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Artificial intelligence technologies, skills demand and employment: evidence from linked job ads data

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Abstract

We study how artificial intelligence (AI) affects labour demand at the establishment level. We use the share of AI related vacancy postings at the establishment level to measure efforts to develop, implement or use AI technologies. Low overall AI vacancy shares show that we study a phase of early AI adoption. At the establishment level, the AI vacancy share relates to a small reduction in those skills which are not related to AI technologies. We further find no effects on overall employment growth but slightly higher employment growth in jobs for highly skilled workers.

Zusammenfassung

Wir untersuchen, wie künstliche Intelligenz (KI) die Arbeitsnachfrage auf der Betriebsebene beeinflusst. Um die Aktivitäten in der Entwicklung, Implementierung oder Nutzung von KI-Technologien zu messen, verwenden wir den Anteil derjenigen Stellenausschreibungen, die einen Bezug zu KI haben. Niedrige KI-Stellenanteile insgesamt zeigen, dass wir eine frühe Phase der KI-Einführung untersuchen. Auf der Betriebsebene hängt der KI-Stellenanteil mit einem relativ geringen Rückgang derjenigen Kompetenzanforderungen zusammen, die nicht mit KI-Technologien in Verbindung stehen. Darüber hinaus finden wir keine Auswirkungen auf die Gesamtbeschäftigung in den Betrieben, aber ein leicht höheres Beschäftigungswachstum in Jobs mit hoch komplexen Tätigkeiten.

JEL classification

J23, J24, J63, O33

Keywords

Artificial Intelligence, Vacancies, Skills, Employment

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1 Introduction

The increased availability of big data and machine learning algorithms enabled a large number of innovations in the area of artificial intelligence (AI). These new technologies fostered again the public debate about technological automation of human labour. AI chatbots are a popular example which could potentially substitute humans in a broad range of tasks (Eloundou et al. 2023). At the same there is large and growing number of very specific applications; for example, Automated Optical Inspection machines could potentially substitute humans in the specific tasks of inspecting printed circuit boards. Due to its increasing capabilities, AI technologies are expected to have important quantitative and qualitative impacts on the demand for human labour. However, the directions of these implications are ex-ante unclear: AI can replace human workers, AI can complement the work done by humans or AI requires the performance of human tasks that are new to the workforce (Acemoglu and Restrepo 2018). All this can happen at the same time, because AI as a technology is broadly defined and its implications on existing work places may be conditional on its specific forms, purposes, and how the workplaces are organised (Acemoglu and Restrepo 2020).[1]

In this paper, we contribute to the scarce empirical literature on labour demand effects of AI technologies at the establishment level during a phase of early AI adoption (2015-2019). To do so, we use novel and highly representative job ads text data to extract those skill requirements from the job descriptions that are required to use, implement, or develop AI (AI skills henceforth). The observed demand for AI skills serves as an indicator for different establishment activities in using, implementing or developing AI (AI activity henceforth). These job ads texts are provided by the Federal Employment Agency in Germany. Based on an establishment identifier, we can directly link the job ads data to rich administrative establishment data, which allows us to observe establishment characteristics related to AI activity. We use this data to test whether and how AI activity is related to a general change of non-AI hard skill requirements (non-AI skills henceforth) and to employment growth at the establishment level.

The major contribution of this paper is to address the current lack of adequate establishment data (Raj and Seamans 2019) and to analyse the impact of AI at the establishment level. We have full access to the original job ads text data and do not have to rely on web scraping methods to obtain the data. This ensures full control of the text data analyses. Moreover, the job ads data is provided with a row of further meta information like, beside others, the establishment identifier, the very detailed occupational information, and the number of vacancies per job ad. Since the job ads receive full support by the Federal Employment Agency, severe measurement errors of these meta information are unlikely. The establishment identifier allows us to link our data to administrative data and to analyse, at the establishment level, employment growth in total, in jobs with different required skill levels, or in worker groups with different education levels.

First, we find a low but increasing share of AI vacancies posted in the German labour market, i.e., the share of vacancies containing at least one AI skill. The share ranges from approximately 0.02

[1] We consider AI technologies as available algorithms that process, identify, and act on patterns in unstructured data, like speech data, text, or images in systematic ways for different purposes, together with the machines, devices, and services that are controlled by these algorithms.

per cent in 2015 to 0.22 per cent in 2019. Throughout this paper we will use the AI vacancy share as an empirical measure for AI activity, i.e., different establishment activities in using, implementing or developing AI. Therefore, the low AI vacancy shares indicate that Germany was in the starting phase of companies' AI activities between 2015 and 2019. Consistent with the US literature (e.g., Alekseeva et al. 2021, Acemoglu et al. 2022a), AI activity differs strongly across economic sectors. We find the highest AI vacancy shares in the information and communication technologies sector and the professional services sector, which we consider as industries where the development of AI and the provision of corresponding services are the main objectives. In contrast, we find lower AI vacancy shares in economic sectors in which establishments are more likely to use AI, like manufacturing and finance.

Second, we find that AI activity has diminishing effects on the demand for other non-AI skills at the establishment level. We start by measuring establishments' changes in the demand for non-AI skills using different skill change indices based on Deming and Noray (2020) and Acemoglu et al. (2022a). Changes in the requirement of non-AI skills are an observable indication for changes in the task content besides the tasks that are directly related to the use, implementation or development of AI. We distinguish between a negative skill change index, that quantifies the rate of change for skills with decreasing demand, and a positive skill change, that quantifies the rate of change for skills with increasing demand. The negative skill change could indicate a displacement of skill requirements (and hence tasks) while the positive skill change could indicate the introduction of new skill requirements (and hence new tasks).

Then, the net skill change index considers both directions of skill changes and hence the net effect on non-AI skills or tasks. We find that AI activity is related to a lower positive skill change and a higher negative skill change although both point estimates are not statistically significant. This indicates that AI activity is related to a less pronounced introduction of new non-AI skills and a stronger decline in the demand for other non-AI skills simultaneously. Since both effects contribute to a lower demand for non-AI skills, we find that AI activity is related to a decline of 0.01 non-AI skills per posted vacancy over four years as indicated by the net skill change index. Overall, although AI activity is related to a decline in the demand for non-AI skills, the small magnitude provides evidence against a sizeable displacement of human tasks due to AI technologies.

Third, in line with the diminishing effects on the skill change, we find no significant overall employment growth that is related to AI activity. The analysis of employment growth by required skill levels additionally reveals that AI activity is related to a slightly larger employment growth rate in highly complex jobs. Overall, these findings indicate that among considered establishments AI technologies tend to increase the demand for highly specialised workers which can implement or develop those technologies whereas we do not find any effect for other employees, yet.

So far, the empirical evidence about the effects of AI on labour demand at the establishment level is limited and the results are mixed. In particular, none of the existing studies uses detailed administrative data to study employment effects of AI with the exception of Genz et al. (2021) who, however, analyse the effects of a broad set of Industry 4.0 technologies (including AI but also further technologies[2]). Genz et al. (2021) link survey data on firms' adoption of Industry 4.0 technologies to administrative individual level data to document employment histories of exposed workers. They find no effects on overall employment stability in adopting firms but larger employment stability in jobs with high skill requirements.

Closely related to our study is Acemoglu et al. (2022a) who show that establishments' exposure to AI relates to changes in non-AI skills and a decline of non-AI job postings.[3] We complement this paper in three major points. First, this study exploits establishments' AI exposure instead of the direct indicator for AI activity. As we study a setting of early AI adoption and evidence suggests that AI is not strongly diffused yet, we prefer to exploit the demand for AI skills as a measure for AI activity directly instead of exploiting AI exposure measures. The reason is that although some establishments are strongly exposed to AI, they still may not meet the requirements to implement AI. Hence, we avoid that our estimated results are driven by the variation in AI exposure by establishments without any AI activity. Second, we focus on employment growth from administrative records as the main outcome while ibid. consider changes in the number of non-AI job postings at the establishment level. Third, we additionally consider heterogeneous effects on employment in jobs with different required skill levels.

The study by Gonschor and Storm (2023) also utilizes job ads data to exploit the posting intensity of AI job ads in Germany at a regional level. This study also did not find any overall employment effects.

In contrast to Acemoglu et al. (2022a), Babina et al. (2022) find higher employment growth related to investments into AI technologies identified in establishments' employee resumes based on a sample of publicly listed firms. In a follow up study, Babina et al. (2023) find that AI investments are related to increasing shares of highly skilled workers. We build up on this paper by analysing a broader sample of establishments besides publicly listed firms.

Finally, AI using firms self-report in the 2019 Annual Business Survey conducted by the US Census Bureau ambiguous effects on overall employment but an increase in the average skill level of their workers due to the use of AI (Acemoglu et al. 2022b). We complement this paper by considering employment growth based on administrative data besides a self-reported effect on employment.

Another strand of literature exploits variation in average AI exposure across aggregate levels like occupations (e.g., Felten et al. 2018, Webb 2020, Albanesi et al. 2023) or industries Gathmann and Grimm (2022) or both combined (Prytkova et al. 2024). These studies find also mixed results from negative effects Gathmann and Grimm (2022), to zero effects (Felten et al. 2018), to positive effects Albanesi et al. (2023) on employment. Instead of exploiting variation in average AI exposure, we exploit a direct measure of AI activity indicated by the demand for AI skills across establishments.

The rest of the paper is organised as follows. Section 2 describes potential theoretical effects of advances in AI on the labour task content and employment. Section 3 describes the data. Section

[2] According to ibid. the term refers to a broad cluster of different younger technological developments such as AI, augmented reality, or 3D printing as base for technologies that connect physical and digital (data) spheres to so-called cyber-physical systems.

[3] Copestake et al. (2023) use a similar approach and instrument change in the AI postings with AI exposure with Indian job ads data. They also find a decline in the non-AI job postings.

4 describes our empirical strategy and shows the estimation results. Section 5 shows robustness checks for our main results. Section 6 concludes.

2 Effect channels of AI activities

The establishment's AI activities can influence its workforce needs in partially opposite directions through three channels (Acemoglu and Restrepo 2018, 2019). First, AI may automate tasks so that human workers produce fewer tasks relative to machines, implying ceteris paribus a decrease of labour demand (the displacement effect). Second, the development and the adoption of AI in the production process may also require new tasks that human workers have to perform implying an increase of the labour demand (the reinstatement effect). Third, AI may decrease production costs substantially so that establishments may expand production and increase their labour demand (the productivity effect).

According to this, AI activities may affect directly labour demand by changing the amount and composition of required tasks for human workers (i.e., the labour task content) and, indirectly, by productivity changes. If displacement effects outweigh reinstatement and productivity effects, overall labour demand may decline. Therefore, the net effect on labour demand is conditional on the magnitude of the three effect channels.

In our empirical analysis we focus on short to medium-term effects. Whereas displacement and reinstatement effects on labour task content due to AI activities should set in within our observation period, recent evidence suggests that productivity gains due to digitisation appear pretty slow (see, e.g., Elstner et al. 2022). According to this, we assume for the following analysis that displacement and reinstatement effects on tasks are the main drivers.

The relative strengths of the displacement and the reinstatement effect may depend on the specific form of AI activities by a particular establishment.

First, there may be establishments that mainly develop AI based goods and services. The recruitment of workers with AI skills may enable those establishments to develop AI technologies without primarily aiming at automation or decreasing own production costs. For instance, those establishments recruit a data engineer to develop an AI chatbot. Hence, AI activities mainly reinstate the labour task content, because AI activities broaden the task set that workers must perform while the displacement of human tasks by AI is not intended.

Second, there may be establishments which mainly implement AI technologies to use those technologies as an input in the production process. In establishments with such AI activities both the displacement and the reinstatement effect can be present. The displacement effect appears because advances in AI may expose tasks which are currently performed by human workers. For instance, an AI chatbot may automate tasks in customer support that have previously been performed by a human being, so that AI displaces these tasks. The reinstatement effect appears, because the new AI technology may induce the need for new or additional tasks to be performed by human beings like the implementation and maintenance of the technology or training the algorithm. Even if such establishments buy AI technology from outside, they may need to hire human workers who maintain, operate or occasionally re-train the respective devices.

Reinstatement and displacement effects may alter the task content within the AI using establishments at the same time. This can be even true within the same jobs: a chatbot may be supportive to complete some of the tasks of a journalist who wants to write an article. The bot could displace human tasks like writing a first draft or collecting relevant facts. At the same time, the journalist may have to complete new tasks like additionally operating the chatbot by formulating instructions or assuring the validity of the answers and the draft.

One approach to distinguish between establishment activities empirically in producing AI technologies and using AI technologies is to exploit the data on the economic sectors of the posting establishments. We follow Acemoglu et al. (2022a) and conduct our analyses based on two samples. First, we consider establishments from all economic sectors to gain impression about the average effect of AI activities in the form of developing, implementing and using AI. Second, we will exclude establishments from presumably AI producing sectors, i.e., economic sectors that tend to produce AI based goods and services to sell them also to other establishments.

3 Data and descriptive findings

3.1 AI activities and job ads

To identify AI activity at the establishment level we use job ads text data published and provided by the JOBBÖRSE of the Federal Employment Agency (BA-JOBBÖRSE) for the years 2015 to 2019. The BA-JOBBÖRSE is one of the largest online job portals in Germany; this portal is free of charge for job seekers as well as for companies. Job offers can be searched for directly (without registration) on the BA-JOBBÖRSE site.[4]

Our data provides a rich set of meta information. Besides the establishment identifier we can directly make use of the job title measured on the 5-digit level of the German classification of occupations from 2010 (KldB 2010). The 5th digit of this code denotes the required skill level of a job. Hereby, jobs can be distinguished with tasks that require no formal qualification or only short term training (unskilled jobs); with tasks that usually require a formal vocational education training of at least 2 years (skilled jobs); with complex tasks that usually require a university degree or master craftman’s certificate (complex jobs); and with highly complex tasks that usually require a university degree or similar and, beyond that, profound professional experience or further formal highly specialised qualification certificates like a doctorate or a habilitation (highly complex jobs).

The data consists of cross-sectional samples for each of the years 2015 to 2019. We focus on job ads for employment subject to social security contributions and exclude job postings for vocational training, trainees and self-employment. Moreover, we exclude vacancies posted by temporary work agencies from our empirical analysis. While generally job postings by temporary work agencies may be a relevant indicator of labour demand, hired individuals usually do not work in the hiring temporary work agency but in a using establishment. Hence, for temporary

[4] In the meantime, in March 2022, the BA-JOBBÖRSE was renamed in BA-Jobsuche. The BA-Jobsuche can be accessed via https://www.arbeitsagentur.de/jobsuche/.

work establishments the posting of AI vacancies does not suggest AI activities in the temporary work establishment itself but in other establishments which employ the respective worker temporarily. This blurs our measurement of AI activities at the establishment level. Since our sample has a greater share of vacancies posted by temporary work establishments (approximately 30 per cent per year), we hence conduct our analysis based on a sample without such establishments.

Furthermore, the data provides information on the number of vacancies and work locations a job ad was posted for. In our analysis we will refer to the number of vacancies. For each year the sample contains between 297,888 and 481,569 vacancies (see Table 1). The sample entails all posted vacancies that are published at the cutoff dates in each year as indicated in Table 1.

Table 1: Number of vacancies by observation period

Year	Number of vacancies	Reference date
2015	297,888	15/10
2016	375,179	15/10
2017	442,383	15/10
2018	481,569	15/10
2019	446,693	15/10

Notes: The data is taken from the JOBBÖRSE of the German Federal Employment Agency (FEA, BA-JOBBÖRSE). We only consider registered job ads with the full support by the FEA. The numbers of vacancies correspond to cross-sectional samples. They cover vacancies for employment subject to social security contributions. Vacancies for vocational training, trainees and self-employment are excluded. Moreover, we exclude vacancies posted by temporary work agencies.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year.

For the relevant period the sample covers approximately 40 to 50 per cent of all job postings in Germany, according to representative key figures of the IAB job vacancy survey (IAB JVS, Bossler et al. 2020). To get a further notion how representative our job ads data for the German labour market is, we compare the structure of our data with the structure of the IAB JVS. This is generally possible for the vacancy shares across industries and required skill levels. As for the job ads data we exclude temporary work agencies from the IAB JVS to make the distribution of vacancies comparable. According to this comparison, the job ads data is highly representative across economic sectors. Furthermore, the shares of our job vacancy sample and the IAB JVS across required skill levels are very similar.[5]

We identify AI activity by extracting required AI skills in the job ad texts based on the approach developed by Stops et al. (2021). In case that AI skills appear, we interpret this as an indicator for AI activity in the respective job and the respective establishment. Accordingly, we interpret the occurrence of AI skills demand in vacancies as an indicator for establishments that actively develop, implement or use AI technologies. Referring to that, there may be a restriction that our study has in common with previous studies (e.g., Alekseeva et al. 2021, Acemoglu et al. (2022a), Bessen et al. 2023, Gonschor and Storm 2023). Although we have a rich data base, we cannot fully

[5] AppendixAppendixAppendix contains more details.

exclude that the other establishments that posted vacancies without AI skills requirements nevertheless became active in the field of AI. For instance, workers who previously developed or implemented other software technologies may be retrained within the establishment to work with AI so that no hiring of a worker with AI skills via the external labour markets becomes necessary. Alternatively, establishments may not require a hiring of a worker with AI skills to adopt an AI-based technology in case it delegates this task to an external supplier which implements the technology instead. Survey evidence suggests that the largest fraction of AI using establishments mainly uses externally developed AI technologies (Rammer et al. 2021). We therefore interpret our measures as lower bound measures for establishments being actively working with AI.[6]

We set up a novel and comprehensive AI dictionary that includes AI skill terms and corresponding search words.

Generally, we decided to include a certain term in our dictionary according to the restriction that AI skill terms must refer to skill requirements that are directly related to the development, implementation or usage of AI technologies.

We generated the dictionary in two steps. First, we collected relevant AI skills from the literature and further web search and defined appropriate search items for the AI skills. Second, we applied a word embedding approach based on the job ads text data to identify additional AI skills that employers ask for in the job ads. To ensure the validity of these generated suggestions three experts reviewed them applying a consensual validation procedure (as it was also applied for other skill categories in Stops et al. 2021, pp. 91-93). Overall, we carefully selected the AI skills since we aimed at minimising false-positively identified AI activity in the establishments. Finally, our AI dictionary consists of 231 AI skill terms and 474 search terms. Table A1 in the appendix contains all considered AI skill terms from the AI dictionary.

To extract the AI skills, first, a segmentation procedure identifies the relevant part of the job ad, which is the job description,[7] because the establishments indicate their skill requirements in this part. Second, we use an exact matching algorithm based on stemmed pre-specified search terms for the AI skills and stemmed vacancy texts.

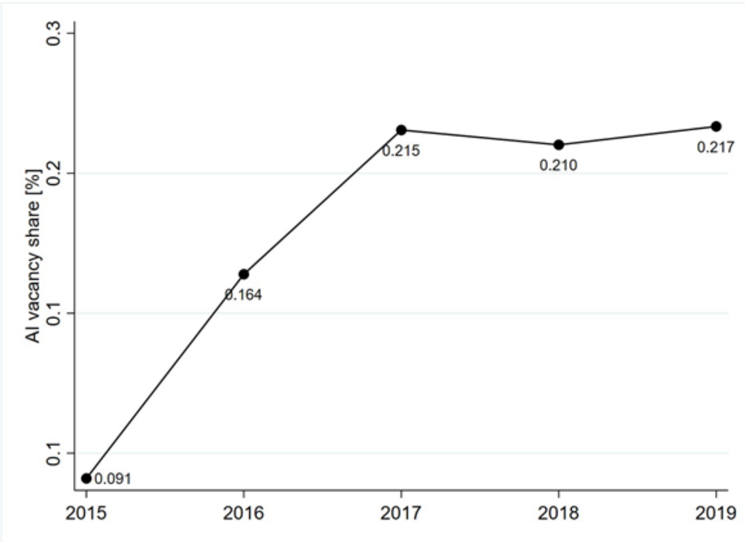
Figure 1 plots the share of AI vacancies, i.e., the number of vacancies containing AI skills divided by the total number of posted vacancies per year. AI activity shows an upward trend in Germany but is rather low compared to AI activity in other countries. For instance, in the year 2019 with highest AI activity we find an AI vacancy share of 0.217 per cent. For the US, Acemoglu et al. (2022a) find AI vacancy shares of approximately 0.6 per cent for the latest considered year 2018.

[6] This stands in contrast to patent data based exposure measures that should measure the potential usage of AI technology to perform certain tasks (compare, e.g., with Webb 2020, Gathmann and Grimm 2022). Those measures reflect an upper level of AI activities that can be related to existing jobs. For a variety of reasons, companies may not be able to capitalize on the potential usage. E.g., the patents don’t evolve in functioning or marketable products or services, the usage of AI is too costly (yet), or there are ethical or legal concerns.

[7] The procedure consists of three steps: (1) transforming the job ad texts by using a term frequency/ inverse document frequency algorithm (TFIDF); (2) 1,182 job ad texts were segmented manually by assigning tags for “job description” and “other” to the adequate text parts; (3) based on this, a binary Support Vector Machines classifier model was trained; (4) the classifier applied the “learned” patterns and segmented the texts; for further details see Stops et al. (2021), pp. 88-91.

Overall, this suggests that the German economy is at an early stage of the adoption of AI technologies in the observation period.[8]

Figure 1: Share of AI vacancies



Note: Data on the vacancies are from the BA-JOBBÖRSE. Vacancies from temporary work agencies are excluded. The AI vacancy share is the share of vacancies requiring at least one AI skill.
Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross-sections.

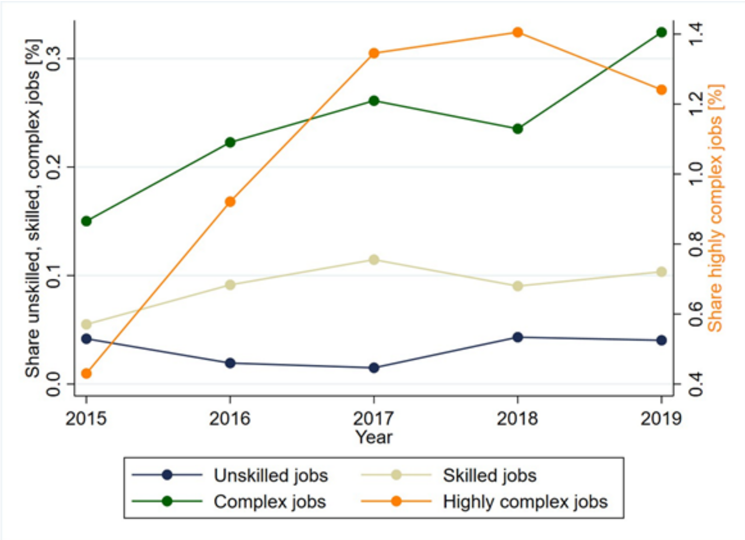
Compared with studies using German job ads from other data sources for the same observation period our identified AI vacancy shares are lower. For instance, Büchel et al. (2021) find an AI vacancy share of 0.58 per cent in 2019 for Germany. This may have two reasons. First, the definition of AI skills differs. Ibid. search not only for AI skills but also for other terms that could be indirectly related to AI activity but does not have to; examples are the programming language ”Python” or the cloud service ”Microsoft Azure” that were explicitly annotated; due to a named entity recognition approach (NER), the authors even allowed more terms to be considered as ”somewhat related” to AI (see Büchel et al. 2021, pp. 6-8). In contrast, our approach is restrictive to the AI skill terms we defined in our dictionary. This may explain the difference of our findings and the findings of ibid. The second argument refers to the representativeness of the job ads data. While the job ads from the BA-JOBBÖRSE are highly representative compared to vacancies indicated in the IAB JVS, there may be differences to other used job ads samples regarding the sectoral shares and composition by required skill levels.

Next, we show how AI vacancy shares are distributed across jobs of different required skill levels. We find that the share of AI vacancies for highly complex jobs is much larger than the shares of AI vacancies in the other required skill levels (compare the line for the AI vacancy share for highly complex jobs and its related right axis with each of the other lines for the other skill levels and their related left axis in Figure 2). This mirrors studies on the AI exposure of occupations

[8] We come to the same conclusion by plotting the share of establishments that post at least one AI vacancy in a given year (see Figure A1 for the unweighted establishment share and Figure A2 for the establishment share weighted by overall employment in the appendix).

suggesting that on average highly skilled employees are more exposed to AI technology than lower skilled employees (Felten et al. 2018, Webb 2020).[9]

Figure 2: Share of AI vacancies by required skill levels



Note: Data on the vacancies are from the BA-JOBBÖRSE. Vacancies from temporary work agencies are excluded. The AI vacancy share is the share of vacancies requiring at least one AI skill.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year.

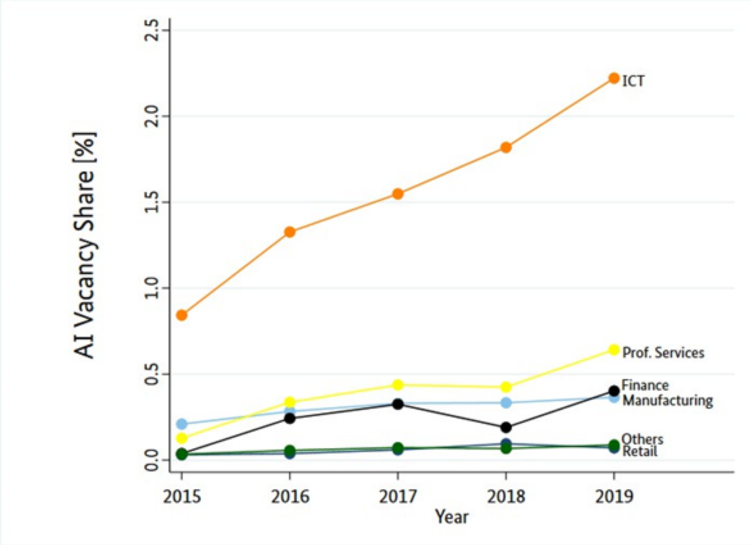
The job ads from the BA-JOBBÖRSE have the particular feature that they can be directly linked with the Establishment History Panel (BHP) that is also provided by the Federal Employment Agency. The BHP is a cross-sectional data set for German establishments from 1975 to the most recent year. It entails data on all establishments which have at least one employee subject to social security contributions in Germany (Ganzer et al. 2022). In the empirical analysis we exploit the establishments' employment levels for the relevant period and make use of a broad set of provided establishment characteristics as control variables.

Based on this data, Figure 3 shows the AI vacancy share by industries. Though relatively low in their level, the AI vacancy shares show similarities to the patterns presented in Acemoglu et al. (2022a) and Babina et al. (2022) for the US labour market. According to the results, AI activity mainly takes places in the sectors of ICT and professional services. These sectors typically either develop or implement AI technologies for other sectors. In the following, we will refer to the both sectors as the AI producing sectors. The other sectors rather utilise AI technologies and hence we will refer to these sectors as the AI using sectors. We find that AI activities in these sectors are considerably lower than in the AI producing sectors. The manufacturing and finance sectors reveal highest AI activities whereas other sectors show even lower levels of AI activity. For the AI using sectors we generally don't find upward dynamics in the observation period.[10]

[9] AI exposure means the overlap of capabilities of AI technologies and required worker skills in each occupation. Therefore, the index primarily aims at the question which of the skills are not longer required from the worker, but the index also points to those occupations (and their required skill levels) that can be potentially complemented by AI skills.

[10] As for the overall AI vacancy share the same conclusion applies based on shares of establishments that post at least one AI vacancy across industries (see Figure A3 in the appendix).

Figure 3: Share of AI vacancies per sector



Note: Data on the vacancies are from the BA-JOBBÖRSE. Vacancies from temporary work agencies are excluded. The AI vacancy share is the share of vacancies requiring at least one AI skill. Data on the sectors of the posting establishments are from the BHP.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP).

3.2 Establishments and AI activities – some stylized facts

The exact linkage of the job ads data and the establishment data allows us to further exploit establishment characteristics that are related to AI activity. We characterise establishments with and without AI vacancy postings in 2015 along further vacancy posting behaviour in 2015 and further establishment properties. Further establishment properties include the establishment-specific wage premia (the so-called AKM effects) provided by Bellmann et al. (2020) for the period 2010 to 2017, based on Abowd et al. (1999) and firstly applied for German establishments by Card et al. (2013), and variables referring to 2015 from the BHP. The variables for 2015 are overall employment, establishment age in years, and employment shares in jobs of the four different required skill levels. This documentation of stylised facts on establishment characteristics guides the selection of control variables in our empirical analysis.

Table 2: Summary statistics for establishment properties with and w/o AI activity in 2015

	Mean			Median	
	With AI activity (1)	w/o AI activity (2)	Difference (2)-(1) (3)	With AI activity (4)	w/o AI activity (5)
Further vacancy posting Number of all vacancies in 2015	9.839	3.413	-6.426***	5.000	2.000
Establishment properties AKM effect 2010-2017 (log points) referring to 2015	0.312	0.183	-0.130***	0.350	0.197
Overall employees]	410.333	96.644	-313.690**	113.000	28.000
Establishment age (years)	21.043	20.110	-0.933	19.000	28.000
Employment share unskilled jobs [%]	9.708	20.389	10.681	5.495	13.333
Employment share skilled jobs [%]	47.662	62.877	15.215***	48.905	66.667
Employment share complex jobs [%]	23.092	10.459	-12.633***	17.241	4.878
Employment share highly complex jobs [%]	19.538	6.272	-13.266***	14.286	1.587

Notes: All industries included. Temporary work excluded. Establishments with overall employment growth above the 95^{th} percentile are excluded. All variables (other than the AKM effects) refer to the year 2015. AI activity means that establishments posted at least one AI vacancy in 2015. Column (3) shows significance levels from mean comparisons establishments with AI activity (1) and without AI activity (2) based on t-tests. *** $p<0.01$, ** $p<0.05$, * $p<0.10$

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP).

Table 2 shows the mean and the median of the considered variables for establishments with and without AI activity in 2015.[11] We excluded establishments with an extraordinary growth in their employment.[12]

According to Table 2 we find, first, that establishments with AI activity post more overall vacancies in 2015 than other establishments on average (approximately 10 vacancies vs. 3 vacancies with medians of 5 vs. 2 vacancies). Second, establishments with AI activity in 2015 reveal larger AKM effects 2010-2017 (0.31 log points vs. 0.18 log points on average with means close to the medians in both groups). Third, establishments with AI activity in 2015 tend to be larger (mean of approximately 410 employees vs. 97 employees). We observe a relatively large difference in mean and median overall employment within both groups. For both groups the mean exceeds the median (approximately 113 employees vs. 28 employees) by a factor of approximately four. This larger average establishment size confirms further evidence for Germany (Rammer et al. 2021) and for the USA (Acemoglu et al. 2022b, Acemoglu et al. 2023) relying on survey data. Fourth, establishments with AI activity have a similar mean and median establishment age (mean of approximately 21 years vs. 20 years). Taken together with the finding that AI vacancies are rather posted by larger establishments points against the notion that start up establishments strongly select

[11] We discuss the distribution of each these variables in Appendix.

[12] In doing so, we excluded establishments with an employment growth that lies above the 95th percentile of the overall employment growth rates distribution across all establishments.

themselves into AI activities in 2015.[13] Fifth, establishments with AI activity tend to have higher employment shares in complex jobs (approximate mean of 23 vs. 10 per cent) and highly complex jobs (20 vs. 6 per cent). The opposite is true for the employment shares in unskilled (approximately 10 vs. 20 per cent) and skilled jobs (approximately 48 per cent vs. 63 per cent). This finding of higher employment shares in (highly) complex jobs is consistent with findings for US data (Babina et al. 2023).

3.3 AI vacancies and the potential exposure of AI (and other) tools on jobs at the establishment level

We now want to explore whether the observed AI activities are conditional on the specific occupational structure within the establishment or, as the current debate about AI suggests, whether AI as a "general purpose" technology is utilized for (almost) all jobs.

We utilize the AI exposure measure by Webb (2020), that links information on concrete functions of existing AI technology with tasks that have to be performed within occupations. This measure implies indeed that the usage of AI is conditional on specific typical tasks within occupations.

We now descriptively evaluate this assumption by analysing the relationship of the exposure measures by Webb (2020) and the AI vacancy share within the establishment.

The Webb exposure indices quantify the overlap of abilities of AI and (traditional) Soft- ware technologies and occupational tasks using patent data and occupations' task descriptions from O*NET provided by the U.S. Department of Labor. The overlap is defined as a 5-digit occupational AI or Software exposure score. Thereby, the Webb AI and Software exposure measures predict each at which intensity typical tasks within occupations could be potentially performed by the respective technology. A low value indicates that few tasks in an occupation can be automated by the respective technology and a high value indicates that a large fraction of tasks may be automated.

To compute the AI and software exposure for each establishment we aggregate the occupation-specific AI and Software exposure indices at the establishment level following Acemoglu et al. (2022a) based on individual data from the Integrated Employment Biographies (IEB) provided by the Federal Employment Agency.[14] Formally, we construct the measures of Webb AI and Software exposure in 2015 at the establishment level as

$$Webb\ exposure_{e,t_0}^{c} = \sum_{o\, \in\, O_e} \frac{emp_{e,t_0}^{o}}{emp_{e,t_0}^{total}} * Webb\ score_o^c$$

where $Webb\ score_o^c$ are Webb exposure scores of the respective technology $c \in \{AI, Software\}$ for each 5-digit occupation $o \in O_e$ in an establishment e. These occupation-specific scores are weighted by $\frac{emp_{e,t_0}^{o}}{emp_{e,t_0}^{total}}$ which are the employment shares in the respective occupations within the

[13] The potential selection of startups into AI activity is highly relevant for our empirical analysis, in which we examine the relationship of establishment level outcomes and AI activity, because establishment growth
trajectories in start-ups may differ from those of other establishments.

[14] The IEB provides longitudinal individual employment spells for the universe of employment subject to social security (Schmucker et al. 2023).

establishment in 2015. In contrast to Acemoglu et al. (2022a) our direct link of the job ads data to administrative data allows us to compute the $Webb\ exposure^{c}_{e,t_0}$ measures for each establishment relying on the actual employment structure instead of the employment structure indicated in the job postings. The weighted occupational AI exposure scores are then summed up for all occupations within the establishment $o \in O_e$. Finally, we standardise the AI exposure measure in the sample so that it has a mean zero and standard deviation of one. By averaging these exposure scores at the establishment level each of the resulting average values quantifies how strongly the task content of the whole establishment is exposed to automation by either AI or software technology.

Table 3 shows the results from estimating the relationship between the AI vacancy share measured in per cent and the standardised AI and Software exposure measure. Columns (1) to (3) refer to the sample including all establishments and columns (4) to (6) refer to the sample excluding the AI producing sectors ICT and professional services. Columns (1) and (4) refer to the relationship of the AI vacancy share and Webb AI exposure only, columns (2) and (5) to the relationship of the AI vacancy share and Webb Software exposure only, and finally columns (3) and columns (6) refer to the relationship of the AI vacancy share and the both Webb exposure measures. All specifications include variables for the number of overall posted vacancies in 2015 and for establishment properties, i.e., AKM effects from 2010-2017, and establishment size, age, economic sector and federal state referring to 2015.

Table 3: **Relationship of AI activity and Webb AI/software exposure 2015**

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent variable: AI vacancy share in 2015					
	All establishments			AI using sectors		
Webb AI exposure 2015	0.056*** (0.020)		0.079*** (0.027)	0.041** (0.017)		0.056** (0.024)
Webb software exposure 2015		0.023 (0.020)	-0.040 (0.027)		0.017 (0.016)	-0.027 (0.023)
Observations	33310	33310	33310	31630	31630	31630
Covariates: Further vacancy posting						
Number of all vacancies in 2015	yes	yes	yes	yes	yes	yes
Establishment properties						
AKM effects 2010-2017	yes	yes	yes	yes	yes	yes
...referring to 2015						
Establishment size	yes	yes	yes	yes	yes	yes
Establishment age	yes	yes	yes	yes	yes	yes
Economic sectors	yes	yes	yes	yes	yes	yes
Federal states	yes	yes	yes	yes	yes	yes

Notes: This tables shows the relationship between our AI activity measures and the Webb (2020) AI and software exposure index at the establishment level in 2015. Our AI activity measure is the AI vacancy share in 2015. The Webb AI (software) exposure index is a weighted average of occupation-specific AI (software) scores at the establishment level where employment shares of the respective occupations are the weights. We estimate the model with OLS. Included covariates are the number of all vacancies in 2015, AKM effects 2010-2017 and establishment size, establishment age, federal state, economic sector in 2015. *** p<0.01, ** p<0.05, * p<0.10

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP). AI exposure index from Webb (2020).

We find that the AI vacancy share in 2015 positively correlates with the Webb AI expo- sure. Column (1) shows that, considering all establishments in the sample, an increase in the Webb AI exposure by one standard deviation is associated with a higher AI vacancy share by 0.056 percentage points (standard error of 0.024). The estimate is highly statistically significant at the one per cent level. The next column (2) shows that Webb software exposure does not correlate with the AI vacancy share as the point estimate is much lower 0.023 per- centage points but the standard error is nearly the same (0.023) as for AI exposure. In the specification with both Webb exposure indices, the coefficient on the Webb AI exposure be- comes slightly stronger (0.079 pp) and remains highly statistically significant at the one per cent level. The main results change only slightly once we exclude AI producing sectors ICT and professional services and thereby focusing on AI using sectors. The point estimate for the coefficient of the Webb AI exposure is slightly lower compared to the full sample (0.041 vs. 0.056). However, again we find no significant relationship between the Webb Software exposure and the AI vacancy share and after including both Webb exposure measures the coefficient of the Webb AI exposure is slightly lower but statistically significant at the five per cent level whereas the coefficient or the Webb software exposure remains insignificant.

Overall, we find a robust relationship between the AI vacancy share in 2015 and the Webb AI exposure while the AI vacancy share is unrelated to the Webb Software exposure. This finding confirms that the demand for AI skills also reflects that the potential usage of AI is conditional on occupational structures with specific tasks that are performed within the establishment.

We will take these findings into account by including control variables for the occupational structure at the establishment level. Particularly, we will make use of the same individual data linked with our establishment data from the Integrated Employment Biographies (IEB). Therefore, we can exploit how the variation of AI skills demand within comparable occupational structures have an impact on skills and employment in the establishment.

3.4 Skill change and employment growth

We now explore changes for 2015 to 2019, first, in the establishment's skills demand and, second, of the establishment's employment.

We construct establishment level skill change indices similar to those in Deming and Noray (2020), Acemoglu et al. (2022a). Assuming that skill requirements in job ads approximate which tasks workers must complete within an establishment, changes in those skill requirements for establishments with AI activity are an observable indication of changes in the labour task content. The emergence of new skills indicates that the establishment introduced new tasks. Analogously, the disappearance of skills indicates a displacement of tasks which previously human workers performed. If more skills disappear from an establishment's job ad than new ones emerge, this indicates a redundancy of skills required by the establishment. If AI activity is related to a sizeable skill redundancy, we see this as evidence for a sizeable displacement of human tasks.

We measure the net skill change from t_0 = 2015 to t_1 = 2019 as

$$net\ skill\ change_{e,t_0-t_1} \ = \sum_{s=1}^{S} \left[\left(\frac{skill_{e,t_1}^{s}}{v_{e,t_1}^{ALL}}\right) - \left(\frac{skill_{e,t_0}^{s}}{v_{e,t_0}^{ALL}}\right)\right],$$

with s denoting a specific skill from the universe of total skills S. The measure relies on the relative occurrence of skills. Therefore, we sum all occurrences of a certain skill s required by establishment e in a given year $\left(skill_{e,t}^{s}\right)$[15], and divide this by the number of all vacancies of establishment e in year $t\left(v_{e,t}^{ALL}\right)$.

Finally, we sum up the differences in the relative occurrences of all posted skills be- tween both years 2015 and 2019 in each establishment and refer to this measure as the $net\ skill\ change$. This measure includes two different types of skill changes: skills which establishments demand more frequently over time ($positive\ skill\ change$) and those skills which establishments demand less frequently over time ($negative\ skill\ change$). A negative net skill change for an establishment results from the negative skill change being larger than the positive skill change. We interpret this as a proxy for the indication of a sizeable skill redundancy in this establishment.

The net skill change indicator differs to the measure proposed by Deming and Noray (2020) as we do not sum up absolute values of skill changes but allow negative and positive skill changes to balance out. Thereby, our net skill change measure can take both negative and positive values. This enables us to assess which direction of the skill change, i.e., whether the positive or the

[15] Note that in case a vacancy lists a skill at more than one place in the text, the skill is nevertheless counted only once.

negative skill change dominates, and to decompose the total skill change into the negative skill change and the positive skill change:

$$net\ skill\ change_{e,t_0-t_1} = positive\ skill\ change_{e,t_0-t_1} - negative\ skill\ change_{e,t_0-t_1}$$

where we group skills which appear more often in vacancies in 2019 relative to 2015 and skills which appear more seldom or tend to disappear in 2019 relative to 2015:

$$positive\ skill\ change_{e,t_0-t_1} = \sum_{s=1}^{S}\left[max\left\{\left(\frac{skill_{e,t_1}^{s}}{v_{e,t_1}^{ALL}}\right)-\left(\frac{skill_{e,t_0}^{s}}{v_{e,t_0}^{ALL}}\right),0\right\}\right]$$

$$nageative\ skill\ change_{e,t_0-t_1} = \sum_{s=1}^{S}\left[min\left\{\left(\frac{skill_{e,t_1}^{s}}{v_{e,t_1}^{ALL}}\right)-\left(\frac{skill_{e,t_0}^{s}}{v_{e,t_0}^{ALL}}\right),0\right\}\right]$$

Our positive and negative skill change indices differ from Acemoglu et al. (2022a) since we assign each establishment a positive as well as a negative skill change value. Moreover, we strictly separate both skill change directions and consider for the positive skill change only those skills which appear at least with the same frequency while not adjusting for diminishing skills (and vice versa). Thereby, we can exploit the variation in the negative skill change and the positive skill change in each establishment regardless of which effect dominates.

A hard skills dictionary provided by Stops et al. (2021) serves as the base to compute the skill change indicators.[16] Thereby, besides others we capture the change in the task content that arises due to displacement of tasks, introduction of complementary AI development/maintaining tasks (e.g., further software or programming skills), and the introduction of new tasks that are complementary to the use of AI (e.g., new tasks due to new business models).

[16] The hard skills dictionary consists of 7,270 skill terms (excluding AI terms) that are clearly defined in their meaning; this includes 10,116 keywords and 23,158 different keyword combinations. For the interpretation of the number of keywords, it must be noted that word stems are counted. These where generated as part of the pre-processing procedure where a German word stemming procedure was adopted (the base stemming procedure is CISTEM by Weissweiler and Fraser (2018)). This implies that the number of potentially identifiable words not reduced to the word stem is much larger.

Table 4: Summary statistics for outcome variables

Outcome Variable	Mean	Median	Min	Max
Skill change indices (2015-2019):				
Net skill change	0.483	0.500	-4.086	5.000
Positive skill change	1.633	1.000	0.000	13.000
Negative skill change	1.150	0.667	0.000	12.000
Employment growth (2015-2019) [%]:				
Overall employment growth	7.817	5.263	-99.687	100.000
Employment growth (unskilled jobs)	6.777	0.000	-100.000	200.000
Employment growth (skilled jobs)	5.826	0.000	-100.000	120.000
Employment growth (complex jobs)	-2.812	0.000	-100.000	100.000
Employment growth (highly complex jobs)	-0.748	0.000	-100.000	100.000

Notes: All industries included. Skill changes and employment growth refer to the period 2015 to 2019. The skill change indices are measured as the differences of the totals of occurrences of skills relative to all job ads of an establishment in the respective years; see also the definitions in the text. Employment growth rates are in per cent. We exclude potential outlier establishments. For the skill change indices, we exclude establishments with the lowest 2.5 per cent and the highest 2.5 per cent values in the net skill change change index. For the employment growth rates we exclude establishments with the 5 per cent highest growth rates. Unskilled jobs require no formal qualification or only short term training. Skilled jobs require a formal vocational education training of at least 2 years. Complex jobs require a university degree or master craftman's certificate. Highly complex jobs require a university degree or similar and, beyond that, profound professional experience or further formal highly specialised qualification certificates like a doctorate or a habilitation.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP).

The upper part of Table 4 presents descriptive statistics for our skill changes indices based on our sample. For our analysis, we drop potential outliers by excluding establishments with the largest and the lowest 2.5 percentile of the net skill change distribution. We find that, on average, the establishments reveal a slightly positive net skill change with a mean of approximately 0.49 (median: 0.5), resulting from a positive skill change (mean: 1.63) that is a larger than the negative skill change (mean: 1.15).

Table 5: Descriptive Statistics of the outcome variables for establishments with AI activity and establishments without AI activity in 2015

	Mean		Median	
	With AI activity	w/o AI activity	With AI activity	w/o AI activity
Skill change indices (2015-2019):				
Net skill change	0.091	0.485	0.000	0.500
Positive skill change	3.255	1.629	3.250	1.000
Negative skill change	3.164	1.144	3.251	0.667
Employment growth (2015-2019) [%]:				
Overall employment growth	13.306	7.802	12.685	5.263
Employment growth (unskilled jobs)	10.218	6.768	0.000	0.000
Employment growth (skilled jobs)	13.060	5.807	9.878	0.000
Employment growth (complex jobs)	10.538	-2.849	0.000	0.000
Employment growth (highly complex jobs)	14.443	-0.787	10.819	0.000

Notes: All industries included. Skill changes and employment growth refer to the period 2015 to 2019. The skill change indices are measured as the differences of the totals of occurrences of skills relative to all job ads of an establishment in the respective years; see also the definitions in the text. Employment growth is measured in per cent. For the skill change indices we exclude establishments with the lowest 2.5 per cent and the highest 2.5 per cent values of the net skill change. AI activity refers to posting at least one AI vacancy in 2015. For the employment growth rates we exclude establishments with the 5 per cent highest growth rates. Unskilled jobs require no formal qualification or only short term training. Skilled jobs require a formal vocational education training of at least 2 years. Complex jobs require a university degree or master craftman's certificate. Highly complex jobs require a university degree or similar and, beyond that, profound professional experience or further formal highly specialised qualification certificates like a doctorate or a habilitation.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP).

We now distinguish establishments with AI activities and establishments without AI activities. The upper part of Table 5 shows the mean and median of the considered skill change variables. Establishments with AI activity in 2015 have a larger turnover of skills, i.e., they have a larger negative skill change (3.16 vs. 1.14 skills per vacancy) and a higher positive skill change on average (3.26 vs. 1.63 skills per vacancy). The same conclusion holds for the median of both indices. However, for establishments with AI activity both indices are of a more similar magnitude so that AI activity is related to a lower (but still positive) net skill change.

We further calculate employment growth rates in per cent from 2015 to 2019 based on the linked establishment history panel (BHP). Here we can distinguish employment growth in total from employment growth in either unskilled, skilled, complex, and highly complex jobs.

The lower part of Table 4 shows descriptive statistics for employment growth for all establishments in our sample. Again, we drop potential outliers by excluding establishments with the highest larges five percentile of the respective employment growth rates distribution. Overall, and for unskilled and skilled jobs we find positive employment growth rates between 5.93 per cent (for skilled jobs), 6.78 per cent (for unskilled jobs) and 7.82 per cent in total. Employment growth rates were negative, though in lower magnitudes, for complex jobs (-2.81 per cent) and, quite smaller, for highly complex jobs (-0.75 per cent).

Again, we now distinguish establishments with AI activities and establishments without AI activities. The lower part of Table 5 shows the mean and median of the employment growth variables. Establishments with AI activity in 2015 tend to grow faster overall than the other establishments (13.31 vs. 7.80 per cent) on average. The same holds true for the employment growth rates in the different required skill levels. However, it stands out that establishments without AI activity 2015 are shrinking in terms of employment in complex (- 2.85 per cent) and highly complex jobs (-0.79 per cent) while establishments with AI activity grow with similar percentage rates as in overall employment (10.54 per cent in complex and 14.44 per cent in highly complex jobs). Moreover, the median for employment growth in unskilled and in complex jobs is equal between establishments with AI activity and others.

We will take the various characteristics, that we have described here, as controls in our analyses on the relationship of establishments' AI activities and their skill demand change and their employment growth.

4 Empirical strategy and results

4.1 Baseline model

To further analyse the impact of establishments' AI activity on the change of labour demand at both the skill level and the employment level, we estimate different model specifications based on the following ordinary least squares model:

$$\Delta y_{e,t_0-t_1} = \alpha + \beta \frac{v_{e,t_0}^{AI}}{v_{e,t_0}^{ALL}} + x'_{e,t_0} y + \epsilon_{e,t_0-t_1}$$

Given the years 2015 t_0 and 2019 t_1, the outcome variable $\Delta y_{e,t_0-t_1}$ denotes, first, the establishment's skill demand indices *(net skill change, positive skill change, negative skill change)* and, second, the establishment's employment growth measures (total, unskilled, skilled, complex, and highly complex jobs).

We measure establishments' AI activity with the establishment's AI vacancy share $\frac{v_{e,t_0}^{AI}}{v_{e,t_0}^{ALL}}$ where v_{e,t_0}^{AI} is the number of AI vacancies and v_{e,t_0}^{ALL} the number of all vacancies of establishment e in t_0. Particularly, we exploit the $share$ of AI vacancies to take into account the relative importance of AI activity in establishments' vacancies relative to all of its posted vacancies. The coefficient β indicates the average change of the outcome variable from 2015 to 2019 according to a change of the AI vacancy share of 1 percentage point in 2015. Since we consider different forms of AI activities with potentially different effects on demand for other non-AI skills and employment, we interpret β as an average effect on the respective outcome variable of these different AI activities. To identify the effects of $implementing$ and $using$ AI technologies in the production process we exclude establishments from the AI producing sectors ICT and professional services. We refer to the remaining sectors as the AI using sectors.[17]

[17] We discussed these classifications in Section 3.1 around Figure 3.

The intercept α captures the mean value for the respective change in the outcome for establishments without AI activity in t_0.

The vector x'_{e,t_0} entails covariates denoting either the establishment's e further vacancy posting behaviour or further establishment properties.

The establishment's further vacancy posting behaviour comprises a control variable for the number of all posted vacancies in 2015. We therefore take into account the possibility of a (purely) mechanical impact if vacancies reflect companies' additional labour needs[18] Furthermore, we include the average AI vacancy share across the subsequent years 2016 to 2019 as a further control since we aim to exploit AI activity in 2015 and to isolate this effect from further AI activity indicators in the following years in the observation period. Thereby, we also control for the effect of those establishments that catch up on AI activity in subsequent periods on the outcomes.

Further establishment properties include the AKM effects 2010-2017 and control variables referring to 2015 for establishment size groups (1-5, 6-19, 20-49, 50 and more employees), establishment age in years, economic sector, the federal state where the establishment is located and occupational shares in terms of the share of employees in each 3-digit occupation on all employees. With the latter variable we take into account that employment in the different occupations in an establishment may also differ in their employment growth irrespective of AI activity (e.g., due to occupation specific labour shortages) and in their tasks structure that may be differently exposed to AI technology.[19]

The error term ϵe,t0−t1 captures the effect of remaining unobservable factors on the establishment outcome. We estimate standard errors that are robust to heteroscedasticity.

4.2 Skills demand turnover

We now turn to models that further examine the skill demand change indices as dependent variables. Those variables are measured in the occurrence of skills per vacancy. Thus, the coefficient β denotes the number of additional skills per vacancy according to a one percentage point change of the AI vacancy share.

Table 6 shows the results for all three skill demand change indices and for all industries. We present the results of nine specifications that differ in the set of included covariates. Across all specifications the estimated effect on the net skill change is negatively related to an increase in the AI vacancy share in 2015.

[18] Besides of that, vacancies could also reflect the need for replacement hires, e.g., because the former employee of the respective job has retired.

[19] See also the discussion at the end of section 3.3.

Table 6: Skill requirement change 2015 - 2019, and AI skills demand 2015, all establishments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Net skill change									
AI vacancy share in 2015	-0.007*	-0.011**	-0.011**	-0.011**	-0.011**	-0.011**	-0.010**	-0.011**	-0.010**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Observations	27579	27579	27579	27579	27579	27579	27579	27579	27579
Positive skill change									
AI vacancy share in 2015	0.021***	0.003	0.003	0.002	0.003	-0.002	0.003	-0.003	-0.003
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.005)	(0.005)
Observations	27579	27579	27579	27579	27579	27579	27579	27579	27579
Negative skill change									
AI vacancy share in 2015	0.028***	0.013**	0.013**	0.013**	0.013**	0.008	0.009	0.014**	0.007
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.006)	(0.006)	(0.005)
Observations	27579	27579	27579	27579	27579	27579	27579	27579	27579
Covariates: **Further vacancy posting**									
Average AI vacancy share 2016-19	no	yes	yes	yes	yes	yes	yes	yes	yes
Number of all vacancies in 2015	no	no	yes	no	no	no	no	no	yes
Establishment properties AKM effects 2010-2017	no	no	no	yes	no	no	no	no	yes
... referring to 2015 Establishment size	no	yes	yes	yes	yes	yes	yes	yes	yes
Establishment age	no	no	no	no	yes	no	no	no	yes
Economic sectors	no	no	no	no	no	yes	no	no	yes
Federal states	no	no	no	no	no	no	yes	no	yes
Occupational shares	no	no	no	no	no	no	no	yes	yes

Notes: This table reports the estimation results for regressing the net, positive and negative skill change indices on the variable for the AI vacancy share in 2015. All industries are included except of temporary work establishments. For all regressions we exclude establishments with the lowest 2.5 per cent and the highest 2.5 per cent values of the net skill change. Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.10

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP). Integrated Employment Biographies (IEB).

In the bivariate relationship without any covariates (col. 1 of Table 6) the effects are -0.007 skills per vacancy for the net skill change, 0.021 for the positive skill change, and 0.028 for the negative skill change related to an increase in the AI vacancy share by one percentage point in 2015.[20] While the point estimate of the AI vacancy share for the net skill change is statistically significant at the five per cent level, the estimates for the positive and the negative skill change indices are significant at the one per cent level.

In the further seven specifications in columns (2) to (8) of Table 6 we control for the aver- age AI vacancy share in the subsequent years and establishment size in 2015. In columns (3) to (8) we subsequently include one further variable of our set of covariates; thus, the number of posted vacancies in column (3), *AKM effects 2010-2017* in column (4), establishment age in column (5), economic sectors in column (6), federal states in column (7), and occupational employment shares in column (8).

For the net skill change, when we control for the average AI vacancy share 2016-2019 and establishment size (col. 2-8) the magnitudes of the point estimate increase. That also results in a higher statistical significance, i.e., at the five per cent level. However, the magnitudes of the estimates in the different specifications vary only slightly (-0.011 in all specifications vs. -0.010 when we control for federal states).

For the positive skill change as the dependent variable, the estimates of the different specifications with further control variables vary quite stronger. Compared with the bivariate specification (col. 1), the coefficients decrease strongly to a magnitude that is not statistically significant different from zero. The point estimates are close to zero across all these specifications and turn negative once we control for economic sectors (col. 6) and/or occupational shares (col. 8).

For the negative skill change as dependent variable, the estimates are also lower when we include covariates. After controlling for the average AI vacancy share 2016-2019 and establishment size (col. 2), the point estimate drops by almost half to 0.013 and is statistically significant at the five per cent level. Moreover, if we control for economic sectors (col. 6) or Federal states (col. 7), the estimated effect on the negative skill change is not significant anymore.

Finally, column (9) of Table 6 presents the estimates of the model that includes the full set of covariates. For the net skill change indicator as dependent variable, the point estimate of -0.010 is slightly lower compared to the point estimate of the bivariate specification in column (1). For the positive skill change as dependent variable, the point estimate of -0.003 is substantially lower than the estimate of the bivariate specification in column (1) and the estimate is not statistically significant. The point estimate of the model with the negative skill change as dependent variable is 0.007 and insignificant. This estimate is reduced to one quarter of the estimate of the bivariate specification in column (1).

Although the lower estimated positive skill change and higher estimated negative skill change are not statistically significant, both effects point to the same direction. Related to more AI activity, the smaller positive skill change indicates less skills with increasing demand over time

[20] As introduced in section 3.4, the magnitudes of the skill change indices are interpreted as the change in the number of skills per vacancy between 2015 and 2019.

and the larger negative skill change indicates more skills with decreasing demand over time. Both effects contribute to a lower net skill change rate related to AI activity in 2015. As a result, the estimated effect on the net skill change is negative and statistically significant, but rather small. In the fully specified model, an increase in the AI vacancy share by one percentage point is associated with a decrease in the demand for non-AI skills by 0.01 non-AI skills. This signals a skill redundancy related to AI activity although it is rather small. We interpret this as first evidence against sizeable displacement of skill requirements (and tasks) that are not directly related to the use, implementation or development of AI.

Next, we consider the difference in the skills turnover for establishments that rather utilize AI (AI using industries) by excluding those establishments that rather develop or implement AI technologies (AI producing industries, i.e., ICT and professional services), because the relative importance of reinstatement effects and displacement effects may differ in AI using and AI producing industries. Especially, we would expect that displacement effects are less likely to appear in AI developing industries. Hence, from a theoretical perspective, by excluding these industries, displacement effects and hence a higher negative skill change become more likely. However, the estimates do not support this view. Table 7 presents the results in the same structure as before.

Table 7: Skill requirement change 2015 - 2019, and AI skills demand 2015, establishments w/o AI producing sectors (ICT and professional services)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Net skill change									
AI vacancy share in 2015	-0.007* (0.004)	-0.011*** (0.004)	-0.011*** (0.004)	-0.011*** (0.004)	-0.011** (0.004)	-0.011** (0.004)	-0.011** (0.004)	-0.011** (0.004)	-0.011** (0.005)
Observations	26106	26106	26106	26106	26106	26106	26106	26106	26106
Positive skill change									
AI vacancy share in 2015	0.015*** (0.005)	-0.001 (0.006)	-0.001 (0.006)	-0.001 (0.006)	-0.001 (0.006)	-0.004 (0.006)	-0.000 (0.006)	-0.005 (0.006)	-0.006 (0.005)
Observations	26106	26106	26106	26106	26106	26106	26106	26106	26106
Negative skill change									
AI vacancy share in 2015	0.023*** (0.006)	0.010 (0.007)	0.010 (0.007)	0.010 (0.007)	0.010 (0.007)	0.006 (0.005)	0.007 (0.006)	0.011 (0.007)	0.005 (0.005)
Observations	26106:	26106:	26106	26106	26106	26106	26106	26106	26106
Covariates: **Further vacancy posting**									
Average AI vacancy share 2016-19	no	yes	yes	yes	yes	yes	yes	yes	yes
Number of all vacancies in 2015	no	no	yes	no	no	no	no	no	yes
Establishment properties									
AKM effects 2010-2017	no	no	no	yes	no	no	no	no	yes
... referring to 2015									
Establishment size	no	yes	yes	yes	yes	yes	yes	yes	yes
Establishment age	no	no	no	no	yes	no	no	no	yes
Economic sectors	no	no	no	no	no	yes	no	no	yes
Federal states	no	no	no	no	no	no	yes	no	yes
Occupational shares	no	no	no	no	no	no	no	yes	yes

Notes: This table reports the estimation results for regressing the net, positive and negative skill change indices on the variable for the AI vacancy share in 2015. Establishments in ICT and professional services are excluded. Additionally, we exclude temporary work agencies. For all regressions we exclude establishments with the lowest 2.5 per cent and the highest 2.5 per cent values of the net skill change. Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.10

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP). Integrated Employment Biographies (IEB).

In the fully specified model (see col. 9 of Table 7) the effect on the net skill change amounts to -0.011 skills per vacancy which is a similar magnitude like the estimate of the same regression based on the full sample of establishments. The estimate is statistically significant at the five per cent level. The estimates for the effects on the positive and negative skill change rates (-0.006 and 0.005 skills per vacancy, resp.) are also rather similar compared to the corresponding point estimates from the sample including all establishments. Both point estimates are not statistically significant in this sample, too. Thus, in establishments that rather utilize AI we also find only a weak relation between non-AI skills redundancies and AI activities.

Overall, considering all establishments we find only small effects of AI activity on the skills turnover. Although AI activity is related to a slightly higher rate at which skills become redundant, the effect is small. For AI using sectors we find similar results. Since we assume that changes in the skills demand indicate changes in the labour task content, our results suggest only small changes in the labour task content related to AI activity apart from the introduction of AI-specific tasks.

4.3 Employment

Next, we analyse establishment employment growth in per cent across all jobs and across jobs in each of the four required skill levels. Thus, the coefficient β denotes a change in employment growth in percentage points according to a one percentage point change of the AI vacancy share. AI activity in 2015 associated with subsequent lower employment growth either in total or in a particular required skill level would provide evidence for displacement effects outweighing reinstatement effects within the establishment.

Table 8 provides the estimation results of nine different specifications. Again, we start by estimating the bivariate relationship of employment growth and AI activity in 2015 (col. 1) and subsequently include covariates into the model (col. 2-8) and, finally, include all covariates (col. 9).

Table 8: Employment growth 2015 - 2019 and AI skills demand 2015, all establishments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Overall Employment Growth				
AI vacancy share in 2015	0.055	0.006	0.006	0.002	-0.003	-0.007	0.006	-0.016	-0.030
	(0.049)	(0.049)	(0.049)	(0.048)	(0.049)	(0.047)	(0.048)	(0.045)	(0.045)
Observations	33771	33771	33771	33771	33771	33771	33771	33771	33771
					Unskilled jobs				
AI vacancy share in 2015	0.112	0.182	0.181	0.182	0.181	0.179	0.182	0.186	0.175
	(0.122)	(0.126)	(0.126)	(0.126)	(0.126)	(0.125)	(0.126)	(0.126)	(0.125)
Observations	34169	34169	34169	34169	34169	34169	34169	34169	34169
					Skilled jobs				
AI vacancy share in 2015	0.037	0.016	0.016	0.011	0.011	0.008	0.020	-0.001	-0.011
	(0.068)	(0.067)	(0.067)	(0.066)	(0.066)	(0.067)	(0.067)	(0.066)	(0.066)
Observations	33653	33653	33653	33653	33653	33653	33653	33653	33653
					Complex jobs				
AI vacancy share in 2015	0.154**	0.054	0.053	0.049	0.057	0.033	0.057	0.026	0.024
	(0.077)	(0.074)	(0.074)	(0.073)	(0.073)	(0.072)	(0.074)	(0.072)	(0.072)
Observations	33699	33699	33699	33699	33699	33699	33699	33699	33699
					Highly complex jobs				
AI vacancy share in 2015	0.218***	0.152**	0.152**	0.148**	0.155**	0.135*	0.142*	0.151**	0.132*
	(0.073)	(0.076)	(0.076)	(0.075)	(0.076)	(0.073)	(0.075)	(0.076)	(0.072)
Observations	34094	34094	34094	34094	34094	34094	34094	34094	34094
Covariates:									
Further vacancy posting									
Average AI vacancy share 2016-19	no	yes	yes	yes	yes	yes	yes	yes	yes
Number of all vacancies in 2015	no	no	yes	no	no	no	no	no	yes
Establishment properties									
AKM effects 2010-2017	no	no	no	yes	no	no	no	no	yes
... referring to 2015									
Establishment size	no	yes	yes	yes	yes	yes	yes	yes	yes
Establishment age	no	no	no	no	yes	no	no	no	yes
Economic sectors	no	no	no	no	no	yes	no	no	yes
Federal states	no	no	no	no	no	no	yes	no	yes
Occupational shares	no	no	no	no	no	no	no	yes	yes

Notes: This table reports the estimation results for regressing the overall employment growth and employment growth in jobs differentiated by skill requirement level on the AI vacancy share in 2015. Unskilled jobs require no formal qualification or only short term training. Skilled jobs require a formal vocational education training of at least 2 years. Complex jobs require a university degree or master craftman's certificate. Highly complex jobs require a university degree or similar and, beyond that, profound professional experience or further formal highly specialised qualification certificates like a doctorate or a habilitation. All industries are included. For regressions with the employment growth rates we exclude establishments with the 5 per cent highest growth rates. Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.10

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP). Integrated Employment Biographies (IEB).

Across all specifications the coefficient for the effect on overall employment growth is statistically insignificant. In most specifications the overall employment growth is positively related to AI activity but turns negative when we include establishment age (col. 5), economic sectors (col. 6) and/or occupational shares (col. 8) as covariates into the model. After including all covariates (col. 9), the establishments have a lower employment growth of 0.03 percentage points per 1 percentage point increase in the AI vacancy share on average. Given an average overall employment growth of 7.8 per cent in the sample considering all establishments[21], this effect on the growth rate is rather small and not statistically significant.

However, we observe heterogeneity of employment growth differences across the required skill levels. The estimated effect for employment growth in unskilled jobs is rather stable but statistically insignificant across all specifications. Compared to the bivariate relationship (0.112, see col. 1), the estimated effect on employment growth in unskilled jobs changes only slightly (0.175) in the fully specified model (col. 9). However, considering the fully specified model the estimated effect on employment growth in these jobs has the highest magnitude compared to the other required skill levels. In skilled jobs the magnitude of the point estimate in the fully specified model is similar to the point estimate for overall employment growth (-0.011) but also not statistically significant. In complex jobs an increase in AI activity in 2015 by one percentage point is associated with an increase in employment growth by 0.154 percentage points. The estimate is statistically significant at the 5 per cent level. However, in the fully specified model the effect on employment growth is much smaller than in the bivariate relationship but also positively associated with AI activity (0.024). Despite of different magnitudes we find no significant effects on employment growth in unskilled, skilled and complex jobs once we include the covariates.

We only find a statistically significant effect in employment growth in highly complex jobs related to AI activity. Without any covariates we estimate positive employment growth by 0.218 percentage points which is significant at the one per cent level. However, even after including all covariates establishments have a 0.132 percentage points higher employment growth rate in highly complex jobs per 1 percentage point increase in the AI vacancy share in 2015. The estimate is significant at the 10 per cent level. Notably, once we control for further AI vacancy postings in 2016-2019 and establishment size (col. 2), the magnitude of the estimated coefficient is rather stable across specifications (col. 3-9). The estimated effect in employment growth is positive and indicates a reversed direction to the average employment growth in highly complex jobs across all establishments of -0.716 per cent in our sample (Table 4). Given that the estimated coefficient is much lower than one and is related to a one percentage point increase in the AI vacancy share, the effect is small. Since additionally, on average the share of employees in highly complex jobs is rather low across establishments (6.3 per cent), the observed higher employment growth in highly complex jobs does not translates into a higher overall employment growth.

Next, we again exclude the ICT and the professional services sectors from our analysis (Table 9). The point estimate of -0.065 after controlling for all covariates has a similar magnitude like the estimate based on all establishments for overall employment growth. Again, as in the sample considering all establishments the point estimate is not statistically significant. The major

[21] See Table 4 for average outcome growth rates for establishments without AI activity and others.

difference of the sample excluding AI producing sectors relative to the sample of all establishments is the insignificant estimate of 0.126 in employment growth in highly complex jobs due to a slightly smaller magnitude and a larger standard error.

Table 9: Employment growth 2015 - 2019 and AI skills demand 2015, establishments in sectors outside ICT and professional services

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
					Overall Employment Growth				
AI vacancy share in 2015	-0.002	-0.042	-0.042	-0.045	-0.046	-0.046	-0.040	-0.052	-0.065
	(0.052)	(0.055)	(0.055)	(0.054)	(0.055)	(0.055)	(0.055)	(0.051)	(0.051)
Observations	32082	32082	32082	32082	32082	32082	32082	32082	32082
					Unskilled jobs				
AI vacancy share in 2015	0.168	0.232	0.232	0.231	0.231	0.204	0.233	0.219	0.206
	(0.160)	(0.163)	(0.163)	(0.163)	(0.163)	(0.163)	(0.163)	(0.165)	(0.164)
Observations	32388	32388	32388	32388	32388	32388	32388	32388	32388
					Skilled jobs				
AI vacancy share in 2015	-0.001	-0.008	-0.008	-0.011	-0.010	-0.015	-0.005	-0.022	-0.028
	(0.063)	(0.061)	(0.061)	(0.060)	(0.061)	(0.062)	(0.062)	(0.059)	(0.059)
Observations	31893	31893	31893	31893	31893	31893	31893	31893	31893
					Complex jobs				
AI vacancy share in 2015	0.138	0.035	0.035	0.031	0.037	0.021	0.038	0.009	0.004
	(0.086)	(0.083)	(0.083)	(0.083)	(0.083)	(0.082)	(0.083)	(0.083)	(0.082)
Observations	32034	32034	32034	32034	32034	32034	32034	32034	32034
					Highly complex jobs				
AI vacancy share in 2015	0.204**	0.139	0.139	0.135	0.141*	0.131	0.134	0.139	0.126
	(0.084)	(0.086)	(0.086)	(0.084)	(0.085)	(0.081)	(0.084)	(0.086)	(0.081)
Observations	32483	32483	32483	32483	32483	32483	32483	32483	32483
Covariates: **Further vacancy posting**									
Average AI vacancy share 2016-19	no	yes	yes	yes	yes	yes	yes	yes	yes
Number of all vacancies in 2015	no	no	yes	no	no	no	no	no	yes
Establishment properties									
AKM effects 2010-2017	no	no	no	yes	no	no	no	no	yes
... referring to 2015									
Establishment size	no	yes	yes	yes	yes	yes	yes	yes	yes
Establishment age	no	no	no	no	yes	no	no	no	yes
Economic sectors	no	no	no	no	no	yes	no	no	yes
Federal states	no	no	no	no	no	no	yes	no	yes
Occupational shares	no	no	no	no	no	no	no	yes	yes

Notes: This table reports the estimation results for regressing the overall employment growth and employment growth in jobs differentiated by skill requirement level on the AI vacancy share in 2015. Unskilled jobs require no formal qualification or only short term training. Skilled jobs require a formal vocational education training of at least 2 years. Complex jobs require a university degree or master craftman's certificate. Highly complex jobs require a university degree or similar and, beyond that, profound professional experience or further formal highly specialised qualification certificates like a doctorate or a habilitation. Establishments in ICT and professional services are excluded. For regressions with the employment growth rates we exclude establishments with the 5 per cent highest growth rates. Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.10

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP). Integrated Employment Biographies (IEB).

Overall, in line with our analysis for the relationship of the skill change of establishments and AI activity, we do not find supportive evidence for sizeable displacement effects. In the sample considering all establishments we find a higher employment growth in highly complex jobs. This may reflect the requirement of additional employees for jobs where the development or implementation of AI technologies are the main tasks. Our finding is also in line with recent literature that show that highly educated workers tend to benefit from AI activity (Albanesi et al. 2023, Babina et al. 2023) in terms of employment growth.

5 Robustness Checks

5.1 Employment and employees' qualification

As a first robustness check we change from the job requirement perspective to the employee perspective. Instead of considering the different required skill levels we now define the worker groups according to the employees' qualification levels. A change of the number of jobs in a certain required skill level must not necessarily coincide with a change in the number of employees with the corresponding qualification level. The reason is that establishments occasionally employ individuals on jobs that require normally a qualification that is lower or a higher than the individual's qualification (see, for instance, Rohrbach-Schmidt and Tiemann 2016, Erdsiek 2021).

In what follows, we present estimates of employment growth for worker groups defined by the workers' reached qualification level. Hereby we can distinguish unskilled employees without a formal qualification, qualified employees with a certified vocational educational training of at least 2 years, and highly qualified employees with a university degree or similar.

Table 10 presents the results for all establishments and Table 11 presents the results for establishments without AI producing sectors ICT and professional services. Again, the first panel reports results for overall employment growth and, therefore, repeats the previous results in the first panels of Table 8 or Table 9, respectively.

Table 10: Employment growth 2015 - 2019 by employee's qualification levels, and AI skills demand, all establishments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Overall Employment Growth									
AI vacancy share in 2015	0.055	0.006	0.006	0.002	-0.003	-0.007	0.006	-0.016	-0.030
	(0.049)	(0.049)	(0.049)	(0.048)	(0.049)	(0.047)	(0.048)	(0.045)	(0.045)
Observations	33771	33771	33771	33771	33771	33771	33771	33771	33771
Unskilled Employment Growth									
AI vacancy share in 2015	-0.043	-0.075	-0.075	-0.076	-0.082	-0.089	-0.074	-0.093	-0.101
	(0.101)	(0.101)	(0.101)	(0.101)	(0.101)	(0.100)	(0.101)	(0.100)	(0.101)
Observations	34210	34210	34210	34210	34210	34210	34210	34210	34210
Qualified Employment Growth									
AI vacancy share in 2015	0.036	-0.014	-0.014	-0.019	-0.019	-0.028	-0.013	-0.039	-0.049
	(0.048)	(0.049)	(0.049)	(0.048)	(0.049)	(0.047)	(0.048)	(0.045)	(0.045)
Observations	33918	33918	33918	33918	33918	33918	33918	33918	33918
Highly Qualified Employment Growth									
AI vacancy share in 2015	0.203***	0.074	0.074	0.068	0.075	0.047	0.055	0.069	0.037
	(0.055)	(0.063)	(0.063)	(0.061)	(0.063)	(0.061)	(0.062)	(0.062)	(0.059)
Observations	33611	33611	33611	33611	33611	33611	33611	33611	33611
Covariates:									
Further vacancy posting									
Average AI vacancy share 2016-19	no	yes	yes	yes	yes	yes	yes	yes	yes
Number of all vacancies in 2015	no	no	yes	no	no	no	no	no	yes
Establishment properties									
AKM effects 2010-2017	no	no	no	yes	no	no	no	no	yes
... referring to 2015									
Establishment size	no	yes	yes	yes	yes	yes	yes	yes	yes
Establishment age	no	no	no	no	yes	no	no	no	yes
Economic sectors	no	no	no	no	no	yes	no	no	yes
Federal states	no	no	no	no	no	no	yes	no	yes
Occupational shares	no	no	no	no	no	no	no	yes	yes

Notes: This table reports the estimation results for regressing overall employment growth and employment growth in jobs differentiated by qualification levels on the AI vacancy share in 2015. All sectors are included but we exclude temporary work agencies. For regressions with the employment growth rates we exclude establishments with the 5 per cent highest growth rates. Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.10

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP). Integrated Employment Biographies (IEB).

Table 11: Employment growth 2015 - 2019 by employee's qualification levels, and AI skills demand, Establishments w/o AI producing sectors

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Overall Employment Growth									
AI vacancy share in 2015	-0.002	-0.042	-0.042	-0.045	-0.046	-0.046	-0.040	-0.052	-0.065
	(0.052)	(0.055)	(0.055)	(0.054)	(0.055)	(0.055)	(0.055)	(0.051)	(0.051)
Observations	32082	32082	32082	32082	32082	32082	32082	32082	32082
Unskilled Employment Growth									
AI vacancy share in 2015	-0.138	-0.149	-0.149	-0.150	-0.153	-0.154	-0.145	-0.159	-0.162
	(0.109)	(0.106)	(0.106)	(0.107)	(0.107)	(0.107)	(0.107)	(0.107)	(0.109)
Observations	32454	32454	32454	32454	32454	32454	32454	32454	32454
Qualified Employment Growth									
AI vacancy share in 2015	0.016	-0.015	-0.015	-0.019	-0.018	-0.023	-0.014	-0.029	-0.040
	(0.055)	(0.056)	(0.056)	(0.054)	(0.057)	(0.054)	(0.056)	(0.050)	(0.050)
Observations	32229	32229	32229	32229	32229	32229	32229	32229	32229
Highly Qualified Employment Growth									
AI vacancy share in 2015	0.198***	0.074	0.074	0.070	0.075	0.062	0.068	0.071	0.051
	(0.070)	(0.081)	(0.081)	(0.078)	(0.081)	(0.077)	(0.079)	(0.078)	(0.074)
Observations	31837	31837	31837	31837	31837	31837	31837	31837	31837
Covariates:									
Further vacancy posting									
Average AI vacancy share 2016-19	no	yes	yes	yes	yes	yes	yes	yes	yes
Number of all vacancies in 2015	no	no	yes	no	no	no	no	no	yes
Establishment properties									
AKM effects 2010-2017	no	no	no	yes	no	no	no	no	yes
... referring to 2015									
Establishment size	no	yes	yes	yes	yes	yes	yes	yes	yes
Establishment age	no	no	no	no	yes	no	no	no	yes
Economic sectors	no	no	no	no	no	yes	no	no	yes
Federal states	no	no	no	no	no	no	yes	no	yes
Occupational shares	no	no	no	no	no	no	no	yes	yes

Notes: This table reports the estimation results for regressing overall employment growth and the employment growth in jobs differentiated by qualification levels on the AI vacancy share in 2015. Establishments from ICT and professional services are excluded. Additionally, we exclude temporary work agencies. For regressions with the employment growth rates we exclude establishments with the 5 per cent highest growth rates. Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.10

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP). Integrated Employment Biographies (IEB).

The further panels show results for employment growth by the different qualification levels. Overall, we see only small differences of the employment growth rates related to AI activity: first, the point estimates for unskilled employment growth now turn negative in the two tables implying a lower employment growth for unskilled employees in establishment with AI activity. However, the effects are insignificant.

For qualified employment growth we find similar results as for the required skill levels. The point estimates of the growth rate differences are also negative and of similar magnitude as for the skilled jobs.

The second difference is that the positive employment growth for the highly qualified employees turns insignificant based on the sample with all establishments in the fully specified model (col. 9 in each of the Table 8 or Table 9). Moreover, the magnitude of the growth rate difference is much smaller for all establishments (0.037, col. 9 in Table 8). When we exclude establishments from ICT and professional services, the point estimate has a magnitude of 0.051 (col. 9 in Table 9). However, both estimates are insignificant.

The results again point to the absence of sizeable displacement effects. However, in contrast to our main analysis we find no higher growth in highly qualified employment.

This may be driven by the fact that the group of highly qualified employees entails a larger group than employees in highly complex jobs; because formally the group of highly qualified employees comprises a mix of qualifications that allow individuals access to either complex or highly complex jobs.

5.2 Exploiting the panel dimension of the data

Next, we exploit the panel structure of our data to estimate a short run relationship between AI activity and employment growth. Thereby, we test whether the results in the main analysis change if we exploit further variation in the AI vacancy share from other years. Since our job ads data are repeated cross sections, we do not observe all job postings of an establishment in each year. Hence, we have a unbalanced panel of establishments and their job posting activity in each year. Moreover, together with the small time span we can consider, which is five years, we cannot include a large number of lags in the model (e.g., Babina et al. 2022 find that AI investments translate into employment growth after about three years). However, in line with our previous analyses the findings from this exercise further provide no evidence for sizeable displacement effects.

We estimate the following model as a robustness check:

$$\Delta y_{e,t} = \alpha + \beta \frac{v_{e,t-1}^{AI}}{v_{e,t-1}^{all}} + x'_{e,t-1}\gamma + \epsilon_{e,t}$$

where we test for a relationship of the AI vacancy share in $t - 1$ and employment growth from the same period $t - 1$ to the next period t. The vector $x'_{e,t-1}$ the same covariates as in the main analysis and we additionally control for year fixed effects. We start by estimating equation (3) with pooled OLS and contrast the results with the results from using a fixed effects estimator. Moreover, to address the unbalanced nature of our panel we estimate the same model but restrict the data to establishments for which we have at least three observations. As for our main analysis we measure employment growth in per cent and we estimate standard errors that are robust to heteroscedasticity.

Table 12: Employment growth and AI skills demand in the panel data set, all establishments

	OLS (1)	OLS (2)	OLS (3)	FE (4)	FE (5)
Overall Employment					
AI vacancy share (t-1)	0.016**	0.014*	0.013	-0.000	-0.000
	(0.007)	(0.007)	(0.008)	(0.011)	(0.011)
Observations	448460	448460	321464	448460	321464
Unskilled jobs					
AI vacancy share (t-1)	0.016	0.015	0.004	0.018	0.012
	(0.012)	(0.012)	(0.016)	(0.029)	(0.030)
Observations	446619	446619	320507	446619	320507
Skilled jobs					
AI vacancy share (t-1)	0.013	0.011	0.010	-0.001	-0.001
	(0.010)	(0.010)	(0.011)	(0.018)	(0.018)
Observations	454456	454456	324268	454456	324268
Complex jobs					
AI vacancy share (t-1)	0.017	0.016	0.011	0.002	-0.004
	(0.012)	(0.012)	(0.014)	(0.022)	(0.022)
Observations	442545	442545	318002	442545	318002
Highly complex jobs					
AI vacancy share (t-1)	0.012	0.012	0.022*	-0.008	-0.017
	(0.010)	(0.010)	(0.012)	(0.021)	(0.019)
Observations	439970	439970	317487	439970	317487
Covariates: **Fixed Effects**					
Year fixed effects	yes	yes	yes	yes	yes
Further vacancy posting (t-1)					
Number of all vacancies	yes	yes	yes	yes	yes
Establishment properties					
AKM effects 2010-2017	no	yes	yes	no	no
... referring to t-1					
Establishment size	yes	yes	yes	yes	yes
Establishment age	yes	yes	yes	yes	yes
Economic sectors	yes	yes	yes	yes	yes
Federal states	yes	yes	yes	yes	yes
Occupational shares	yes	yes	yes	yes	yes
Observations requirement					
Restricted to ≥ 3 observations	no	no	yes	no	yes

Notes: This table reports the estimation results for regressing the overall employment growth and employment growth in jobs differentiated by skill requirement level on the AI vacancy share using panel data. Unskilled jobs require no formal qualification or only short term training. Skilled jobs require a formal vocational education training of at least 2 years. Complex jobs require a university degree or master craftman's certificate. Highly complex jobs require a university degree or similar and, beyond that, profound professional experience or further formal highly specialised qualification certificates like a doctorate or a habilitation. All industries are included. For regressions with the employment growth rates we exclude establishments with the 5 per cent highest growth rates. Robust standard errors are in parentheses.
*** $p<0.01$, ** $p<0.05$, * $p<0.10$

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP). Integrated Employment Biographies (IEB).

Table 12 shows the results including all sectors in the sample. Column (1) shows the pooled OLS estimation without including *AKM effects 2010-2017* and a restriction on the minimum number of observations, then we include *AKM effects 2010-2017* (col. 2) and restrict to establishments with at least 3 observations (col. 3). Then, we apply the fixed effects estimator (col. 4) and again restrict the sample to establishments with at least three observations (col. 5).

The first row shows the relationship of an increase in the AI vacancy share by one per- centage point and subsequent overall employment growth measured in percentage points. Without considering *AKM effects 2010-2017* an increase in the AI vacancy share by one percentage point is associated with an overall employment growth rate of 0.016 percentage points. The estimate is statistically significant at the five per cent level (standard error 0.007). After including *AKM effects 2010-2017* the point estimate is only slightly reduced (0.014). Restricting the data to establishments that have at least three observations slightly further decreases the point estimate and slightly increases the estimated standard error so that the estimate is not statistically significant anymore. As soon as we apply a fixed effects estimator to exploit the variation of the AI vacancy share over time within the establishment, the point estimate becomes negligible small and statistically insignificant. We only find a statistically significant larger employment growth in highly complex jobs once we include *AKM effects 2010-2017* and restrict the sample to establishments with at least three observations (col. 3). In the further specifications we find no statistically significant effects on the respective employment growth rates.

Table 13: Employment growth and AI skills demand in the panel data set, establishments in sectors outside ICT and professional services

	OLS (1)	OLS (2)	OLS (3)	FE (4)	FE (5)
Overall Employment					
AI vacancy share (t-1)	0.010	0.009	0.010	-0.000	-0.000
	(0.008)	(0.008)	(0.009)	(0.013)	(0.013)
Observations	422913	422913	303833	422913	303833
Unskilled jobs					
AI vacancy share (t-1)	0.024	0.023	0.009	0.004	-0.006
	(0.015)	(0.015)	(0.018)	(0.033)	(0.034)
Observations	419927	419927	302326	419927	302326
Skilled jobs					
AI vacancy share (t-1)	0.010	0.009	0.003	-0.019	-0.019
	(0.011)	(0.011)	(0.012)	(0.019)	(0.019)
Observations	428639	428639	306622	428639	306622
Complex jobs					
AI vacancy share (t-1)	0.024**	0.024*	0.024*	0.014	0.012
	(0.012)	(0.012)	(0.013)	(0.022)	(0.022)
Observations	418786	418786	301138	418786	301138
Highly complex jobs					
AI vacancy share (t-1)	0.001	0.001	0.009	-0.027	-0.026
	(0.012)	(0.012)	(0.014)	(0.023)	(0.020)
Observations	414175	414175	301030	414175	301030
Covariates: Fixed Effects					
Year fixed effects	yes	yes	yes	yes	yes
Further vacancy posting (t-1)					
Number of all vacancies	yes	yes	yes	yes	yes
Establishment properties					
AKM effects 2010-2017	no	yes	yes	no	no
... referring to t-1					
Establishment size	yes	yes	yes	yes	yes
Establishment age	yes	yes	yes	yes	yes
Economic sectors	yes	yes	yes	yes	yes
Federal states	yes	yes	yes	yes	yes
Occupational shares	yes	yes	yes	yes	yes
Observations requirement					
Restricted to ≥ 3 observations	no	no	yes	no	yes

Notes: This table reports the estimation results for regressing the overall employment growth and employment growth in jobs differentiated by skill requirement level on the AI vacancy share using panel data. Unskilled jobs require no formal qualification or only short term training. Skilled jobs require a formal vocational education training of at least 2 years. Complex jobs require a university degree or master craftman's certificate. Highly complex jobs require a university degree or similar and, beyond that, profound professional experience or further formal highly specialised qualification certificates like a doctorate or a habilitation. Establishments in ICT and professional services are excluded. For regressions with the employment growth rates we exclude establishments with the 5 per cent highest growth rates. Robust standard errors are in parentheses.
*** p<0.01, ** p<0.05, * p<0.10

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP). Integrated Employment Biographies (IEB).

Table 13 shows the same estimations but excluding AI producing industries ICT and professional services. We find no significant effects on overall employment growth. We only find statistically significant effects on employment growth in complex jobs based on the pooled OLS estimation.

Without including *AKM effects 2010-2017* and without restricting to a minimum number of observations per establishment (col. 1) we find a higher employment growth in complex jobs by 0.024 percentage points associated with an increase in the AI vacancy share in the previous year by one percentage point (standard error of 0.012). In the specification that also includes *AKM effects 2010-2017* and based on the restricted data set with establishments with at least three observations (col. 3) the point estimate (0.024) remains statistically significant at the 10 percent level. However, after applying the fixed effects estimator the estimated effects become smaller and not significant (col. 4-5). Overall, these estimations corroborate our main finding that we do not find evidence for sizeable displacement effects at the establishment level.

6 Conclusion

In this study we analyse whether and how AI activities, i.e., efforts to develop, implement or use artificial intelligence technologies, have implications on the labour demand at the establishment level.

In doing so, we measure a proxy for AI activities by extracting skill requirements that are directly related to AI technologies from job postings. To better understand how those activities are related to the demand for other skills, we also extract detailed hard skill requirements. Since our job ads data further allows an exact and direct link to administrative establishment data, we also analyse how AI activities in the establishments are related to employment growth in total and in four different job groups according to a standardized measure of required skill levels that we also obtain from our administrative job ads data.

Besides our general implications of our analyses regarding the relationship of establishments' AI activities and their labour demand, our study also presents some novel stylized facts about the implementation and utilization of AI technologies in Germany for the years 2015 to 2019.

We find AI activity to be low in Germany which we measure by the share of identified AI vacancies. Still, we observe an upward trend in the AI vacancy shares between 2015 and 2019. This suggests that German establishments were at an early stage of AI development. Consistent with this, we find that AI activity has diminishing effects on the demand for other non-AI skills. Put differently, we find no evidence for a sizeable redundancy of workers' skills among the considered establishments. Assuming that the changes in the demand for skills indicate changes in the labour task content this finding suggests that AI technologies have little impact on the tasks for exposed workers, yet. Consequently, this provides evidence against sizeable displacement effects at the task level related to AI.

We further find no evidence for sizeable displacement effects. Even after excluding industries that typically develop or implement AI for other industries, establishments with AI activity do not reveal significant effects in their overall employment growth. The analysis of employment growth in jobs grouped by different required skill levels suggests that AI activity is related to a higher employment growth in highly complex jobs. These jobs potentially cover tasks for developing or implementing technologies which may explain the positive relationship between AI activity and higher employment growth in these jobs.

So far, our results describe some robust implications of utilising AI technologies for the labour market in an early adoption phase.

Future research may further exploit the (causal) mechanisms of the implementation of more specific technologies like the widely discussed generative AI on task contents and employment structures.

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A Appendix on additional tables

Table A1: Overview of the AI skills from the AI dictionary

Number	AI skill
1	AI ChatBot
2	AI KIBIT
3	ANTLR
4	AWS Panorama
5	AdaBoost algorithm
6	Affective Computing
7	Amazon CodeGuru
8	Amazon Comprehend
9	Amazon Comprehend Medical
10	Amazon DevOps Guru
11	Amazon Forecast
12	Amazon Fraud Detector
13	Amazon HealthLake
14	Amazon Kendra
15	Amazon Lex
16	Amazon Lookout für Equipment
17	Amazon Lookout für Metrics
18	Amazon Lookout für Vision
19	Amazon Monitron
20	Amazon Omics
21	Amazon Personalize
22	Amazon Polly
23	Amazon Rekognition
24	Amazon SageMaker
25	Amazon Textract
26	Amazon Transcribe
27	Amazon Translate
28	Apertium
29	Applicant Tracking System
30	Artificial Intelligence
31	Augmented Analytics
32	Automated Driving
33	Automated optical inspection (AOI)
34	Autonomous Driving
35	Autonomous Systems
36	Azure AI Content Safety
37	Azure Anomaly Detector
38	Azure Bot Service
39	Azure Cognitive Search
40	Azure Cognitive Services
41	Azure Content Moderator
42	Azure Custom Vision
43	Azure Data Science Virtual Machines
44	Azure Databricks
45	Azure Form Recogniser
46	Azure Health Bot
47	Azure Immersive Reader
48	Azure Kinect DK
49	Azure Language Understanding (LUIS)
50	Azure Machine Learning
51	Azure Metrics Advisor
52	Azure Open Datasets
53	Azure OpenAI Service
54	Azure Personaliser
55	Azure Project Bonsai
56	Azure QnA Maker
57	Azure Speaker Recognition
58	Azure Speech translation
59	Azure Speech-to-Text
60	Azure Translator

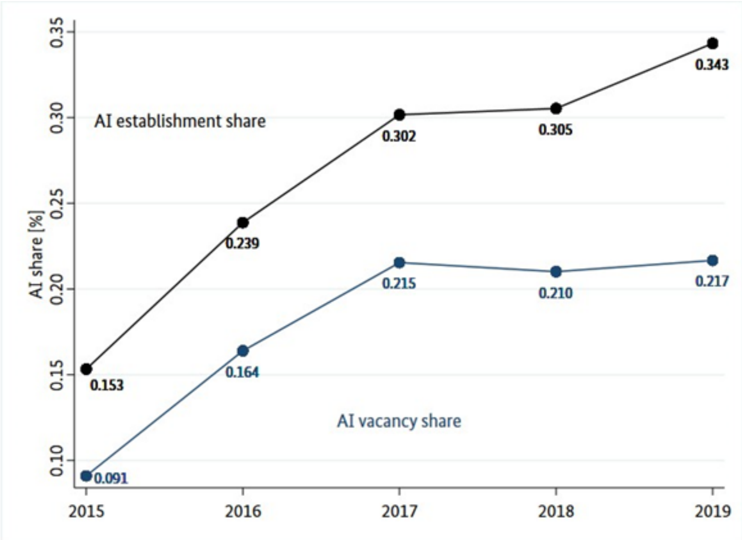
Number	AI skill
61	Azure Video Indexer
62	Bayesian optimization
63	BindsNET
64	Blue Prism
65	Boosting
66	Business intelligence
67	Caffe
68	Character generation
69	Character recognition
70	ChatGPT
71	Chi Square Automatic Interaction Detection (CHAID)
72	Classification Algorithms
73	Clustering Algorithms
74	Cognitive Computing
75	Colab
76	Collaborative Filtering
77	Computational Linguistics
78	Computer Vision
79	Curated Shopping
80	DALL-E
81	Dauerstrichradar
82	Decision Trees
83	Deep Learning
84	Deeplearning4j
85	Dimensionality Reduction
86	Direction generation
87	Direction recognition
88	Distinguo
89	Electromechanical Systems
90	Embedded Vision
91	Environment Perception
92	Expert System
93	Face generation
94	Face recognition
95	Feature Extraction
96	GPT-1
97	GPT-2
98	GPT-3
99	GPT-4
100	Generative Adversarial Networks
101	Google AI Infrastructure
102	Google AutoML
103	Google Cloud Machine Learning Platform
104	Google Contact Center AI
105	Google Dialogflow
106	Google Document AI
107	Google Media Translation
108	Google Natural Language API
109	Google Recommendations AI
110	Google Text-to-Speech
111	Google Translation AI
112	Google Vertex AI
113	Google Video AI
114	Google Vision AI
115	Gradient boosting
116	H2O
117	IBM Cloud Paks
118	IBM Watson
119	IPSoft Amelia
120	Image Processing
121	Image Recognition
122	Image Tagging
123	Image generation
124	Information Extraction
125	Ithink
126	KNIME
127	Keras
128	Kernel Methods
129	Knowledge Engineering

Number	AI skill
130	Knowledge Extraction
131	Knowledge Representation and Reasoning
132	Kubeflow
133	Latent Dirichlet Allocation
134	Latent Semantic Analysis
135	Least absolute shrinkage and selection operator
136	Legal Technology
137	Lexalytics
138	Lexical Acquisition
139	Lexical Semantics
140	Libsvm
141	Lidar
142	Long Short-Term Memory (LSTM)
143	MLPACK (C++ library)
144	MLlib
145	MXNet
146	Machine Learning
147	Machine Learning Operations (MLOps)
148	Machine Translation
149	Machine Vision
150	Madlib
151	Mahout
152	Mask R-CNN
153	Matplotlib
154	Microsoft Cognitive Toolkit
155	Mlflow
156	Mlpy
157	MoSes
158	Modular Audio Recognition Framework
159	Motion Planning
160	Motoman Robot Programming
161	ND4J (software)
162	Natural Language Inference
163	Natural Language Processing
164	Natural Language Toolkit
165	Natural Language Understanding
166	Nearest Neighbor Algorithm
167	Neural Networks
168	Neuromorphic Computing
169	Numpy
170	Object Recognition
171	Object Tracking
172	OpenCV
173	OpenNLP
174	Path Planning
175	Pattern Recognition
176	Perceptron
177	Predictive Maintenance
178	Predictive Models
179	Pybrain
180	Random Forests
181	RapidMiner
182	Recommender Systems
183	Reinforcement Learning
184	Remote Sensing
185	Robot Framework
186	Robot Operating System (ROS)
187	Robot Programming
188	Robot learning
189	Robotic Process Automation
190	Robotic Systems
191	Semantic Driven Subtractive Clustering Method (SDSCM)
192	Sentiment Analysis / Opinion Mining
193	Sentiment Classification
194	Servo Drives/Motors
195	Shogun
196	Simultaneous Localization and Mapping (SLAM)
197	Speech Recognition
198	Speech generation

Number	AI skill
199	Stochastic Gradient Descent
200	Superml
201	Supervised Learning
202	Support Vector Machines
203	TensorFlow
204	TensorQuant
205	Text Mining
206	Text generation
207	Text recognition
208	Text to Speech
209	Theano
210	Tokenization
211	Torch
212	Unsupervised Learning
213	Video generation
214	Video processing
215	Video recognition
216	Video-based Driver Assistance Systems
217	Virtual Agents
218	Visual inventory management
219	Voicebot
220	Vowpal Wabbit
221	Weka
222	Word2Vec
223	Xgboost
224	Zero-shot learning
225	alteryx
226	kernLab
227	mlr3
228	pytorch
229	scikit-learn
230	spaCy
231	uipath

B Appendix on additional figures

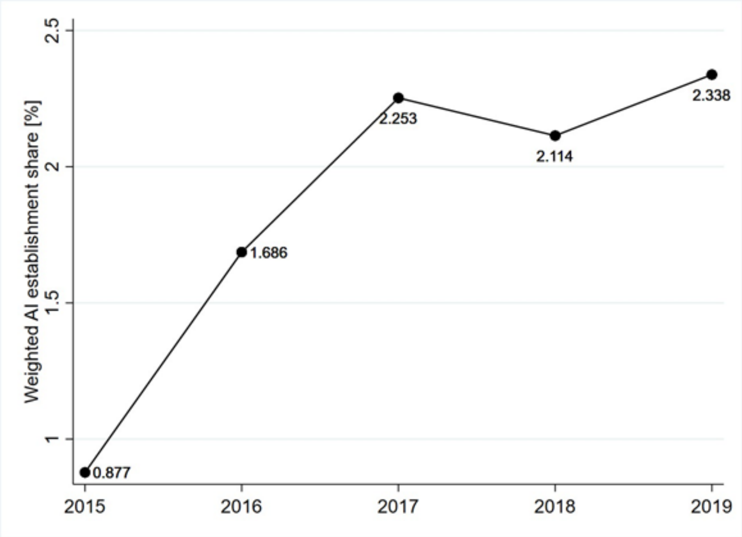
Figure A1: AI establishment shares and AI vacancy shares



Note: Vacancies from temporary work agencies are excluded. The AI vacancy share is defined as the share of vacancies containing at least one AI skill in the job description on all vacancies. The AI establishment share is calculated by dividing the number of establishments that post at least one AI vacancy in a given year by the number of all establishments in our sample. Both shares are measured in per cent.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year.

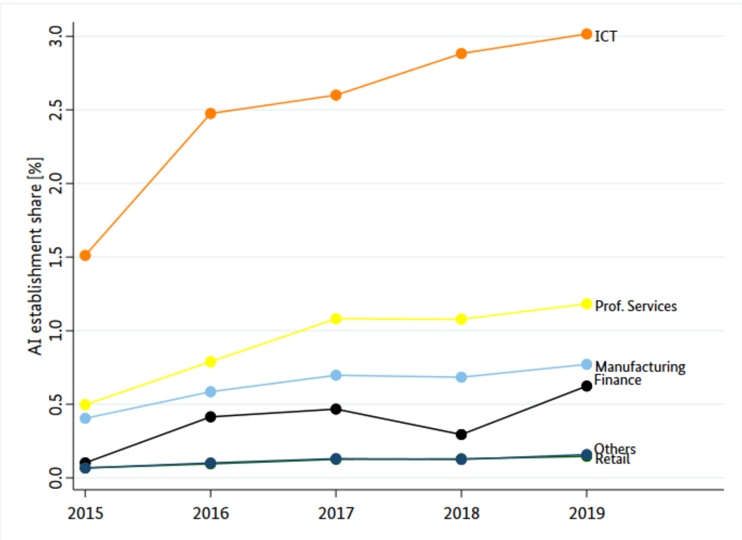
Figure A2: AI establishment shares weighted by employment



Note: Vacancies from temporary work agencies are excluded. The AI establishment share is calculated by dividing the number of establishments that post at least one AI vacancy in a given year by the number of all establishments in our sample. The shares are measured in per cent.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP).

Figure A3: Shares of establishments posting at least one AI vacancy across industries



Note: Vacancies from temporary work agencies are excluded. Establishments with overall employment growth above the 95th percentile are excluded. The AI establishment shares are calculated by dividing the number of establishments that post at least one AI vacancy in a given year and by the number of all establishments in a given industry. The shares are measured in per cent.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP).

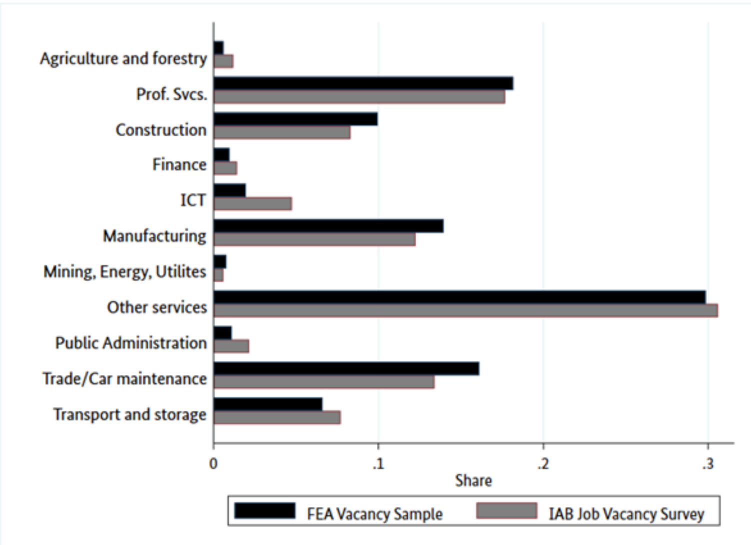
C Appendix on data representativeness

We compare the structure of the job ads data with the structure of the IAB JVS to get information on how representative our job ads data is. Both data sets can be characterised as cross sectional data sets. Our job ads data refers to mid of October of each year. The IAB JVS refers to an unspecific point in time in the 4th quarter of each year. Therefore both data refer roughly to the same time period. We compare the vacancy shares across industries and required skill levels.

Figure A4 shows vacancy shares of the job ads data and the IAB JVS for 2015 across economic sectors. In 2015 there are only slight differences in the sectoral shares of the job ads data and the IAB JVS. The Information and Communication Technology (ICT) sector seems to be slightly underrepresented in the job ads data. In contrast, the trade and car maintanance, the construction and the manufacturing sector are slightly overrepresented. The next Figure Figure A5 shows the corresponding sectoral shares for 2019. In 2019 the overrepresentation in the manufacturing and the trade and car maintenance sector is larger compared 2015. Simultaneously, other services (besides professional services) are now more underrepresented.

Regarding the required skill levels, in the IAB JVS the information on ”complex jobs” and ”highly complex jobs” are aggregated. For the comparison, we, therefore, also aggregated the information on these skill levels in our job ads data. We find only small differences (Figure A6). As for the sectoral shares, in 2015 the distributions of the of the IAB JVS and the job ads data across required skill levels match very closely. In 2019 ”skilled jobs” are slightly underrepresented in the while the group of complex and ”highly complex jobs” are slightly overrepresented in the job ads data compared to the IAB JVS.

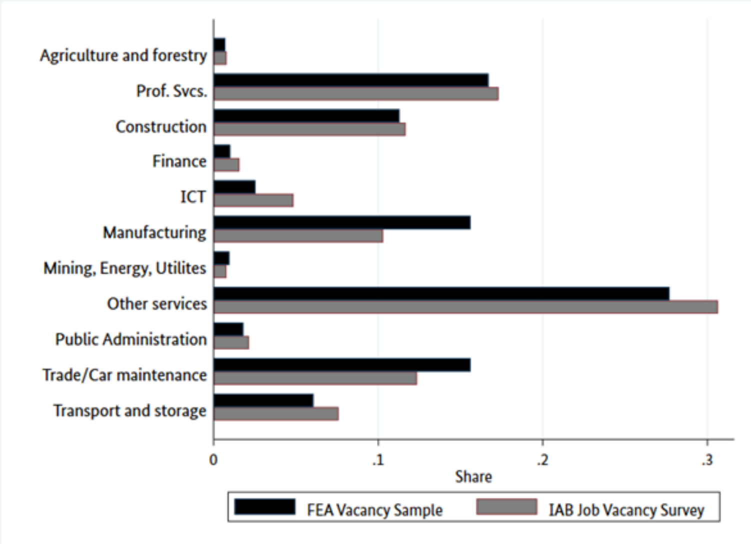
Figure A4: Industry shares in the vacancy data and the IAB Job Vacancy Survey (2015)



Note: Data on the vacancies are from the BA-JOBBÖRSE. Vacancies from temporary work agencies are excluded.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. IAB Job Vacancy Survey (see Bossler et al. 2022 for details).

Figure A5: Industry shares in the vacancy data and the IAB Job Vacancy Survey (2019)



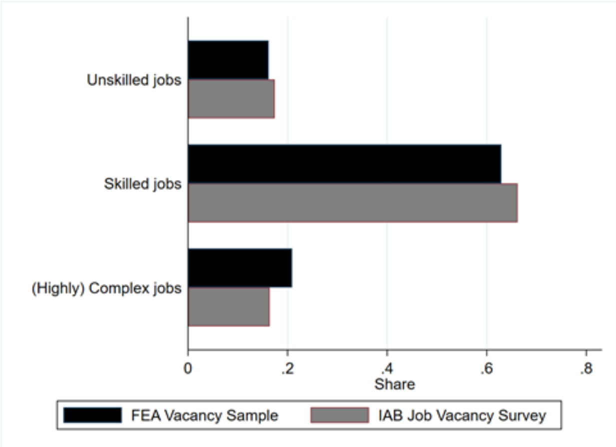
Note: Data on the vacancies are from the BA-JOBBÖRSE. Vacancies from temporary work agencies are excluded.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. IAB Job Vacancy Survey (see Bossler et al. 2022 for details).

Figure A6: Shares in the vacancy data and the IAB Job Vacancy Survey across required skill levels (2015 and 2019)

(a) 2015

(b) 2019



Note: Vacancies from temporary work agencies are excluded.

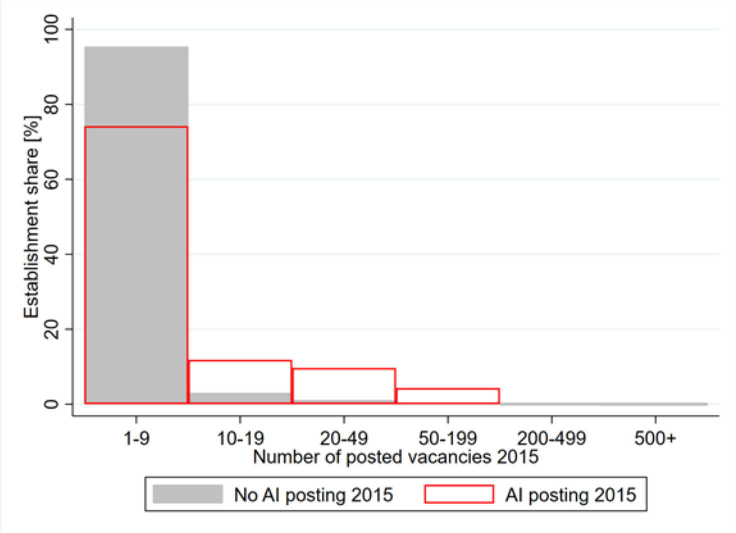
Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. IAB Job Vacancy Survey (see Bossler et al. 2022 for details).

D Appendix on establishment properties

In this section we describe the distribution of establishment property variables across establishments either with or without AI activity in 2015 more in detail (see also section 3.2 of the main text).

Figure A7 shows the establishment shares posting between 1-9, 10-19, 20-49, 50-199, 200-499 or 500 and more vacancies for both groups. Establishments with AI activity are less likely to post 1-9 vacancies but more likely to post between 10-19, 20-49 or 50-199 vacancies in 2015. However, there are no establishments with AI activity with 200-499 or 500 and more posted vacancies while there are very few other establishments with overall vacancies within these ranges.

Figure A7: Distribution of overall vacancy postings 2015 across establishments

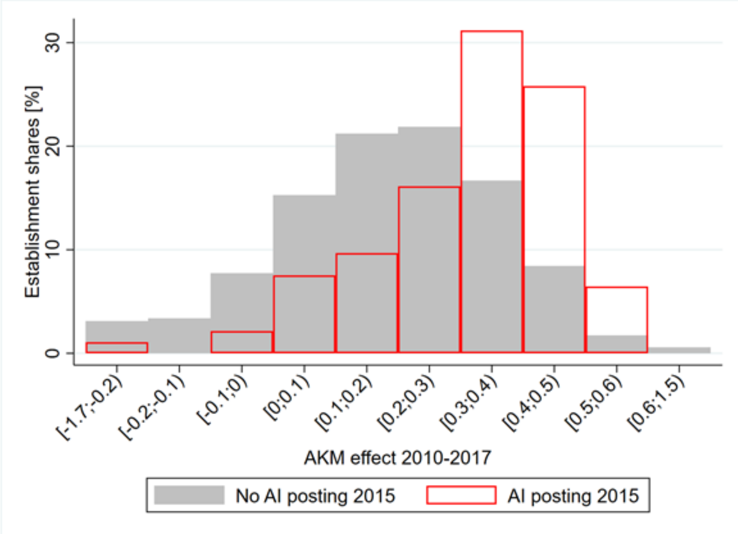


Note: Vacancies from temporary work agencies are excluded. Establishments with overall employment growth above the 95th percentile are excluded.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP).

Figure A8 shows the distribution of establishments across ten AKM effects 2010-2017 value bins. Those bins, with exception of the two bins containing the minimum and the maximum value, include establishments within an AKM effect value range of 0.1 log points. The distribution of establishments with AI vacancy posting in 2015 along AKM effects is clearly right skewed compared to the distribution of other establishments. This indicates that establishments with AI activity at this early stage of development of AI tend to pay higher establishment-specific wage premia to their employees than other establishments in our sample.

Figure A8: Distribution of establishments over AKM effects



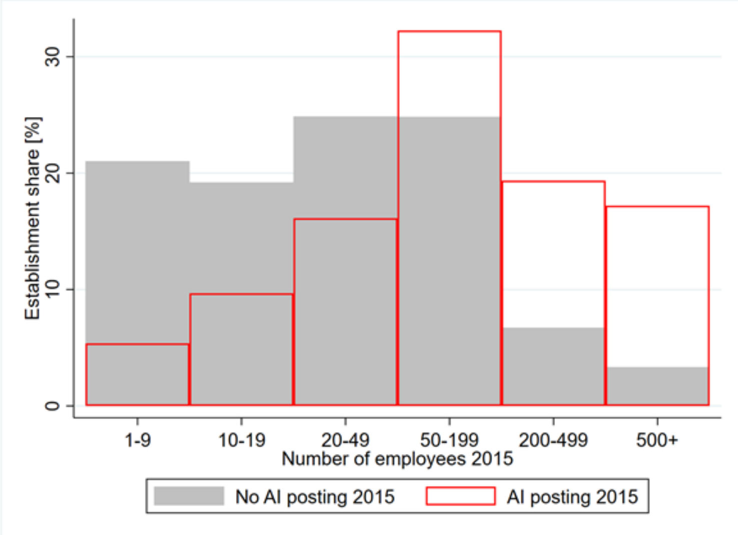
Note: Establishments with overall employment growth above the 95th percentile are excluded. AKM effects are estimated by Bellmann et al. (2020) and represent establishment-specific wage premia (considering the log daily real wage) as further described in the main text. Ranges of AKM effects 2010-2017 are on the horizontal axis. E.g, the value range [0.1;0.2) refers to all establishments with AKM effects between 0.1 and smaller than 0.2. Both ends of the distribution of AKM effects are cropped so that the first value range entails AKM effects between -2.3 and smaller than -0.6. The last value range entails AKM effects between 0.3 and smaller than 1.6.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP).

Figure A9 plots the share of establishments in our sample having by different size groups according to their number of employees.[22] As before, it contrasts the distribution of establishments across different employment size classes for establishments with AI activity in 2015 to other establishments. E.g., the share of establishments with AI activity amounts to 36.08 per cent for the group of establishments with 200 and more employees whereas the same share for establishments without AI activity amounts to 9.4 per cent (consider the last two columns on the right hand side of Figure A9). Generally, the distribution of establishments with AI activity across the bins containing different ranges of employment levels is skewed to the right compared to other establishments.

[22] We distinguish establishments with 1 to 9, 10 to 19, 20 to 49, 50 to 199, 200 to 499 and 500 and more employees in 2015.

Figure A9: Establishment shares for different size classes, with and without AI vacancy posting, 2015



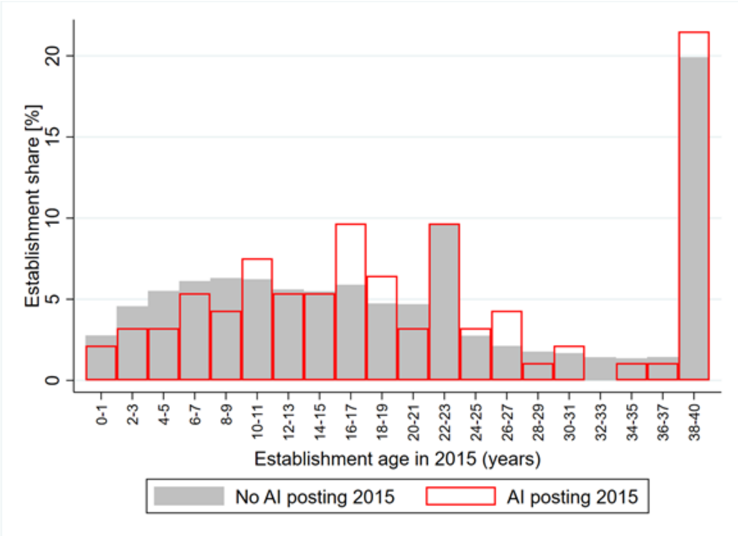
Note: Establishments with overall employment growth above the 95th percentile are excluded. Establishment employment levels based on data from the Establishment History Panel (BHP).

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP).

Figure A10 shows the shares of establishments per age group. The distributions of establishments across different ages with and without AI vacancy postings in 2015 are very similar. However, the share of the youngest age cohort, thus start up establishments, is even lower compared with the (low) share of establishments in the respective age group that did not post AI vacancies.

We finally compare the establishment distributions of those with and without AI activities in 2015 across employment share bins separately for each of the four required skill levels; see Figure A11. While more establishments with AI activity tend to have higher employment shares in complex and highly complex jobs compared to other establishments, the opposite is true for the employment shares in unskilled and skilled jobs.

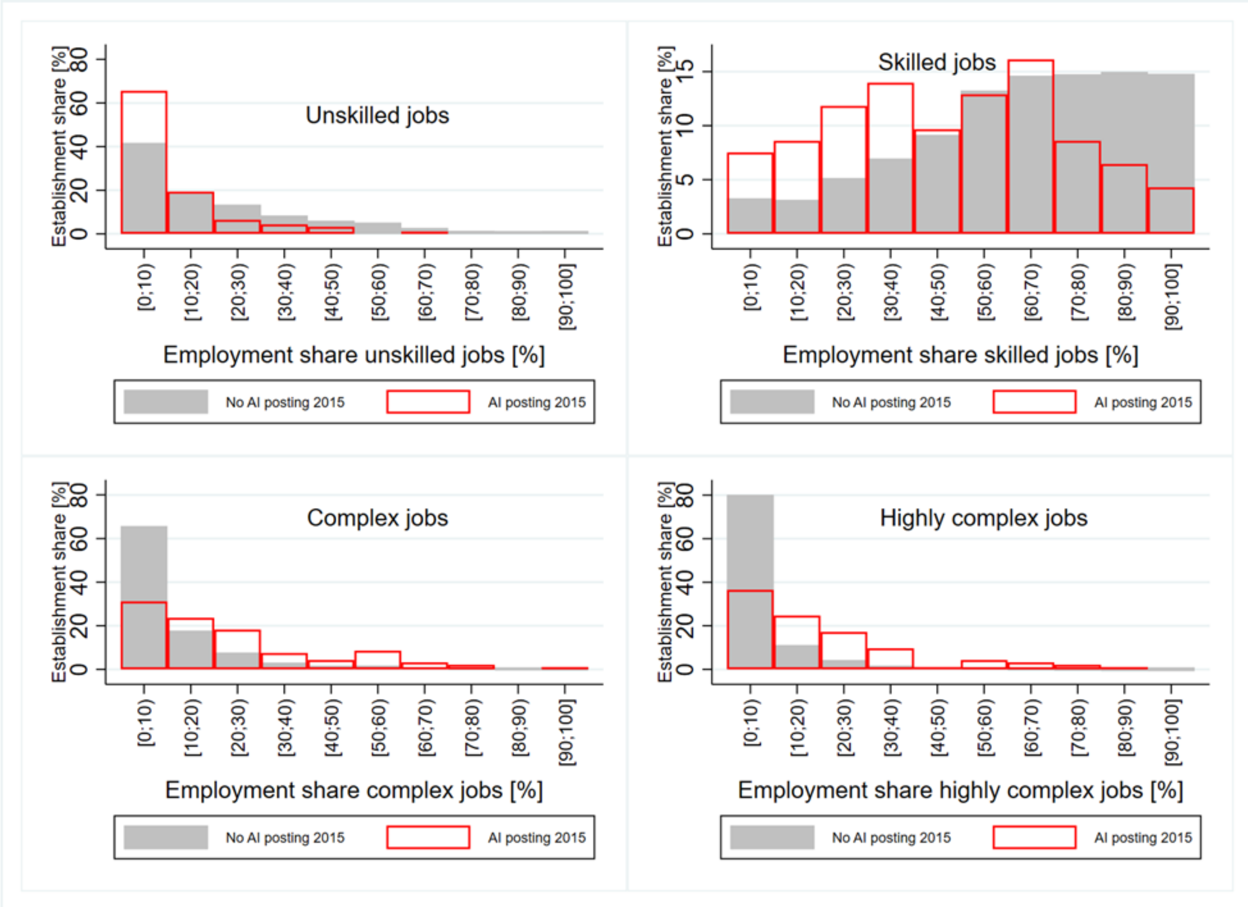
Figure A10: Establishment shares by establishment age in years, with and without AI vacancy posting, 2015



Note: Establishments with overall employment growth above the 95th percentile are excluded. Establishment age calculated based on data from the Establishment History Panel (BHP). Since the BHP contains data starting in 1975, there is a high share of firms being documented as founded in 1975. The relatively high share of establishments with an age of 25 years arises due to reunification in Germany. Each bin contains two establishment age years so that the first bin represents the share of establishments with age zero and one.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP).

Figure A11: Distribution of establishments by job shares in different required skill levels, with and without AI vacancy posting, 2015



Note: Establishments with overall employment growth above the 95th percentile are excluded. Job shares are calculated based on data from the Establishment History Panel. The shares are measured in per cent. The columns show the distribution of establishments entailing a particular range of employment shares in the respective skill level. The horizontal axis denotes a range of employment shares. E.g., in each figure the value range [0;10) refers to all establishments with employment share values between 0 and lower 10.

Source: JOBBÖRSE of the German Federal Employment Agency (FEA). Job ads with full support by the FEA. Cross sections for the years 2015 to 2019 with a reference date of October 15th of each year. Establishment History Panel (BHP).

Figures

Tables

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