employers require AI skills, separately for IT-specialist and IT-exposed occupations. The figure reveals that these AI skills became more frequently required (starting in 2023) in job postings for IT-specialist occupations, but not in job postings for IT-exposed occupations. The decline in IT-exposed and IT-specialist occupations closely followed the emergence of a demand for IT specialists capable of organizing the use of AI within companies. However, it must be emphasized that the proportion of job postings requiring AI skills remains very small (less than 1%), even within IT-specialist occupations. Furthermore, this increase is highly concentrated in a few occupations. Software developers account for approximately 69% of the aggregate increase in the share of postings requiring AI skills, followed by functional IT consultants , who account for a further 14%. There is no widespread increase in AI-skills across occupations.

To complement these analyses, Figure 4A shows the trend in (relative) posted wages for IT-specialist and IT-exposed occupations. It shows that the relative decline in job postings for IT-exposed and IT specialist occupations observed after 2023 cannot be interpreted as a response to a rise in their relative wages. For IT specialists, there is even a slight decline after 2023. For IT-exposed occupations, the figure does not reveal any significant shift in the period following the emergence of GenAI. Figure 4B further shows the evolution of relative posted wages for IT-exposed jobs depending on whether or not the employer requires specific IT skills. Again, the figure does not reveal any significant shifts in the period after 2022.

V.1.2 Applications and Hiring

In this subsection, we examine whether and how workers' labor supply has adapted to the post-2022 changes in job postings described in the previous section. We shed light on this issue by first analyzing trends in the number of (unique) applicants for the various categories of job postings. Figure A2A shows the evolution of this number separately for IT-specialist and IT-exposed job postings, while Figure A2B shows the evolution of this number for IT-exposed job postings depending on whether or not the employer requires IT skills.

Using the same models and control group as the previous figures, Figure A2A reveals that the number of applicants for IT-exposed or IT-specialist positions remained stable through the end of 2023 before increasing slightly toward the end of the period. In a context where relative wages are not rising, this upward trend in the number of applicants can be interpreted as a consequence of the decline in the technical skills required for IT-exposed or IT specialist roles - a decline that may have expanded the pool of potential candidates. Regarding IT-exposed occupations, Figure A2B further shows that the number of applicants decreased for jobs requiring IT skills, but increased for those not requiring such skills. The slight increase in the number of applicants for IT-exposed positions observed after 2023 is indeed driven by applications for positions with the lowest skill requirements.

Change in the number of unique applicants is just one possible way in which the labor supply can adapt. The number of applications per applicant may also change, and with it, the number of applications per job opening. An analysis of this latter outcome, as shown in Figure 5A, reveals that it has increased very significantly since late 2023 for IT specialist positions, and to a lesser extent for IT-exposed positions. By the middle of 2025, the number of candidates per IT specialist position is about 50% higher than it was at the end of 2022. For IT-exposed positions, the increase between those same two dates is approximately 10%. These increases in the number of applications per job opening mirror the declines in the number of job postings shown in Figure 2A and can be interpreted as the direct result of the combination of these declines and the near-stability in the number of unique applicants per position shown in Figure A2A, without any necessary change in the number of applications per applicant.[10]

With regard to IT-exposed occupations, Figure 5B further shows that the rise in the number of applications per job posting is just as pronounced for jobs that do not require IT skills as it is for those that do. For jobs that do not require IT skills, the rise in the number of applications per posting reflects a combination of a rise in the number of applicants and a stable number of job openings. For jobs that require IT skills, it reflects a combination of a decline in the number of applicants that is less pronounced than the decline in the number of job openings.

With regard to the hires that were actually made, we expect that they will decline for the occupations most affected by the drop in job postings, particularly IT-specialist occupations. However, we cannot rule out the possibility that the job postings that disappear after 2022 are those that would have had the most difficulty finding qualified candidates. It is also possible that the increase in the number of candidates per posted position for IT-specialist (or IT-exposed) occupations led to an increase in the number of candidates actually hired per posted position. These various mechanisms may have helped mitigate the impact of the decline in job postings on the volume of actual hiring. To shed light on these questions, Figures 6A and 6B use our data on actual hires among candidates for different types of job postings. Using the same control group and the same event study specifications as the figures in the previous sections, Figure 6A confirms a very marked decline in hiring for IT specialist occupations and a more modest one for IT-exposed occupations (compared to the control group). Figure 6B shows that the decline in hiring for IT-exposed occupations is primarily driven by a drop in hiring for jobs requiring specific IT skills. Ultimately, the trends in hiring closely mirror that of job postings, reflecting a significant decline in demand for IT specialists as well as a decline in demand for IT skills in IT-exposed jobs.

V.2 Difference-in-Differences Regressions

To complement the event study presented above, Table 2 shows the estimation results for model (7) where the treatment group consists, in turn, of IT-exposed occupations (column 1), IT-specialist occupations (column 2), and occupations with low exposure to IT technologies (column 3) - the latter analysis serving as a placebo test.[11] The first lines of the table correspond to the main dependent variables analyzed in the previous section, namely the number of job postings (in log), the shares of the various types of skills (IT, writing, teamwork, speaking in public), required in job postings, the (log) average wage, the number of distinct applicants, the number of applicants per job posting, and the number of actual hires. Regarding IT skills, we present the overall effect, as well as the specific effects associated with programming skills,

[10] We can write: (nb. applications/nb job offers) = (nb. applications/nb. applicants) x nb. applicants x(1/nb. job offers). If the number of applicants remains stable while the number of job offers declines (our case), the number of applications per job offer will increase - all the more so given that the number of applications per applicant is also rising. If the increase in applications per job offer mirrors the decrease in the number of job offers, then the number of applications per applicant is necessarily stable.

[11] These low-exposure occupations are those described in Panel C of Table 1 and correspond to those falling within the middle two quartiles of the distribution of the proportion of job postings requiring IT skills during the 2021–2022 pre-event period. During this pre-shock period, the proportion of job postings requiring IT skills averaged only 5.4% for these occupations (as shown in Table 1).

software skills and data analysis skills. We also present the estimated effects on AI skills and office software skills. Finally, the dependent variables in the last two rows are the share of women and the share of people 35 and younger among those actually hired. For each dependent variable and treatment group, the table reports the coefficient associated with $Treat_i \times Post_{2022t}$ in model (7). In substance, this coefficient captures the change in the gap between the treatment and control groups observed, on average, between the period after and before the ChatGPT shock in the fourth quarter of 2022.

In line with previous event-study results, the first column of the table confirms that the shock was followed by a decline in job postings for IT-exposed occupations as well as a decline in the share of job postings for IT-exposed occupations requiring IT skills. This share is estimated to be, on average, about 5 percentage points lower after the shock than before. This decline primarily reflects a decrease in demand for office software skills. These trends are not accompanied by any significant change in relative wages, but rather by an increase in the number of candidates per available position. This number is estimated to be, on average, about 0.11 log points higher after 2022. Ultimately, the total number of hires in IT-exposed occupations declines after 2023 (-0.088 log points), but there is no significant change in the profile of the individuals hired.

The second column further confirms that the technological shock was followed by a marked decline in the number of job postings for IT-specialist occupations. Compared to the control group, the quarterly number of postings for IT-specialist positions is estimated to be on average about 0.116 log points lower after 2023 than in the preceding quarters. While there are fewer job postings overall, the proportion requiring AI skills and public speaking skills is increasing, whereas the share requiring programming skills is declining, in line with the notion that GenAI has made these skills less critical. The table also confirms that the launch of ChatGPT was followed by a significant increase in the number of applicants per IT-specialist position offered, while relative posted wages have changed very little. Compared to the control group, the number of applicants per IT-specialist position offered is estimated to be on average about 0.248 log points higher after 2022 than in the preceding quarters. Consistent with the previous event study, the decline in the number of hires is even more pronounced than the decline in the number of job postings, but no change is observed in the proportion of women or in the share of people 35 and younger among newly hired IT specialists.

Finally, regarding occupations with low exposure to IT technologies, the third column reveals no major changes in the period following the technological shock. Compared to the control group, only very slight variations are detected in the proportion of job postings requiring IT skills or in hiring volumes - nothing comparable in magnitude to the changes observed for IT-exposed or IT-specialist occupations. This result aligns with our central working hypothesis: the impact of the emergence of GenAI and the ability to use IT tools via natural language is directly linked to the extent to which jobs relied on IT skills prior to the shock.

V.3 Alternative Control Group

In the preceding sections, the control group consists of occupations for which employers never or almost never require IT skills in the pre-ChatGPT period. Our working assumption is that these occupations have been spared from the emergence of vibe coding and the associated efficiency gains in programming tasks or the use of office software. However, we cannot rule out the possibility that these occupations have been impacted by other forms of efficiency gains linked to GenAI, particularly in tasks that require writing skills. Writing skills are indeed - along with computer skills - the skills most typically associated with occupations most exposed to GenAI (Eloundou et al., 2024). Given this reality, the parameters shown in Table 2 do not necessarily isolate the effects of GenAI on the treatment group; they also potentially capture the differential effect that GenAI has had on the skills of workers in the control group, beyond programming or office software usage.

To test this hypothesis, one possible initial approach is to change the control group. More specifically, the idea is to use an alternative control group consisting of occupations that the task-based literature identifies as being the least exposed to all effects associated with GenAI tools, whether these effects relate to computer skills, writing skills or any other type of skills. Following this idea, Table 3 shows the results of Model (7) obtained with the control group comprising occupations identified by Eloundou et al. (2024) as not affected by GenAI.[12] Reassuringly, most of the effects estimated using this alternative control group are similar to those estimated using the initial control group. In particular, we obtain similar estimates of the impact of GenAI on the share of IT skills or on posted wages or on the number of applicants per job opening or on the number of hires. Only the estimated effects on the number of job postings appear to be weaker with the new control group, although the differences between these estimated effects and the initial estimates are not statistically significant. It should be noted that the new control group includes fewer occupations than the baseline control group (38 vs. 130), resulting in smaller number of (occupation level) observations and lower precision of the estimates with this approach. Ultimately, the main results shown in Table 2 do not appear to reflect an impact of GenAI on control group skills that are independent of IT skills. The results in Table 3 are consistent with the fact that none of the occupations identified by Eloundou et al. (2024) as being highly exposed to GenAI appear in our control group, whereas nearly three-quarters are found in our treatment groups. Conversely, occupations identified by Eloundou et al. (2024) as not exposed to GenAI are almost never found in our treatment groups (only about 6% of them fall into this category), but are predominantly found in our control group.

A second possible approach is to directly test the extent to which our results are driven by the impact of GenAI on occupations requiring writing skills. To explore this idea, we augmented model (7) with a control variable representing the interaction between the $\text{Post}_{2022\text{-}4}$ dummy variable and a dummy variable indicating whether the proportion of job postings requiring writing skills in the pre-2022-4 period was above the median.[13] Table B4 in the appendix shows that the results obtained with this model are similar to those in Table 2. To be more precise, this new model yields very similar estimates of the effect of the technological shock on the share of IT skills, on the number of applicants per job posting, and on the volume of hires, as well as even stronger effects on the number of job postings. Ultimately, our main results cannot be interpreted as reflecting the differential impact that generative AI has had on occupations requiring writing skills.

[12]These occupations are listed in Table 8.1 of Eloundou et al. (2024). In Appendix Table B3, we present the correspondence between these occupations and the items of the French classification used in this article.

[13]For approximately half of the occupations, the proportion of job postings requiring writing skills is zero or negligible (the median of this proportion across occupations is 0.3%). For occupations above the median, the average proportion of job postings requiring writing skills is 20%. The dummy variable used to identify the new treatment group thus distinguishes between occupations based on whether or not they never - or almost never - require writing skills.

V.4 Augmented Model

The event studies discussed above suggest that the impact of GenAI tools only began to be felt after the launch of paid versions of these tools - aimed at professionals - in late 2023. To further test this hypothesis and better quantify the magnitude of the post-2023 effects, Table 4 presents the results obtained using our basic DiD model augmented with the variable $Treat_i \times Post_{2023t}$ (i.e., model (8)). For each of the main two treatment groups and each dependent variable, the first column reports the coefficient corresponding to the variable $Treat_i \times Post_{2022t}$ in model (8), while the second column reports the coefficient corresponding to the variable $Treat_i \times Post_{2023t}$ in the same model. The coefficient in the second column captures the incremental change in the gap between the treatment and control groups observed, on average, between the period after the fourth quarter of 2023 and the period spanning the fourth quarter of 2022 to the fourth quarter of 2023. The coefficient in the first column captures the change in this same gap between the one-year period following the fourth quarter of 2022 and the preceding period. If only the coefficient in the first column is significant, this means that the effect of the technological shock was evident from the outset, in the months following the shock in the fourth quarter of 2022. If only the coefficient in the second column is significant, this means that the effect of the technological shock became apparent only after the developments of 2023.

Whether considering the number of job postings, the share of IT skills within those postings, or hiring trends, the available data clearly support this second scenario: the decline in postings and hiring intensifies primarily after 2023, coinciding with the period when the drop in employer demand for IT skills is most pronounced. The proportion of workers under 35 among new hires also appears to have increased significantly in IT specialist roles after 2023, perhaps due to the growing need for AI expertise in these roles - a shift that the non-augmented model had failed to detect accurately.

To complement this analysis, Table B5 in the appendix presents the results of the augmented model using the alternative small control group from Eloundou et al. (2024). With this control group as well, the main effects on IT specialist outcomes appear particularly significant only after 2023, including for job postings and hires. Regarding IT-exposed occupations, effects on the share of job postings requiring IT skills or on applicants per posting also appear only after 2023, whereas effects on hires begin to be detected as soon as 2022.

V.5 Disaggregated Model

Table 5 tests the robustness of the results in Table 4 by dis-aggregating the data to the occupation $\times$ industry level and allowing for industry-specific post-treatment shocks, i.e. by augmenting the regression model with controls for industry effects (21-item classification) and for the full set of interactions between these industry effects and the $Post_{2022t}$ variable. The weights assigned to each observation are also recalculated at the occupation$\times$industry level.

It should be noted that, since occupation $\times$ industry-level data contains a significant proportion of quarters with zero job postings (or with zero applications or zero hires), standard log-linear specifications could lead to biased estimates due to the omission of zero observations or the arbitrary transformation of the dependent variable. To address this issue, the effects of the treatment on job postings, applications and hires in Table 5 are estimated using a multiplicative model and the Poisson Pseudo-Maximum Likelihood (PPML) estimator, as recommended by Silva and Tenreyro (2006). However, the estimated coefficients can still be interpreted as log linear coefficients: if the estimated treatment effect is β, this means that the impact on the volume of job postings (or hires) is $(exp(\beta) - 1) \times 100\%$.

The first two columns of Table 5 shows that the estimated effects for IT-exposed occupations are very similar to those in Table 4, that is, estimated effects are very similar regardless of the level of data aggregation we use. Similarly, when considering IT specialist occupations, the estimated impacts on the number of job postings, posted wages, required skills, or the number of applicants and hires are very similar regardless of the level of data aggregation. When working at the most disaggregated level, the only notable changes concern the impact of the treatment on the proportion of people under the age of 35 among new hires in IT specialist roles : the positive effect on this proportion appears larger when working at the more disaggregated level. Apart from this difference (which is not statistically significant), the results in Table 4 are very similar to those in Table 5 and the latter cannot be interpreted as an indirect consequence of a decline in the industries where IT-exposed or IT-specialist occupations are concentrated and where demand for IT skills is generally strongest.

V.6 Interpretation and Mechanisms

To interpret our econometric results, we can revisit the conceptual framework developed in Section 3. In this model, the decline in demand for IT skills in IT-exposed occupations can be explained in two ways: either as a response to a rise in the relative wages of workers possessing such skills, or as a response to technological progress that specifically boosts the productivity of workers lacking these skills (i.e., $\Delta\alpha_t > 0$ in Equation 1 above). This second scenario also relies on the assumption that workers with high and low IT proficiency are substitutable (i.e., $s > 1$). Given that relative wages have not risen, this second scenario appears the most plausible and aligns best with the nature of the efficiency gains driven by GenAI, particularly in office-based roles. In essence, technological progress is driving both a decline in demand for office jobs and a decline in demand for the IT skills needed to perform those jobs.

Turning to IT specialists, given that their wages have not increased compared to those of the control group, the most plausible interpretation of the relative decline in job postings is technical progress that specifically boosts their productive efficiency (i.e.,$\Delta\beta_t > 0$ in Equation 2), combined with the assumption of complementarity with other employees ($\sigma < 1$). Essentially, technological progress is driving both a decline in demand for IT experts and a redefinition of the skills required for these expert roles, with a decreasing demand for pure programming skills and an increasing demand for the ability to communicate and explain solutions—particularly AI solutions—beyond the circle of experts.

With regard to labor supply, the increase in the number of candidates for IT-specialist and IT-exposed roles can be interpreted as the result of a reduction in the specific difficulties associated with performing these jobs - a shift captured in the model by a rise in the a_{2st} or a_{1t} parameters. Technological progress has not only lowered firm demand for these jobs but, by making pure IT skills less critical, has also made these jobs attractive and accessible to a larger pool of candidates. In a context where relative wages adjust slowly, the primary consequence of these opposing supply and demand trends has been a sharp rise in the number of candidates per vacancy.

VI Conclusion

Within a few months starting in late 2022, GenAI tools became widely adopted throughout society and the economy. By enabling anyone to leverage computing resources using natural language, these technologies opened the door to significant efficiency gains across all occupations that - prior to 2022 - required at least some level of IT skills. In this article, we show that this shift was accompanied by a drop in job postings for these roles as well as a reduction in the IT skills employers required for them. While the decline in job postings led to a similarly sharp drop in actual hiring, the number of applicants did not decrease; consequently, there was a marked rise in the number of candidates per vacancy—not only for IT-specialist roles but, more broadly, for all positions requiring IT skills (particularly in office-based jobs).

As stark as they may be, these developments did not emerge immediately after the arrival of ChatGPT in late 2022, but rather nearly a year later, when players in the GenAI sector began releasing paid versions of their tools—versions that were more powerful and better suited to corporate needs.

The technological revolution driven by AI is still unfolding, notably with the shift toward agentic AI, namely systems capable of organizing themselves end-to-end to achieve a goal and far more autonomous than standard GenAI. These tools are already being deployed in sectors such as banking and logistics. Future research will need to determine whether this new stage in AI development will exacerbate or, conversely, mitigate the labor market trends highlighted in this study.

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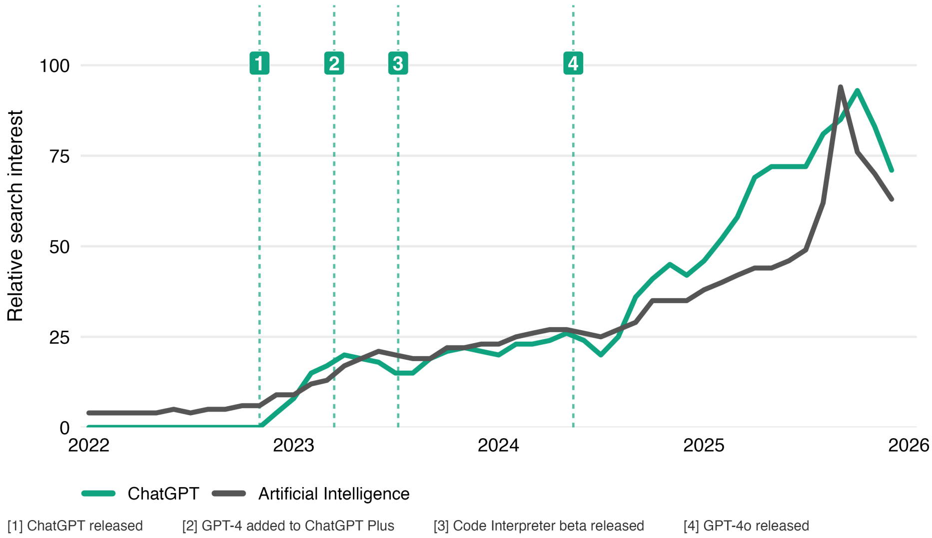
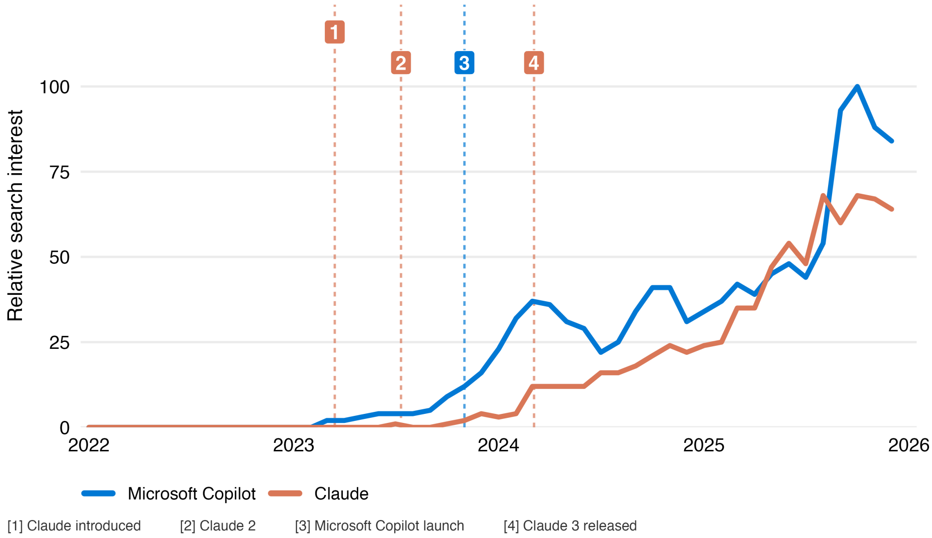
VII Main Figures



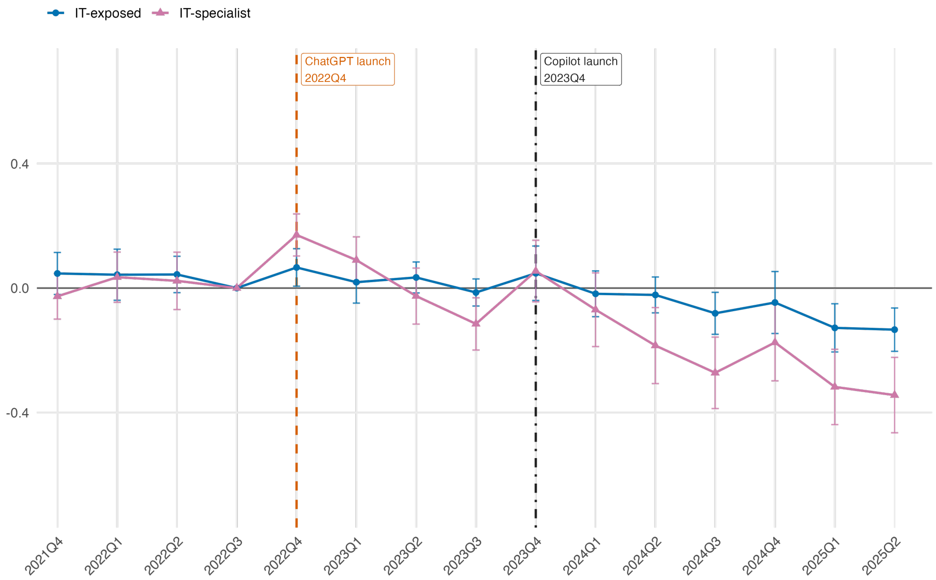
A Google Search Interest in ChatGPT and Artificial Intelligence



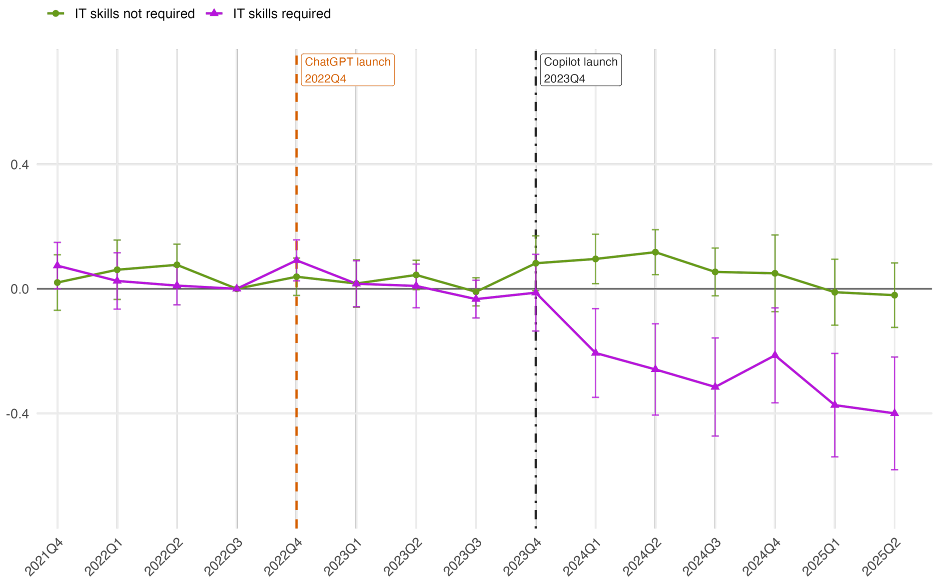
B Google Search Interest in Microsoft Copilot and Claude

Figure 1: **Worldwide Google Search Interest in Generative AI Tools**

Notes: Each panel is normalized separately from 0 to 100 over January 2022–December 2025. Values can therefore be compared over time and across search terms within a panel, but not across Panels A and B. Source: Google Trends.



A IT-specialist and IT-exposed occupations



B IT-exposed occupations, by IT skill requirement

Figure 2: **Trends in Job Postings**

Notes: Figure 2A shows the results of our event study model applied to the (log) number of job postings when the treatment group is defined either by IT-exposed occupations or by IT-specialist occupations. Figure 2B shows the results of the same event study model when the treatment group is defined either by IT-exposed jobs requiring specific IT skills or by IT-exposed jobs that do not require such specific skills. Vertical bars show 95% confidence intervals. The vertical dashed lines indicate the fourth quarter of 2022 and the fourth quarter of 2023.

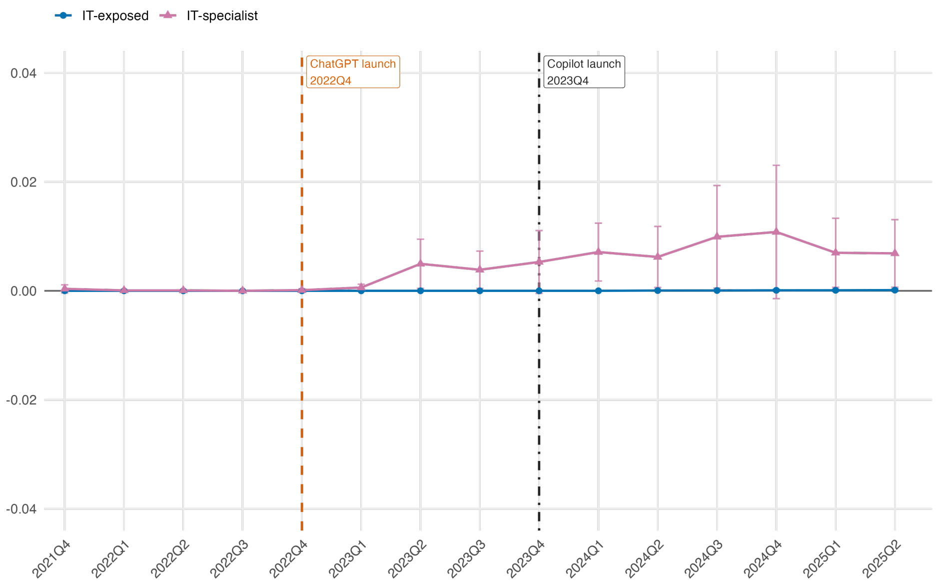
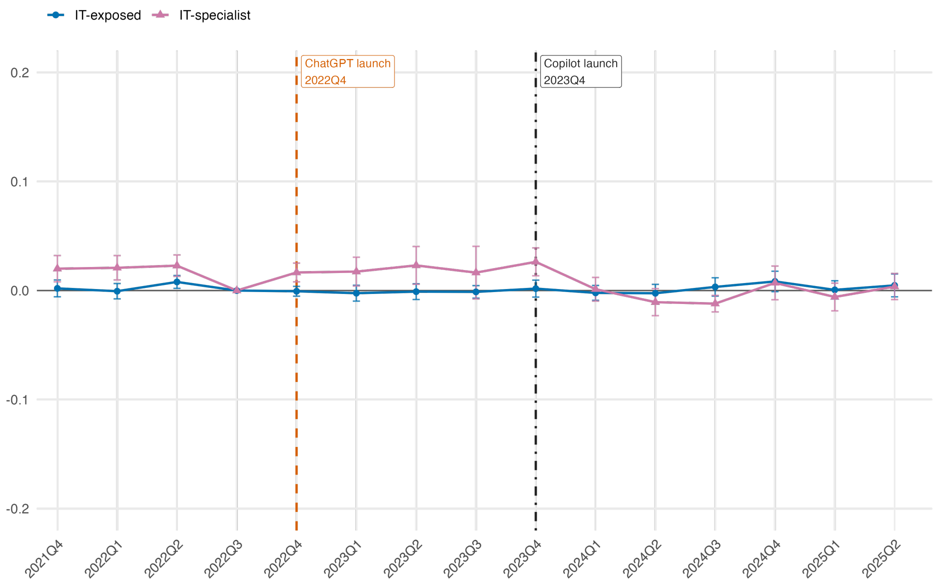
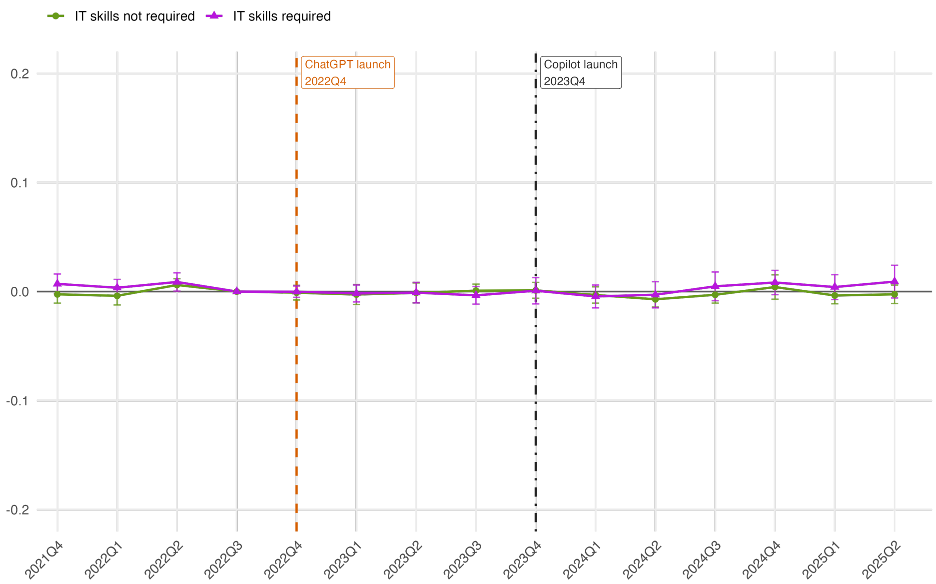


Figure 3: **Trends in the Share of Job Postings Requiring AI skills**

Notes: The figure shows the results of our event study model applied to share of job postings requiring AI skills when the treatment group is defined either by IT-exposed occupations or by IT-specialist occupations. Vertical bars show 95% confidence intervals. The vertical dashed lines indicate the fourth quarter of 2022 and the fourth quarter of 2023.



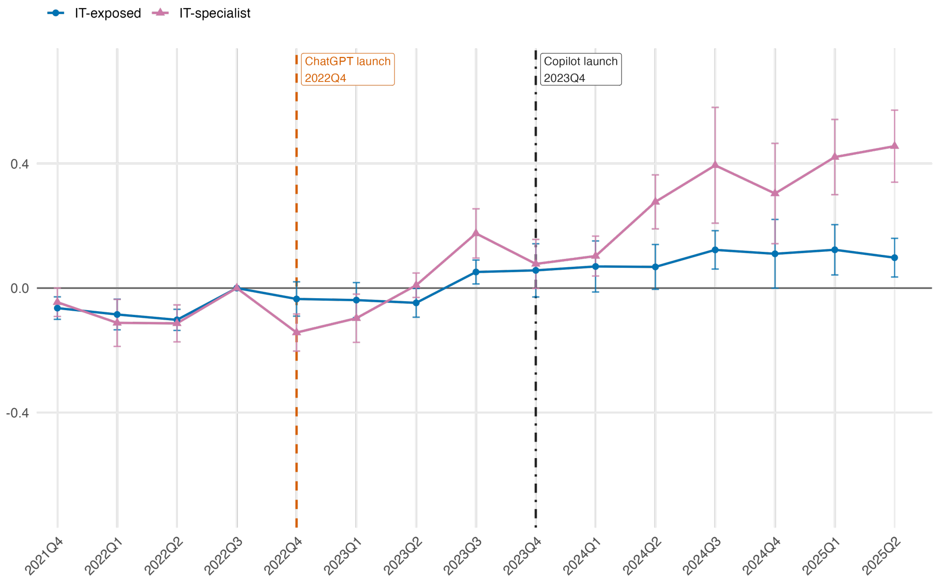
A IT-specialist and IT-exposed occupations



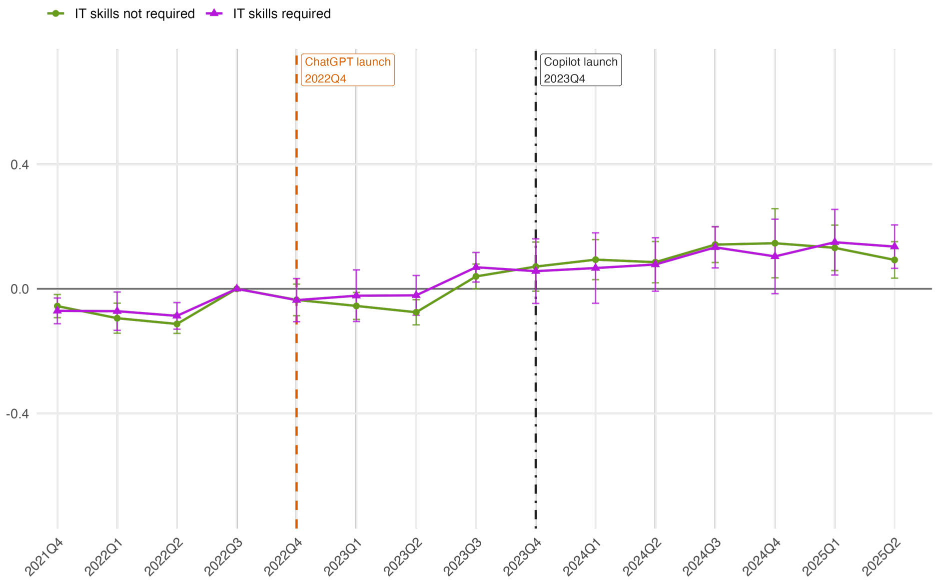
B IT-exposed occupations, by IT skill requirement

Figure 4: **Trends in Relative Wages**

Notes: Figure 4A shows the results of our event study model applied to (log) average posted wages when the treatment group is defined either by IT-exposed occupations or by IT-specialist occupations. Figure 4B shows the results of the same event study model when the treatment group is defined either by IT-exposed jobs requiring specific IT skills or by IT-exposed jobs that do not require such specific skills. Vertical bars show 95% confidence intervals. The vertical dashed lines indicate the fourth quarter of 2022 and the fourth quarter of 2023.



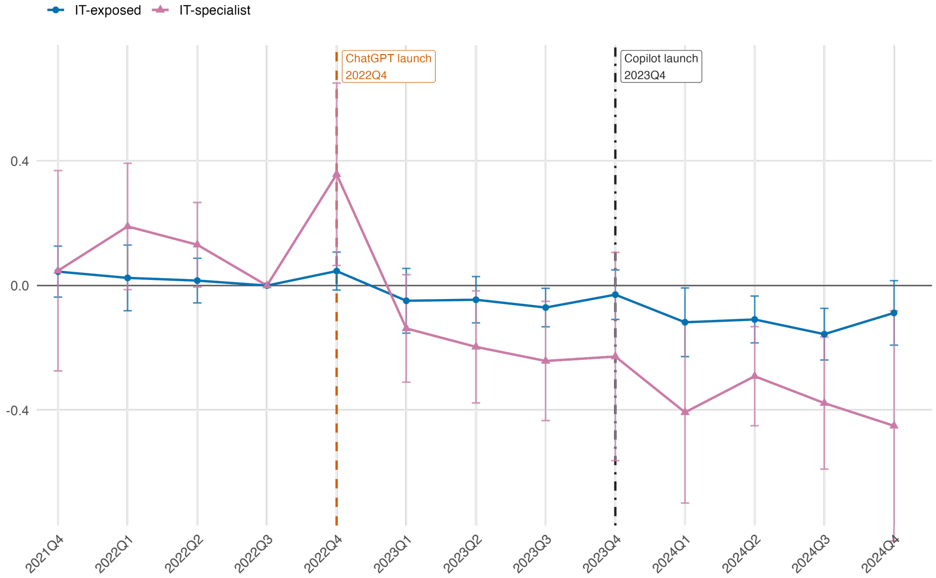
A IT-specialist and IT-exposed occupations



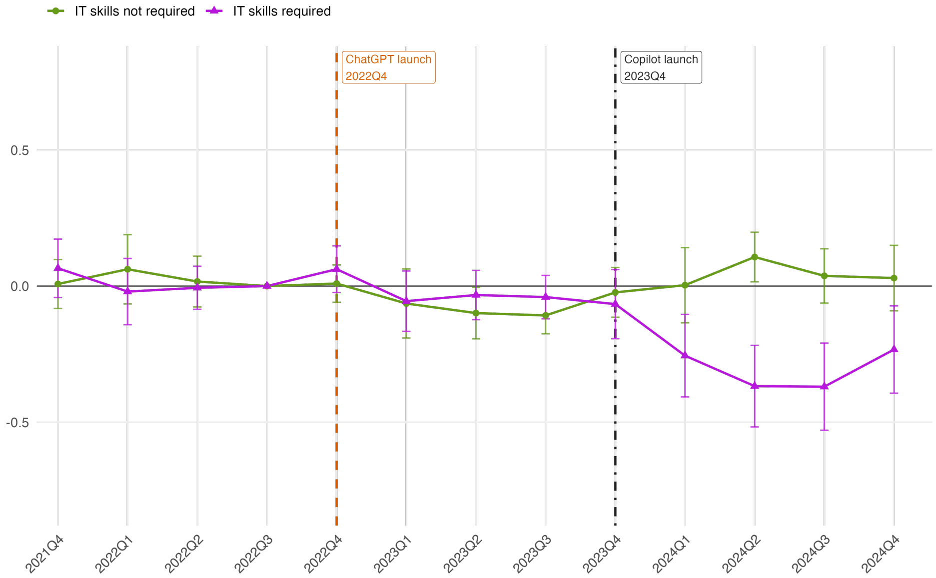
B IT-exposed occupations, by IT skill requirement

Figure 5: **Trends in the Number of Applications per Job Posting**

Notes: Figure 5A shows the results of our event study model applied to (log) number of applications per job posting when the treatment group is defined either by IT-exposed occupations or by IT-specialist occupations. Figure 5B shows the results of the same event study model when the treatment group is defined either by IT-exposed jobs requiring specific IT skills or by IT-exposed jobs that do not require such specific skills. Vertical bars show 95% confidence intervals. The vertical dashed lines indicate the fourth quarter of 2022 and the fourth quarter of 2023.



A IT-specialist and IT-exposed occupations



B IT-exposed occupations, by IT skill requirement

Figure 6: **Trends in the Number of Hires**

Notes: Figure 6A shows the results of our event study model applied to (log) number of hires when the treatment group is defined either by IT-exposed occupations or by IT-specialist occupations. Figure 6B shows the results of the same event study model when the treatment group is defined either by IT-exposed jobs requiring specific IT skills or by IT-exposed jobs that do not require such specific skills. Vertical bars show 95% confidence intervals. The vertical dashed lines indicate the fourth quarter of 2022 and the fourth quarter of 2023.

VIII Main Tables

Table 1: Descriptive statistics

	2021–22	2023–25
Panel A: IT-specialist occupations		
Average number of job postings per quarter	1,451	1,144
Share of postings requiring IT skills	0.742	0.634
Log average posted wage	7.796	7.878
Number of applicants per posting	8.42	13.27
Female share among hires	0.221	0.252
Share of hires aged 35 or below	0.685	0.700
Panel B: Occup. with high exposure to IT skill requirements.		
Average number of job postings per quarter	895	739
Share of postings requiring IT skills	0.436	0.383
Log average posted wage	7.629	7.717
Number of applicants per posting	12.74	17.55
Female share among hires	0.524	0.529
Share of hires aged 35 or below	0.589	0.567
Panel C: Occup. with low exposure to IT skill requirements.		
Average number of job postings per quarter	1,365	1,166
Share of postings requiring IT skills	0.054	0.048
Log average posted wage	7.573	7.665
Number of applicants per posting	9.62	12.64
Female share among hires	0.415	0.414
Share of hires aged 35 or below	0.582	0.561
Panel D: Occup. with no exposure to IT skill requirements.		
Average number of job postings per quarter	1,575	1,354
Share of postings requiring IT skills	0.009	0.012
Log average posted wage	7.514	7.602
Number of applicants per posting	10.56	12.95
Female share among hires	0.449	0.470
Share of hires aged 35 or below	0.589	0.563

Notes: Panel A refers to the eight main IT specialist occupations in the French classification system (i.e., software developer, information system managers, computer system expert, IT system consultant, computer operation technician). Panel B refers to occupations (other than those in Panel A) belonging to the fourth quartile of the distribution of the proportions of job postings requiring IT skills (proportions calculated for the period preceding the fourth quarter of 2022). Panel C refers to occupations in the second and third quartiles of this same distribution. Panel D refers to occupations in the first quartile of this same distribution.

Table 2: Main Difference-in-Differences Estimates

	IT-exposed (1)	IT-specialist (2)	Low-exposure group (3)
Nb offers (log)	-0.059**	-0.116***	-0.032
	(0.027)	(0.038)	(0.030)
Share offers requiring IT skills (Total):	-0.051***	-0.068***	-0.008**
	(0.007)	(0.010)	(0.003)
AI skills	0.000	0.006**	0.000
	(0.000)	(0.003)	(0.000)
Programming skills	-0.008*	-0.065***	-0.003
	(0.004)	(0.011)	(0.003)
Software skills	-0.044***	-0.082***	-0.004***
	(0.007)	(0.024)	(0.001)
Office software skills	-0.038***	0.001	-0.002*
	(0.008)	(0.002)	(0.001)
Data analysis skills	-0.007	0.015***	0.000
	(0.005)	(0.004)	(0.001)
Share offers requiring public relations skills	-0.054	0.071**	-0.023
	(0.048)	(0.028)	(0.038)
Share offers requiring writing skills	0.003	-0.130*	-0.004
	(0.006)	(0.067)	(0.006)
Share offers with teamwork skills	0.003	0.002	0.001*
	(0.002)	(0.001)	(0.001)
Average posted wage (log)	-0.002	-0.008***	0.000
	(0.002)	(0.002)	(0.003)
Nb distinct applicants (log)	0.046**	0.064*	0.008
	(0.019)	(0.037)	(0.021)
Nb applicants per offer (log)	0.115***	0.248***	0.044
	(0.030)	(0.051)	(0.028)
Number of hires (log)	-0.088***	-0.311***	-0.010
	(0.026)	(0.105)	(0.028)
Female share among hires	0.001	0.012	0.002
	(0.006)	(0.017)	(0.004)
Share hired people, aged 35 or below	-0.004	0.013	-0.001
	(0.007)	(0.017)	(0.005)
Observations	3,827	2,073	5,941

Notes: Columns (1)–(3) report the coefficient of $Treat_i \times Post_{2022t}$ from the basic difference-in-differences specification (Model (7) in the text). The treatment groups are, respectively, IT-exposed occupations (col. (1)), IT-specialist occupations (col. (2)), and occupations in the second and third quartiles of the pre-treatment distribution of IT-skill requirements (col. (3)). All three groups are compared with occupations in the first quartile. The regressions use occupation-by-quarter observations from 2021Q4 to 2025Q2 and are weighted by the total number of job postings in each occupation before 2022Q4. All models include occupation fixed effect and a full set of calendar-quarter fixed effects. Standard errors clustered at the occupation level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Robustness to the Use of an Alternative Control Group

	IT-exposed (1)	IT-specialist (2)	Low-exposure group (3)
Nb offers (log)	-0.011	-0.065	0.016
	(0.044)	(0.052)	(0.046)
Share offers requiring IT skills (Total):	-0.045***	-0.064***	-0.004
	(0.007)	(0.010)	(0.004)
AI skills	0.000	0.006*	0.000**
	(0.000)	(0.003)	(0.000)
Programming skills	-0.008**	-0.065***	-0.005
	(0.004)	(0.011)	(0.003)
Software skills	-0.043***	-0.080***	-0.003
	(0.008)	(0.024)	(0.002)
Office software skills	-0.038***	0.003	-0.001
	(0.008)	(0.002)	(0.001)
Data analysis skills	-0.003	0.017***	0.003*
	(0.005)	(0.005)	(0.002)
Share offers requiring public relations skills	-0.070	0.058	-0.049
	(0.061)	(0.047)	(0.055)
Share offers requiring writing skills	-0.006	-0.138**	-0.014**
	(0.005)	(0.068)	(0.006)
Share offers with teamwork skills	0.002	0.001	0.001
	(0.002)	(0.002)	(0.001)
Average posted wage (log)	0.002	-0.005	0.005
	(0.003)	(0.003)	(0.004)
Nb distinct applicants (log)	0.067*	0.083	0.028
	(0.040)	(0.051)	(0.039)
Nb applicants per offer (log)	0.072**	0.198***	0.001
	(0.030)	(0.052)	(0.030)
Number of hires (log)	-0.071	-0.293**	0.004
	(0.049)	(0.115)	(0.050)
Female share among hires	-0.002	0.010	-0.001
	(0.006)	(0.017)	(0.005)
Share hired people, aged 35 or below	-0.005	0.012	-0.003
	(0.006)	(0.017)	(0.004)
Observations	2,354	630	4,273

Notes: Columns (1)–(3) report the coefficient of $Treat_i \times Post_{2022t}$ from the basic difference-in-differences specification (Model (7) in the text), using as the control group the occupations identified by Eloundou et al. (2024) as unaffected by generative AI. The treatment groups are, respectively, IT-exposed occupations (col. (1)), IT-specialist occupations (col. (2)), and occupations in the second and third quartiles of the pre-treatment distribution of IT-skill requirements (col. (3)). The regressions use occupation-by-quarter observations from 2021Q4 to 2025Q2 and are weighted by the total number of job postings in each occupation before 2022Q4. All models include occupation fixed effect, a full set of calendar-quarter fixed effects. Standard errors clustered at the occupation level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Augmented Model

	IT-exposed		IT-specialist	
	$T \times \text{Post}_{2022}$ effect	$T \times \text{Post}_{2023}$ effect	$T \times \text{Post}_{2022}$ effect	$T \times \text{Post}_{2023}$ effect
	(1)	(2)	(3)	(4)
Nb offers (log)	-0.007	-0.081***	0.022	-0.217***
	(0.019)	(0.021)	(0.033)	(0.022)
Share offers requiring IT skills (Total):	-0.006	-0.071***	-0.017***	-0.080***
	(0.005)	(0.012)	(0.006)	(0.016)
AI skills	0.000	0.000	0.002**	0.005*
	(0.000)	(0.000)	(0.001)	(0.003)
Programming skills	-0.003*	-0.008	-0.013*	-0.081***
	(0.001)	(0.006)	(0.007)	(0.016)
Software skills	-0.004	-0.063***	-0.016*	-0.103**
	(0.005)	(0.013)	(0.010)	(0.043)
Office software skills	0.002	-0.063***	0.001	-0.001
	(0.005)	(0.014)	(0.002)	(0.000)
Data analysis skills	-0.001	-0.008	0.003***	0.018***
	(0.003)	(0.005)	(0.001)	(0.006)
Share offers requiring public relations skills	-0.026	-0.044	0.027**	0.068**
	(0.024)	(0.048)	(0.011)	(0.028)
Share offers requiring writing skills	-0.001	0.006	-0.038*	-0.145*
	(0.003)	(0.006)	(0.020)	(0.080)
Share offers with teamwork skills	0.002	0.002	0.001**	0.000
	(0.001)	(0.002)	(0.001)	(0.002)
Average posted wage (log)	-0.004*	0.003	0.002	-0.017***
	(0.002)	(0.003)	(0.004)	(0.005)
Nb distinct applicants (log)	0.026*	0.036**	0.041**	0.041
	(0.015)	(0.017)	(0.019)	(0.043)
Nb applicants per offer (log)	0.045**	0.110***	0.054*	0.304***
	(0.021)	(0.023)	(0.031)	(0.047)
Number of hires (log)	-0.049**	-0.070***	-0.153*	-0.287***
	(0.023)	(0.024)	(0.080)	(0.068)
Female share among hires	0.002	-0.003	0.012	-0.000
	(0.005)	(0.004)	(0.019)	(0.020)
Share hired people, aged 35 or below	-0.004	-0.000	-0.001	0.027**
	(0.006)	(0.006)	(0.015)	(0.012)
Observations	3,827	3,827	2,073	2,073

Notes: Columns (1) and (3) report the coefficient on $Treat_i \times Post_{2022t}$ from the augmented difference-in-differences specification (Model (8) in the text). Columns (2) and (4) report the coefficient on $Treat_i \times Post_{2023t}$ from the same model, which captures the incremental effect of the treatment beginning in 2023Q4. The treatment group consists of IT-exposed occupations in columns (1)–(2) and IT- specialist occupations in columns (3)–(4); both are compared with occupations in the first quartile of the pre-treatment distribution of IT-skill requirements. The regressions are weighted by the total number of job postings in each occupation before 2022Q4. All models include occupation fixed effect (based on French detailed classification) and a full set of calendar-quarter fixed effects. Standard errors clustered at the occupation level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Augmented Model Controlling for Industry-specific Post-treatment Changes

	IT-exposed		IT-specialist	
	$T \times \text{Post}_{2022}$ effect	$T \times \text{Post}_{2023}$ effect	$T \times \text{Post}_{2022}$ effect	$T \times \text{Post}_{2023}$ effect
	(1)	(2)	(3)	(4)
Nb offers (PPML)	-0.031	-0.113***	-0.027	-0.156***
	(0.022)	(0.021)	(0.025)	(0.041)
Share offers requiring IT skills (Total):	-0.004	-0.065***	-0.031***	-0.059***
	(0.004)	(0.012)	(0.010)	(0.014)
AI skills	0.000	0.000	0.002*	0.004*
	(0.000)	(0.000)	(0.001)	(0.002)
Programming skills	-0.001	-0.005	-0.028**	-0.057***
	(0.002)	(0.007)	(0.013)	(0.014)
Software skills	-0.006	-0.061***	-0.023	-0.095**
	(0.005)	(0.012)	(0.018)	(0.044)
Office software skills	0.001	-0.062***	0.006	-0.002**
	(0.005)	(0.013)	(0.005)	(0.001)
Data analysis skills	-0.001	-0.007	0.002**	0.018***
	(0.002)	(0.005)	(0.001)	(0.005)
Share offers requiring public relations skills	-0.026	-0.035	0.032***	0.084***
	(0.025)	(0.044)	(0.010)	(0.028)
Share offers requiring writing skills	0.000	0.007	-0.041*	-0.109
	(0.003)	(0.007)	(0.024)	(0.071)
Share offers with teamwork skills	0.002	0.002	0.002**	0.001
	(0.001)	(0.001)	(0.001)	(0.002)
Average posted wage (PPML)	-0.001	0.003	0.004	-0.005
	(0.003)	(0.002)	(0.016)	(0.006)
Nb distinct applicants (PPML)	0.028	0.005	0.046***	0.063
	(0.031)	(0.023)	(0.011)	(0.046)
Nb applicants per offer (PPML)	0.043**	0.110***	0.077***	0.228***
	(0.018)	(0.019)	(0.030)	(0.031)
Number of hires (PPML)	-0.067***	-0.132***	-0.133**	-0.254***
	(0.018)	(0.018)	(0.053)	(0.024)
Female share among hires	0.002	-0.008	0.016	0.003
	(0.008)	(0.007)	(0.030)	(0.033)
Share hired people, aged 35 or below	-0.004	-0.003	-0.001	0.087***
	(0.007)	(0.007)	(0.026)	(0.024)
Observations	49,275	49,275	25,815	25,815

Notes: Columns (1) and (3) report the coefficient on $Treat_i \times Post_{2022t}$ from the augmented difference-in-differences specification (Model (8) in the text). Columns (2) and (4) report the coefficient on $Treat_i \times Post_{2023t}$ from the same model, which captures the incremental effect of the treatment beginning in 2023Q4. The treatment group consists of IT-exposed occupations in columns (1)–(2) and IT- specialist occupations in columns (3)–(4); both are compared with occupations in the first quartile of the pre-treatment distribution of IT-skill requirements. Outcomes identified as PPML are estimated in levels using Poisson pseudo-maximum likelihood, thereby retaining zero-valued observations. Share outcomes are estimated using linear fixed-effects regressions. Regressions use occupation-by-industry-by-quarter observations and control for industry-specific changes after 2022Q4. The regressions are weighted by the total number of job postings in each occupation-industry cell before 2022Q4. All models include occupation fixed effect (based on French detailed classification), a full set of calendar-quarter fixed effects, a full set of interactions between industry dummies (21-item classification) and the $Post_{2022}$ dummy, as well as interactions between the industry indicators and the $Post_{2023}$ dummy. Standard errors clustered at the occupation level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

A Supplementary Figures

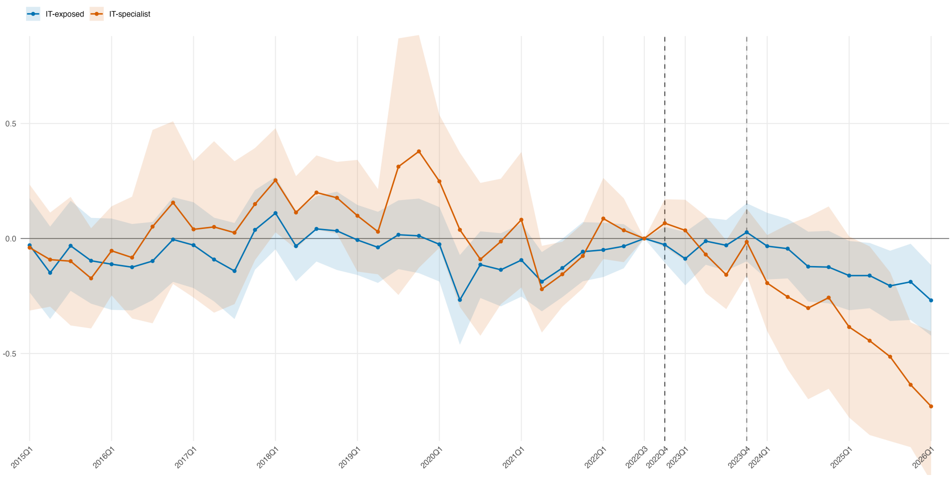
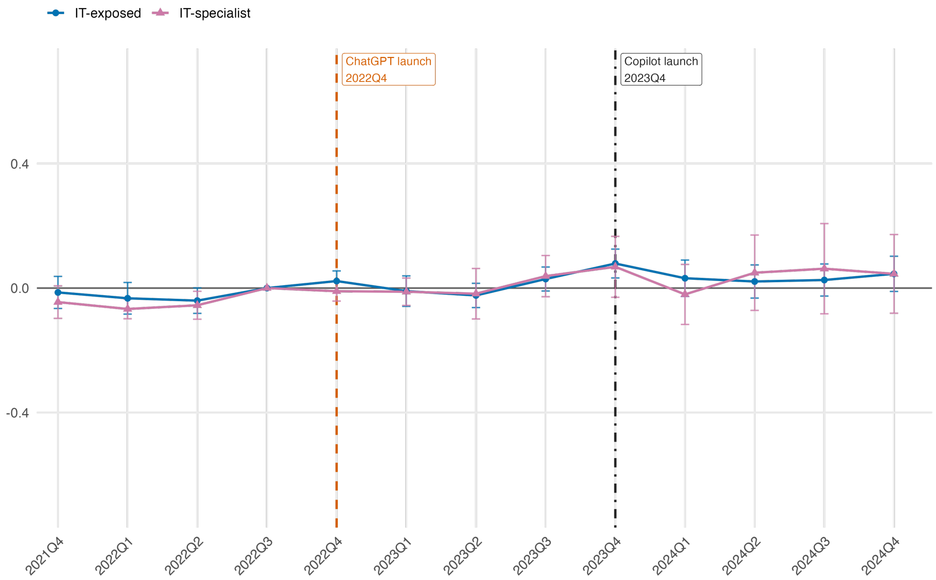
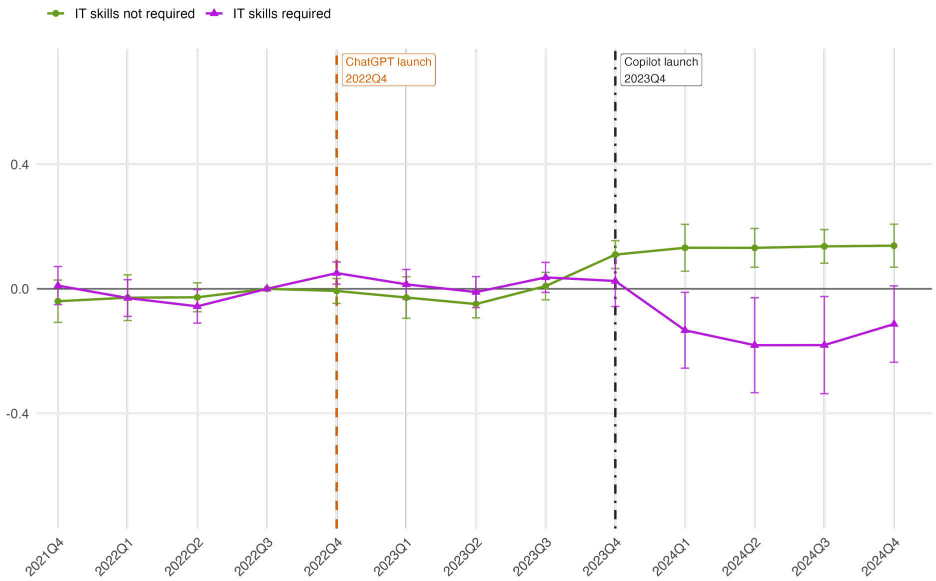


Figure A1: **Longer-term Trends in Job Postings**

Notes: The figure shows the results of our event study model applied to the (log) number of job postings when the treatment group is defined either by IT-exposed occupations or by IT-specialist occupations. Shaded areas show 95% confidence intervals. The vertical dashed lines indicate the fourth quarter of 2022 and the fourth quarter of 2023.



A IT-specialist and IT-exposed occupations



B IT-exposed occupations, by IT skill requirement

Figure A2: **Trends in the Number of Applicants**

Notes: Figure A2A shows the results of our event study model applied to (log) number of distinct applicants when the treatment group is defined either by IT-exposed occupations or by IT-specialist occupations. Figure A2B shows the results of the same event study model when the treatment group is defined either by IT-exposed jobs requiring specific IT skills or by IT-exposed jobs that do not require such specific skills. Vertical bars show 95% confidence intervals. The vertical dashed lines indicate the fourth quarter of 2022 and the fourth quarter of 2023.

B Supplementary Tables

Table B1: ROME Occupations by IT-Exposure Group

ROME code	Occupation
Panel A. IT-specialist occupations ($N = 8$)	
M1805	Software developer
I1401	Computer support and maintenance technician
M1810	IT operations technician
M1801	Information-systems administrator
M1806	Functional information-systems consultant
M1802	Computer systems and network specialist
M1804	Telecommunications engineer
M1807	Military telecommunications operator
Panel B. Occup. with high exposure to IT skill requirements. ($N = 125$)	
M1203	Accountant
D1401	Sales assistant
M1607	Secretary
N4105	Delivery driver
M1601	Reception officer
G1703	Receptionist
M1501	Human resources assistant
F1106	Construction cost engineer
M1605	Technical secretary
H2102	Food production line operator
K1801	Employment-integration adviser
M1604	Executive assistant
M1609	Medical secretary
K2104	School supervisor
M1602	Administrative assistant
H1203	Mechanical design drafter
F1104	Construction design drafter
H1404	Industrial methods technician
H2902	Boilermaker and sheet-metal worker
E1103	Public relations officer
M1608	Accounting secretary
M1603	Postal worker
D1502	Food department manager
C1502	Residential property manager
F1503	Carpenter
M1503	Human resources director
M1704	Customer relationship manager
N4203	Road-freight dispatcher
F1107	Land surveyor
K2501	Building caretaker
N1301	Logistics manager
H1202	Electrical and electronics drafter
K2102	Educational coordinator
K1601	Information and documentation specialist
M1403	Socio-economic research officer
G1303	Travel adviser

Continued on next page

Table B1 (continued)

ROME code	Occupation
M1606	Data-entry operator
E1205	Graphic designer
K1205	Social-services reception officer
J1102	General practitioner
G1404	Institutional catering manager
F1204	Construction quality, safety, and environmental coordinator
K1404	Territorial-development project officer
K1102	Court-appointed representative for protected adults
J1410	Dental prosthetist
H1208	Automation systems design specialist
F1105	Geologist
E1101	Community manager
N1202	Transit agent
F1101	Building architect
H2209	Timber structures drafter
H1209	Electrical and electronics R&D technician
M1102	Head of procurement
M1701	Sales administration manager
N1201	Freight forwarder
K2402	Scientific research engineer
K2602	Funeral adviser
M1808	Cartographer
K2302	Waste-collection manager
E1306	Prepress operator
N4204	Road-passenger transport dispatcher
C1401	Banking or insurance administrative officer
E1201	Photographer
I1303	Vending-machine maintenance technician
H1204	Industrial designer
J1504	Operating-room nurse
H2701	Energy technician
F1102	Interior architect
L1302	Film producer
A1409	Poultry farmer
D1405	Medical information adviser
E1104	Multimedia content designer
H2804	Concrete batching-plant operator
M1201	Financial analyst
E1106	Journalist
E1108	Translator
H3402	Surface-treatment operator
A1411	Pig farmer
H1207	Technical writer
M1706	Sales promotion manager
E1308	Graphic industries technician
N4201	Road-freight branch manager
E1307	Reprographics operator
E1402	Media planner
G1701	Hotel concierge

Continued on next page

ROME code	Occupation
B1601	Art metalworker
H2801	Glass production operator
N2201	Airport passenger-service agent
A1503	Pet groomer
K2401	Humanities and social-sciences researcher
L1507	Video editor
N2204	Airline operations agent
E1401	Advertising manager
K1402	Medical adviser
K1602	Heritage curator
H3403	Heat-treatment operator
E1204	Cinema projection technician
L1303	Talent agent
B1805	Fashion designer
N3101	Port officer
N4202	Road-passenger transport operations manager
K1504	Public-treasury tax collector
M1404	Field-survey manager
J1201	Clinical laboratory biologist
E1203	Photographic laboratory technician
K1401	Senior central-government administrator
L1503	Props master
E1105	Publishing editor
H1505	Perfumer
C1105	Actuary
L1510	3D animation artist
E1303	Print production manager
E1305	Prepress copy editor
N2202	Air traffic controller
K1704	Police officer
K1503	Tax auditor
K1505	Customs inspector
C1301	Trader
N3202	Inland-waterway transport operations manager
L1304	First assistant director
H2412	Pattern maker
C1204	Banking product manager
E1102	Writer
K1703	Defense operations manager
N2205	Airport station manager
Panel C. Occup. with no exposure to IT skill requirements. ($N = 133$)	
K1304	Domestic worker
K2204	Industrial cleaner
G1803	Restaurant server
G1603	Fast-food crew member
J1501	Nursing assistant
J1506	Registered general nurse
K1207	Special-education professional
I1203	Building maintenance worker

Continued on next page

ROME code	Occupation
F1603	Plumber
G1605	Kitchen porter
F1703	Mason
G1501	Hotel room attendant
F1704	Construction laborer
F1602	Building electrician
N1105	Warehouse handler
J1301	Hospital services assistant
K1201	Social worker
F1607	Aluminium joiner
K1301	Orientation and mobility instructor
G1204	Sports instructor
F1604	Drywall installer
K1104	Psychologist
F1606	Building painter
J1304	Childcare assistant
D1101	Butcher
K1403	Director of a healthcare, social-service, or correctional facility
F1302	Construction-equipment operator
K1202	Early-childhood educator
G1604	Pizza maker
J1307	Pharmacy technician
J1305	Ambulance crew member
N4102	Passenger-transport driver
F1608	Tiler
F1702	Road construction worker
D1501	Sales promoter
F1701	Formwork carpenter
F1611	External thermal-insulation installer
F1605	Electrical-network installer
K1903	Legal adviser
K2303	Refuse collector
J1202	Pharmacist
H2602	Control-panel wirer
J1502	Healthcare unit manager
F1502	Structural-steel erector
J1505	Occupational health nurse
K1204	Social mediator
J1507	Pediatric nurse
J1412	Psychomotor therapist
F1613	Waterproofing installer
J1403	Occupational therapist
F1705	Pipe layer
A1201	Logger
K2202	Window cleaner
D1105	Fishmonger
J1405	Optician
I1301	Elevator technician
A1402	Crop-farm worker

Continued on next page

ROME code	Occupation
J1404	Physiotherapist
F1301	Crane operator
H2911	Metalworker
J1406	Speech and language therapist
M1301	Private-sector business executive
H2605	Electronics assembler and wirer
F1609	Floor layer
K2601	Funeral bearer
D1103	Delicatessen butcher and caterer
H2401	Leather and related-materials production operator
G1205	Amusement-ride operator
N1104	Overhead-crane operator
A1202	Natural-area maintenance worker
A1404	Aquaculture worker
J1306	Medical radiologic technologist
I1503	Technological-risk technician
G1201	Tour guide
A1403	Livestock-farm worker
F1401	Driller
L1203	Actor
G1702	Hotel porter
I1601	Boat-preparation technician
A1408	Wild-animal breeder
N4301	Train driver
D1201	Antiques dealer
G1206	Casino dealer
D1207	Clothing alterations tailor
B1806	Upholsterer
C1110	Insurance underwriter
J1104	Midwife
J1401	Hearing-aid specialist
N2203	Airport ramp agent
H2803	Ceramics-production operator
L1401	Professional athlete
K1901	Notary
H2404	Yarn-production machine operator
J1407	Orthoptist
B1302	Decorative-arts craftsperson
H2601	Electrical coil winder
L1201	Dancer
N3103	Inland-waterway deckhand
H2413	Textile-preparation operator
H2910	Foundry molder and coremaker
A1415	Fisher
L1101	DJ
H2406	Textile-treatment machine operator
N3102	Seafarer
H2410	Textile-finishing operator
L1103	Radio or television host

Continued on next page

Table B1 (continued)

ROME code	Occupation
B1303	Art engraver
N3203	Dock worker
B1804	Embroiderer
C1108	Insurance department manager
H3102	Pulp-production plant operator
B1602	Glassblower
K2603	Embalmer
H2407	Leather-processing and finishing-machine operator
K1502	Labor inspector
L1204	Circus artist
B1501	Keyboard-instrument maker
L1501	Theatrical makeup artist
L1502	Costume designer and maker
H2414	Leather-goods preparation and finishing operator
L1102	Fashion model
N2101	Cabin crew member
A1502	Farrier
J1409	Podiatrist
B1402	Bookbinder
A1406	Fishing-vessel captain
J1408	Osteopath
B1801	Milliner
A1417	Salt producer
L1301	Stage director
B1401	Basket weaver
B1701	Taxidermist
K1904	Judge

Notes: This table reports the items of the French (ROME) occupational classification that are used to construct the three occupational groups. Occupations are ordered within each panel by the pre-treatment number of job postings.

Table B2: Most Frequently Required Basic IT Skills, by Skill Category

Rank	Basic skill	Number of job postings
Panel A: Programming and IT-development skills		
1	Produce and update software documentation	132,040
2	Define programming specifications and parameters	95,736
3	Design and develop a web application	85,868
4	Design and update detailed information system, component, and subsystem diagrams	71,885
5	Develop component specifications and technical nomenclatures	69,946
6	Produce detailed technical layouts and software specifications	64,507
7	Configure user workstations according to user requirements	52,423
8	Gather requirements and produce preliminary information system, component, and subsystem designs	52,235
9	Create and update information system diagrams, technical specifications, and implementation plans in accordance with standards and evolving requirements	43,920
10	Administer an information system	41,054
Panel B: Software-use skills		
1	Accounting software	325,543
2	Use digital tools	318,754
3	Use route-management software	146,572
4	Web application use	56,642
5	Remotely diagnose computer hardware or software malfunctions	49,778
6	Use computer-aided design and drafting (CAD) software	37,460
7	Customer relationship management (CRM) software	32,454
8	Inventory management	29,807
9	Payroll software	24,215
10	Modeling and simulation	17,193
Panel C: Data-management and analysis skills		
1	Assign a code to a mandate/nomenclature	244,917
2	Analyze data from a study or project	87,027
3	Update a patient's medical record	77,712
4	Analyze a production document	52,564
5	Analyze a distribution plan	36,075
6	Update displays and information made available to the public	32,058
7	Lay out an entire data structure according to technical specifications	24,907
8	Adapt statistical data-processing tools	11,445
9	Select electronic and electrical components using databases and supplier catalogs	9,333
10	Classify data collected in a survey	9,215

Notes: The table reports the ten basic skills most frequently required in job postings within each of the three main IT-skill categories used in the analysis. The last column gives the number of job postings requiring the corresponding skill. A job posting may require several skills, so the counts are not mutually exclusive. Skill labels are English translations of the original labels in the French public employment service classification.

Table B3: Correspondence between the occupations without exposed tasks in Eloundou et al. (2024) and French occupational classification (ROME)

Occupation in Eloundou et al.	ROME code	ROME occupation name
Agricultural Equipment Operators	A1101	Agricultural machinery operator
	A1102	Forestry machinery operator
Athletes and Sports Competitors	L1401	Professional athlete
Automotive Glass Installers and Repairers	I1606	Auto-body repairer and painter
	I1629	Vehicle-glass repair and installation technician
Bus and Truck Mechanics and Diesel Engine Specialists	I1604	Automobile mechanic
Cement Masons and Concrete Finishers	F1703	Mason
Cooks, Short Order	G1601	Head chef
	G1602	Kitchen assistant
	G1603	Fast-food crew member
	G1604	Pizza maker
	G1606	Institutional-catering cook
	G1609	Cook
Cutters and Trimmers, Hand	H2902	Metalwork layout marker
	H2903	Turner-miller / machinist
	H2905	Metal cutter / shearer
	H3201	Plastics-processing operator
Derrick Operators, Oil and Gas	F1401	Driller
Dining Room and Cafeteria Attendants and Bartender Helpers	G1607	Institutional-catering employee
	G1803	Restaurant server
Dishwashers	G1605	Dishwasher / kitchen porter
Dredge Operators	F1302	Construction machinery operator
Electrical Power-Line Installers and Repairers	F1502	Metal-structure assembler
	F1605	Electrical-network installer
Excavating and Loading Machine and Dragline Operators, Surface Mining	F1302	Construction machinery operator
Floor Layers, Except Carpet, Wood, and Hard Tiles	F1608	Tile and flooring installer
Foundry Mold and Coremakers	H2908	Patternmaker and coremaker
Helpers–Brickmasons, Blockmasons, Stonemasons, and Tile and Marble Setters	F1608	Tile setter
	F1703	Mason
	F1704	Construction laborer
Helpers–Carpenters	F1501	Timber-structure assembler
	F1503	Carpenter
	F1704	Construction laborer
Helpers–Painters, Paperhangers, Plasterers, and Stucco Masons	F1604	Drywall installer / plasterboard fitter
	F1606	Building painter
	F1704	Construction laborer
Helpers–Pipelayers, Plumbers, Pipefitters, and Steamfitters	F1603	Plumber
	F1704	Construction laborer
Helpers–Roofers	F1619	Roofer
	F1704	Construction laborer
Meat, Poultry, and Fish Cutters and Trimmers	G1608	Shellfish preparer
	H2101	Slaughterhouse worker
Motorcycle Mechanics	I1607	Motorcycle mechanic
Paving, Surfacing, and Tamping Equipment Operators	F1302	Construction machinery operator
	F1303	Surface-grooming machine operator

Continued on next page

Table B3 – continued from previous page

Occupation in Eloundou et al.	ROME code	ROME occupation name
Pile Driver Operators	F1302	Construction machinery operator
Pourers and Casters, Metal	H2908	Patternmaker and foundry-mold maker
Rail-Track Laying and Maintenance Equipment Operators	F1302	Construction machinery operator
Refractory Materials Repairers, Except Brickmasons	F1703	Mason
Roof Bolters, Mining	F1402	Rock-extraction worker
Roustabouts, Oil and Gas	F1401	Driller and drilling-site worker
Slaughterers and Meat Packers	H2101	Slaughterhouse worker
Stonemasons	F1402	Rock-extraction worker
	F1703	Stone mason
Tapers	F1604	Drywall finisher / plasterboard jointer
Tire Repairers and Changers	I1604	Automobile mechanic and tire-service technician
Wellhead Pumpers	F1401	Driller and well-site worker

Notes: Eloundou et al. (2024, Supplementary Materials, Section 8.1 and Table 8) list 34 occupations for which none of their measures label any task as exposed to GPTs. The table reports the corresponding items in the French (ROME) classification which we retained in our alternative control group. Several occupations in Eloundou et al. (2024) correspond to more than one ROME occupation. Conversely, a ROME occupation may appear more than once when its appellations cover several occupations in the original list. ROME occupation names are English translations of the French denominations used in the correspondence.

Table B4: Robustness of Results when Controlling for Baseline Writing Skills

	IT-exposed (1)	IT-specialist (2)	Low-exposure group (3)
Nb offers (log)	-0.118***	-0.200***	-0.038
	(0.026)	(0.044)	(0.028)
Share offers requiring IT skills (Total):	-0.051***	-0.068***	-0.008**
	(0.008)	(0.012)	(0.004)
AI skills	0.000	0.005**	0.000*
	(0.000)	(0.003)	(0.000)
Programming skills	-0.006	-0.060***	-0.003
	(0.006)	(0.012)	(0.003)
Software skills	-0.045***	-0.088***	-0.004***
	(0.006)	(0.024)	(0.002)
Office software skills	-0.035***	-0.001	-0.002
	(0.008)	(0.003)	(0.001)
Data analysis skills	-0.008	0.015***	0.000
	(0.005)	(0.004)	(0.001)
Share offers requiring public relations skills	-0.016	0.092***	-0.029
	(0.043)	(0.033)	(0.040)
Share offers requiring writing skills	0.020**	-0.103*	0.001
	(0.010)	(0.061)	(0.005)
Share offers with teamwork skills	0.003	0.000	0.001
	(0.003)	(0.002)	(0.001)
Average posted wage (log)	-0.002	-0.008**	0.000
	(0.004)	(0.004)	(0.003)
Nb distinct applicants (log)	0.018	0.014	0.003
	(0.022)	(0.031)	(0.020)
Nb applicants per offer (log)	0.150***	0.283***	0.046
	(0.026)	(0.059)	(0.028)
Number of hires (log)	-0.130***	-0.369***	-0.012
	(0.027)	(0.102)	(0.029)
Female share among hires	0.003	0.010	0.002
	(0.005)	(0.016)	(0.004)
Share hired people, aged 35 or below	0.009	0.026	0.000
	(0.006)	(0.020)	(0.005)
Observations	3,827	2,073	5,941

Notes: Columns (1)–(3) report the coefficient on $Treat_i \times Post_{2022t}$ from the basic difference-in-differences specification (Model (7) in the text). The treatment and control groups are defined as in Table 2. In addition to the controls used in Table 2, each model includes the interaction between $Post_{2022t}$ and an indicator for occupations whose mean share of job postings requiring writing skills before 2022Q4 was above the median. The regressions are weighted by the total number of job postings in each occupation before 2022Q4. Standard errors clustered at the occupation level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B5: Augmented Model - Robustness to the Use of an Alternative Control Group

	IT-exposed		IT-specialist	
	$T \times \text{Post}_{2022}$ effect (1)	$T \times \text{Post}_{2023}$ effect (2)	$T \times \text{Post}_{2022}$ effect (3)	$T \times \text{Post}_{2023}$ effect (4)
Nb offers (log)	0.014	-0.039	0.045	-0.173**
	(0.019)	(0.065)	(0.033)	(0.067)
Share offers requiring IT skills (Total):	-0.003	-0.066***	-0.016**	-0.076***
	(0.005)	(0.012)	(0.006)	(0.016)
AI skills	0.000	0.000	0.002**	0.005*
	(0.000)	(0.000)	(0.001)	(0.003)
Programming skills	-0.002	-0.010*	-0.012*	-0.083***
	(0.001)	(0.006)	(0.007)	(0.016)
Software skills	-0.004	-0.062***	-0.016	-0.101**
	(0.005)	(0.013)	(0.010)	(0.044)
Office software skills	0.003	-0.064***	0.002	0.000
	(0.005)	(0.015)	(0.002)	(0.001)
Data analysis skills	-0.001	-0.003	0.004***	0.022***
	(0.003)	(0.005)	(0.001)	(0.006)
Share offers requiring public relations skills	-0.029	-0.064	0.025	0.051
	(0.029)	(0.060)	(0.018)	(0.045)
Share offers requiring writing skills	-0.003	-0.004	-0.040*	-0.155*
	(0.002)	(0.005)	(0.020)	(0.081)
Share offers with teamwork skills	0.002	0.001	0.002**	-0.001
	(0.001)	(0.002)	(0.001)	(0.002)
Average posted wage (log)	-0.004**	0.010**	0.002	-0.010*
	(0.002)	(0.004)	(0.004)	(0.006)
Nb distinct applicants (log)	0.028	0.069	0.043*	0.072
	(0.018)	(0.055)	(0.021)	(0.069)
Nb applicants per offer (log)	0.011	0.096***	0.016	0.287***
	(0.022)	(0.023)	(0.032)	(0.048)
Number of hires (log)	-0.061*	-0.018	-0.166*	-0.229**
	(0.031)	(0.090)	(0.084)	(0.112)
Female share among hires	0.006	-0.015	0.016	-0.011
	(0.005)	(0.010)	(0.020)	(0.022)
Share hired people, aged 35 or below	0.000	-0.010	0.003	0.016
	(0.006)	(0.009)	(0.015)	(0.014)
Observations	2,354	2,354	630	630

Notes: Columns (1) and (3) report the coefficient on $Treat_i \times Post2022_t$ from the augmented difference-in-differences specification (Model (8) in the text). Columns (2) and (4) report the coefficient on $Treat_i \times Post2023_t$ from the same model, which captures the incremental effect of the treatment beginning in 2023Q4. The treatment group consists of IT-exposed occupations in columns (1)–(2) and IT- specialist occupations in columns (3)–(4); both are compared with the occupations identified by Eloundou et al. (2024) as unaffected by generative AI. The regressions are weighted by the total number of job postings in each occupation before 2022Q4. All models include occupation fixed effect (based on French detailed classification) and a full set of calendar-quarter fixed effects. Standard errors clustered at the occupation level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.