From Aspiration to Disillusion? The Political Consequences of AI-driven Employment Threats

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Abstract

The expansion of higher education in knowledge economies has fostered the belief that investment in education brings economic rewards and enhances security. However, the fast-growing advancements in Artificial Intelligence are transforming highly skilled sectors, fueling perceptions of risk and uncertainty among highly educated workers. What are the political implications of this new trend? This paper examines whether AI-driven threats to graduates' employability erode their faith in the meritocratic system, leading to shifts in economic preferences and voting intentions as a consequence. The paper builds on a dataset linking individual-level surveys and administrative data on online job vacancies in the United Kingdom with novel indices of occupational exposure to AI. Leveraging the introduction of ChatGPT in December 2022, the paper demonstrates how AI causally affects the employability of graduates across different fields of higher education. Negative shifts alter individuals' fairness beliefs, shift ideological self-placement to the left and drive anti-incumbent voting intentions. The study importantly underscores how AI is likely to influence the political views and behaviours of the young and highly educated, suggesting important and long-lasting political repercussions for knowledge economies.

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1 Introduction

When OpenAI released ChatGPT in late 2022, a tool capable of processing text, images, and audio with unprecedented computational power, commentators across the globe quickly raised concerns about its disruptive effects on the economy. Across OECD countries, nearly 28% of jobs are at high risk of automation (OECD 2023). Similarly, the World Economic Forum has warned that AI could displace 85 million jobs globally by 2025 (Forum 2020). While policymakers, researchers and firms are in a bid to understand how to exploit the potential of this new technology, the rapid advancements of Artificial Intelligence (AI) technologies are likely transforming the future of work, and with it possibly bringing about serious political change.

No longer limited to manual or routine tasks, emerging AI technologies are now capable of performing complex cognitive functions, challenging long-standing assumptions about which jobs are safe from automation. Previously, technological advancements disproportionately rewarded skilled and highly educated over less educated or low-skilled workers, widening inequalities and fueling divergent political reactions between these two groups (Gallego et al. 2022). In contemporary knowledge economies, highly-skilled workers benefited from rising productivity, anchoring support for the economic and political status quo (Iversen and Soskice 2019; Oesch 2013). Crucially, however, AI has the potential to break from past trends. Unlike earlier technologies, which relied on rule-based programming, modern machine learning and large-language models operate in unstructured environments and can learn without explicit instructions, posing an increasing threat to high-skilled labour involved in cognitive and non-routine tasks (Acemoglu et al. 2022). This raises the question that even the traditionally secure strata of the workforce may now face insecurity, contrary to their expectations. If so, AI is likely to draw new political and economic fault lines, dividing the very coalition that once benefited most from technological change (Häusermann et al. 2015).

Initial evidence suggests that the occupations most susceptible to automation are those involving cognitive tasks, typically requiring higher levels of education (Felten et al. 2019). While it remains uncertain whether AI will ultimately replace or complement human labour (Acemoglu and Restrepo 2020), emerging evidence suggests that AI adoption is already reducing labour demand in occupations whose tasks can be performed by AI as well as humans (Green 2024; Cardenas-Rubio and Anelli-Lopez 2023).

Entering this debate, this paper asks the following question: How do AI-driven labour market disruptions shape the political attitudes and electoral choices of the highly educated? This question is of exceptional relevance today because, within this group, perceptions of economic security are closely tied to education. In advanced political economies, according to the shared norm of meritocracy (Sandel 2021; Alesina and Angeletos 2005; Cavaillé 2023), people form expectations about their economic outcomes based on the effort they put into education and in light of their academic choices. Consequently, the deterioration of their employment prospects may create perceptions of unfairness and increase demands for the regulation of the market economy. These attitudinal shifts also likely influence electoral preferences. The disruption of education-embedded expectations may lead to disillusionment with mainstream politics and turn towards anti-status-quo parties.

To examine these important mechanisms, the paper proposes a new measure of AI-driven threats to employability linking fields of higher education to employment prospects. Assuming that individuals form expectations about their employability by observing the labour market demand for occupations most closely aligned with their chosen field of study, I argue that downward changes in employability affect attitudes and behaviours by amplifying concerns about labour market vulnerability, while eroding faith in the meritocratic promise of rewards proportional to effort (Cavaillé 2023). When expectations decline, individuals feel less in control of their economic outcomes, less capable of achieving what they consider a fair result. By contrast, those whose employment prospects improve attribute their success to personal effort, reinforcing their perceived security and optimism about future outcomes.

The study draws on a dataset that merges the British Election Study Internet Panel with monthly job vacancy data from Textkernel-ONS, covering UK-SOC occupations at the 4-digit level from January 2017 to July 2024. The dataset is enriched with new indices of occupational exposure to AI for a wide range of UK-SOC occupations (Felten et al. 2021; Cazzaniga et al. 2023; Gmyrek et al. 2023). To estimate the causal effect of changes in employability, the analysis leverages the quasi-exogenous labour market shock triggered by the release of ChatGPT in December 2022. This event serves as a source of exogenous variation in employability for individuals who had already enrolled in higher education by that date.

The measure of AI-driven threats to employability assigns each individual a vector of occupational probabilities, based on their field of study and occupation-specific vacancy trends between 2017 and 2024. Graduates in fields more exposed to AI revise their beliefs about market fairness, redistribution and left-right ideology in response to improvements or declines in labour demand for their most probable jobs. Additionally, this effect translates into voting intentions.

The remainder of the article proceeds as follows. First, I outline the theoretical framework that explains why AI poses a serious threat to the occupational expectations of highly educated individuals in the knowledge economy, and present the core hypotheses. Second, I detail the empirical strategy, including the data sources and measurement approach. Finally, I present the results of the analysis and conclude with a discussion of the broader theoretical implications of the empirical evidence.

2 Technology and Politics, So Far

To date, a rich body of literature has examined the political effects of technological transformations. Influential studies in this field have examined voting behaviour (Anelli et al. 2021; Colantone and Stanig 2018; Anelli et al. 2019), economic policy attitudes (Margalit 2019), and attitudes towards immigration and cultural integration (Pardos-Prado and Xena 2019; Laaker 2024). The literature broadly argues that technological shocks, by increasing unemployment or decreasing wages for obsolescent jobs, heighten economic risk and push people to demand more insurance against those risks (Gallego and Kurer 2022). Moreover, economic transformations produce winners and losers (Margalit 2019), and the nature of these technologies matters for the resulting political divides across these two groups.

Technologies such as computers and robots, by automating large sectors of the industrial economy, have driven a skill-biased technological change (Gallego and Kurer 2022). With such technologies, occupations that require routine manual skills are more at risk of automation. Routine skills are those that are repetitive and performed in a rule-based environment (Susskind 2020). Thus, occupations that demand such skills are often associated with lower levels of educational attainment. The result of this process is job polarisation across the skills spectrum (Goos and Manning 2003; Autor et al. 2003), a well-known phenomenon that exposes low-educated workers to the risk of unemployment following a decline in demand for routine skills (Rehm et al. 2012). Research in political science has also linked such a historical decline in industrial labour to the rise of the far right in recent times (Hopkin 2020). Indeed, there is evidence that workers with lower educational attainments tend to translate increasing economic risks into cultural grievances, fueling support for parties capitalising on group-based cultural appeals (Anelli et al. 2021, 2019; Kurer 2020).

2.1 AI, Skills and Employability

However, and most importantly, advancements in the field of AI technologies, especially Generative AI, depart from previous technological waves. Unlike previous technologies, LLMs appear to possess a broad set of skills, able to perform a wide range of non-manual tasks. This means that a broader set of occupations is within the reach of AI (Susskind 2020). Generative AI is better suited to perform non-routine tasks, namely tasks that are non-repetitive and for which learning and experience are essential in human labour (Bone et al. 2025). Therefore, AI targets occupations that usually require higher education degrees (Felten et al. 2023). Yet, its impact is unobvious. Far from exposing highly-skilled occupations to the risk of automation evenly, AI increases labour demand and wages for occupations where AI complements human skills or where AI-related skills are required. Recent work by Bone et al. (2025) has shown that AI-exposed roles that require skills like resilience, fast problem-solving, or analytical thinking are booming and receiving a wage premium. Conversely, tasks like basic data management skills or translation are more vulnerable to AI substitution. Thus, this new technology may produce both opportunities and risks for highly educated individuals, as it does not polarise based on the level of skills, as previous technologies did, but based on the competencies and specificities of the skill set developed through education. While previous technologies fueled polarisation between educational groups (Thewissen and Rueda 2019), AI is likely to divide workers within the same educational groups due to its uneven impact across the skills spectrum. This raises crucial questions about its political implications, and yet only a few studies have started to examine them (Green et al. 2023; Magistro et al. 2024).

As discussed, such a bias towards the highly educated is highly relevant not only because this is the group most likely exposed to AI (Green et al. 2023), but also because higher education likely mediates the consequences of technological shocks. People who decide to pursue university-level degrees today attach great importance to education, as higher education fuels expectations of upward mobility (Gingrich et al. 2024; Oesch 2015). The choice of pursuing higher education indeed relies on the meritocratic belief that rewards in the labour market are proportional to effort put in education and training, consistent with a norm of fairness according to which individuals are in control of their employment prospects (Sandel 2021; Alesina et al. 2018). In a merit-driven environment such as knowledge economies, the field of education becomes key as it builds skills by training for specific jobs, sectors and occupational roles (Hooghe et al. 2024b). While employment expectations have been tied to social class backgrounds in the past (Goyette 2008), today individuals feel entitled to specific outcomes based on degree type and grades (Lindskog 2024; Cox 2024). Thus, meritocratic beliefs anchor occupational expectations on educational choices. Several possible outcomes may emerge when AI hits the labour market, disrupting such expectations. Individuals who, based on the selected field of study, feel entitled to achieve specific occupational outcomes (Lindskog 2024). They select the field of study based on how many jobs are linked to that field when they start graduate education, and their expectation depends critically on the skill set developed in a specific subject area. If people select a field of higher education based on these parameters, when the demand for the field declines unexpectedly, they may perceive themselves as less employable.

2.2 Expectations

This leads to my hypotheses. I first expect that when the chosen degree does not grant the expected employability, the perceived labour market potential is reduced. While this situation does not strictly reflect exposure to the risk of unemployment (Rehm et al. 2012; Rehm 2009), the affected individual experiences a perception of unfairness deriving from the lower employment potential of the field of education chosen. In other words, when occupational expectations decline, individuals perceive a sense of betrayal by the market, as their degree does not entitle them to the desired economic outcomes. Conversely, if employability increases, perceptions of fairness increase because the individual perceives success as linked to educational choices.

Furthermore, in line with extant theories of technological change (Thewissen and Rueda 2019; Gallego et al. 2022), this paper argues that a decline in employability influences attitudes towards economic redistribution. An individual who suffers a downward shock will be more in support of a more active role of government in the economy to equalise rewards and reduce perceived risk (Rehm 2009). While different academic disciplines are associated with different positions along the left-right ideological spectrum (Hooghe et al. 2024a), the shock induced by AI-related changes in job prospects will push graduates towards the left or the right, depending on whether AI enhances or diminishes employment opportunities within their field. Those in AI-favoured fields are likely to perceive greater fairness in the market and attribute their economic success to personal merit, which in turn fosters more anti-redistributive attitudes. Conversely, individuals in fields negatively affected by AI are expected to view the market as less fair and their economic outcomes as driven by chance, leading to pro-redistributive attitudes.

Such a shift is likely to translate into electoral preferences when perceptions of market unfairness and rising insecurity are mobilised by opposition parties campaigning against the incumbent. Economic anxiety has been shown to erode support for the political status quo, as in the aftermath of the Great Recession (Hobolt and Tilley 2018), and opposition parties tend to benefit from voters' perceptions of negative economic performance under incumbents (Margalit 2019). Yet, as discussed, the political consequences of AI-induced shifts in employability are shaped by the merit-based occupational expectations of highly educated individuals. This suggests that reactions may not be limited to positional shifts along the left–right spectrum, but may also reflect expressive discontent. In other words, AI-driven insecurity is likely to foster an expressive realignment, with highly educated voters turning to challenger parties as a channel for their frustration, rather than leaning towards the parties offering the most advantageous policy platforms. Accordingly, I hypothesise that a downward shock in employability reduces fairness beliefs, increases support for redistribution, shifts ideological self-placement to the left, and raises the likelihood of voting for a challenger party. Overall, the paper tests four main hypotheses:

H1: Individuals who experience negative (positive) AI-driven changes in their occupational expectations develop lower (higher) beliefs in the fairness of the market system.

H2: Individuals who experience negative (positive) AI-driven changes in their occupational expectations develop higher (lower) support for redistribution.

H3: Individuals who experience negative (positive) AI-driven changes in their occupational expectations develop more left-wing (right-wing) attitudes.

H4: Individuals who experience negative (positive) AI-driven changes in their occupational expectations develop higher (lower) support for anti-status quo parties.

3 Data and Research Design

3.1 Description of the Dataset

This study focuses on the United Kingdom, building upon a novel dataset that integrates individual-level political data with administrative records on job vacancies and occupation-specific AI exposure indices. The construction of the dataset proceeded in three main stages. First, I have built a monthly panel of online job vacancies by occupation using the Textkernel-ONS dataset, which provides detailed information on the number of job postings for each 4-digit UK Standard Occupational Classification (UK-SOC) code from January 2017 to July 2024. Second, I enriched this dataset by incorporating recently published indices of occupational exposure to AI, which I mapped to UK-SOC codes via official occupational crosswalks (Felten et al. 2021; Cazzaniga et al. 2023; Gmyrek et al. 2023). The three indices of AI occupational exposure reflect the extent to which the task structure of an occupation overlaps with the tasks that can be performed by AI, Large Language Models, image recognition and GPT algorithms. While Felten et al. (2019) Artificial Intelligence Occupational Exposure (AIOE) score is agnostic to whether AI exposure substantively implies substitutive or augmentation effects, the complementarity-adjusted AIOE by Cazzaniga et al. (2023) adjusts for complementarity, giving higher scores to occupations at higher risk of replacement. Finally, Gmyrek et al. (2023) accounts for occupational exposure to threats posed by LLMs and GPT algorithms. Third, I merged the vacancy panel with individual-level data from the British Election Study Internet Panel (BES), which covers 25 waves from November 2016 to July 2024. To ensure temporal alignment between the datasets, I adjusted the monthly vacancy figures to match the structure of the BES waves: for each wave t, the vacancy measure represents the average number of postings for a given occupation between wave $t-1$ and t. The resulting dataset is a panel where each observation corresponds to an individual nested within one of the BES waves. For my analysis, the dataset contains information on 18 different fields of education, UK-SOC occupations, the national volume of vacancies for each occupation, and three occupation-specific AI exposure scores. In total, vacancy and AI exposure data are available for 370 distinct 4-digit UK-SOC occupations.

3.2 Empirical Strategy

Studying the political effects of AI poses serious concerns of endogeneity. The hypothesised mechanism is that AI changes occupational expectations, either boosting or blowing field-related employability. However, reverse causality stands out as a possible concern. The ideological background of individuals may strongly influence the selection of the field of study and occupational expectations as a result. Individuals with strong beliefs in meritocracy may be oriented towards fields that ensure better employment outcomes. Thus, it is essential to identify a source of variation in employability that is exogenous to individuals' educational choices. Sudden and unexpected economic shocks are a good case study in this case (Gallego and Kurer 2022; Autor et al. 2016). Yet, economic shocks are not always sharp. They mostly occur as lasting transformations, displaying empirically more as fluctuations than discontinuities.

Acknowledging the non-sharp nature of the AI shock, this study privileges a longitudinal approach exploiting Chat-GPT as an exogenous shock occurring after individuals have chosen their education and field of study. The empirical strategy pursued in this paper resonates with previous work on automation exploiting exogenous variation in individual-level exposure to the adoption of robots (Anelli et al. 2021). In their study, these authors compute an individual-specific vector of employment probabilities in each occupation based on estimates from historical labour market data. Weighting them by an AI automation risk score (Felten et al. 2019), they produce a scalar measure of the occupations most affected by automation. They multiply this matrix by the pace of robot adoption at the national level in a post-automation period to derive a time-varying measure of exposure to automation. The logic is that individuals with the highest probability of employment in automatable occupations in the pre-automation period are also those most at risk afterwards.

In this paper, I follow a similar logic to examine how AI affects political attitudes and voting intentions. Focusing on individuals who were enrolled in higher education before ChatGPT was released, I measure how likely their field is to employ them in occupations that are threatened by AI. I adopt this measure in an FE panel context, and then I employ a Difference-in-Difference estimation strategy using ChatGPT as a shock. Since the treatment is not sharp, and every field is differently exposed, my Difference-in-Difference strategy applies a continuous treatment, relaxing assumptions about parallel trends before the shock.

3.3 Measurement

First, I construct a measure of the field of education's AI exposure. I do this in three main steps. First, I assign to each individual a time-invariant vector of predicted probability of employment in each possible occupation, based on their chosen field of study and other fixed characteristics, as shown in Equation 1. This vector reflects the individual's baseline employment prospects, mainly derived from the field of study. In addition, I multiply these occupational probabilities by the three different AI exposure scores:

$$\hat{\text{Expectation}}_i^{(k)} = \sum_{j=1}^{373} \Pr(\text{SOC}_j \mid \text{field}_i, \text{gender}_i, \cdot \theta_j^{(k)} \tag{1}$$

In this equation, $\Pr(\text{SOC}_j \mid \text{field}_i, \text{gender}_i$ denotes the predicted probability that individual i will work in occupation j, conditional on their fixed observable attributes. The term $\theta_j^{(k)}$ represents the AI exposure score for occupation j, where k indexes one of the three exposure indices drawn from recent studies (Felten et al. 2021; Cazzaniga et al. 2023; Gmyrek et al. 2023).

Expanding on the logic of Anelli et al. (2021), this measure represents a translation matrix of time-invariant AI occupational exposure into a field of education AI exposure. Empirically, the measure assigns higher values to individuals who are in fields that make them more amenable to occupations exposed to AI technologies. In the Appendix, I show

which occupations are the most exposed according to the AIOE score.
Yet, the problem with this measure is that it remains insufficient to grasp concretely the labour market implications of AI exposure. While the complementarity-adjusted measure of AIOE by Cazzaniga et al. (2023) helps measure substitution more directly, it is still uncertain whether AI will lead to an increase or decrease in demand for human work in occupations defined as exposed (Mäkelä and Stephany 2025). Moreover, while this approach builds on the assumption that students form employment expectations based on the observed distribution of graduates in the labour market, students may also experience growing concerns about employability due to increasing competition within their field (Donald et al. 2018). For this reason, in the second step, I integrate time-varying information on online job postings by occupation as an indicator of job demand in different occupations. I multiply each AI-weighted occupational probability by the change in job vacancies over time for the corresponding occupation:

$$\text{Expec}\hat{\text{t}}\text{ation}_{it}^{(k)} = \text{Expec}\hat{\text{t}}\text{ation}_{i}^{(k)} \cdot \Delta\text{Vac}_{jt} \tag{2}$$

Here, $Delta\text{Vac}_{jt}$ represents the change in job vacancies for occupation j at time t relative to the previous wave. The result is a time-varying, individual-level measure of employability that incorporates both occupational exposure to AI and real-time shifts in labour market demand. This step is crucial in accurately capturing dynamic shifts in labour market demand and potential employment threats.
Finally, I collapse the resulting vector by each unique field of study at each time point, and assign it to individuals based on their specific field.

$$\text{Expectation Shock}_{izt}^{(k)} = \frac{1}{N_z} \sum_{i \in z} \left(\text{Expec}\hat{\text{t}}\text{ation}_{it}^{(k)} \right) \tag{3}$$

In this expression, Expectation Shock$_{izt}^{(k)}$ denotes the average employability for individual i in the field of study z at time t, under AI exposure index k. Thus, for individual i, the final measure captures dynamic shifts in employability attributable to both technological disruption and evolving vacancy patterns in AI-exposed occupations.

3.4 Models and Assumptions of Exogeneity

I exploit the launch of ChatGPT in the UK in December 2022 as an exogenous shock to vacancies in AI-exposed occupations. Focusing on individuals who enrolled in higher education before this date, I argue that ChatGPT provoked unexpected shifts in their employability.

First, I use this measure in a fixed-effects panel model. The key identifying assumption is that students could not have anticipated the shock when choosing their field of study. Unlike previous technological innovations, whose long-term labour market consequences were relatively predictable, the impact of ChatGPT is highly uncertain, making it difficult for individuals to anticipate which fields would be most affected (Bonfiglioli et al. 2023). Despite its recent introduction, early evidence suggests negative effects on occupations where tasks are easily automated (Cardenas-Rubio and Anelli-Lopez 2023). Whereas earlier technologies typically reshaped labour market structures gradually, ChatGPT can be viewed as a discrete event with an immediate impact on labour demand. In this sense, although AI technologies predated it, I argue that ChatGPT constitutes a distinct shock to occupations at risk of substitution or augmentation by AI.

If individuals did not anticipate this shock, their expected employability shifts as labour demand for their chosen field changes. Before ChatGPT, students self-selected into occupations through their educational choices, only to become more vulnerable once the technology was introduced. Field-level exposure to AI should remain stable if the task content of occupations is unchanged, meaning the same skills are required. However, if ChatGPT alters task composition, it may shift demand for specific skills, thereby generating exogenous variation in exposure after 2022. My measure captures whether an individual's field of study is insulated from, or exposed to, vacancy shocks. Fields threatened by declining vacancies face exogenous reductions in perceived employability, independent of students' initial expectations. Importantly, AI exposure does not imply uniform effects: some occupations may be displaced by automation, while others become more valuable through complementarity with AI (Autor 2022). By using changes in vacancies as an indicator of realised labour market trends, my approach disentangles these heterogeneous effects across AI-exposed occupations.

To prove this assumption, I have conducted an original survey on a representative sample of British adults. This allows me to assess the extent to which people in higher education were aware of the effects of ChatGPT before choosing their field of study. I tested this question using a purposely tailored survey item fielded in April 2025, asking: "Which of the following fields of study, if any, do you think will see the highest increase in job opportunities through the use of AI in the field?

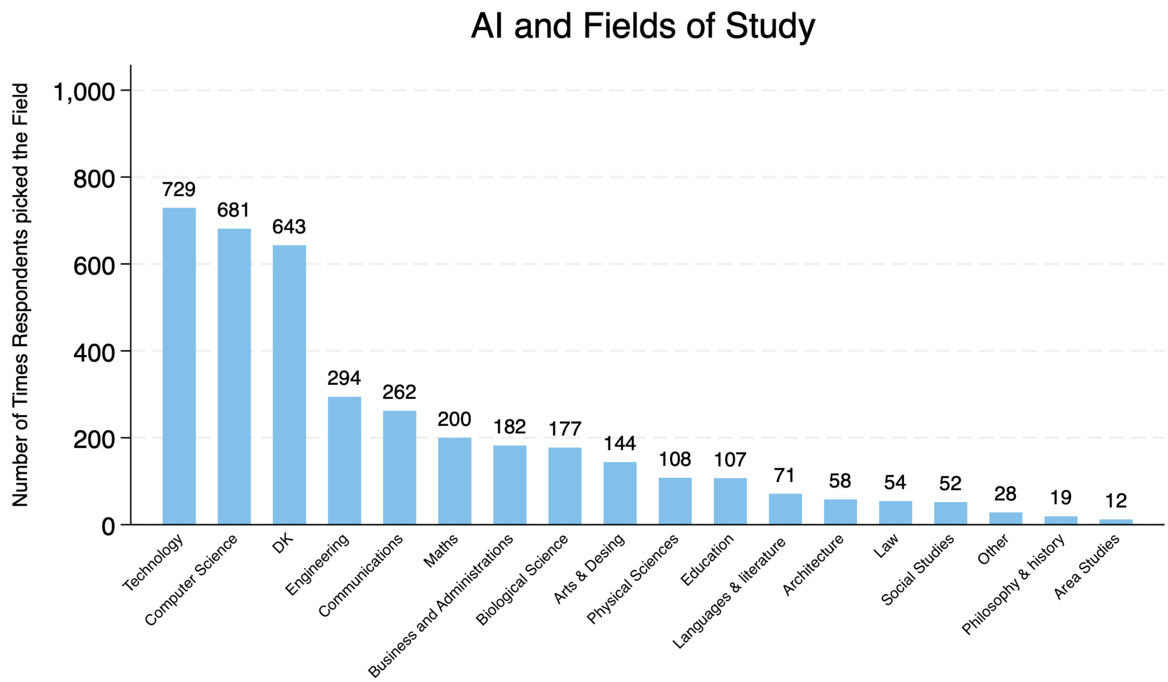

Figure 1: Number of times respondents selected the field, replying to the question: "Which of the following fields of study, if any, do you think will see the highest increase in job opportunities through the use of AI in the field? Please pick up to three."

Figure 1 shows that, in 2025, individuals rate fields such as Technology, Computer Science and Engineering as the ones that will benefit the most from the AI revolution. Notably, a considerable portion of the sample indicates that they are unsure which field AI will benefit the most. This evidence highlights that people see AI as a tech-augmenting tool, or cannot predict its effects across various sectors of the labour market.

Such a broad opinion, true in 2025, appears largely distant from the real-world effects of ChatGPT on higher education curricula. Indeed, my objective measure portrays a different, and more multifaceted, scenario. Figure 2 shows the difference in vacancy-weighted exposure to AI across the various fields of education. It estimates the predicted probability of employment across different occupations and weights them by AI occupational exposure and vacancies. The fields of study whose demand falls after the Chat-GPT shock are several. Architecture, Communication, Mathematical Sciences, Social Studies and Computer Science seem most affected.

Interestingly, the sectors augmented the most are Education, Engineering, Business & Administration, while Languages & Literature is the field that seems not to be substantially exposed or affected by a change in vacancies.

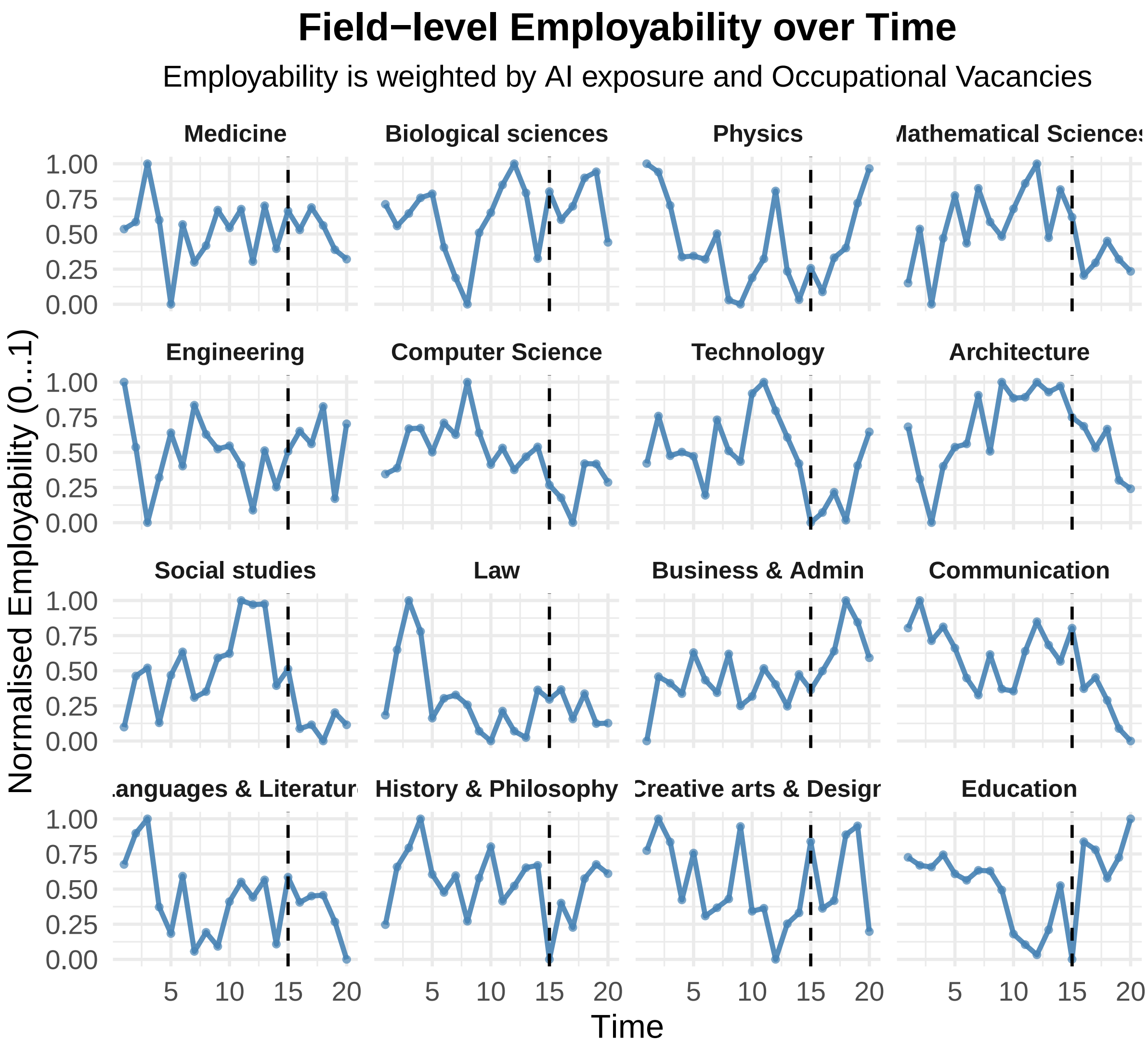

Figure 2: Vacancy weighted employability for individuals across different fields of education. The y-axis shows a normalised 0-1 measure of employability, and the dashed line on the x-axis corresponds to the introduction of ChatGPT (December 2022).

This shows that the impact of Chat-GPT on employability is complex and uneven, with some fields of education that benefit from an increasing demand in exposed occupations and others suffering from a loss in demand. Taken together, these two pieces of evidence support the assumption of the exogeneity of Chat-GPT to people's choice of their field of education. It is implausible that, before 2022, students had accurate knowledge of the employment effects of AI, enabling them to select their career paths strategically, as it is also proven by the high proportion of respondents who do not know how to answer. Being students not aware of the real exposure of various fields to AI, it is credible to claim that any change in their employability after 2022 comes as an exogenous shock to their expectations.

Furthermore, to estimate the causal effect of AI-driven shocks, I rely on a difference-in-differences design with a continuous treatment intensity. Rather than comparing binary treated versus untreated groups, I exploit field-level heterogeneity in predicted AI exposure. In this case, some fields are more likely, before the shock, to lead to occupations exposed to AI, while others are less so. The identifying assumption is that, without ChatGPT, employability across fields would have trended similarly. As ChatGPT alter vacancies only for some occupations linked to certain fields, post-shock divergences can be attributed to differential exposure intensity. Formally, the model interacts a post-shock indicator with the pre-period measure of field-level exposure, thus estimating how outcomes shift in proportion to initial exposure levels. This approach improves on FE panel models, as it is still not known whether the effect is due to ChatGPT or other shocks affecting the measure. By leveraging continuous variation in exposure at a common shock date, the Diff-in-diff specification isolates the dynamic effect of ChatGPT on outcomes while controlling for unit and time fixed effects, thus strengthening the causal interpretation. Formally, I estimate the following difference-in-differences model with continuous treatment intensity:

$$Y_{it} = \alpha_i + \delta_t + \beta \left(\text{Post}_{t(Dec2022)} \times Exposure_{z(i)} \right) + \varepsilon_{it}, \tag{4}$$

where Y_{it} is the outcome for individual i in field z at time t, α_i are individual fixed effects, δ_t are time fixed effects, Post_t is an indicator for the post-shock period (December 2022 onward), and $E_{z(i)}$ is the pre-period exposure of i in field z. The coefficient β captures how outcomes shift after the shock for each one-standard-deviation higher pre-period exposure. This specification identifies the causal effect of AI exposure under the assumption of parallel trends across fields in the absence of the shock.

4 Descriptive Statistics and Validations

4.1 Vacancy Trends and Field-level AI Exposure

My measure works empirically only if vacancies for jobs exposed to AI have changed after the introduction of ChatGPT in December 2022, thus changing the employability of people enrolled in higher education. To shed light on this, I examine the proportion of vacancies in occupations most exposed to AI from January 2017 to August 2024. Figure 3 shows the vacancy trends for the 20 most exposed and the 20 least exposed occupations, following the approach in Felten et al. (2021). The red dashed line on the x-axis corresponds to the wave in the survey corresponding to the Chat GPT launch. Further evidence on AI-related vacancy trends is shown in the Appendix.

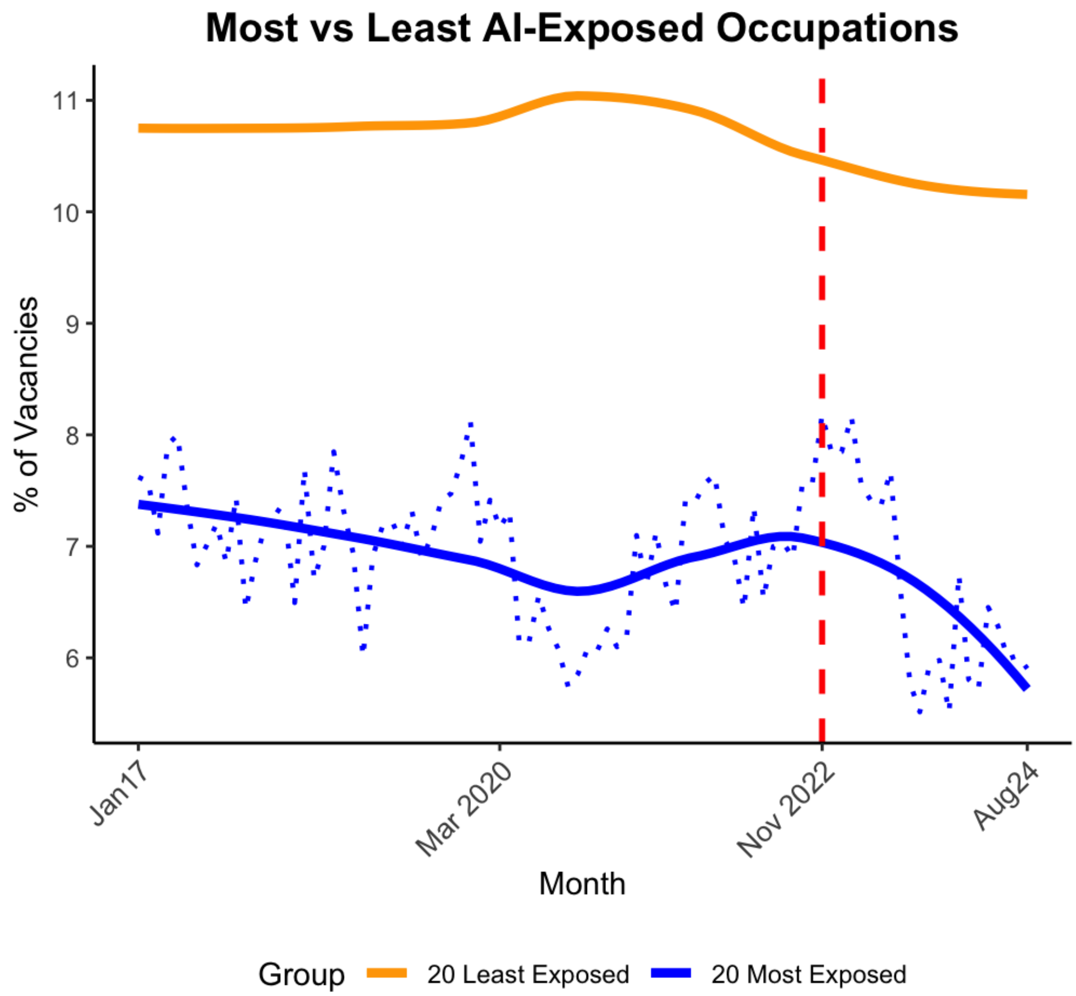

Figure 3: Share of AI-related vacancies over time. The lines show the vacancy trend for the 20 most AI-exposed and AI-non-exposed occupations.

The figure shows that vacancies have started to seriously decline after 2022 among occupations that can be classified as most exposed according to available indicators. In parallel, less exposed occupations are less affected. These trends provide some evidence that, during the period of study, ChatGPT affects the demand for some occupations. Moreover, this evidence confirms other studies of job vacancy data in the United Kingdom, which show a similar pattern (Cardenas-Rubio and Anelli-Lopez 2023; **?**).

Does this change reflect the perception of increased or decreased job opportunities? As discussed, the measure proposed in this paper aims to capture exogenous shocks in the employability of individuals deriving from their field of education. To what extent these individuals experience these objective changes as a deterioration or improvement of their employment prospects remains an open question. To shed light on this point, I use a purposely designed survey question asking a representative sample of the British public in April 2025: "Do you expect your chances of finding a job to get better, stay the same, or get worse over the next five years?"

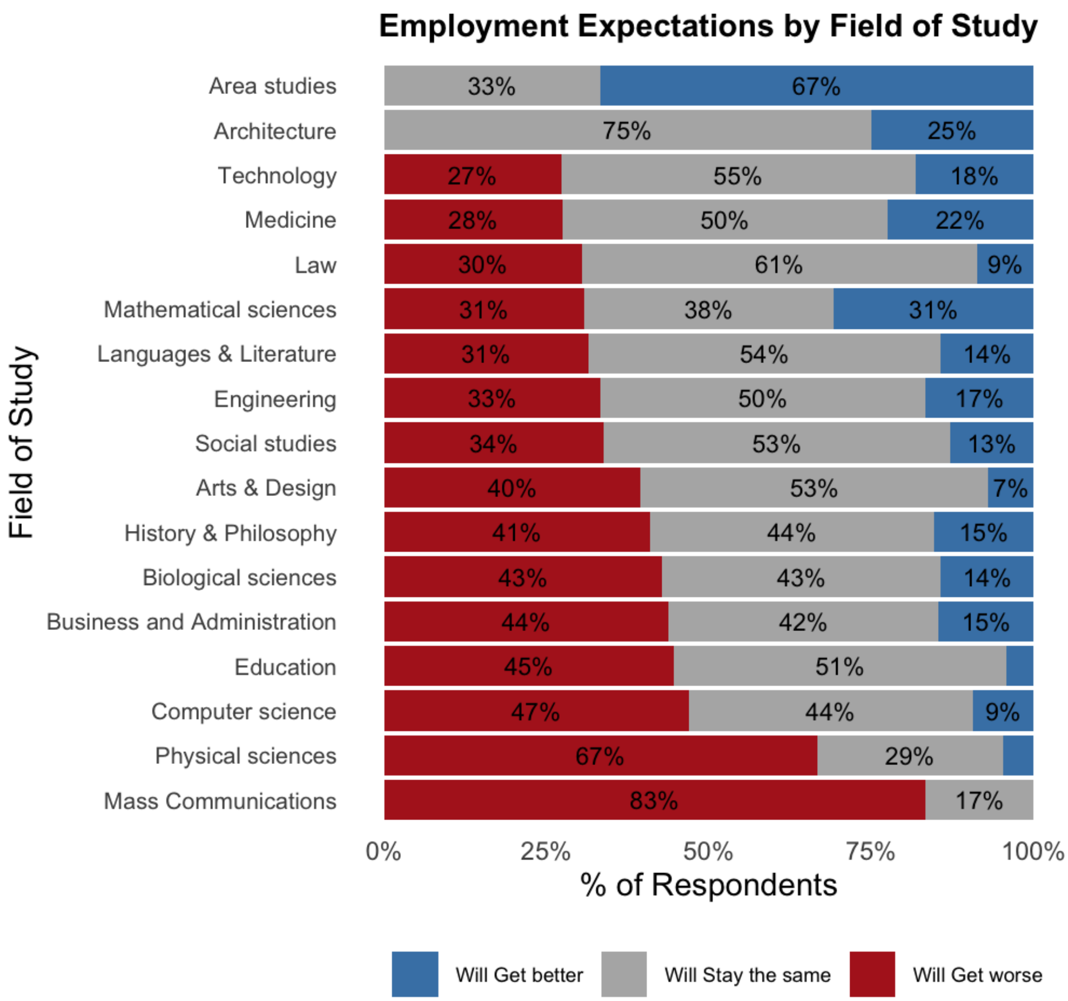

Figure 4: Employability Expectations across Different Fields of Higher Education.

Figure 4 shows how people perceive their future employment prospects across different fields of higher education. Excluding Area Studies, which stands out as an outlier case, more than half of graduates in Mass Communications and Physical Sciences think their employment prospects will get worse. While we do not know how these perceptions have changed over time, it is still striking that more than a third in Computer Science and Mathematical Sciences are pessimistic about their prospects. This pattern appears in line with the results of my measure as expressed in Figure 2, where the fields that suffer the worst decline in employability are Architecture, Communication, Mathematical Sciences and Computer Science. Graduates in Architecture largely see no improvement for their field, yet my measure predicts a strong decline in vacancies in architecture-related jobs after ChatGPT. This effect is possibly driven by the very high meritocratic beliefs that graduates in Architecture seem to have, according to Figure 10 in the Appendix, which may positively bias their perceptions. With this evidence at hand, I can claim that my measure credibly reflects graduates' occupational expectations and is valid to study how Chat-GPT has exogenously disrupted such expectations for people who enrolled in higher education before its introduction.

5 Models and Results

In what follows, I examine the effects of AI-driven changes in employability on fairness beliefs, redistribution preferences, Left-Right ideology, and voting intentions. Across all models, I restrict the sample to individuals who were enrolled in higher education before December 2022.

First, employing the measure described in Equation 3, I present the results of an individual fixed-effects panel model. This model does not apply time-fixed effects, since they would absorb the impact of Chat-GPT. Thus, while not a Two-way Fixed-effects model, my first measure remains conservative in its causal claims. For this reason, in a second step, I will adopt a Diff-in-diff estimator.

A few remarks on the time-varying measure of AI-driven changes in employability are needed, which I will now refer to as "shift exposure" for brevity. As discussed, my measure weights employability with AI exposure and changes in vacancies over time. Crucially, the delta of vacancies is a negative number when vacancies decline compared to the previous time point. Thus, for a given occupation in the vector, when calculating the differences between each time point and the baseline period, as shown in Equation 3, values are negative if vacancies have declined. Thus, by construction, positive values in the measure at any given time point indicate improved occupational prospects, while negative values signal a deterioration. To facilitate interpretation, I reverse the sign of the shift exposure measure before estimation. Reversing the sign ensures that higher values of the variable correspond to greater AI-induced employment threat, making the direction of effects more intuitively interpretable. A positive coefficient in the regression models can thus be read as indicating that declining employability is associated with stronger perceptions of economic unfairness or other attitudinal shifts.

5.1 Panel Models

5.1.1 Attitudinal Effects

I first examine three relevant outcomes, addressing H1, H2 and H3: perceptions of market fairness, attitudes towards income redistribution and general left-right economic attitudes. The dependent variables are two 5-category outcomes for the statement "Ordinary people do not get their fair share of the nation's wealth", and "The government should redistribute incomes from those who are more well-off to those who are less well-off", with higher values meaning "strongly agree", and a 10-point scale where higher values mean economic right.

First, in Table 1, I estimate a within-effect on fairness beliefs, accounting for all time-invariant confounding characteristics. Columns are the FE panel models described in Equation 3. The different models' specifications correspond to the three different AI exposure indices (Felten et al. 2021; Cazzaniga et al. 2023; Gmyrek et al. 2023).

Table 1: FE regressions on attitudes

	Dependent variable:								
	Fairness Beliefs			Redistribution			Left–Right		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Std Field Exposure1	0.006			0.007			−0.014		
	(0.006)			(0.007)			(0.009)		
Std Field Exposure2		0.011**			0.019***			−0.029***	
		(0.006)			(0.006)			(0.009)	
Std Field Exposure3			0.007			0.014**			−0.020**
			(0.005)			(0.006)			(0.009)
Id FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,640	12,640	12,640	12,433	12,433	12,433	11,741	11,741	11,741
R^2	0.0001	0.0002	0.0001	0.0001	0.0010	0.0004	0.0002	0.0010	0.0003

Note: FE panel regressions with robust standard errors clustered at the individual level.
*p<0.1; **p<0.05; ***p<0.01

Taken together, these results show partial evidence in support of my first three hypotheses. Across the three different operationalisations, a 1 standard deviation increase in AI exposure produces a 1% point increase in unfairness beliefs within the same individual over time, namely, beliefs that ordinary people do not get their fair share of the nation's wealth. Substantively, this result demonstrates that when AI causes a deterioration of prospects, graduates perceive the market as more unfair and suspect higher levels of distributive injustice. Whereas they previously believed that personal merit drives success, AI-affected graduates tend to believe that economic outcomes are unfairly distributed and that ordinary people cannot rely on individual merit.

This result strongly resonates with studies analysing the role of fairness norms in shaping individual behaviour. Unfairness beliefs are associated with stronger preferences for redistribution policy (Cavaillé 2023). As redistribution models show, in fact, when graduates become aware that their prospects have declined, they demand more redistribution of income, up to 2 percentage points more Rueda and Stegmueller (2019). Finally, this economic leftward shift is strongly reflected in the third set of models, where AI exposure predicts a 3% points shift to the left over time among affected individuals. Importantly, results seem to hold stronger where AI exposure is weighted either through the complementarity-adjust AIOE score (Cazzaniga et al. 2023) or through the score which explicitly weights occupational exposure to LLMs (Gmyrek et al. 2023).

5.1.2 Electoral Effects

I now turn to test the effect of AI exposure on voting intentions. As before, I restrict the models to respondents who were enrolled in higher education before ChatGPT and apply individual fixed effects. The dependent variables are voting intentions retrieved from the question "if there were a UK General Election tomorrow, which party would you vote for?", asked at every wave. I operationalise two voting intention variables. The first takes the value of 1 if the respondent intends to vote for the Brexit Party/Reform UK and 0 otherwise. The second takes the value of 1 if the respondent intends to vote for the Labour Party and 0 otherwise.

Table 2: FE regressions on Labour and Reform vote

	Dependent variable:					
	Labour (vote_anti_lab)			Reform (vote_anti_ref)		
	(1)	(2)	(3)	(4)	(5)	(6)
Std Field Exposure1	−0.003			0.007		
	(0.003)			(0.007)		
Std Field Exposure2		−0.002			−0.0001	
		(0.003)			(0.003)	
Std Field Exposure3			−0.003			0.003
			(0.003)			(0.006)
Id FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7,280	7,280	7,280	2,729	2,729	2,729
R^2	0.0003	0.0001	0.0002	0.0004	0.0000	0.0001

Note: FE panel regressions with robust standard errors clustered at the individual level. *p<0.1; **p<0.05; ***p<0.01

The results in Table 2 indicate that AI-induced threats have inconsistent effects on electoral preferences. In the fixed effects models, higher AI-driven threats to employability are associated with a statistically insignificant decrease in support for Labour but higher preferences for Reform UK. While standard errors remain low and effects go in the expected directions, the non-significance of these effects deserves to be explored further, as it may hide a power problem due to a small number of observations. At a glance, results show that AI is more likely to shift voting in favour of Reform UK, fueling perceptions of unfairness and a lack of meritocracy among young graduates. These results also resonate in part with the finding that AI-driven changes in employability seem to boost both demands of government intervention in the market, redistributing incomes, but also beliefs of market unfairness.

5.2 DiD with Continuous Treatment

I now use a Diff-in-diff estimator where ChatGPT is used explicitly as an exogenous source of variation in field-level exposure to AI. Before implementing it, it is essential to verify the plausibility of the parallel trends assumption with an event study analysis (Callaway et al. 2024). By interacting the pre-treatment exposure with a time variable setting December 2022 as the start of the treatment, differences across the various outcomes before and after the shock are shown. If units with higher exposure already exhibited systematic differences in trends before treatment, the identification strategy would be invalid. In contrast, flat and statistically indistinguishable pre-treatment coefficients provide evidence that more and less pre-exposed units were evolving similarly before the intervention.

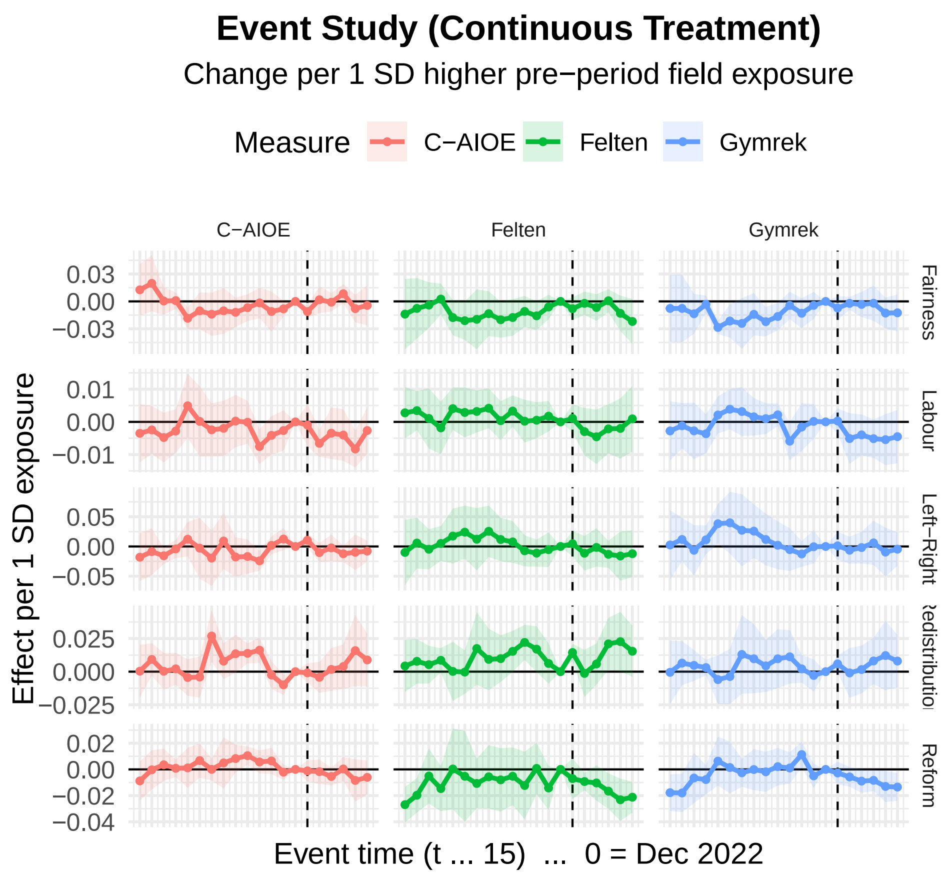

Figure 5: Event Study Plots for relevant outcomes. December 2022 was used as the start date of the treatment. TWFE models with standard errors clustered at the field of study level.

In the figure, the plotted coefficients show that before the event date, the estimates hover around zero without consistent patterns, supporting the idea of parallel pre-trends. After the treatment point, the coefficients begin to diverge, showing that the introduction of Chat GPT generated heterogeneous responses across fields, more or less exposed.

5.2.1 Attitudinal Effects

I study the relationship between AI exposure and redistribution preferences using a diff-in-diff estimator with continuous treatment. Applying individual and time fixed effects, these models approximate an exogenous variation in the measure for AI-driven employability threats, thus allowing us to study the causal effect of AI field exposure among people enrolled in higher education degrees before 2022.

Results from Table 3 show that 1 standard deviation growth in exposure to AI-driven employability threats produces around a 2 percentage point increase in redistribution preferences. These models apply individual and time fixed effects, thus excluding the alternative explanation that such changes are driven by other events affecting individuals idiosyncratically or all at the same time equally. The results are important and confirm previous panel models in showing how, after ChatGPT, people in those fields of education whose employability declines demand more redistribution of income, feeling more insecure about their future income prospects. Regarding fairness perceptions, namely the extent to which people believe that income is fairly redistributed in society, I do not find that exogenous changes in employability shift these perceptions over time. Coefficients remain insignificant and point in inconsistent directions. Yet, I still find a positive effect on the left-right scale, pointing to the fact that AI-driven threats shift attitudes to the economic left.

Table 3: Continuous-treatment DiD regressions on attitudes

	Dependent variable:								
	Redistribution			Fairness			Left–Right		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post × Std Field Exposure 1	0.026*			0.005			−0.043*		
	(0.015)			(0.022)			(0.024)		
Post × Std Field Exposure 2		0.004			−0.017			0.004	
		(0.026)			(0.023)			(0.015)	
Post × Std Field Exposure 3			0.022**			0.011			−0.025
			(0.010)			(0.026)			(0.022)
Observations	12,433	12,433	12,433	12,640	12,640	12,640	11,741	11,741	11,741
R^2	0.730	0.730	0.730	0.658	0.658	0.658	0.784	0.784	0.784
Id FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: Continuous-treatment DiD regressions with individual and time fixed effects. Reference period set at December 2022. Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.2.2 Electoral Effects

I now extend the analysis to electoral outcomes. The results point to divergent effects of AI field exposure on vote choice. For Labour, higher exposure to AI—particularly when weighted by occupations' substitution potential—is associated with a small but statistically significant increase in the likelihood of intending to vote for the Labour Party rather than for other parties. By contrast, the alternative operationalisations of exposure do not yield consistent effects. For Reform UK, none of the exposure measures are statistically significant, and all coefficients remain close to zero. This contrast suggests that deteriorating employability expectations may have greater relevance for mainstream party support than for challenger parties such as Reform. Overall, the findings highlight that shocks to expectations can shift voter preferences even over a short time horizon, though the effects remain uneven and context-dependent. These findings contrast with the hypothesis of an expressive rather than positional reaction to AI exposure among graduates. In turn, these findings may suggest that increased economic anxiety drives anti-incumbent voting, in general, a shift towards the main opposition party. Yet, attitudinal models may show that feelings of insecurity and market unfairness hide the potential for a deeper political discontent, possibly exploitable by a challenger force such as Reform UK under conditions of normalisation.

Table 4: Continuous-treatment DiD regressions on vote choice

	Dependent variable:					
	Labour (vote_anti_lab)			Reform (vote_anti_ref)		
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Std Field Exposure 1	−0.012			−0.0005		
	(0.010)			(0.003)		
Post × Std Field Exposure 2		0.010**			−0.002	
		(0.004)			(0.002)	
Post × Std Field Exposure 3			0.003			−0.003
			(0.010)			(0.002)
Observations	11,005	11,005	11,005	11,005	11,005	11,005
R^2	0.650	0.650	0.650	0.367	0.367	0.367
Id FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Note: Continuous-treatment DiD regressions with individual and time fixed effects. Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

6 Conclusions

This paper provides one of the first systematic assessments of the political implications of AI among highly educated individuals in advanced capitalist democracies. Focusing on the UK and using a panel dataset that links individual-level political attitudes and voting intentions with vacancy trends and AI occupational exposure indices, it offers new empirical evidence on how AI-driven transformations in the labour market affect attitudes and political behaviour. Grounded in the idea that individuals choose their field of study under a shared meritocratic norm—expecting that educational effort will translate into stable and rewarding employment opportunities (Sandel 2021; Cavaillé 2023), the paper demonstrates that AI can disrupt these expectations, reshaping both perceptions of fairness and political preferences. Deteriorating employability prospects generate heightened concerns about distributive justice and, in some specifications, a stronger demand for redistribution. At the same time, exposure to AI is associated with a modest but consistent shift towards the economic left, indicating that unmet expectations can erode trust in market-based meritocracy and foster support for state intervention.

The evidence on electoral preferences, however, is more nuanced. Continuous-treatment DiD models suggest that AI exposure may increase support for Labour in some specifications, while fixed effects models indicate instead a weak association with higher support for Reform UK. Across both approaches, effects remain small and often inconsistent, pointing to the need for further research with longer panels and larger samples. Still, the emerging pattern suggests that expectation shocks generated by AI may influence mainstream party support more than challenger parties, with potential implications for the stability of partisan alignments.

Empirically, the paper contributes in two main ways. First, it develops a time-varying measure of AI exposure that combines occupational risk indices with vacancy trends, allowing a more precise distinction between the augmenting and substitutive effects of AI in the labour market (Anelli et al. 2021). Second, it shows that AI-driven changes in employability affect not only material conditions at present but also expectations, which act as crucial mediators of political attitudes and behaviour (Kurer and Staalduinen 2022). Overall, the findings highlight that AI can create new cleavages even within the highly educated, a group often seen as politically homogeneous and aligned with progressive parties (Green et al. 2023; Hooghe et al. 2024a). As AI continues to diffuse across sectors, its political consequences are likely to transform knowledge-intensive occupations. Understanding how shifting expectations of employability shape fairness concerns, redistribution demands, and partisan support will be essential for anticipating the political challenges of knowledge economies in the years to come.

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7 Appendix

7.1 Key Descriptive Statistics

This Appendix shows further evidence on the relationship between AI exposure, vacancy change and its impact across different fields of higher education. First, I show, based on AI exposure indices, the occupations coded in UK-SOC 4-digit codes that are most exposed to AI. Inspecting the Textkernel-ONS data, the table below shows the top 20 most and least exposed occupations according to the AI Occupational Exposure (AIOE) score by Felten et al. (2021). Higher values indicate occupations whose tasks align closely with those performable by AI (e.g., LLMs), as of 2021 per O*NET.

Table 5: Top 20 Most and Least AI-Exposed Occupations

Rank	Most Exposed Occupation	AIOE Score	Least Exposed Occupation	AIOE Score
1	Education managers	1.461	Fitness and recreation instructors	-2.670
2	Psychologists	1.456	House builders	-2.112
3	Financial and insurance branch managers	1.446	Gardeners, horticultural/nursery growers	-1.971
4	Credit and loans officers	1.440	Athletes and sports players	-1.824
5	Transport clerks	1.405	Structural metal preparers/erectors	-1.795
6	Mathematicians, actuaries, statisticians	1.374	Glass and ceramics plant operators	-1.780
7	Personnel clerks	1.353	Bricklayers and related workers	-1.777
8	Vocational education teachers	1.349	Roofers	-1.754
9	University/higher education teachers	1.349	Sweepers and related labourers	-1.753
10	Financial and investment advisers	1.345	Plasterers	-1.715
11	Chemists	1.341	Vehicle cleaners	-1.709
12	Mechanical engineers	1.339	Building construction labourers	-1.648
13	Policy and planning managers	1.334	Mixed crop and livestock farm labourers	-1.630
14	Legislators	1.334	Painters and related workers	-1.623
15	Lawyers	1.329	Floor layers and tile setters	-1.588
16	Insurance representatives	1.327	Building frame/trades workers	-1.565
17	Staff development professionals	1.325	Manufacturing labourers n.e.c.	-1.541
18	Archivists/librarians	1.322	Construction workers n.e.c.	-1.530
19	Social work professionals	1.319	Machine operators n.e.c.	-1.509
20	Management and organization analysts	1.317	Forestry workers	-1.487

Note: AIOE scores by Felten et al. (2021). Positive scores indicate greater overlap with AI-performable tasks; negative scores reflect low exposure.

In addition, in the table below, I report occupations with the highest scores under Gmyrek et al. (2023)'s AI exposure taxonomy, distinguishing between automation and augmentation potential.

Table 6: Top 20 Occupations by AI Exposure Type (Gymrek et al.)

Rank	Automation Potential Occupation	Score	Augmentation Potential Occupation	Score
1	Librarians	0.65	Managers and directors in mining and energy	0.36
2	Authors, writers and translators	0.68	Managers in logistics	0.39
3	Brokers	0.67	Managers in transport and distribution	0.39
4	Personal assistants and other secretaries	0.64	Purchasing managers and directors	0.39
5	Typists and related keyboard occupations	0.77	Directors in logistics, warehousing and transport	0.39
6	Data entry administrators	0.70	Managers in storage and warehousing	0.39
7	Bank and post office clerks	0.72	Other researchers, unspecified discipline	0.35
8	Travel agents	0.74	Natural and social science professionals n.e.c.	0.35
9	Call and contact centre occupations	0.72	Biochemists and biomedical scientists	0.35
10	Customer service occupations n.e.c.	0.72	Architects	0.39
11	Market research interviewers	0.71	Design occupations n.e.c.	0.38
12	Book-keepers, payroll managers and wages clerks	0.69	Clothing, fashion and accessories designers	0.38
13	Finance officers	0.66	Chartered surveyors	0.38
14	Financial administrative occupations n.e.c.	0.66	Generalist medical practitioners	0.29
15	Pensions and insurance clerks and assistants	0.66	Specialist medical practitioners	0.29
16	Human resources administrative occupations	0.71	Pharmacists	0.33
17	Records clerks and assistants	0.72	Further education teaching professionals	0.39
18	Other administrative occupations n.e.c.	0.72	Secondary education teaching professionals	0.33
19	Sales administrators	0.72	Primary education teaching professionals	0.32
20	Telephone salespersons	0.69	Education advisers and school inspectors	0.35

Note: Occupations are ranked based on their automation and augmentation potential predicted by Gmyrek et al. (2023).

To complement the evidence shown in Figure 3, I show the vacancy trends for two groups of occupations: those that score above 1 SD from the mean and those that score below 1 SD from the mean of the AIOE score by Felten et al. (2021).

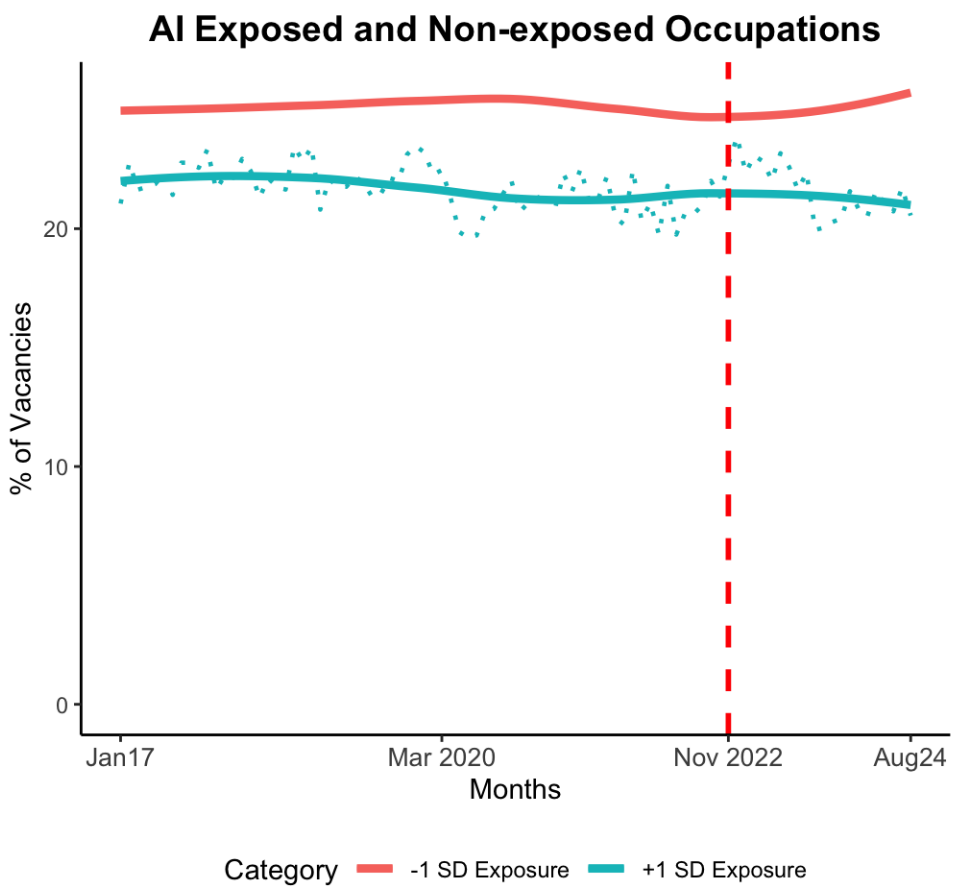

Figure 6: Normalised Employability across different fields of education weighted by AIOE index by (Felten et al. 2021) on average after December 2022

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Secondly, I show further descriptive evidence of the relationship between occupational exposure to AI and the various fields of graduate education in my dataset. This study uses a categorical variable in the British Election Study, distinguishing the following fields of higher education: "Medicine", "Biological sciences", "Physical sciences", "Mathematical sciences", "Engineering", "Computer science", "Technology", "Architecture", "Social studies", "Law", "Business & administration", "Communication", "Languages & Literature", "Area studies", "Historical & philosophical studies", "Creative arts & design", "Education".

The following three figures show how much a field is exposed to AI according to the three AI exposure score indices (Felten et al. 2021; Cazzaniga et al. 2023; Gmyrek et al. 2023). This measure is AI-weighted employability as shown in Equation 1, on average after December 2022. The figures reply to the question, which fields of education are more exposed to AI after Chat-GPT is introduced?

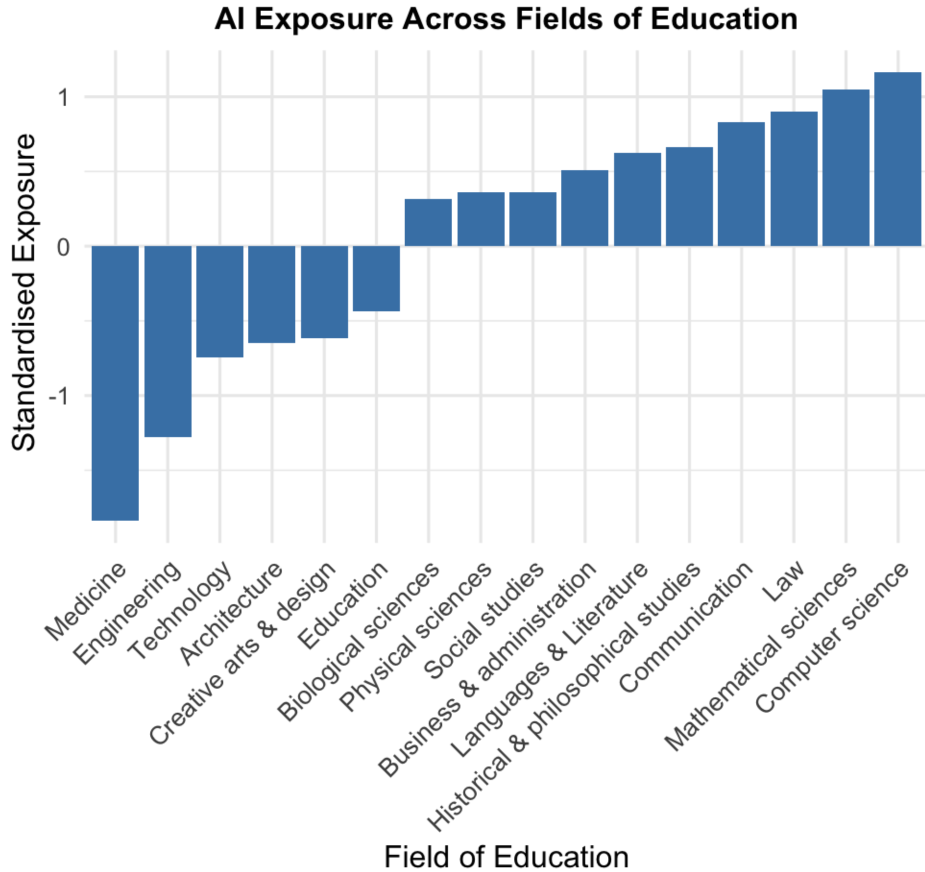

Figure 7: Normalised Employability across different fields of education weighted by AIOE index by (Felten et al. 2021) on average after December 2022.

Figure 5 shows that the fields whose employability is least exposed after the launch of Chat GPT are Technology, Medicine, Engineering, Creative Arts and Design, Architecture and Education. This evidence is crucial in understanding the effects of AI. Indeed, these fields are exposed to AI insofar as they are most likely linked to occupations whose tasks overlap with AI capabilities. However, remaining agnostic about the labour market effects of such exposure, fields like Technology are most likely to be negatively affected by AI, while Creative Arts & Design stands out as the one that will benefit the most.

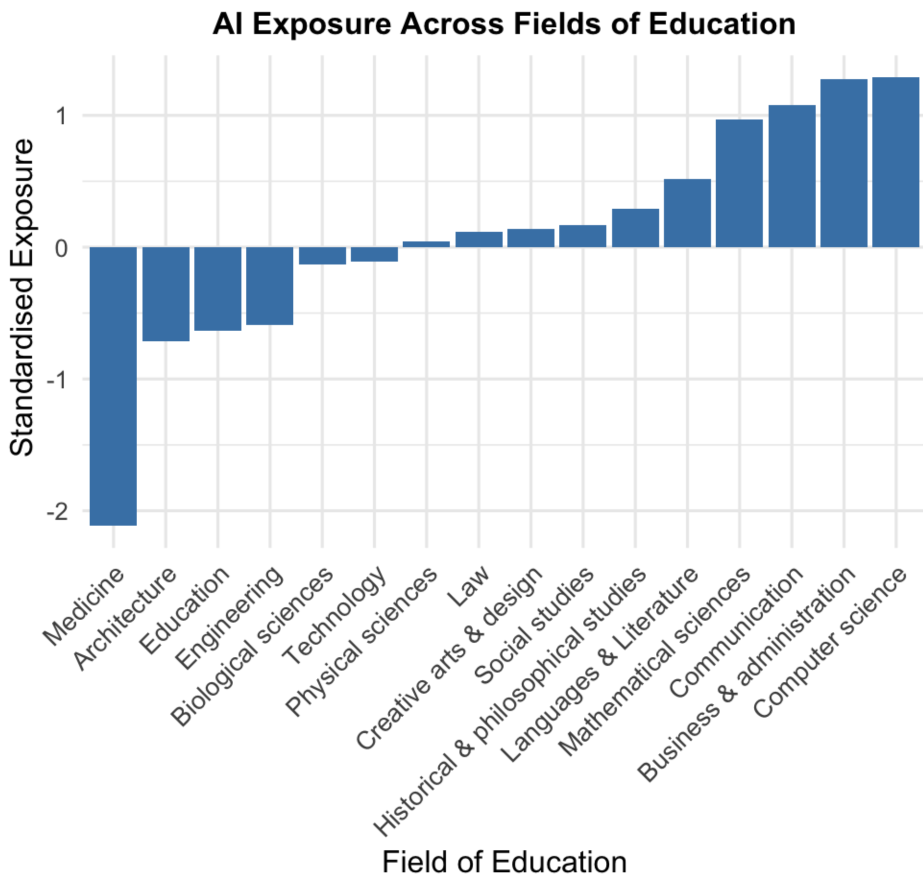

Figure 8: Normalised Employability across different fields of education weighted by AIOE index by (Cazzaniga et al. 2023) on average after December 2022.

Figure 6 shows the same evidence but weighting employability more accurately with AI substitutive potential, according to Cazzaniga et al. (2023). It shows that fields whose employability is least exposed to AI replacement after the launch of Chat GPT are Medicine, Architecture and Education, and to a lesser extent, Engineering and Technology. Communication, Computer Science and Business & Administration are more exposed to AI replacement. This evidence is particularly interesting, as it more closely aligns with the prediction shown in 2, where Computer Science, Law, Physics and Communication are among the fields whose related vacancies decrease after Chat-GPT. However, the evidence regarding Technology and Architecture is mixed, as they seem to be less exposed, but their labour market trend seems to decline after Chat-GPT.

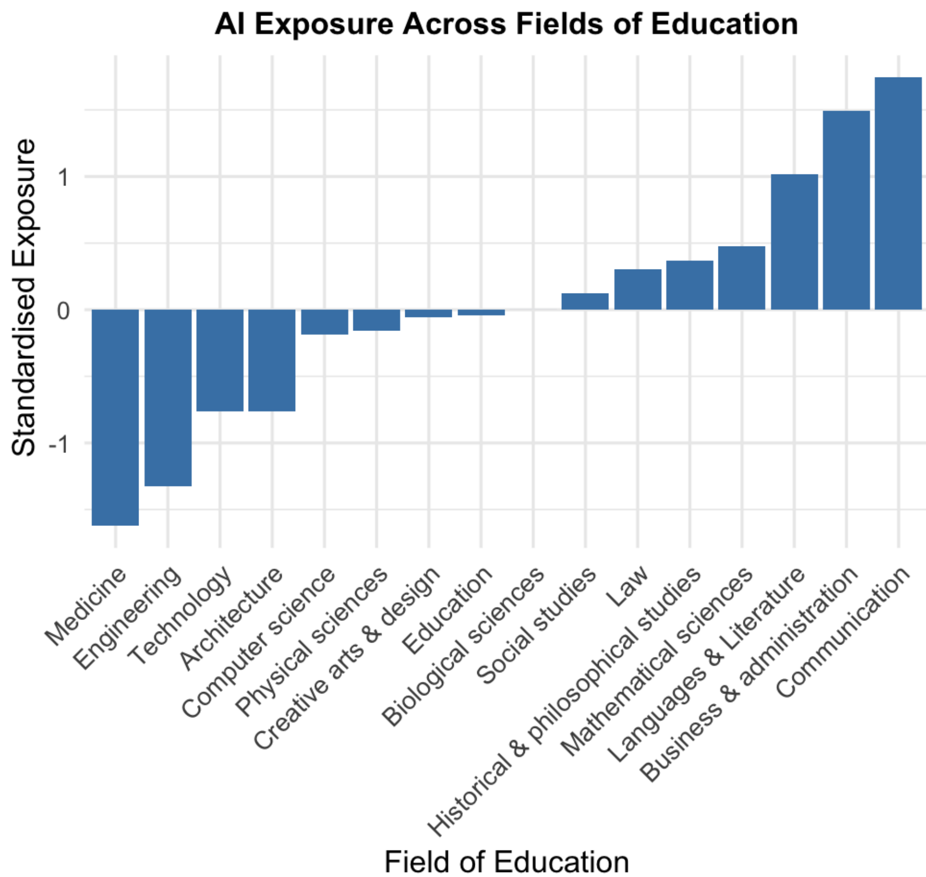

Figure 9: Normalised Employability across different fields of education weighted by AIOE index by (Gmyrek et al. 2023) on average after December 2022.

Figure 7 shows AOIE according to Gmyrek et al. (2023). This final index directly accounts for LLMs, after 2022, in the various AI applications that can be applied in the labour market. The least exposed fields are Medicine, Engineering, Technology and Architecture, while the most exposed ones are Communication and Business & Administration. In this case, an interesting pattern emerges for Computer Science. When accounting for LLMs explicitly, as Gmyrek et al. (2023), this field appears not to be exposed more than average. However, according to the two previous indices, this field is particularly threatened by AI.

7.2 Who are the students believing more in meritocracy?

In what follows, I use a purposely tailored survey item to show how meritocracy beliefs are distributed across fields of education. From Figure 9 below, it emerges that Architecture, Creative Arts & Design, History & Philosophy are among those who have stronger beliefs in meritocracy. On average, across fields, meritocratic beliefs are evenly distributed.

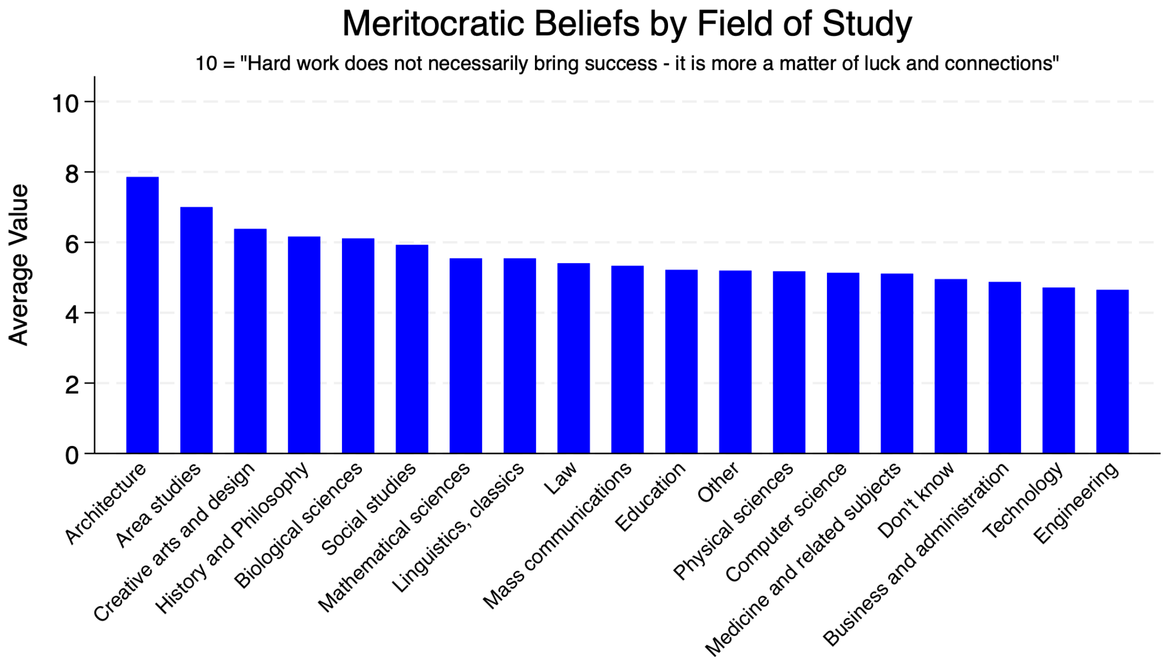

Figure 10: Meritocracy Beliefs across Fields of Education. The outcome is a 10-point scale, where higher values mean lower meritocracy beliefs.

This evidence is important in understanding the substantive meaning of the results of this study. If baseline beliefs in meritocracy are higher, the impact of AI on employability is likely to have a stronger effect on fairness perceptions. As Architecture appears, according to Figure 2, the worst effect field, changes in fairness perceptions should be the highest for them. In contrast, as Creative Arts & Design seems to be the field whose demand increases the most after Chat-GPT, students in this field will have stronger fairness perceptions, as they will attribute their occupational success to their effort.

7.3 Validation of the Chat-GPT shock and IV Regressions

IS vacancy-weighted employability changing after the launch of ChatGPT on average across all fields of education? This question helps validate the assumption that Chat-GPT represents a shock for field-level employability. I use an IV model to corroborate the assumption that ChatGPT is linked to a change in employability among exposed fields of education. I regress a vector of predicted occupational probabilities weighted by AI occupation exposure score which is multiplied by a binary time variable on endogenous employment expectations. The latter are predicted probabilities of employment weighted by mean occupational vacancies.

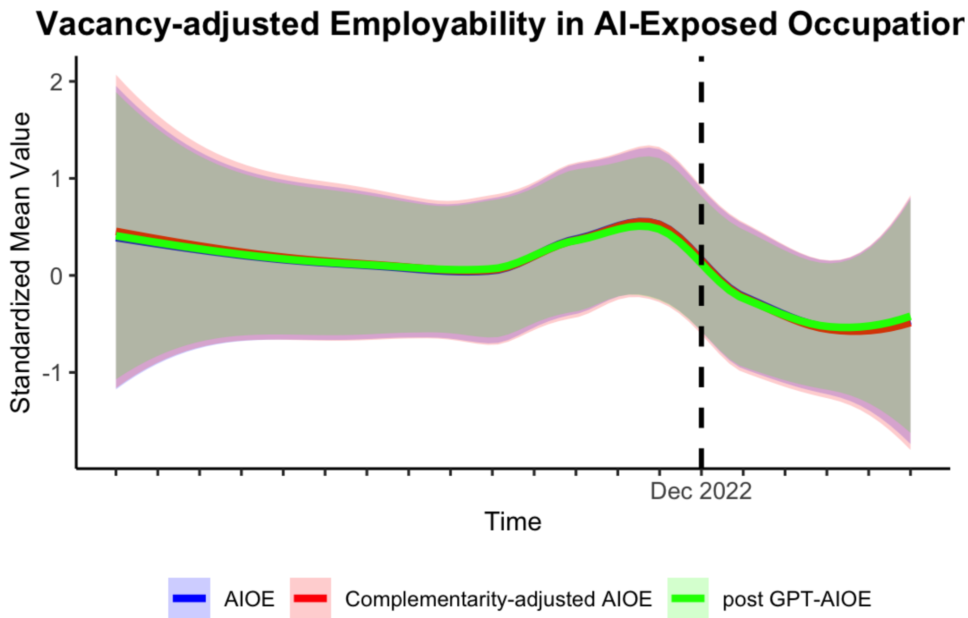

Figure 11: Normalised Employability across different fields of education weighted by AIOE index by (Gmyrek et al. 2023) on average after December 2022

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The figure shows that while AI-weighted employability appears flat in the period before the launch of Chat-GPT, it starts going below the mean in the period after Chat-GPT. This provides tentative evidence that Chat-GPT can be considered a shock for employability in AI-related occupations, on average and across all fields of education. In sum, this evidence corroborates exogeneity assumptions behind Equation 3, which is applied in the context of individual FE models.

The results below from the First-Stage regression further corroborate the claim that Chat-GPT is correlated with changes in AI-exposed employability. The following table shows the results from the first-stage regression, where the endogenous measure of employability is regressed on the Chat-GPT shock. The three different specifications of the IV correspond to the three different AI occupational exposure indices used in this study (Felten et al. 2021; Cazzaniga et al. 2023; Gmyrek et al. 2023). All three instruments are strongly associated with the endogenous outcome variable.

	(1)	(2)	(3)
DV: Vacancy-Weighted Employability			
IV AIOE	0.063***		
	(0.006)		
IV C-AIOE		0.061***	
		(0.006)	
IV GPT-AIOE			0.065***
			(0.006)
R-squared	0.003	0.003	0.003
Observations	29043	29043	29043

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: First Stage Regressions. The outcome variable is an endogenous measure of employability defined as the vacancy-weighted predicted probability of employment across all occupations based chiefly on field of education, as shown in Equation **??**. The independent variables are the three different IVs, as shown in Equation **??**, based on different exposure indices.