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Abstract

This paper investigates the impact of artificial intelligence (AI) adoption in production processes on workplace training practices, using firm-level data from the BIBB establishment panel on training and competence development (2019-2021). The findings reveal that AI adoption reduces the provision of continuing training for incumbent workers while increasing the share of high-skilled new hires and decreasing medium-skilled hires, thereby contributing to skill polarization. However, AI adoption also increases the number of apprenticeship contracts, particularly in small and medium-sized enterprises (SMEs), underscoring the ongoing importance of apprenticeships in preparing future workers with the skills needed to apply AI in production.

JEL Classification: J23, J24, M53, O33
Keywords: Artificial Intelligence, Technological Change, Automation, Apprenticeship Training, Human Capital.

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1 Introduction

The adoption of artificial intelligence (AI) is fundamentally transforming production processes across industries, leading to significant shifts in labor demand (Acemoglu et al., 2022; Acemoglu and Restrepo, 2019). As AI-driven systems become more prevalent, concerns have arisen about task displacement and reconfiguration across all skill levels, including high-skill tasks (Webb, 2020), as well as their effects on workers' well-being (Giuntella et al., 2023). Conversely, Autor (2024) argues that AI can strengthen the middle class by democratizing decision-making tasks traditionally reserved for elite professionals, enabling workers with intermediate training to perform higher-value roles. By augmenting, rather than replacing, human expertise, AI can narrow skill gaps, enhance productivity, and create new labor market opportunities. In this context, a critical yet underexplored aspect of this transformation is how AI adoption influences human resource development, particularly in the provision of continuing training for incumbent workers and apprenticeship programs.

While a recent U.S. survey revealed that 94% of individuals are willing to learn new skills to work with AI, only 5% of organizations are undertaking large-scale reskilling efforts (Shook and Daugherty, 2024). Similar concerns about the adequacy of human resource development in response to AI adoption are echoed in reports by World Economic Forum (2024) and Deloitte (2023). In Germany, where the dual apprenticeship system is a key pathway into the labor market, changes in firms' investment in apprenticeship training could have far-reaching implications. More than half of each cohort earns upper secondary education through apprenticeships, making any reduction in these opportunities potentially detrimental for young people's education pathways. Meanwhile, AI-induced automation could lead to layoffs, particularly among older workers. Understanding whether AI adoption is accompanied by upskilling initiatives for current employees is thus critical.

Raj and Seamans (2019) highlighted the importance of firm-level data for understanding the effects of AI adoption, but progress in this area has been limited. A notable exception is Czarnitzki et al. (2023), who, using German firm-level data, found that AI adoption is linked to increased productivity, but their data does not include any information on workplace training. Firms may automate tasks that require significant training, as argued by Feng and Graetz (2020), potentially contributing to job polarization by shifting workers toward either simpler tasks or more complex ones requiring higher skills. U.S. evidence supports this trend, showing that technological advances increase demand for both high- and low-skilled workers while reducing demand for medium-skilled tasks. However, in Germany, the cost-effectiveness of apprenticeship training, with its state-supported vocational education and lower wages for apprentices, may result in a different response to AI adoption. Moreover, younger workers, often considered "digital natives," may adapt more easily to AI, making apprenticeships an attractive option for firms seeking to develop future talent.

This paper provides the first empirical investigation of AI adoption's effects on firms' training behavior, and focusing on incumbent workers and new hires across different skill levels. Using firm-level data from the German BIBB establishment panel on training and competence development (Friedrich et al., 2023) from 2019 to 2021, I find that AI adoption is associated with a reduction in continuing training for incumbent workers. Furthermore, AI-adopting SMEs tend to hire more high-skilled workers while reducing their hiring of medium-skilled workers, consistent with Feng and Graetz (2020)'s evidence of job polarization. However, AI adoption is also linked to an increase in apprenticeship contracts, particularly in SMEs, suggesting that German firms continue to value medium-skilled workers in the AI era. Finally, I find no robust significant association between AI adoption and firm-level average wages, except for a decline in low-skilled workers' wages in firms without collective bargaining agreements.

The paper is structured as follows: Section 2 reviews the relevant literature, Section 3 presents the data and descriptive statistics, Section 4 outlines the identification strategy, Section 5 discusses the results, and the final section concludes.

2 Relevant literature

Technological change has long been a key driver of labor market outcomes, as machines increasingly take over tasks once performed by humans (Acemoglu and Autor, 2011; Autor et al., 2024). The effects of technological advancement were often pronounced in low-skilled jobs, particularly those involving routine tasks, such as in agriculture. However, inventions of machines at times also affected skilled craftsmen, for example, in the textile industry in eighteenth-century Britain, or when firms started to adopt steam power and electricity (Acemoglu and Johnson, 2023; Aghion et al., 2021; Feng and Graetz, 2020). Thus, over time, advances in technologies also had the potential to substitute tasks previously carried out by skilled workers, leading to the polarization of labor markets. More recently, AI technologies have demonstrated the ability to substitute many tasks previously performed by high-skilled workers, including those of doctors and lawyers (Autor, 2024).

2.1 AI adoption and changing skill requirements

Autor et al. (2024) highlight the transformative impact of technological innovations on labor market dynamics from 1940–2018, which, in turn, imply significant shifts in hiring and workplace training practices, depending on whether an innovation can be characterized as an automation or an augmentation innovation. Automation innovations substitute for human labor, typically displacing workers by allowing machines or software to perform tasks previously done by humans.[1] Examples include AI systems that replace clerical or repetitive tasks, leading to a reduction in labor demand for specific occupations. Augmentation innovations, on the other hand, "increase the capabilities, quality, variety, or utility of the outputs of occupations, potentially generating new demands for worker expertise and specialization" (Autor et al., 2024, 1402). They argue that while automation and

[1] Schmidpeter and Winter-Ebmer (2021) find that automation risk negatively affects job-finding probabilities for unemployed Austrian workers, particularly men, with this impact worsening over time. However, training programs for unemployed individuals help mitigate these effects by improving re-employment chances.

augmentation are closely related, they have opposite effects on labor demand. Automation tends to reduce labor demand in the occupations it affects, while augmentation increases it by creating new tasks. While AI can automate a wide range of tasks, not limited to routine functions, the extent to which it creates new tasks remains unclear and likely depends on the specific use case of AI within a given firm. If AI functions as an augmentation innovation, it will increase labor demand by introducing new tasks, necessitating upskilling and reskilling initiatives for incumbent workers in the workplace, as well as updates to curricula in vocational schools, continuing training programs, and universities.

Recent empirical studies have sought to quantify the effects of automation technologies on employment and wages, with particular emphasis on the role of industrial robots (Acemoglu and Restrepo, 2018, 2019, 2020; Graetz and Michaels, 2018). These studies consistently point to a reduction in employment at the macro level. However, using firm-level data on robot adoption, Koch et al. (2021) show that robot adoption in Spanish firms not only increased productivity but also increased employment, while observing job losses in non-adopting firms. Acemoglu et al. (2023) report similar results for the Netherlands, and Bessen et al. (2023) find an increase in job separation in Dutch firms following investments in automation technology, but not for investments in IT. Bartel et al. (2007) also provide firm-level evidence that adopting new technologies, such as CNC machines, can yield productivity gains and lead to new or higher-level skill requirements. Using robot exposure as an indicator of automation technologies, Heß et al. (2023) show that workers exposed to automation are significantly less likely to participate in training, particularly in ICT and soft skills, primarily due to a lack of firm-financed support. This training gap is most pronounced among medium-skilled and male workers. However, in the context of AI, the expected effects may differ, as Autor et al. (2024) recently emphasized. While some AI technologies may be viewed as augmenting innovations that reduce the need for workplace training by assuming tasks previously performed by humans, other AI technologies may augment labor, necessitating new skills training to enhance human-machine interactions.

However, to the best of my knowledge, no empirical studies have directly analyzed the effects AI adoption on training behavior in firms.[2]

Unions also play a significant role in shaping the scope and nature of workplace training (Dustmann and Schönberg, 2009). Through collective bargaining and participation in the vocational education and training system, unions may help to ensure that workers are equipped with the skills necessary to adapt to AI-driven changes. Unions may advocate for expanded reskilling and upskilling initiatives to mitigate job displacement, pushing firms to offer comprehensive training programs that prepare employees for new roles in AI-augmented environments. As in previous technological transitions, unions are likely to emphasize training that enhances worker adaptability, ensuring that employees can transition to new tasks or occupations within or outside the firm (Battisti et al., 2023). Dauth et al. (2021) show that the displacement effects of increased robot use in German manufacturing (1994–2014) were stronger in regions with lower worker protection, as proxied by union membership share, and Brunello et al. (2023) find that advanced digital technologies (2018–2020) have positive effects on training in countries with high employment protection but negative effects in countries with lower protection. In line with these findings, Gathmann et al. (2024) provide insights into the relationship between digital technology investments—primarily hardware, as well as communication and collaboration software—and training. They find that German firms investing in digital technologies during the COVID-19 pandemic were more likely to report a need to provide continuous training.

[2]Note that AI technologies are included in the advanced digital technologies index used in Brunello et al. (2023), but together with many other digital technologies, such as 3D printers, advanced robotics, or augmented reality. Moreover, Caselli et al. (2024) find for a sample of Italian firms that investments in Information Digital Technologies significantly increase their engagement in apprenticeship contracts and IT-specific training, but they do not have information on the adoption of AI.

2.2 AI adoption and training costs

The increasing use of AI in production processes is expected to impact the complexity of the remaining tasks performed by employees. Feng and Graetz (2020) propose a theoretical model in which firms are more likely to automate tasks that require learned skills (i.e., skills that demand training to achieve mastery), while humans retain a comparative advantage in tasks that rely primarily on innate abilities and are costly to automate. This dynamic leads firms to automate more complex tasks. Consequently, affected workers may either be downgraded to jobs requiring fewer skills (more innate tasks) or undergo additional training. Using U.S. data, Feng and Graetz (2020) document that employment growth was strongest in jobs requiring complex tasks, while the relationship between job complexity and employment growth was weakest in occupations with lower training requirements.

In the context of apprenticeship training, Feng and Graetz (2020)'s model implies that as automation technologies advance, fewer new apprenticeship contracts will be concluded, all else being equal. However, the remaining apprenticeships are likely to increase in complexity as automation shifts demand toward more skilled tasks. Unlike continuous training, where firms provide all the necessary skills, apprenticeship training is partially conducted in publicly funded vocational schools. As a result, firms' training investments may be lower for apprentices than for regular employees, mitigating the displacement effects of automation. Additionally, apprenticeships tend to have lower opportunity costs, as apprentices earn only a fraction of a skilled worker's wage during training. In some cases, firms may not incur net training costs during apprenticeships, effectively reducing the marginal training cost of employing future skilled workers in learned tasks to near zero (Muehlemann and Wolter, 2020; Wolter and Ryan, 2011). Consequently, in countries with strong apprenticeship systems, such as Germany, labor costs for workers with the skills needed to apply AI in production can be significantly lower through apprenticeship training compared to continuous training or external hiring.

3 Data and descriptive statistics

3.1 Data

The BIBB establishment panel on training and competence development is an establishment-level survey by the Federal Institute for Vocational Education and Training (BIBB) (Friedrich et al., 2023). It is a comprehensive and longitudinal data set with information on a firm's qualification structure, training behavior, and detailed information on the organization of a firm, including information about the use of AI in the production process. The data set is representative of the population of German firms, and has a panel structure for many variables, including training, technology use, and employment and wage information by skill levels.

The questionnaire includes a question on AI adoption in a firm's production process starting in the 2019 wave. The phrasing of the question is: "Which digital technologies are used in your company for production, work, and business processes?" [*Welche digitalen Technologien werden in Ihrem Betrieb für Produktions-, Arbeits- und Geschäftsprozesse genutzt?*], and firms had the option to tick the following item: "Digital technologies based on the use of artificial intelligence and machine learning, e.g., deep learning, pattern recognition" [*Digitale Technologien, die auf dem Einsatz künstlicher Intelligenz und Maschinellem Lernen basieren, z. B. Deep Learning, Mustererkennung*]. In 2020 and 2021, the survey question was adjusted so that firms could tick the following two options related to AI adoption: 1) "Use of artificial intelligence and machine learning for physical work processes, e.g., deep learning and pattern recognition in production and maintenance, building management, or healthcare" [*Einsatz künstlicher Intelligenz und Maschinellem Lernen für physische Arbeitsprozesse, z. B. Deep Learning und Mustererkennung in Produktion und Wartung, Gebäudemanagement oder Pflege*], and 2) "Use of artificial intelligence and machine learning for non-physical work processes, e.g., deep learning and pattern recognition in marketing, procurement, or human resources" [*Einsatz künstlicher Intelligenz* *und Maschinellem Lernen für nicht-physische Arbeitsprozesse, z. B. Deep Learning und Mustererkennung in Marketing, Beschaffung oder Personalwesen*]. Due to the relatively low share of firms adopting AI, the two categories were merged into one category of AI adoption, making it a simple binary variable over the entire three-year sample period.

In addition to AI adoption, the survey provides detailed insights into a firm's training practices, including the number of employees at various skill levels participating in workplace training, as well as the number of apprentices trained. It also includes information on wages, new hires, and employee turnover, categorized by skill levels, and sales growth.

3.2 Descriptive statistics

Table 1 shows that, on average, 3.7% of firms in our sample adopted AI in the surveys conducted from 2019-2021. This value is lower than that reported by Czarnitzki et al. (2023), whose findings, based on the German Innovation Survey, show that 7% of firms with at least five employees have adopted AI in the production process by 2018. In contrast, the BIBB establishment panel on training and competence development includes firms of all sizes, which explains why AI adoption is lower on average. The average number of employees in the sample is 20.8. Of these employees, 15% are engaged in simple tasks, 57% perform skilled tasks, and 28% are involved in high-skilled tasks. Note that in the BIBB survey, the question explicitly refers to the tasks that employees perform, rather than their formal qualification levels. In the context of this paper, focusing on tasks is preferable, as AI adoption is expected to influence the nature of tasks assigned to workers. This approach helps to reveal effects that might otherwise be obscured. For example, as predicted by Feng and Graetz (2020), a skilled worker with vocational qualifications may end up performing simpler tasks. Thus, this type of data is well-suited to capturing such task-related shifts due to AI adoption. Regarding training outcomes, on average a firm hires 0.25 apprentices each period, while 62% of all firms offer continuing training in the workplace, with 35% of employees participating.[3] The share of employees participating in continuing training varies based on the tasks they perform. Employees engaged in low-skilled tasks are underrepresented in training relative to their employment share, while those performing higher-skilled tasks are overrepresented.

Table A.1 presents the distribution of AI adoption across different sectors. Business services exhibit the highest rate of AI adoption, with 6.37% of firms in this sector using AI technologies. This is followed by personal services (4.55%) and trade and repair services (4.25%). In contrast, sectors such as agriculture, mining, and energy, as well as public service and education, report significantly lower AI adoption rates, at 0.74% and 1.71%, respectively. Manufacturing shows a moderate adoption rate of 2.97%, while construction is slightly lower at 1.58%.

Table 2 presents descriptive statistics for firms that have adopted AI in their production processes and those that have not. While 29.43% of AI-adopting firms provide apprenticeship training, only 22.01% of non-AI firms do. Moreover, the mean number of newly concluded apprenticeships in AI firms is 0.68, compared to 0.24 in non-AI firms. Continuing training programs are also more prevalent in AI-using firms, with 73.30% offering such programs, compared to 61.43% of non-AI firms. Additionally, the share of employees participating in continuing training is 9.3 percentage points higher in AI firms, at 44.24%, compared to 34.92% in non-AI firms. Moreover, AI firms have almost the same share of employees performing low-skilled tasks (15%), but a significantly lower share of employees performing skilled tasks (49.8% vs. 57.1%) and a 7.8% higher share of employees performing high-skilled tasks. However, regarding employee skill composition of employees participating in continuing training, there are only minor differences between AI and

[3] The question about the provision of continuing training in the survey is as follows: Have employees of your company participated in other training measures in the form of internal or external courses, seminars, or workshops in 2019, which were supported by your company either fully or partially through time off or financial contributions? Please do not include apprentices. [*"Haben Beschäftigte Ihres Betriebes im Jahr 2019 an sonstigen Weiterbildungsmaßnahmen in Form von internen oder externen Kursen, Seminaren oder Lehrgängen teilgenommen, die von Ihrem Betrieb durch Freistellung oder Kostenübernahme ganz oder teilweise gefördert wurden? Auszubildende bitte nicht berücksichtigen."*]

Table 1: Descriptive Statistics

Variable	Mean	SD	Min	Max	N
AI adopted	0.037	0.189	0	1	7027
Apprenticeship training	0.223	0.416	0	1	7027
Newly concluded apprenticeships	0.256	1.939	0	460	7027
Continuing training	0.619	0.486	0	1	7027
Share of employees in training	0.353	0.374	0	1	7027
Share of employees (low-skilled)	0.155	0.236	0	1	7027
Share of employees (skilled)	0.568	0.299	0	1	7027
Share of employees (high-skilled)	0.277	0.275	0	1	7027
Share employees in CT (low-skilled)	0.044	0.160	0	1	5709
Share employees in CT (skilled)	0.620	0.383	0	1	5709
Share employees in CT (high-skilled)	0.314	0.370	0	1	5709
Share of leavers	0.094	0.169	0	1	6818
Share of leavers (low-skilled)	0.196	0.365	0	1	5044
Share of leavers (skilled)	0.597	0.449	0	1	5038
Share of leavers (high-skilled)	0.154	0.335	0	1	5039
Share of hires	0.090	0.197	0	5.556	7027
Share of hires (low-skilled)	0.231	0.389	0	3	5132
Share of hires (skilled)	0.590	0.447	0	1	5130
Share of hires (high-skilled)	0.180	0.355	0	1	5130
Collective bargaining agreement	0.358	0.479	0	1	7027
Number of employees	20.800	158.724	1	18349	7027
Average wage	2868.916	859.378	1424	9119	7027
Wage (high-skilled)	4051.051	1277.310	1800	9430	6152
Wage (skilled)	2677.835	662.741	1250	5600	6758
Wage (low-skilled)	1883.678	452.782	762	3500	4479
Sales increased	0.328	0.469	0	1	7027

Notes: BIBB establishment panel on training and competence development 2019-2021 long version. Weighted statistics.

non-AI firms.

There are notable differences in worker flows between AI-adopting and non-adopting firms. AI-adopting firms hire 2 percentage points more new employees, relative to their workforce size, than non-adopters. However, they disproportionately hire more high-skilled workers compared to skilled workers, with no significant differences observed for low-skilled employees. In contrast, differences in employee turnover are less pronounced, though AI-adopting firms see a higher relative share of high-skilled workers among those leaving the firm compared to non-adopters. Moreover, the average wage in AI firms is higher than in non-AI firms, which holds for all skill levels.[4] Finally, AI-adopting firms report a higher incidence of sales growth, with 46.60% of AI firms experiencing growth compared to 32.24% of non-AI firms, which is in line with the findings of Czarnitzki et al. (2023), who show that AI adoption increases productivity in German firms.

Overall, AI-adopting firms differ from non-adopters by employing a higher proportion of high-skilled workers, offering more apprenticeships and continuing training, paying higher wages across all skill levels, and experiencing greater sales growth.

Table A.2 compares small and medium-sized firms (fewer than 200 employees) and large firms (200 or more employees) in terms of AI adoption and other key variables. AI adoption is more prevalent in large firms, with 9.6% of large firms adopting AI compared to only 3.7% of SMEs. Large firms also report a higher number of new apprenticeships, with an average of 6.68 compared to 0.18 in SMEs. Training programs are more common in large firms, with 79.2% offering apprenticeship training compared to 21.7% of SMEs. Similarly, 93.2% of large firms offer continuing training, compared to 61.5% of SMEs. However, the share of employees participating in continuing training is similar between large and SMEs, with 35% of employees participating in such programs. Another notable difference is that 79.5% of large firms being covered by collective bargaining agreements, compared to 35.3% of SMEs. Finally, wages are generally higher in large firms. The average wage in large

[4]Firms in the top and bottom percentile of the average wage distribution were dropped from the sample for the analysis.

firms is €3,191, compared to €2,865 in SMEs. Wages for high-skilled employees are higher in large firms (€4,754) compared to SMEs (€4,041). The same trend holds for skilled and low-skilled employees, with large firms offering higher wages across the board. Large firms also report a higher incidence of sales growth, with 42.2% experiencing sales growth compared to 32.7% of SMEs.

In summary, the descriptive statistics reveal significant differences between AI-adopting and non-AI firms, as well as between small and large firms. AI-adopting firms tend to offer more training and pay higher wages. Similarly, large firms are more likely to adopt AI, but at the same time also offer more training programs, and pay higher wages compared to SMEs.

Table 2: Descriptive Statistics: AI Firms vs Non-AI Firms

	AI Firms			**Non-AI Firms**			**Difference**
Variable	Mean	SD	N	Mean	SD	N	Mean Diff
Apprenticeship training	0.294	0.456	569	0.220	0.414	6458	0.074***
Newly concluded apprenticeships	0.677	6.372	569	0.240	1.527	6458	0.438***
Continuing training (CT)	0.733	0.443	569	0.614	0.487	6458	0.119***
Share of employees (low-skilled)	0.150	0.240	569	0.155	0.236	6458	-0.005
Share of employees (skilled)	0.498	0.300	569	0.571	0.299	6458	-0.073***
Share of employees (high-skilled)	0.352	0.310	569	0.274	0.273	6458	0.078***
Share of employees in CT	0.442	0.393	569	0.349	0.373	6458	0.093***
Share employees in CT (low-skilled)	0.059	0.205	507	0.043	0.158	5202	0.016
Share employees in CT (skilled)	0.605	0.370	507	0.621	0.384	5202	-0.016
Share employees in CT (high-skilled)	0.309	0.344	507	0.315	0.372	5202	-0.006
Share of leavers	0.100	0.215	545	0.093	0.167	6273	0.007
Share of leavers (low-skilled)	0.190	0.364	468	0.197	0.366	4576	-0.007
Share of leavers (skilled)	0.545	0.440	467	0.599	0.449	4571	-0.054*
Share of leavers (high-skilled)	0.256	0.392	467	0.150	0.332	4572	0.106***
Share of hires	0.108	0.185	569	0.089	0.197	6458	0.019*
Share of hires (low-skilled)	0.265	0.416	467	0.230	0.388	4665	0.036
Share of hires (skilled)	0.472	0.454	467	0.596	0.446	4663	-0.124***
Share of hires (high-skilled)	0.263	0.406	467	0.176	0.352	4663	0.087***
Collective bargaining agreement	0.318	0.466	569	0.359	0.480	6458	-0.041
Number of employees	60.340	480.690	569	19.270	131.110	6458	41.070
Average wage	3239.020	990.090	569	2854.610	850.740	6458	384.410***
Wage (high-skilled)	4655.960	1534.980	529	4024.770	1258.430	5623	631.190***
Wage (skilled)	2846.490	688.440	550	2671.430	660.920	6208	175.060***
Wage (low-skilled)	1927.640	521.200	397	1881.810	449.580	4082	45.830
Sales increased	0.466	0.499	569	0.322	0.467	6458	0.144***

Notes: AI adoption over the period from 2019 to 2021. BIBB establishment panel on training and competence development 2019-2021 long version. Weighted statistics. The last column shows the mean difference between AI and non-AI firms, with significance levels based on a t-test for differences in means: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

4 Identification strategy

The identification strategy employs a simple panel fixed effects regression at the firm level, similar to Koch et al. (2021) who analyze the effects of robot adoption in firms on productivity, although in this context I regress firm-level training outcomes on AI adoption in the production process, controlling for both firm and year fixed effects. This approach effectively accounts for time-invariant unobserved heterogeneity across firms, as well as common temporal shocks.

The empirical specification is given by:

$$Y_{it} = \alpha + \beta AI_{it} + \lambda_i + \delta_t + \epsilon_{it}$$

where Y_{it} represents the (training) outcomes of interest for firm i in year t, and AI_{it} is a binary indicator for whether firm i adopted AI in its production processes in period t, λ_i and δ_t represent firm fixed effects and year fixed effects, respectively. ϵ_{it} captures the error term.

The decision to adopt AI is clearly endogenous. Therefore, the causal effect of AI adoption on the outcome variables can only be identified to the extent that it depends solely on observable firm characteristics and time-invariant unobserved factors at the firm level (λ_i). However, if time-varying unobserved factors, ϵ_{it}, related to the firm's training behavior are correlated with AI adoption, the coefficient β will be biased. The validity of the parallel trends assumption is essential for establishing causal inference in this context. For the relationship between AI adoption and training outcomes to be interpreted causally, firms adopting AI must exhibit similar (counterfactual) trends in these outcomes as non-adopting firms. To evaluate the parallel trends assumption, I assess whether AI adopters and non-adopters exhibited different patterns in training behavior prior to adoption. For instance, if AI adopters reduced training investments in the period prior to AI adoption, this could lead to an upward bias in the estimated treatment effect, analogous to the well-known Ashenfelter's Dip observed when evaluating the effects of training programs on earnings (Ashenfelter, 1978).[5]

Another approach would be to employ instrumental variables regression, provided an instrument is available that generates plausibly exogenous variation in AI adoption and is thus unrelated to a firm's training behavior. Czarnitzki et al. (2023) employ an instrumental variables approach, using AI adoption by other firms within the same two-digit industry as an instrument for AI adoption. However, their analysis is cross-sectional, as they do not have repeated observations of AI adoption at the firm level. Replicating this approach within the context of the BIBB establishment panel did not produce a significant first-stage association between average AI adoption in the industry and AI adoption in a fixed effects panel regression. A possible explanation for this non-significant result is the relatively small number of industries in the BIBB panel (N=8) and the limited within-firm variation in AI adoption over time. Nevertheless, using AI adoption in otherwise similar firms as an instrument may offer a viable strategy to address the endogeneity of AI adoption, particularly as future waves are added to the BIBB establishment panel and AI adoption becomes more widespread over time.

5 Results

This section the results of fixed effects panel regressions, analyzing the association between AI adoption and key workplace outcomes, namely workplace training, worker flows, and wages. By exploring these dimensions, the results provide a comprehensive view of how AI adoption may be transforming the labor market and human resource practices within firms, offering insights into the effects of AI adoption across different firm types, including SMEs and large firms, as well as firms with and without collective bargaining agreements.

[5]Given the limited time periods and the relatively low number of firms that adopted AI in the sample, I report and discuss estimates without including a lead variable ($AI_{i,t+1}$) in the main text, but provide the estimates including a lead for the subsample of firms that are observed in all three periods in the appendix.

5.1 AI adoption and workplace training

Table 3 presents the relationship between AI adoption and firms' training outcomes, focusing on apprenticeship and continuing training for incumbent workers.

The results in Panel A show no statistically significant association between AI adoption and the likelihood of offering apprenticeship training, with point estimates near zero. However, in Panel B, there is a statistically significant positive association between AI adoption and the log of new apprenticeships, particularly driven by SMEs, although the point estimate is positive for large firms as well. The magnitude is also economically meaningful, with AI adoption being associated with an almost 10% increase in the number of newly concluded apprenticeships.

Panel C examines the relationship between AI adoption and the likelihood of offering continuing training to incumbent workers. The results indicate a statistically significant negative association in the full sample, largely driven by SMEs and firms without collective bargaining agreements. This decline in the probability of offering continuing training is economically substantial, amounting to a 3.9 percentage point decrease, or a 6.3 percent reduction, as on average, just over 60 percent of firms offer continuing training (Table 1). Moreover, Panel D shows that AI adoption is not significantly associated with the share of employees participating in continuing training.

Finally, there is no statistically significant evidence of anticipation effects in firms' training behavior prior to AI adoption, as reflected by the insignificant point estimates of AI_{t+1} (Table A.3). The only exception is found in firms with collective bargaining agreements, there is a marginally statistically significant increase in the share of employees participating in continuing training in the period prior to AI adoption (Table A.3, Panel D), though no such association is observed in the period when AI was adopted. These findings indicate that firms generally did not modify their training practices in anticipation of AI adoption, reinforcing the plausibility of the common trend assumption and supporting a causal interpretation of the results. In addition, the results in Table A.4 show that AI adoption is

Table 3: AI adoption and training outcomes

Variable	Full Sample	Large Firms	SMEs	CBA Firms	Non-CBA Firms
Panel A: Dependent variable: Apprenticeship training (yes/no)					
AI Adoption	0.010	0.009	0.010	0.019	-0.016
	(0.013)	(0.014)	(0.019)	(0.019)	(0.023)
Adjusted R^2	0.002	-0.001	0.004	0.001	0.007
Observations	7,027	1,599	5,428	3,927	3,100
Panel B: Dependent variable: log new apprenticeships					
AI Adoption	0.094***	0.076	0.122**	0.069	0.041
	(0.036)	(0.052)	(0.052)	(0.052)	(0.060)
Adjusted R^2	0.016	0.015	0.016	0.018	0.013
Observations	2,738	1,147	1,591	1,763	975
Panel C: Dependent variable: Continuing training (yes/no)					
AI Adoption	-0.039**	-0.020	-0.050*	-0.038	-0.056*
	(0.018)	(0.022)	(0.026)	(0.025)	(0.033)
Adjusted R^2	0.049	0.014	0.059	0.055	0.051
Observations	7,027	1,599	5,428	3,927	3,100
Panel D: Dependent variable: Share of employees in continuing training					
AI Adoption	0.006	0.019	-0.001	-0.011	0.000
	(0.018)	(0.027)	(0.023)	(0.025)	(0.028)
Adjusted R^2	0.039	0.047	0.037	0.058	0.014
Observations	7,027	1,599	5,428	3,927	3,100

Notes: BIBB establishment panel on training and competence development 2019-2021 long version. Heteroskedasticity and autocorrelation robust (HAC) standard errors are in parentheses. Full sample includes all firms, with subsamples for large firms (200+ employees) and SMEs (<200 employees). CBA: Collective bargaining agreement (1=yes, 0=no). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

not significantly associated with the corresponding skill shares of training participants in the year when AI was adopted, and Table A.5 also does not provide any evidence that she relative shares of employees in terms of their skill level changed in anticipation of adopting AI in the production process.

5.2 AI adoption and worker flows

Instead of investing in training to equip existing employees with the necessary skills for using AI in the production process, firms may opt to lay off employees who lack the required skills, and hire new workers from the external labor market who already possess the relevant expertise. The results in Table 4 provide insights into the effects of AI adoption on the share of separations, with additional breakdowns by skill level among those leaving.[6] For the full sample, AI adoption has a marginally statistically significant effect on the overall share of separations. The results suggest that AI adoption is associated with a 1.1 percentage point decrease in the share of separations, which, when evaluated at the average, corresponds to an 11 percent reduction—a notable and economically meaningful effect. This finding suggests that, contrary to common fears, AI adoption does not lead to mass layoffs but may instead even reduce the separation rate in AI-adopting firms, at least in the short run.[7]

Panels B–D examine the composition of employees leaving firms where at least one employee departs. There is no evidence of any significant shift in the composition of departing employees by skill level. Additionally, Table A.6 provides no evidence of significant anticipation effects, except for the subsample of firms without a collective bargaining agreement. These firms hired more high-skilled workers at the expense of low-skilled workers in the period preceding AI adoption.

Table 5 presents the relationship between AI adoption and the share of new hires, as

[6]Note that the data does not provide information about whether employees were laid off or if they decided to quit in anticipation, or as a consequence of AI adoption.

[7]Table A.6 shows that overall, there is no evidence for important anticipation effects.

Table 4: AI Adoption on share of separations, by skill level

Variable	**Full Sample**	**Large Firms**	**SMEs**	**CBA Firms**	**Non-CBA Firms**
Panel A: Dependent variable: Share of separations					
AI Adoption	-0.011*	-0.002	-0.016	-0.013	-0.012
	(0.006)	(0.005)	(0.009)	(0.009)	(0.010)
Adjusted R^2	0.001	0.011	0.001	0.000	0.002
Observations	6,818	1,540	5,278	3,786	3,032
Panel B: Dependent variable: Share of separations (low-skilled)					
AI Adoption	-0.018	-0.016	-0.014	-0.028	-0.019
	(0.016)	(0.018)	(0.025)	(0.020)	(0.032)
Adjusted R^2	0.005	0.005	0.004	0.003	0.005
Observations	5,044	1,486	3,558	3,032	2,012
Panel C: Dependent variable: Share of separations (skilled)					
AI Adoption	-0.001	0.008	-0.012	0.004	0.011
	(0.020)	(0.020)	(0.032)	(0.024)	(0.041)
Adjusted R^2	0.003	-0.000	0.005	0.004	0.001
Observations	5,038	1,482	3,556	3,026	2,012
Panel D: Dependent variable: Share of separations (high-skilled)					
AI Adoption	0.020	0.014	0.024	0.033	-0.000
	(0.015)	(0.017)	(0.024)	(0.017)	(0.032)
Adjusted R^2	0.000	0.000	0.000	0.002	0.000
Observations	5,039	1,482	3,557	3,026	2,013

Notes: BIBB establishment panel on training and competence development 2019-2021 long version. Heteroskedasticity and autocorrelation robust (HAC) standard errors are in parentheses. Full sample includes all firms, with subsamples for large firms (200+ employees) and SMEs (<200 employees). CBA: Collective bargaining agreement (1=yes, 0=no). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 5: AI Adoption and hiring behavior, by skill level

Variable	**Full Sample**	**Large Firms**	**SMEs**	**CBA Firms**	**Non-CBA Firms**
Panel A: Dependent variable: Number of new hires / employees					
AI Adoption	-0.003	0.002	-0.007	-0.002	-0.002
	(0.008)	(0.005)	(0.012)	(0.010)	(0.014)
Adjusted R^2	0.019	0.021	0.020	0.011	0.032
Observations	7,027	1,599	5,428	3,927	3,100
Panel B: Dependent variable: Share of low-skilled new hires					
AI Adoption	0.002	0.002	0.007	0.006	-0.029
	(0.017)	(0.021)	(0.025)	(0.024)	(0.028)
Adjusted R^2	0.002	0.000	0.004	0.001	0.002
Observations	5,132	1,521	3,611	3,100	2,032
Panel C: Dependent variable: Share of skilled new hires					
AI Adoption	-0.037	-0.002	-0.075**	-0.050	-0.006
	(0.021)	(0.027)	(0.032)	(0.031)	(0.034)
Adjusted R^2	0.002	0.005	0.003	0.002	0.000
Observations	5,130	1,520	3,610	3,098	2,032
Panel D: Dependent variable: Share of high-skilled new hires					
AI Adoption	0.035**	0.000	0.068***	0.044**	0.035
	(0.016)	(0.022)	(0.024)	(0.022)	(0.025)
Adjusted R^2	0.004	0.010	0.006	0.004	0.009
Observations	5,130	1,520	3,610	3,098	2,032

Notes: BIBB establishment panel on training and competence development 2019-2021 long version. Heteroskedasticity and autocorrelation robust (HAC) standard errors are in parentheses. Full sample includes all firms, with subsamples for large firms (200+ employees) and SMEs (<200 employees). CBA: Collective bargaining agreement (1=yes, 0=no). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

well as the composition of new hires by skill level. In Panel A, there is no statistically significant association between AI adoption and the overall share of new hires. However, among new hires, firms that adopted AI increased the share of high-skilled employees at the expense of skilled employees, which is in line with the theoretical predictions of Feng and Graetz (2020). Since the point estimate is close zero for large firms, this result appears to be driven entirely by SMEs. The effect size is economically meaningful: a 6.8 percentage point increase in the share of high-skilled hires corresponds to a 38% increase when evaluated at the average share of high-skilled hires, which is approximately 18%.

5.3 AI adoption and wages

To the extent that markets are competitive, human capital theory suggests that skills complementary to the use of AI in the production process will be rewarded with higher wages. Thus, AI adoption may coincide with wage increases for worker groups that benefit most from AI usage, or, if AI increases overall productivity, we might observe an increase in average wages within the firm.

The results in Table 6 provide estimates of the association between AI adoption and log average wages in the firm, as well as workers groups by skill levels. In the full sample (Panel A), the coefficient on AI adoption is close to zero and not statistically significant, suggesting that AI adoption does not have a notable effect on the overall average wage, at least in the short run. Similarly, there is no evidence of any statistically significant association for high-skilled and skilled worker wages (Panels B and C). However, Panel D, which focuses on low-skilled workers, shows a negative association between AI adoption and wages, suggesting that AI adoption might adversely affect low-skilled workers' wages in firms not bound by collective bargaining agreements, implying a decrease in the average wage of just over 5 percent. Moreover, Table A.8 shows that average wages at the firm level did not differ significantly between AI adopters and non-adopters in the period before adoption. However, skilled worker wages were, on average, 3.5% lower in the period prior

Table 6: AI Adoption and wages, by skill level

Variable	**Full Sample**	**Large Firms**	**SMEs**	**CBA Firms**	**Non-CBA Firms**
Panel A: Dependent variable: log average wage					
AI Adoption	0.002	-0.001	0.004	0.010	-0.004
	(0.010)	(0.013)	(0.013)	(0.013)	(0.017)
Adjusted R^2	0.020	0.029	0.017	0.028	0.022
Observations	7,027	1,599	5,428	3,927	3,100
Panel B: Dependent variable: log wage for high-skilled workers					
AI Adoption	0.018	0.023	0.018	0.009	0.028
	(0.012)	(0.015)	(0.017)	(0.015)	(0.021)
Adjusted R^2	0.019	0.023	0.017	0.024	0.015
Observations	6,152	1,567	4,585	3,534	2,618
Panel C: Dependent variable: log wage for skilled workers					
AI Adoption	-0.002	0.006	-0.005	-0.003	-0.012
	(0.010)	(0.015)	(0.013)	(0.013)	(0.017)
Adjusted R^2	0.027	0.033	0.025	0.032	0.030
Observations	6,758	1,579	5,179	3,830	2,928
Panel D: Dependent variable: log wage for Low-skilled workers					
AI Adoption	-0.025	-0.014	-0.036*	-0.010	-0.051**
	(0.015)	(0.022)	(0.020)	(0.019)	(0.026)
Adjusted R^2	0.019	0.030	0.018	0.017	0.038
Observations	4,479	1,357	3,122	2,736	1,743

Notes: BIBB establishment panel on training and competence development 2019-2021 long version. Heteroskedasticity and autocorrelation robust (HAC) standard errors are in parentheses. Full sample includes all firms, with subsamples for large firms (200+ employees) and SMEs (<200 employees). CBA: Collective bargaining agreement (1=yes, 0=no). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

to AI adoption. The subgroup analyses indicate that this effect is primarily driven by small firms and firms without collective bargaining agreements.

6 Conclusion

This study provides new insights into the relationship between artificial intelligence (AI) adoption and workplace training, based on firm-level data from the BIBB establishment panel (2019–2021). The findings indicate that AI adoption in the short term increases the number of apprenticeships, especially in small and medium-sized enterprises (SMEs). However, it is associated with a reduction in continuing training for incumbent workers. Additionally, SMEs adopting AI tend to hire more high-skilled workers, while decreasing the intake of medium-skilled workers from the external labor market.

These results highlight the nuanced effects of AI adoption on workforce development. AI appears to also function as an augmentation innovation, creating demand for specialized skills and high-skilled workers rather than simply automating existing tasks (Autor et al. 2024). Similar to findings by Feng and Graetz (2020) for U.S. firms, AI adoption in Germany is linked to a shift towards higher-skilled tasks, as evidenced by an increase in high-skilled new hires and a reduction in medium-skilled hires. Notably, German firms also respond by expanding apprenticeship programs, which remain a key pathway into skilled roles, suggesting that AI complements, rather than replaces, human expertise by enhancing its application (Autor, 2024). History demonstrates that expertise in outdated technologies can quickly lose relevance as innovations transform industries, highlighting the need for continuously updating skills (Mokyr, 2019). Apprenticeships offer a cost-effective strategy for firms to achieve this, partly due to lower training wages and state-supported vocational education. In the age of AI, apprenticeships will remain essential, providing the flexibility needed to adapt to new technologies and evolving skill requirements, just as they did during earlier technological revolutions (Zeev et al., 2017).

Policymakers should consider supporting training initiatives for incumbent workers, particularly in SMEs, to ensure they remain competitive as AI technology evolves and firms reduce their provision of continuing training. Additionally, regularly updating apprenticeship curricula is essential to keep these programs relevant as AI becomes more pervasive in the workplace. This should include AI-related competencies, ensuring that apprentices can perform higher-value roles in their future careers. Future research should investigate the long-term impacts of AI adoption and explore the effects of different AI technologies, including advancements in generative AI.

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Appendix

Table A.1: AI adoption by sector

Sector	**Mean**	**SD**	**Min**	**Max**	**N**
Agriculture, Mining, Energy	0.0074	0.0856	0	1	339
Manufacturing	0.0297	0.1699	0	1	1478
Construction	0.0158	0.1250	0	1	397
Trade and Repair Services	0.0425	0.2018	0	1	852
Business Services	0.0637	0.2444	0	1	1129
Personal Services	0.0455	0.2086	0	1	841
Medical Services	0.0109	0.1038	0	1	838
Public Service and Education	0.0171	0.1296	0	1	1153
Total	0.0372	0.1893	0	1	7027

Table A.2: Descriptive statistics: Large firms vs SMEs

	SMEs			**Large Firms**		
Variable	Mean	SD	N	Mean	SD	N
AI adoption (yes/no)	0.037	0.188	5428	0.096	0.294	1599
Apprenticeship training (yes/no)	0.217	0.412	5428	0.792	0.406	1599
Newly concluded apprenticeships	0.184	0.7304	5428	6.683	15.8857	1599
Share employees in (low-skilled)	0.154	0.2350	5428	0.245	0.2819	1599
Share employees in (skilled)	0.568	0.2998	5428	0.559	0.2547	1599
Share employees in (high-skilled)	0.278	0.2756	5428	0.196	0.2024	1599
Continuing training (yes/no)	0.615	0.487	5428	0.932	0.251	1599
Share of employees in CT	0.353	0.375	5428	0.353	0.319	1599
Share employees in CT (low-skilled)	0.042	0.157	4200	0.153	0.268	1509
Share employees in CT (skilled)	0.620	0.384	4200	0.634	0.311	1509
Share employees in CT (high-skilled)	0.316	0.372	4200	0.196	0.246	1509
Share of leavers	0.094	0.170	5278	0.085	0.081	1540
Share of leavers (low-skilled)	0.193	0.365	3558	0.353	0.366	1486
Share of leavers (skilled)	0.599	0.451	3556	0.492	0.336	1482
Share of leavers (high-skilled)	0.154	0.338	3557	0.149	0.233	1482
Share of hires	0.090	0.198	5428	0.098	0.099	1599
Share of hires (low-skilled)	0.229	0.390	3611	0.310	0.351	1521
Share of hires (skilled)	0.592	0.449	3610	0.503	0.338	1520
Share of hires (high-skilled)	0.179	0.357	3610	0.187	0.261	1520
Number of employees	13.63	28.31	5428	666.19	1341.56	1599
Collective bargaining agreement	0.353	0.478	5428	0.795	0.404	1599
Average wage	2865.34	858.95	5428	3190.90	838.61	1599
Wage (high-skilled)	4040.92	1276.19	4585	4754.00	1155.37	1567
Wage (skilled)	2672.34	661.82	5179	3131.76	577.35	1579
Wage (low-skilled)	1874.82	449.72	3122	2268.01	418.15	1357
Sales increased	0.327	0.469	5428	0.422	0.494	1599

Notes: Data from the establishment panel, weighted statistics. SMEs are defined as firms with less than 200 employees, and large firms as those with 200 or more employees.

Table A.3: Testing for anticipation effects: Training outcomes

Variable	**Full Sample**	**Large Firms**	**SMEs**	**CBA Firms**	**Non-CBA Firms**
Panel A: Dependent variable: Training					
AI Adoption	-0.001	0.000	-0.002	-0.023	-0.006
	(0.024)	(0.001)	(0.039)	(0.038)	(0.033)
AI Adoption (lead)	0.001	0.000	-0.002	-0.010	-0.003
	(0.018)	(0.003)	(0.029)	(0.028)	(0.015)
Adjusted R^2	0.002	.	0.005	-0.000	0.006
Observations	4,228	952	3,276	2,329	1,899
Panel B: Dependent variable: log new apprentices					
AI Adoption	0.162**	0.158	0.180*	0.064	0.257*
	(0.077)	(0.112)	(0.107)	(0.113)	(0.139)
AI Adoption (lead)	0.118	0.124	0.093	0.206	0.113
	(0.087)	(0.131)	(0.105)	(0.127)	(0.141)
Adjusted R^2	0.012	0.012	0.009	0.013	0.072
Observations	1,671	687	984	1,057	614
Panel C: Dependent variable: Continuing training					
AI Adoption	-0.079**	-0.068	-0.079	-0.073	-0.066
	(0.032)	(0.039)	(0.046)	(0.049)	(0.053)
AI Adoption (lead)	-0.006	-0.010	-0.012	-0.032	0.021
	(0.035)	(0.024)	(0.054)	(0.049)	(0.065)
Adjusted R^2	0.004	0.014	0.002	0.002	0.007
Observations	4,228	952	3,276	2,329	1,899
Panel D: Dependent variable: Share of employees in training					
AI Adoption	0.025	0.026	0.028	-0.012	0.029
	(0.037)	(0.064)	(0.045)	(0.057)	(0.053)
AI Adoption (lead)	0.054	-0.002	0.084	0.075*	0.026
	(0.036)	(0.057)	(0.049)	(0.048)	(0.063)
Adjusted R^2	0.002	0.005	0.003	0.007	0.002
Observations	4,228	952	3,276	2,329	1,899

Notes: Regression analysis of AI adoption effects on training variables. Heteroskedasticity and autocorrelation robust standard errors in parentheses. Full sample includes all firms, subsamples for large firms (200+ employees), SMEs (<200 employees), CBA firms (1=yes), and non-CBA firms (0=no). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table A.4: AI adoption and the share of employees in continuing training, by skill level

	Full Sample	**Large Firms**	**SMEs**	**CBA Firms**	**non-CBA Firms**
Panel A: Dependent variable: Share of employees in CT (low-skilled)					
AI Adoption	0.006	-0.014	0.021	-0.015	0.031
	(0.012)	(0.017)	(0.016)	(0.019)	(0.019)
Adjusted R^2	0.000	0.001	0.001	0.001	0.004
Observations	5,709	1,509	4,200	3,363	2,346
Panel B: Dependent variable: Share of employees in CT (skilled)					
AI Adoption	-0.000	0.010	-0.013	0.024	-0.020
	(0.017)	(0.026)	(0.022)	(0.025)	(0.027)
Adjusted R^2	0.001	0.000	0.001	0.001	0.005
Observations	5,709	1,509	4,200	3,363	2,346
Panel C: Dependent variable: Share of employees in CT (high-skilled)					
AI Adoption	-0.011	-0.011	-0.009	-0.012	-0.013
	(0.013)	(0.017)	(0.018)	(0.015)	(0.024)
Adjusted R^2	0.001	0.005	-0.000	0.001	-0.001
Observations	5,709	1,509	4,200	3,363	2,346

Notes: BIBB establishment panel on training and competence development 2019-2021 long version. Heteroskedasticity and autocorrelation robust (HAC) standard errors are in parentheses. Full sample includes all firms, with subsamples for large firms (200+ employees) and SMEs (<200 employees). CBA: Collective bargaining agreement (1=yes, 0=no). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.5: Testing for anticipation effects: AI adoption and share of employees in continuing training, by skill level

Variable	**Full Sample**	**Large Firms**	**SMEs**	**CBA Firms**	**Non-CBA Firms**
Panel A: Dependent variable: Share of employees in CT (low-skilled)					
AI Adoption	-0.002	-0.063	0.048*	-0.029	0.018
	(0.020)	(0.034)	(0.021)	(0.036)	(0.026)
AI Adoption (lead)	-0.004	-0.033	0.009	0.012	-0.058
	(0.022)	(0.032)	(0.029)	(0.034)	(0.032)
Adjusted R^2	-0.001	0.011	0.005	0.002	0.017
Observations	3,610	912	2,698	2,092	1,518
Panel B: Dependent variable: Share of employees in CT (skilled)					
AI Adoption	-0.013	0.071	-0.085	0.071	-0.077
	(0.032)	(0.041)	(0.045)	(0.047)	(0.056)
AI Adoption (lead)	0.016	0.059	-0.004	0.011	0.032
	(0.031)	(0.044)	(0.042)	(0.045)	(0.046)
Adjusted R^2	0.001	0.006	0.005	0.003	0.016
Observations	3,610	912	2,698	2,092	1,518
Panel C: Dependent variable: Share of employees in CT (high-skilled)					
AI Adoption	0.013	-0.045	0.056	-0.047	0.083
	(0.025)	(0.029)	(0.037)	(0.035)	(0.044)
AI Adoption (lead)	0.003	-0.003	0.005	-0.032	0.037
	(0.025)	(0.036)	(0.036)	(0.038)	(0.035)
Adjusted R^2	-0.001	0.003	0.002	0.002	0.005
Observations	3,610	912	2,698	2,092	1,518

Notes: BIBB establishment panel on training and competence development 2019-2021 long version. Heteroskedasticity and autocorrelation robust (HAC) standard errors are in parentheses. Full sample includes all firms, with subsamples for large firms (200+ employees) and SMEs (<200 employees). CBA: Collective bargaining agreement (1=yes, 0=no). $^{***}p < 0.01,^{**}p < 0.05,^{*}p < 0.1$.

Table A.6: Testing for anticipation effects: AI adoption and separations, by skill levels

Variable	**Full Sample**	**Large Firms**	**SMEs**	**CBA Firms**	**Non-CBA Firms**
Panel A: Dependent variable: Share of separations					
AI Adoption	-0.005	-0.001	-0.006	0.007	-0.019
	(0.009)	(0.010)	(0.012)	(0.012)	(0.016)
AI Adoption (lead)	0.005	0.015	-0.001	0.009	-0.006
	(0.008)	(0.009)	(0.012)	(0.011)	(0.016)
Adjusted R^2	-0.000	0.029	-0.001	-0.001	0.002
Observations	4,092	913	3,179	2,241	1,851
Panel B: Dependent variable: Share of low-skilled employees leaving					
AI Adoption	-0.017	-0.008	-0.017	-0.012	-0.008
	(0.027)	(0.043)	(0.032)	(0.038)	(0.039)
AI Adoption (lead)	-0.029	-0.051	-0.014	0.025	-0.144**
	(0.034)	(0.041)	(0.053)	(0.044)	(0.058)
Adjusted R^2	0.009	0.007	0.009	0.009	0.032
Observations	3,031	884	2,147	1,801	1,230
Panel C: Dependent variable: Skilled employees leaving					
AI Adoption	-0.021	-0.007	-0.038	-0.051	-0.015
	(0.035)	(0.039)	(0.056)	(0.045)	(0.063)
AI Adoption (lead)	-0.043	-0.003	-0.068	-0.090	0.031
	(0.040)	(0.039)	(0.066)	(0.050)	(0.077)
Adjusted R^2	0.008	-0.003	0.012	0.017	0.005
Observations	3,028	883	2,145	1,798	1,230
Panel D: Dependent variable: High-skilled employees leaving					
AI Adoption	0.023	-0.002	0.042	0.048	0.000
	(0.034)	(0.041)	(0.055)	(0.037)	(0.071)
AI Adoption (lead)	0.054	0.022	0.077	0.038	0.106*
	(0.031)	(0.032)	(0.050)	(0.038)	(0.061)
Adjusted R^2	0.003	0.003	0.004	0.002	0.016
Observations	3,029	883	2,146	1,798	1,231

Notes: BIBB establishment panel on training and competence development 2019-2021 long version. Heteroskedasticity and autocorrelation robust (HAC) standard errors are in parentheses. Full sample includes all firms, with subsamples for large firms (200+ employees) and SMEs (<200 employees). CBA: Collective bargaining agreement (1=yes, 0=no). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.7: Testing for anticipation effects: AI adoption and the share of new hires, by skills levels

Variable	**Full Sample**	**Large Firms**	**SMEs**	**CBA Firms**	**Non-CBA Firms**
Panel A: Dependent variable: Number of new Hires / employees					
AI Adoption	-0.018	0.016	-0.037	-0.010	-0.007
	(0.014)	(0.012)	(0.021)	(0.018)	(0.021)
AI Adoption (lead)	-0.020	0.014	-0.041	-0.030	-0.013
	(0.016)	(0.011)	(0.026)	(0.028)	(0.021)
Adjusted R^2	0.004	0.004	0.009	0.003	0.015
Observations	4,228	952	3,276	2,329	1,899
Panel B: Dependent variable: Share of low-skilled new hires					
AI Adoption	-0.032	-0.052	0.005	-0.021	-0.067
	(0.033)	(0.042)	(0.048)	(0.050)	(0.057)
AI Adoption (lead)	-0.030	-0.053	0.007	0.006	-0.052
	(0.031)	(0.030)	(0.044)	(0.049)	(0.039)
Adjusted R^2	0.003	0.008	0.004	0.000	0.005
Observations	3,197	916	2,281	1,886	1,311
Panel C: Dependent variable: Share of skilled new hires					
AI Adoption	-0.035	0.023	-0.100	-0.064	0.016
	(0.042)	(0.048)	(0.065)	(0.065)	(0.070)
AI Adoption (lead)	-0.028	-0.015	-0.061	-0.090	0.023
	(0.041)	(0.044)	(0.062)	(0.062)	(0.062)
Adjusted R^2	0.000	-0.001	0.003	0.005	-0.002
Observations	3,195	915	2,280	1,884	1,311
Panel D: Dependent variable: Share of high-skilled new hires					
AI Adoption	0.067**	0.031	0.095**	0.086	0.051
	(0.031)	(0.042)	(0.047)	(0.050)	(0.051)
AI Adoption (lead)	0.059	0.071	0.054	0.085	0.029
	(0.033)	(0.039)	(0.052)	(0.043)	(0.062)
Adjusted R^2	0.010	0.008	0.013	0.014	0.003
Observations	3,195	915	2,280	1,884	1,311

Notes: BIBB establishment panel on training and competence development 2019-2021 long version. Heteroskedasticity and autocorrelation robust (HAC) standard errors are in parentheses. Full sample includes all firms, with subsamples for large firms (200+ employees) and SMEs (<200 employees). CBA: Collective bargaining agreement (1=yes, 0=no). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.

Table A.8: Testing for anticipation effects: AI adoption and wages, by skill levels

Variable	**Full Sample**	**Large Firms**	**SMEs**	**CBA Firms**	**Non-CBA Firms**
Panel A: Dependent variable: log average wage					
AI Adoption	-0.019	-0.019	-0.024	-0.007	-0.042
	(0.020)	(0.029)	(0.027)	(0.030)	(0.031)
AI Adoption (lead)	-0.031	0.014	-0.051*	-0.001	-0.067*
	(0.018)	(0.028)	(0.024)	(0.024)	(0.028)
Adjusted R^2	0.016	0.025	0.016	0.016	0.023
Observations	4,228	952	3,276	2,329	1,899
Panel B: Dependent variable: log wage (high-skilled employees)					
AI Adoption	0.008	-0.004	0.028	0.004	0.010
	(0.024)	(0.030)	(0.034)	(0.033)	(0.036)
AI Adoption (lead)	-0.025	0.010	-0.037	-0.018	-0.013
	(0.022)	(0.025)	(0.031)	(0.027)	(0.034)
Adjusted R^2	0.008	0.036	0.007	0.016	-0.001
Observations	3,698	933	2,765	2,096	1,602
Panel C: Dependent variable: log wage (skilled employees)					
AI Adoption	-0.019	-0.004	-0.028	-0.024	-0.045
	(0.020)	(0.035)	(0.025)	(0.034)	(0.030)
AI Adoption (lead)	-0.035*	0.002	-0.051**	-0.013	-0.082**
	(0.018)	(0.027)	(0.024)	(0.024)	(0.033)
Adjusted R^2	0.028	0.023	0.032	0.027	0.034
Observations	4,069	939	3,130	2,274	1,795
Panel D: Dependent variable: log wage (low-skilled employees)					
AI Adoption	-0.039	-0.024	-0.052	-0.074	-0.017
	(0.029)	(0.044)	(0.039)	(0.049)	(0.032)
AI Adoption (lead)	-0.032	-0.024	-0.037	-0.033	-0.038
	(0.021)	(0.028)	(0.029)	(0.029)	(0.031)
Adjusted R^2	0.034	0.051	0.031	0.030	0.097
Observations	2,686	800	1,886	1,621	1,065

Notes: BIBB establishment panel on training and competence development 2019-2021 long version. Heteroskedasticity and autocorrelation robust (HAC) standard errors are in parentheses. Full sample includes all firms, with subsamples for large firms (200+ employees) and SMEs (<200 employees). CBA: Collective bargaining agreement (1=yes, 0=no). $^{***}p < 0.01, ^{**}p < 0.05, ^{*}p < 0.1$.