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ORIGINAL ARTICLE

The relationship between works councils and firms' further training provision in times of technological change

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[Correction added on April 7, 2023, after first online publication: Year in the reference "Lukowski et al." has been updated in this version.]

Abstract

Participating in further training is strategically important for employees to ensure their employability. Particularly for employees in low-skilled jobs, works councils — firm-level organizations that represent employees — constitute an important employee advocacy instrument in European countries, such as France and Germany. With comprehensive co-determination rights, works councils can influence firms' hiring policies, job design and career paths (e.g. promotions). Using German firm-level data, we empirically investigate the influence of works councils on firms' training provision for employees in firms below and above the industry level of technology. The results show that works councils have a positive effect on the percentage of employees in general, and of employees in low-skilled jobs in particular, participating in training, but only for firms below the industry level of technology. These results show the importance of works councils in supporting training in such firms and enhancing the employment prospects of employees in low-skilled jobs. In contrast, firms above the industry level of technology invest in training with or without

a works council, indicating that the training interests of employers and employees are aligned.

1 INTRODUCTION

As technological change increases firms' demand for skilled labour (Acemoglu & Restrepo, 2019), a common firm strategy for adapting to this demand is to invest in further training (Bresnahan et al., 2002). Indeed, skill updating is critical to ensuring that all employees maintain their employability. However, low-skilled workers, who have the worst labour market prospects (e.g. Frey & Osborne, 2017), participate the least in employer-provided further training. Therefore, this group in particular needs an organization to advocate on their behalf (Wotschack, 2020a, b). In Germany, as in Austria, Belgium, France, the Netherlands and Italy, works councils are the main employee advocates for industrial relations between employees and employers (European Commission, 2013).

According to the 1952 German Works Constitution Act (abbr. WCA, Betriebsverfassungsgesetz), in firms with more than five employees, workers are eligible to set up a works council representing them to the management of the firm. Works councils have comprehensive information, consultation and co-determination rights. Sections 96 to 98 of the WCA establish management's duty to consult the works council with respect to the firm's personnel development and training activities. Empirical studies usually support a positive relationship between works councils and further training (e.g. Gerlach & Jirjahn, 2001; Kriechel et al., 2014; Stegmaier, 2012; Zwick, 2005). Moreover, evidence suggests that the training participation of low-skilled workers particularly benefits from the presence of a works council (Wotschack, 2020a, b). However, thus far, little is known about the impact of works councils on further training following a firm's adoption of new technologies.

This article analyses the impact of the existence of works councils on firms' training provision by investigating their effect on both the extensive and intensive margins for all employees in general and employees in low-skilled jobs (e.g. office cleaners and information desk clerks) in particular. More specifically, the extensive margin is the firm's probability of providing training, and the intensive margin is the percentage of employees participating in training. We perform regression analyses on the presence of a works council, the incidence of firm training and the percentage of employees participating in training. We also differentiate between firms below and above the industry level of technology and consider the heterogeneous effect of works councils on firms' training provision.

We use comprehensive German firm-level data on further training from the BIBB Establishment Panel on Qualification and Competence Development (BIBB Training Panel) conducted by the Federal Institute for Vocational Education and Training (abbr. BIBB). This data set not only provides detailed information on firms' digital equipment and employees' participation in training activities but also allows us to condition on a variety of firm and workforce characteristics. Methodologically, we perform logit and tobit regressions to calculate the probabilities of training incidence (i.e. whether a firm provides training) and the percentage of both total participants and employees in low-skilled jobs. As endogeneity is a concern in works council studies (e.g. Bellmann et al., 2019; Stegmaier, 2012), we apply entropy balancing to consider the selectivity of the presence of a works council (Hainmueller, 2012; Imbens & Wooldridge, 2009).

We contribute to the works councils and training literature in two ways. First, our use of entropy balancing allows us to eliminate the persistent problem in earlier works council studies that the presence of a council in a firm is not random, thereby possibly leading to biased results. Second, our distinction between firms below and above the industry level of technology allows us to provide a novel and differentiated view on works councils, showing that they are more important for training provision in firms below the industry level of technology.

The remainder of this article proceeds as follows. Section 2 elaborates on the relationship between further training and works councils, particularly in the context of new and emerging technologies. Section 3 presents and explains the empirical methodology and the matching approach. Section 4 provides the main results and empirical findings of additional analyses on heterogeneous works council effects by firm size, collective bargaining and sector. Section 5 concludes and discusses policy implications.

2 | LINK BETWEEN WORKS COUNCILS AND FURTHER TRAINING

Technological change and firms' digital equipment are drivers for training investments. In general, we consider the debate focusing on the concepts of skill-biased technological change (SBTC) and routine-biased technological change.[1] From both approaches, we can derive the need for training employees (Lukowski et al., 2021). Considering works councils' far-reaching information, consultation and co-determination rights, it is, however, surprising that we know little about their role in this relationship. Works councils are involved in important strategic decisions that also involve firms' implementation of new technologies. The WCA (Sections 96 to 98) states the works council's rights to co-design firms' training activities, which were even strengthened with the reforms of the WCA in 2001 and 2021. Works councils may request checks regarding the existing demand for training, they can co-determine the selection of participants and training personnel as well as the duration and content of training measures. If the works council and management do not reach an agreement on further training activities, the works council may appeal to the conciliation board for mediation. Thus, the works council is explicitly involved in human resources planning and employees' skills development.

In this article, we combine both strands of the literature and investigate the relevance of works councils to further training in the light of firms' equipment with digital technologies. In the following, we discuss potential channels of how works councils may affect further training and motivate why a heterogeneous view of firms with different digital equipment is essential for understanding the mechanism.

2.1 | Exit–voice hypothesis

The roots of the exit–voice theory (e.g. Hirschman, 1970) regarding works councils lie in the 'collective voice' literature (Addison et al., 2001; Freeman & Medoff, 1984; Freeman, 1976) developed to explain the economic impact of unions. Subsequently, scholars started modelling the role of works councils explicitly with respect to this theory (Freeman & Lazear, 1995; Fitzroy & Kraft, 1987). The theory suggests that workers have two options when they are dissatisfied with their current employment situation. They can either leave the firm (exit) or express their dissatisfaction with supervisors or directly to the management (voice). The works council, as an agent of employee advocacy, provides a collective voice channel for speaking up to supervisors and management.[2] The exit–voice argument leads to the retention of human capital in the firm because satisfied workers are less prone to quit (e.g. Kriechel et al., 2014). Moreover, the presence of works councils leads to lower separation rates and an increase in workers' tenure. This in turn motivates workers and employers to invest more in training, particularly in firm-specific human capital (e.g. Kriechel et al., 2014; Freeman & Lazear, 1995).

Economic considerations on why firms provide training also build upon human capital theory (Becker, 1962, 1964). The basic notion of this approach is that firms invest in further training of their workers since they expect the benefits from increased productivity to exceed the costs of training provision. Since works councils lead to more satisfied workers who are less likely to quit their jobs and thus increase their tenure, the benefits from further training are, therefore, stronger. Hence, a firm's training provision should become more likely when a works council is present. These arguments should apply to both the probability of firms engaging in further training activities and the number of participants, leading to the following hypotheses:

H_1: *Works councils increase the probability of firms' further training activities, that is, works councils have a positive effect on the extensive margin.*

H_2: *Works councils increase the share of employees participating in further training; that is, works councils have a positive effect on the intensive margin.*

2.2 | Fairness considerations

There is an ongoing debate about which group of employees particularly benefits from the existence of employee representation. A useful framework to investigate firm behaviour with respect to different groups of workers is, for example, the insider–outsider theory (Lindbeck & Snower, 1989). While the initial aim of the model was to explain the strategic advantages of employees (insiders) over unemployed (outsiders), it is also applicable to different groups of employees (e.g. skilled and unskilled workers, Lindbeck & Snower, 2001). For example, Schwander and Häusermann (2013) propose a conceptualization of categorizing insiders and outsiders based on employees' risk of unemployment and atypical employment. They show that low-skilled employees face a higher degree of 'outsiderness'. At the same time, their job tasks are more susceptible to automation (e.g. Arntz et al., 2017; Frey & Osborne, 2017).

Traditionally and according to this theory, works councils focus their activities on insiders belonging to the core workforce.[3] However, 'cohesiveness' or fairness considerations of the works councils also play a crucial role in their behaviour. For employee representatives, it is easier to aggregate and voice preferences of the workforce if there is a high degree of cohesion among them (Jirjahn & Smith, 2018). Lower status and wage differentials could foster cohesion among employees (Levine, 1991). At the same time, several empirical studies suggest that work councils mitigate the gap between skilled and unskilled employees with respect to wages (Addison et al., 2010; Jirjahn & Kraft, 2010; Hübler & Meyer, 2001) and further training participation (Wiß, 2017).

Recent research by Wotschack (2020a, b) particularly stresses the positive relationship between works councils and the participation of low-skilled employees in further training. Knowing that low-skilled employees participate the least in employer-provided further training, identifying works councils as promoting factors for their participation is important. The reason is twofold. First, the promotion of training activities for employees in low-skilled jobs reduces the wage differential and fosters cohesion. Second, by treating employees with jobs of varying skill levels the same way in terms of further training, works councils strengthen internal labour markets and employees' upward mobility (Jirjahn, 2009b). Particularly overeducated employees (i.e. high-skilled and skilled employees working in low-skilled jobs) might benefit from their support and receive further training to get a promotion.

Research on employee representation and overeducation is still scarce. Some researchers argue that trade unions foster skill-adequate employment (e.g. Davia et al., 2017; Sloane et al., 1999). However, they explain this relationship by better screening (i.e. by applying stricter entry requirements) in the hiring process instead of internal promotions. Muehlemann and Pfeifer (2016) support the argument for higher screening efforts by showing that the works council increases average hiring costs by roughly 33 per cent.

In this article, we emphasize works councils' importance for cohesion, internal labour markets and employees' upward mobility leading to the following hypothesis:

H$_3$: *For employees in low-skilled jobs, the works council effect on further training is stronger.*

2.3 | Firms' digital equipment

We refer to the digital equipment of firms as the level of accumulation of technologies ranging from basic IT equipment (e.g. PC and laptop) to sophisticated machine learning algorithms and smart factories (see Table A.2 in the online Appendix for an overview).[4] The literature so far discusses isolated effects of works councils on further training (e.g. Kriechel et al., 2014; Stegmaier, 2012; Gerlach & Jirjahn, 2001; Zwick, 2005) as well as technology adoption (e.g. Genz et al., 2019; Belloc et al., 2022). In this article, we extend this knowledge by using a firm's level of technology (i.e. below or above industry average) to distinguish the impact of works councils on further training.

Digital equipment crucially depends on the skill level of the workforce (Bresnahan et al., 2002). For example, smart factories and machine learning only increase efficiency in the production process when the firm employs, trains and retains human capital possessing the right skills. Digital equipment in combination with a higher level of human capital among the workforce attracts highly trained workers, and contributes to firms' competitiveness and firm growth. These outcomes are largely in line with the goals of works councils.

By distinguishing firms below and above the industry level of technology, differences in digital equipment, compared to the technological frontier in the industry, provide heterogeneous opportunities for works councils to interact with management's further training decisions. On the one hand, works councils might impede the introduction of new technologies to protect the core workforce from layoffs while at the same time then reducing the need for further training for the unskilled. On the other hand, works councils might recognize an increased replacement risk for unskilled employees in the future, resulting from increased skill requirements due to new technologies. Therefore, they might support further training measures to prevent future layoffs.

Backes-Gellner et al. (1997) argue that when the interests of employees and employers are aligned with respect to training, there is generally no need for works council intervention. This argument does not seem to hold in general, since several empirical studies show a positive relationship between the works council and further training. However, when we apply this argument to firms below and above the industrylevel of technology, it seems reasonable that firms above the industry level of technology have stronger incentives to invest in further training. To apply certain technologies, employees need sufficient know-how. Therefore, investment in technology ideally coincides with investment in further training irrespective of the works council status. In firms with less investment in technology, an existing works council can potentially play a fostering role in the firms' training strategy—compared to a firm without a works council. Moreover, looking at transitions of workplace representation, Addison et al. (2013) provide evidence that high-tech firms are more likely to abandon their works council, which might show they have less support for high-tech firms. These empirical findings underline the notion of works councils having a weaker position in firms above the industry level of technology.

Management's willingness to involve works councils in the further training process depends on the technological equipment (Rego, 2021). Staples and Whittall (2021) remark that the traditional co-determination habitus of works councils, which is reactive and defensive, makes them reluctant to 'move with the times' and fear of ICT remains. Since members of the works council might have no in-depth expertise of the required skills to support workers efficiently, new technologies could impose a threat to works councils. For example, Haipeter (2020) shows that there is a growing need for training among works council members. A works council without expert knowledge thus might not convince the management regarding the further training requirements of the firm. To resolve this problem, works councils can consult external experts. However, in times of fierce competition and budgetary pressure, external consulting imposes more costs to the employer as well as time delays in decision-making. Since internal networking is an important step for works councils to gain required knowledge (e.g. by getting information from expert teams) to stay up to date (Rego, 2021), the necessary flow of information to works councils could also be hindered in firms above the industry level of technology, which tend to offer more remote work. The Covid-19 pandemic has shown that more remote work could make within-firm communication more difficult (Yang et al., 2022). Staples and Whittall (2021) find that works councils still put a high emphasis on analogue face-to-face interactions with the workforce. Therefore, more remote work in firms above the industry level of technology could make communication between the works councils and employees more difficult.

Due to potentially lacking expertise regarding new technologies and fewer opportunities to effectively support and engage with employees, the works council should have a lower impact on further training activities in firms above the industry level of technology. On the contrary, the effect of works councils on further training in firms below the industry level of technology should be higher. These rationales lead to the following hypothesis:

> **H_4**: *The effect of works councils on further training depends on firms' digital equipment. The works council effect in firms above the industry level of technology is weaker.*

Overall, theoretical predictions in Section 2 regarding the effects of works councils are heterogeneous. First, the effect of works councils on further training is supposed to be stronger for employees in low-skilled jobs than for employees overall. Second, works councils have a stronger influence on firms below the industry level of technology.

3 | EMPIRICAL INVESTIGATION

3.1 | Data and variables

For the analysis, we used data from the BIBB Establishment Panel on Qualification and Competence Development (BIBB Training Panel).[5] The BIBB Training Panel is a representative annual survey of 3500–4000 German firms that contains comprehensive information on their training activities. Data were collected via computer-assisted personal interviews with management (i.e. managing directors, HR managers or training managers). The sample consists of the statistical population of all firms in Germany, with one or more employees subject to mandatory social insurance contributions being selected via a disproportionately stratified sampling method. While the data set provides information starting in 2011, we only use the year 2019 for our analysis (Gerhards et al., 2022). This is rooted in the fact that we need information on the digital equipment of firms, and only the 2019 wave provides insights on firms' technology use in sufficient detail (see Table B.2 and Figure A.2 in the online Appendix). As the information on the founding year of the firm is missing for some observations, we use this information from earlier waves using the 2011–2019 long data set (Friedrich et al., 2022).

3.1.1 | Course-based training measures

We consider employees' participation in internal or external seminars and training courses without obtaining a formal degree, for example IT or product training. The goal of these training measures is to update employees' skills and enable them to meet current work demands. Hence, they play an important role in lifelong learning. For the analysis, we apply four different measures for firms' training activities. First, we create an indicator variable to measure firms' probability of providing training (extensive margin) to employees overall. This variable takes the value of 1 if the firm offers course-based further training and 0 otherwise. We derive the variable from the question: '*Did employees of your company participate in other further training measures in 2018 in the form of internal or external courses, seminars, or training courses that were fully or partially supported by your company through release from work or cost absorption? Please do not include apprentices*'. Second, we also consider the impact of works councils on the intensive margin, that is, the share of participants engaged in further training. For this approach, we calculate the share of employees overall participating in further training. We derive this variable from the question: '*And how many employees in total took part in one or more of these training measures in 2018? Please do not include apprentices and participants in advanced training*'. In addition, we create the two variables—extensive margin and intensive margin of further training—for employees in low-skilled jobs. Unfortunately, the survey does not contain information on the content and duration of further training courses. This missing information constitutes an obvious limitation of our article, especially, when we compare employees in low-skilled jobs to employees overall.

3.1.2 | Works council status

Regarding our explanatory variable of interest, we create a dummy variable with the value of 1 if the firm has a works council and 0 otherwise. We derive this variable from the question: '*Did your company have a works council or staff council elected in accordance with the Works Constitution Act or the Personnel Representation Act in 2018?*' We are aware that an indicator variable is sometimes controversial (e.g. Addison et al., 2004) because it cannot capture the full dynamics and heterogeneity of works councils. The effects of councils may depend on trust and fairness considerations among management and the workforce.[6] Unfortunately, the data set does not provide more detailed information regarding employee representation.

3.1.3 | Firms above and below the industry level of technology

Many studies in the context of technology adoption provide evidence that adjustment effects of new technologies are either occupation- (e.g. Frey & Osborne, 2017) or industry-specific (Autor et al., 2003). While we cannot directly measure the impact of works councils on different occupations, we explicitly take these findings into account in the measurement of our technology indicator. The BIBB Training Panel provides information on firms' technology use for a set of 15 different technologies in the field of information technology. An overview is provided in Table B.2 in the online Appendix. For each of our seven industry categories, we calculate the corresponding means for the number of technologies applied by the firm. We create a dummy variable distinguishing firms above the industry level of technology (1) and firms below the industry level of technology (0). This approach allows us to compare firms in terms of digital equipment within the same industry. Between industries, the use of digital technologies varies widely. Measuring the level of technology across industries hence poses the risk of classification error. For example, the application of artificial intelligence (AI) in agriculture (e.g. yield management and forecasting) would tend to classify a firm as high-tech (since these technologies are not frequently used in this industry), while the application of AI in finance seems to be more common. Our definition provides a more plausible benchmark by comparing technologies within the same industry.[7] This classification, therefore, mitigates measurement error.

For an overview of the average number of technologies used in each industry, see Figures A.1, A.2 and Table A.3 in the online Appendix. We find that industries, such as manufacturing, medical services and agriculture/mining and energy, apply many technologies and are above the average of all industries. On the other end, the construction sector uses the fewest technologies. Furthermore, online Table A.3 provides more insights regarding technology diffusion. We see that at least one firm in each industry applies all 15 technologies and that there are in fact industries in which some firms use no type of technology (such as manufacturing, trade/repair and personal services). These industries also have the highest variance of technology diffusion among firms.

3.1.4 | Control variables

The BIBB Training Panel also provides a comprehensive set of control variables. According to the WCA, the rights of works councils increase with firm size. Following the literature, we thus control for size effects and for increasing bargaining power with rising firm size by using the logarithm of the number of employees. Moreover, we adjust the estimates for the firm age and collective bargaining status. In particular, these variables might affect the incidence of works councils and further training measures (e.g. Kriechel et al., 2014). We also control for the location of the firm, whether there are unfilled vacancies as a measure of labour shortage and the churning rate (e.g. Burgess et al., 2000). Finally, we control for a variety of workforce controls to adjust for differences in taste regarding employee representation.

3.1.5 | Sample restrictions

We first restrict the sample to firms in the private sector. In particular, the private sector is characterized by structural differences, especially by a profit-maximizing framework; thus, further

TABLE 1 Shares of employees by job requirements and qualification

	Mean	Std. dev.	*N*
Share of employees in low-skilled jobs	19.6	25.8	2722
Share of low-skilled employees	11.9	19.7	2722
Share of employees in skilled jobs	60.1	26.7	2722
Share of skilled employees	65.6	25.0	2722
Share of employees in high-skilled jobs	20.3	21.6	2722
Share of high-skilled employees	22.4	22.3	2722

Note: This table shows the distribution of employees by job requirements and qualifications.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

training is highly relevant (Kriechel et al., 2014).[8] Second, we restrict the sample to firms with a minimum of five employees, the threshold for the formation of works councils, as defined in the WCA. Despite this threshold, the introduction of a works council depends on the initiative of the workforce; thus, councils are mandatory but not present in every firm crossing this threshold (e.g. Jirjahn et al., 2022).

3.2 | Descriptive statistics

We analyse training indicators for employees overall, followed by the analysis of training indicators for employees in low-skilled jobs.[9] Table 1 provides an overview of the shares of employees by their level of formal qualification and by the required skill level of their jobs. This distribution shows that the share of employees working in low-skilled jobs exceeds the share of low-skilled employees, which indicates that formally skilled or high-skilled employees work in low-skilled jobs.

Table 2 provides an overview of the shares of our different training measures according to (1) whether there is a works council present, and (2) whether the firm is characterized as above the industry level of technology. What becomes evident is the high fraction of training provision in firms with works councils. Moreover, training also seems to be highly relevant in firms above the industry level of technology. This is the case for both, employees overall and employees in low-skilled jobs. Furthermore, it shows that employees in low-skilled jobs receive less likely and less further training than employees overall. Further descriptions of firms above and firms below the industry level of technology are provided in Table B.27 in the online Appendix.

These descriptive statistics are in line with previous studies reporting a positive relationship between firms' investment in technologies and training. Furthermore, works council status is positively related to employees' training participation, particularly for employees in low-skilled jobs.

Table 3 shows the descriptive statistics for the control variables used and provides differences between firms with and without a works council. A first and simple mean comparison of our dependent variables provides evidence that further training measures in the works council group exceed those in the group of firms without a works council. The differences in column (5) are significant at the 1 per cent level. Similarly, the share of firms above the industry level of technology is significantly higher in the subgroup with a works council compared to the subgroup without a works council. Furthermore, firms with a works council differ significantly from firms without a

TABLE 2 Distribution of further training measures by works council and tech status

	Training (yes/no) overall		Share overall		Training (yes/no) low-skilled jobs		Share low-skilled jobs	
	Above industry level of technology	Below industry level of technology	Above industry level of technology	Below industry level of technology	Above industry level of technology	Below industry level of technology	Above industry level of technology	Below industry level of technology
Panel A: With works councils								
Mean	0.934	0.743	0.398	0.313	0.462	0.408	0.231	0.223
Std. dev.	0.249	0.437	0.327	0.336	0.499	0.492	0.349	0.348
Observations	814	378	799	373	600	262	600	262
Panel B: Without works councils								
Mean	0.839	0.590	0.343	0.251	0.284	0.188	0.140	0.113
Std. dev.	0.368	0.492	0.315	0.314	0.451	0.391	0.288	0.282
Observations	728	802	727	801	472	485	472	485

Note: This table shows the distribution of further training measures according to works council and tech status.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

TABLE 3 Descriptive statistics

	With works council		Without works council		Differences:		
	Mean	Std. dev.	Mean	Std. dev.	(3)–(1)	*p*-value	*N*
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variables							
Course-based further training in total (yes/no)	0.873	0.333	0.708	0.455	−0.165***	0.000	2722
Share of trained employees in total	0.371	0.332	0.294	0.317	−0.077***	0.000	2700
Course-based further training employees in low-skilled jobs (yes/no)	0.445	0.497	0.235	0.424	−0.210***	0.000	1819
Share of trained employees in low-skilled jobs	0.228	0.348	0.126	0.285	−0.102***	0.000	1819
Firm controls							
Above industry level of technology	0.683	0.466	0.476	0.500	−0.207***	0.000	2722
No. of employees (log)	5.052	1.212	3.039	1.415	−2.013***	0.000	2722
Firm age	65.815	73.294	35.205	44.262	−30.609***	0.000	2722
Collective bargaining	0.773	0.419	0.317	0.465	−0.456***	0.000	2722
Apprenticeship training	0.788	0.409	0.543	0.498	−0.245***	0.000	2722
Western Germany	0.773	0.419	0.718	0.450	−0.055***	0.001	2722
Unfilled vacancies	0.418	0.493	0.381	0.486	−0.037*	0.052	2722
Churning rate	0.137	0.228	0.183	0.398	0.046***	0.000	2722
Workforce controls							
Share of employees with skilled tasks	0.608	0.244	0.596	0.283	−0.012	0.261	2722
Share of female employees	0.432	0.266	0.426	0.291	−0.006	0.584	2722
Share of part-time employees	0.248	0.261	0.229	0.249	−0.019**	0.049	2722
Share of fixed-term employees	0.077	0.115	0.058	0.139	−0.019***	0.000	2722

Note: This table shows the unweighted differences in dependent and control variables among the firms with and without works councils.
*, ** and *** significant at the 10%, 5% and 1% levels.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

works council, as shown in column (5), in most of the considered covariates. Further descriptions of our control variables are provided in Table B.1 in the online Appendix.

3.3 | Empirical strategy

We consider four dependent variables in our empirical analysis. To provide a more comprehensive picture of the determinants of further training, we consider both the extensive margin (i.e. the probability of conducting further training) and the intensive margin (i.e. the share of employees participating in training). First, we use a binary dependent variable to determine whether a firm has further training activities. For this analysis, we use a logit model to take the binary nature of the dependent variable into account. Second, to model the intensive margin of further training, we look at the share of further training participants. We consider the share of participants in further training activities for overall employees, independently of the skill level of their jobs. Usually, not every firm conducts further training, which in turn would lead to a high fraction of zeros for the dependent variable. Because ordinary least squares estimation is biased in this case, we apply tobit models that are particularly suited for censored variables (e.g. Cameron and Trivedi, 2005). In addition, we examine the relevance of works councils for the extensive and intensive margin for employees in low-skilled jobs.

3.3.1 | Endogeneity of works councils

The literature extensively discusses the endogeneity of works councils with respect to productivity, innovation and training measures (e.g. Mueller & Stegmaier, 2017; Stegmaier, 2012; Jirjahn, 2009a).[10] Firms with a high level of further training tend to differ systematically from firms with a low level of further training, while these differences are also related to the existence of works councils (e.g. Stegmaier, 2012). For example, it might be possible that firms with a works council tend to provide further training because they are larger or more likely to foster good industrial relations. Managerial differences (e.g. Stegmaier, 2012) or the protection of human capital in times of an economic downturn (e.g. Jirjahn, 2009a) are also related to differences in works council status and further training intensity. Neglecting these differences leads to biased results for the works council effect.

We consider the endogeneity of works councils by applying entropy balancing methods (e.g. Hainmueller, 2012; Hainmueller & Xu, 2013). The idea is to create a control group without a works council presence that matches the specified covariate moments of the treatment group with works councils in terms of control variables. Any remaining differences in the outcome variables between the two groups can then be attributed to the existence of works councils. Thus, we rely on matching observable approach.

3.3.2 | Entropy balancing

Entropy balancing is able to equalize the treatment and control groups with respect to several distributional moments for all covariates (Hainmueller & Xu, 2013; Imbens & Wooldridge, 2009). Furthermore, it creates weights for every control observation in which we do not lose any observations. These weights can be directly implemented in logit and tobit models. As a final advantage, recent research shows that entropy balancing results in very reliable estimates of the treatment effect that are also double robust (Zhao & Percival, 2017).

For the following specification, we consider the usual case of a binary treatment (e.g. the existence of a works council) and calculate the difference in mean outcomes between the treatment and re-weighted control group using entropy balancing (Hainmueller, 2012).[11] We calculate the 'population average treatment effect' (PATT) of the following form:

$$PATT_{\tau} = E\left[Y(1)\,|D = 1\right] - E\left[Y(0)\,|D = 1\right] \tag{1}$$

The idea of entropy balancing is to create a counterfactual control group that is similar to the treatment group (e.g. Rosenbaum & Rubin, 1983). We estimate the counterfactual second term in Equation (1) using the following expression:

$$E\left[Y\ \widehat{(0)|\,D = 1}\right] = \frac{\sum_{[i|D=0]} Y_i \omega_i}{\sum_{[i|D=0]} \omega_i} \tag{2}$$

where ω_i is the weight of each control firm in our sample. The weights for entropy balancing are chosen to fulfil the following reweighting scheme, where $h(\omega_i)$ is a metric that measures the distance between the distributions of the control and treatment observations:

$$\min_{\omega_i} H(\omega) = \sum_{[i|D=0]} h(\omega_i) \tag{3}$$

The matching model does not impose a set of R balancing constraints (i.e. mean, variance and skewness). $\sum_{[i|D=0]} \omega_i c_{ri}(X_i) = m_r$ with $r \in 1, \ldots, R$ which are defined as $c_{ri}(X_i) = m_r$ to re-weight the control group accordingly. Similar to inverse-probability weighting, the weights are normalized to one to ensure finite sample efficiency (e.g. Busso et al., 2014). The entropy balancing method uses the normalizing constraint $\sum_{[i|D=0]} \omega_i = 1$ where $\omega_i \geq 0$ for all i such that $D = 0$.

3.3.3 | Mean comparison

To check the balancing of the variables included in entropy balancing, we use two indicators. First, we use simple t-tests for mean equality between the works council group (treatment) and the control group without works councils (e.g. Caliendo & Kopeinig, 2008). As a second indicator for covariate balance, we calculate the normalized differences between the treatment ($\bar{X}_{t,k}$) and the control group ($\bar{X}_{c,k}$) (Rosenbaum & Rubin, 1985). These differences are adjusted by the square root of the average sample variation in each group $S^2_{X,t,k}$ and $S^2_{X,c,k}$ as shown in Equation (4).

$$\Delta_{X,k} = \frac{\bar{X}_{t,k} - \bar{X}_{c,k}}{\sqrt{0.5\left(S^2_{X,t,k} + S^2_{X,c,k}\right)}} \tag{4}$$

The results of both measures are shown in columns (4) and (5) of Table 4. We follow the literature and consider the balancing of covariates as successful if the normalized mean differences do

TABLE 4 Mean comparison in entropy balancing matching

Variables	Means Controls (1)	Treatments (2)	Difference (1)–(2) (3)	*t*-test (*p*-val) (4)	Std. diff. (in %) (5)
Firm controls					
log(employees)	5.056	5.086	−0.03	0.537	0.78
Firm age	65.505	65.637	−0.132	963	0.97
Collective bargaining	0.769	0.773	−0.004	0.829	0.97
Apprenticeship training	0.785	0.786	−0.001	0.957	0.92
Western Germany	0.776	0.781	−0.005	769	1.00
Unfilled vacancies	0.420	0.420	−0.000	0.999	−0.1
Churning rate	0.135	0.145	−0.010	0.474	1.01
Workforce controls					
Share of employees with skilled tasks	0.607	0.603	0.004	0.702	0.99
Share of female employees	0.429	0.428	0.001	0.854	1.01
Share of part-time employees	0.247	0.245	0.002	0.831	1.00
Share of fixed-term employees	0.077	0.077	0.000	0.952	1.05

Notes: This table shows the difference in variables between the treatment group, that is the works council group with $N = 1231$, and the control group, that is no works council group with $N = 1556$, after entropy balancing (Hainmueller, 2012; Hainmueller and Xu, 2013). Column (4) shows the results for the *t*-test, and column (5) provides the standardized differences between both groups calculated as shown in Equation (4). Entropy balancing considers the first and second moments. The results are very similar when we balance only the first moment.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

not exceed a value of approximately 5 per cent (e.g. Caliendo & Kopeinig, 2008). Although small differences remain in the variables 'firm age', 'churning rate' and 'location in western Germany', the balancing of covariates can be considered as successful.

4 | RESULTS

4.1 | Baseline results

Tables 5 and 6 show estimation results of the logit and tobit regressions, including all firms (Table 5), followed by the regression results for firms above and firms below the industry level of technology separately (Table 6). In columns 1 and 2, the sample includes firms, irrespectively of the composition of their workforce, while in columns 3 and 4, the sample is restricted to firms, with at least one employee in a low-skilled job. In addition, we provide regression results for the extensive and intensive margins on the further training activities for the employees overall, for a restricted sample of firms with at least one employee in a low-skilled job, see Table A.1 in the online Appendix.[12] For the full tables, including average marginal effects (AMEs) for all considered covariates, see online Appendix, Section B.

In line with the empirical literature, we find significant positive correlations of both works councils and firms above the industry level of technology with the four outcomes of further training (Table 5). Based on the regression results for firms above and firms below the industry level of technology in Table 6, it seems that the works councils' role for further training differs in terms

TABLE 5 Results for baseline further training models, unweighted

	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs
	1	2	3	4
Works councils	0.042**	0.037**	0.074***	0.052***
	0.020	0.015	0.026	0.018
Above industry level of technology	0.177***	0.128***	0.068***	0.046***
	0.015	0.012	0.023	0.015
Industry fixed effects	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.1791	0.1391	0.1259	0.0903
Left (0) censored obs.		597		1210
Uncensored obs.		2103		609
Observations	2722	2700	1819	1819

Notes: This table presents results from the logit and tobit models. The average marginal effects and results for covariates can be found in Table B.3 in the online Appendix.
** and *** significant at the 5% and 1% levels.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

TABLE 6 Results for further training models for firms above and below industry level of technology, unweighted

	Above industry level of technology				Below industry level of technology			
	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs
	1	2	3	4	5	6	7	8
Works councils	0.038*	0.042**	0.029	0.029	0.059	0.047**	0.144***	0.094***
	0.020	0.020	0.037	0.025	0.037	0.022	0.037	0.026
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.0681	0.0829	0.1131	0.0722	0.1527	0.1481	0.1483	0.1238
Left (0) censored obs.		171		661		426		549
Uncensored obs.		1355		411		748		198
Observations	1542	1526	1072	1072	1180	1174	747	747

Notes: This table presents results from the logit and tobit models. Firms are divided into above and below industry level of technology. The average marginal effects are presented, and the results for the covariates are listed in Tables B.4 and B.5 in the online Appendix.

*, ** and *** significant at the 10%, 5% and 1% levels.

Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

of the extent of the firms' technology use. Especially in the subgroup of firms below the industry level of technology, works councils make a significant difference in employer-provided further training outcomes, especially for employees in low-skilled jobs. In firms below the industry level of technology with a works council, outcomes of further training exceed the respective values of firms without a works council. In firms above the industry level of technology, the correlation of works councils and further training is only significant for the share of employees of all employees receiving training, while the propensity, that at least one employee receives training, is only significant at the 10 per cent level. In addition, the AMEs of all outcomes are smaller in firms above the industry level of technology than in firms below the industry level of technology. This effect might be due to higher further training investments in firms above the industry level of technology, both with and without a works council, in terms of necessary skill adoption when introducing new technologies (Table 2). In the context of a high extent of technology use, works councils might be less important in fostering further training. While the presented baseline results might be driven by observable differences between firms with and without works councils (i.e. Table 3), they might be biased, so we provide selectivity-adjusted models in the following.

4.2 | Selectivity-adjusted results

We now explicitly consider the endogeneity of works council presence by using entropy balancing.[13] The following tables present the regression results after applying entropy balancing, including the calculated weights in the previous regression equations. Table 7 shows the regression results including all firms, whereas Table 8 presents the regression results for the sub-samples of firms above and firms below the industry level of technology. Complete tables, including the AMEs for all considered covariates, are also included in the online Appendix in Section B.

When all firms are included, firms above the industry level of technology have a significant positive difference in the outcomes of further training. Regarding works councils, we can observe the effect of the intensive and extensive margin of further training (Table 7). In firms below the industry level use of technology, works councils foster the share of further training participants regarding all employees and especially for employees in low-skilled jobs, as well as the probability that at least one employee in a low-skilled job receives training, while there is no significant difference in the probability of employer-provided further training regarding all employees. In firms above the industry level of technology, differences in further training outcomes by works council status are not significant. These results indicate that the works councils' role in the firms' further training investments seems to be different in firms above and firms below the industry level of technology. The result that works councils foster further training in firms below the industry level of technology and especially for employees in low-skilled jobs seems to be in line with the argument of higher further training investments in firms above the industry level of technology, irrespective of the firms' works council status. Works councils play an important role in further training investments, especially in firms below the industry level of technology and for employees in low-skilled jobs, contributing to their long-term employability.

Comparing the estimation results with and without the application of entropy balancing weights, differences with respect to levels of significance appear in the training intensity of all employees in firms above the industry level of technology. Comparing the AME of the regression results before and after matching, it seems as if, without the re-weighting approach of entropy balancing, the works council role is overestimated regarding the training probability of all employees in the firms above the industry level of technology. At the same time, it is underestimated

TABLE 7 Results for baseline further training models, entropy-weighted

	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs
	1	2	3	4
Works councils	0.047**	0.060**	0.100**	0.080***
	0.023	0.027	0.044	0.024
Above industry level of technology	0.135***	0.150***	0.183***	0.122***
	0.018	0.027	0.044	0.030
Industry fixed effects	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.2954	0.2208	0.1432	0.1137
Left (0) censored obs.		597		1210
Uncensored obs.		2103		609
Observations	2722	2700	1819	1819

Notes: This table presents results from the logit and tobit models using entropy balancing weights. The average marginal effects are presented, and the results for the covariates are shown in Table B.6 in the online Appendix.
** and *** significant at the 5% and 1% levels.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

TABLE 8 Results for further training models for firms above and below industry level of technology, entropy-weighted

	Above industry level of technology				Below industry level of technology			
	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs
	1	2	3	4	5	6	7	8
Works councils	0.047*	0.048	−0.014	0.020	0.035	0.074**	0.215***	0.144***
	0.028	0.036	0.062	0.037	0.029	0.029	0.035	0.024
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.1425	0.1234	0.1091	0.0716	0.4372	0.3932	0.2916	0.2542
Left (0) censored obs.		171		661		426		549
Uncensored obs.		1355		411		748		198
Observations	1542	1526	1072	1072	1180	1174	747	747

Notes: This table presents results from the logit and tobit models using entropy balancing weights. The average marginal effects are presented, and the results for the covariates are listed in Tables B.7 and B.8 in the online Appendix.

*, ** and *** significant at the 10%, 5% and 1% levels.

Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

TABLE 9 Distribution of works councils among subgroups

	Firm size		Collective bargaining		Industry	
Works council	**Medium/large**	**Small**	**Not covered**	**Covered**	**Manufacturing**	**Services**
Mean	0.742	0.204	0.207	0.655	0.490	0.411
Std. dev.	0.438	0.403	0.405	0.476	0.500	0.492
Observations	1186	1541	1319	1408	994	1783

Note: This table shows the distribution of works councils.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

regarding the training intensity of all employees and employees in low-skilled jobs in firms below the industry level of technology as well as the training probability of the latter.

4.3 | Channels and heterogeneity

We provide evidence of effect heterogeneity with respect to three channels. First, we consider the impact of works councils on further training among firms of different sizes. Second, we investigate the hypothesis that coverage by a collective bargaining agreement, in addition to the presence of works councils, increases the positive effects of works councils (Hübler & Jirjahn, 2003; Kriechel et al., 2014). Third, we examine the differences in the service and manufacturing industries.

Table 9 shows the distribution of works councils among those six subgroups. As expected, the share of firms with a works council is higher in medium and large firms (in comparison to small ones), higher in firms covered by a collective bargaining agreement (in comparison to those not covered) and as well higher in manufacturing than in the service industry.

4.3.1 | Firm size effects

The following Tables 10 and 11 present the regression results for the subgroups regarding the firm size. Specifically, we define small firms by employing up to 99 employees and medium/large firms by employing 100 and more employees. We define the subgroups for the firm's size at the threshold of 99/100, to ensure a sufficient amount of firms with and without works council in both of the subgroups.[14] Complete tables, including all covariates, are included in the online Appendix in Section B.

First, the works council's effect on the propensity and the share of further training participants of employees in low-skilled jobs identified in firms below the industry level of technology seems to be evident irrespectively of the firm size. Furthermore, the works council's effect on the share of further training participants of all employees in firms below the industry level of technology seems to be driven by small firms. This result is surprising since works council rights increase with firm size. A potential explanation could be that smaller firms are less likely to have strategic human resource development. For example, Della Torre et al. (2021) show that employee voice is less formalized in small firms compared to medium firms. A stronger formalization through having a works council could, therefore, have a positive effect on training outcomes. Since works councils may request checks regarding the existing demand for training, they might have a stronger influence on further training provision in small firms.

TABLE 10 Results for further training models in medium and large firms for above and below industry level of technology, entropy-weighted

	Above industry level of technology				Below industry level of technology			
	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs
	1	2	3	4	5	6	7	8
Works councils	0.036	0.054	−0.041	0.012	0.029	0.042	0.211***	0.127***
	0.034	0.044	0.071	0.042	0.034	0.035	0.043	0.028
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.2088	0.1238	0.1250	0.0838	0.6114	0.5197	0.3548	0.3135
Left (0) censored obs.		53		356		120		169
Uncensored obs.		755		292		237		82
Observations	793	808	648	648	361	357	251	251

Notes: This table shows the estimation results for logit and tobit models on the extensive (training yes/no) and intensive margins (share of participants) for firms with 100 or more employees, entropy-balanced and weighted. The average marginal effects are presented, and the results for the covariates are listed in Tables B.10 and B.11 in the online Appendix.
*** significant at the 1% level.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

TABLE 11 Results for further training models in small firms for above and below industry level of technology, entropy-weighted

	Above industry level of technology				Below industry level of technology			
	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs
	1	2	3	4	5	6	7	8
Works councils	0.033	0.020	0.075	0.059	0.046	0.118***	0.251***	0.169***
	0.032	0.037	0.062	0.049	0.045	0.039	0.069	0.054
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.1755	0.2215	0.2103	0.1514	0.2109	0.2868	0.2451	0.2008
Left (0) censored obs.		118		305		306		380
Uncensored obs.		600		119		511		116
Observations	720	718	424	424	819	817	496	496

Notes: This table shows the estimation results for logit and tobit models on the extensive (training yes/no) and intensive margins (share of participants) for firms with fewer than 100 employees, entropy-balanced and weighted. The average marginal effects are presented, and the results for the covariates are listed in Tables B.13 and B.14 in the online Appendix.
*** significant at the 1% level.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

TABLE 12 Results for further training models not covered by collective bargaining agreements for firms above and below industry level of technology, entropy-weighted

	Above industry level of technology				Below industry level of technology			
	Training overall yes/no	**Share overall**	**Training low-skilled jobs yes/no**	**Share low-skilled jobs**	**Training overall yes/no**	**Share overall**	**Training low-skilled jobs yes/no**	**Share low-skilled jobs**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Works councils	0.019	0.013	0.178***	0.088**	0.073	0.063*	0.178**	0.106**
	0.025	0.031	0.054	0.035	0.062	0.036	0.069	0.046
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.1276	0.2731	0.2635	0.2016	0.2035	0.2135	0.1970	0.1549
Left (0) censored obs.		88		304		255		294
Uncensored obs.		579		140		387		93
Observations	672	667	444	444	644	642	387	387

Notes: This table shows the estimation results for logit and tobit models on the extensive (training yes/no) and intensive margins (share of participants) for firms not covered by collective bargaining agreements, entropy-balanced and weighted. The average marginal effects are presented, and the results for the covariates are listed in Tables B.16 and B.17 in the online Appendix.
*, ** and *** significant at the 10%, 5% and 1% levels.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

TABLE 13 Results for further training models covered by collective bargaining agreement for firms above and below industry level of technology, entropy-weighted

	Above industry level of technology				**Below industry level of technology**			
	Training overall yes/no	**Share overall**	**Training low-skilled jobs yes/no**	**Share low-skilled jobs**	**Training overall yes/no**	**Share overall**	**Training low-skilled jobs yes/no**	**Share low-skilled jobs**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Works councils	0.050	0.063	−0.87	−0.000	0.027	0.074**	0.204***	0.140***
	0.038	0.046	0.079	0.046	0.032	0.032	0.040	0.026
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.1821	0.1485	0.1052	0.0696	0.5103	0.4487	0.3318	0.2895
Left (0) censored obs.		83		357		171		255
Uncensored obs.		776		271		361		105
Observations	870	859	628	628	536	532	360	360

Notes: This table shows the estimation results for logit and tobit models on the extensive (training yes/no) and intensive margins (share of participants) for firms covered by collective bargaining agreements, entropy-balanced and weighted. The average marginal effects are presented, and the results for the covariates are listed in Tables B.19 and B.20 in the online Appendix.
** and *** significant at the 5% and 1% levels.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

TABLE 14 Results for further training models for manufacturing for firms above and below industry level of technology, entropy-weighted

	Above industry level of technology				Below industry level of technology			
	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs	Training overall yes/no	Share overall	Training low-skilled jobs yes/no	Share low-skilled jobs
	1	2	3	4	5	6	7	8
Works councils	0.029	0.049	−0.047	0.027	0.014	0.092**	0.257***	0.174***
	0.030	0.045	0.072	0.042	0.078	0.041	0.061	0.046
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.1719	0.0852	0.2198	0.0991	0.2173	0.1527	0.3499	0.2734
Left (0) censored obs.		46		235		145		175
Uncensored obs.		497		160		244		59
Observations	553	543	395	395	390	389	234	234

Notes: This table shows the estimation results for logit and tobit models on the extensive (training yes/no) and intensive margins (share of participants) for manufacturing firms, entropy-balanced and weighted. The average marginal effects are presented, and the results for the covariates are listed in Tables B.22 and B.23 in the online Appendix.

** and *** significant at the 5% and 1% levels.

Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

TABLE 15 Results for further training models for service firms above and below industry level of technology, entropy-weighted

	Above industry level of technology				Below industry level of technology			
	Training overall yes/no	**Share overall**	**Training low-skilled jobs yes/no**	**Share low-skilled jobs**	**Training overall yes/no**	**Share overall**	**Training low-skilled jobs yes/no**	**Share low-skilled jobs**
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Works councils	0.036	0.035	0.015	0.019	0.037	0.060*	0.215***	0.147***
	0.026	0.050	0.078	0.054	0.025	0.036	0.39	0.029
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2/Pseudo R^2	0.2362	0.1871	0.1072	0.0952	0.5449	0.4738	0.3219	0.2719
Left (0) censored obs.		125		426		281		374
Uncensored obs.		858		251		504		139
Observations	989	983	677	677	790	785	513	513

Notes: This table shows the estimation results for logit and tobit models on the extensive (training yes/no) and intensive margins (share of participants) for service firms, entropy-balanced and weighted. The average marginal effects are presented, and the results for the covariates are presented in Tables B.25 and B.26 in the online Appendix.
* and *** significant at the 10% and 1% levels.
Source: Data from the BIBB Establishment Panel on Qualification and Competence Development, Wave 2019.

4.3.2 | Collective bargaining coverage

Second, we provide results with respect to collective bargaining coverage as shown in Tables 12 and 13. We find the works council's effect on the share of further training participants identified in firms below the industry level of technology irrespective of the firms' coverage by a collective bargaining agreement. In addition, the works council's effect on further training outcomes is stronger in firms covered by a collective bargaining agreement than in non-covered firms. Following Hübler and Jirjahn (2003), in firms covered by a collective bargaining agreement, works councils are more likely to focus on productivity-enhancing activities (e.g. further training), while works councils in uncovered firms are more likely to focus on rent-seeking activities.[15,16]

4.3.3 | Service and manufacturing industry

Third, like the differentiation according to the coverage by a collective bargaining agreement, the results for works councils regarding the further training outcomes in firms below the industry level of technology seem to be robust when differentiated by industry. We present these results in Tables 14 and 15. Inspecting the results for firms below the industry level of technology in more detail, we find that the works council's effect on the share of overall further training participants and on the share of employees in low-skilled jobs as well as on the training propensity of the latter is higher in the manufacturing industry than in the service industry.

5 | CONCLUSION

Our article is motivated by the fact that further training becomes increasingly important in times of technological change. However, training incidence and employee participation in Germany are only average compared to those in other European countries. We study the impact of works councils — the main actor of workplace industrial relations in Germany — on further training which is a key topic for industrial relations because of the increasing importance of new technologies, the change of task composition in firms, and thus the changing demand for skills. While there are many potential determinants of further training activities, depending, for example, on market conditions, we focus on the firm level where decisions regarding further training are made. Compared to trade unions as the second pillar of industrial relations in Germany, not only are works councils able to affect training activities more directly, but this institution also explicitly has co-determination rights outlined in the WCA.

In this article, we analyse the effect of the works council presence on course-based training activities. Given the heterogeneous corporate landscape in Germany, we differentiate the analysis by employee groups with different tasks as well as firms equipped with different technologies. We classify these firms as either above or below the industry level of technology. Using rich firm-level data from the BIBB Establishment Panel on Qualification and Competence Development (BIBB Training Panel), we can provide evidence on training activities measured (1) as the probability to conduct further training and (2) as the share of participants. Moreover, we explicitly tackle the endogeneity issues of works council presence by using entropy balancing as a selection on observable approach.

Our results show that the presence of works councils increases training activities. In firms below the industry level of technology, and especially for employees in low-skilled jobs, we find evidence that is more pronounced. In firms above the industry level of technology, employers and employees' interests seem to be more aligned with respect to further training than in firms below the industry level of technology, so the works councils need to intervene less. The contribution of our study is limited to the indicators of the extensive and intensive margin of further training for selected groups of employees. Due to a lack of data, our results do not include information on the duration and scope of training. Nevertheless, it might be an important issue for future research to analyse, for example, if works councils in firms above the industry level of technology provide a different scope of further training measures for participating employees. As those heterogeneities might be relevant regarding the expected returns to training, duration and the agenda of further training programmes are important issues for future research.

Our findings also stress the role of works councils as a 'voice' for employees in low-skilled jobs, being the group participating the least in further training. In the context of SBTC and its potential consequences, especially for the employability of employees in low-skilled jobs, works councils appear to be an important institution to represent the further training interests of employees in low-skilled jobs.

Firms below the industry level of technology have greater potential for future technology adoption. By supporting employees' skill formation, works councils might help prevent layoffs. Since some technologies, such as AI, substitute for human labour, while others complement it, employees need access to constant training and skill updating. In 2021, the German government, therefore, passed a law to modernize the WCA (*Betriebsrätemodernisierungsgesetz*). By allowing the works council to involve the conciliation board for mediation in cases where the management and works council do not agree on firms' training activities, the law strengthens the works council's position. Moreover, the act extends the information and consultation rights of works councils regarding the use of AI. Therefore, efforts have already been made in Germany to adapt co-determination legislation to issues regarding the technological change.

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DATA AVAILABILITY STATEMENT

The "BIBB Establishment Panel on Qualification and Competence Development" is provided by the Research Data Centre at the Federal Institute for Vocational Education and Training (BIBB-FDZ). Detailed information is provided in the section Data access and the BIBB-FDZ metadata portal.

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NOTES

[1] While the SBTC literature (e.g. Goldin and Katz, 2009; Acemoglu, 2002) postulates a technology-driven demand shift towards skilled labour, the RBTC (e.g. Goos et al., 2014) focuses more on changes in workers' task composition (Autor et al., 2003) and technology-driven demand for non-routine tasks.

[2] Such a 'collective voice' is especially relevant since employment conditions usually are a public good for workers. The free-riding problem would, without the existence of a works council, otherwise impede actions, such as speaking up to management (e.g. Mohrenweiser et al., 2012).

[3] Pfeifer (2009) stresses a similar argument. Firms with a works council are more likely to use fixed-term employment to protect the core workforce from labour adjustments.

[4] With respect to technologies, the works council has comprehensive information, consultation and co-determination rights, for example, to prevent the introduction of new technologies within the workplace. The Works Constitution Act (WCA) provides various channels to support or impede the implementation of digital technologies. The works council, for example, has consultation rights regarding the introduction of fundamentally new working methods and manufacturing processes (Section 111, WCA). In addition, Section 87, WCA grants co-determination rights regarding the introduction and use of technical equipment designed to monitor the behaviour or performance of employees. In contrast, unskilled employees working in ergonomically demanding occupations may endorse the introduction of new technologies. The works councils provide bottom-up communication from employees to management regarding the implementation of new technologies. Works councils, therefore, might lead to less resistance among employees, especially for unskilled workers who are particularly affected.

[5] For further information, see Friedrich and Lukowski (forthcoming), in particular regarding the 2011–2019 panel data set.

[6] See, for example, the discussion of the various types and operations of works councils in Frege (2002).

[7] Industry averages are frequently applied in the literature. For example, Godin (2004) classifies R&D intensity above the industry average as high-tech. Moreover, Servaes (1991) considers Tobin's q ratios as high in case they are larger than the industry average.

[8] See, for example, Oberfichtner and Schnabel (2019) for differences regarding works council's incidence between the private and public sectors. Usually, in the public sector, the works council (i.e. Personalrat) is often a common part of the organization. Moreover, higher competition in the private sector places greater relevance on further training measures to remain competitive.

[9] Note: Instead of eliciting the formal qualification, the survey distinguishes groups of employees by their jobs' task content. Employees in low-skilled jobs may hold a formal qualification certificate, even though it is not necessarily needed for the tasks of their jobs.

[10] Usually, empirical studies address this problem, for example, by applying Lewbel's instrumental variable approach (e.g. Bellmann et al., 2019) or bivariate probit and 2SLS models (e.g. Stegmaier, 2012).

[11] See, for instance, Tübbicke (2020) for recent contributions in applying entropy balancing also for continuous variables.

[12] Regressions on the restricted sample provide a common test for self-selection effects that could bias works council results. For example, Mueller (2012) shows that self-selection into works councils could downward bias the estimate of the true effect by roughly 6.4 per cent. In our case, firms without employees in low-skilled jobs might have different tastes regarding worker representation and further training. In addition, further training decisions of the management also depend on the workforce composition. By restricting our sample to contain at least one employee in low-skilled jobs, we create subsamples that are more balanced in terms of workplace regimes. We also find a downward bias of the estimates in the baseline regressions (Tables 5 and 6) compared to online Table A.1 that shows the estimates with at least one employee in low-skilled jobs. Similar patterns emerge with the entropy-balanced results that we provide in the next section.

[13] As before, we also apply regressions to the restricted sample with at least one employee in a low-skilled job. We find the same pattern as before where the baseline entropy-weighted results are slightly lower compared to the entropy-weighted results when using the restricted sample with at least one employee in a low-skilled job.

[14] In the empirical literature, it is a common strategy to estimate regression models for a sample of all firms and additionally for a subsample of firms with 20 or 21–100 employees. In doing so, we take into account that there hardly exist firms with fewer employees with works councils and firms with more employees without works council (e.g. Kriechel et al., 2014). Following our definition, we end up with sufficient observations in these groups: 359 medium/large firms without works council and 350 small firms with works council.

[15] Although law precludes works councils from wage negotiations on the firm level, research shows that councils use their veto powers in non-wage areas to put pressure on management (Addison et al., 2001).

[16] If a firm is covered by an industry-wide agreement, distributional conflicts are shifted to the industry level. Therefore, the employer might be more willing to invest in a cooperative relationship with employee representatives (Freeman and Lazear 1995). In firms covered by a collective bargaining agreement, the works councils could still try to increase wages, but might be less successful. Moreover, Jirjahn (2021) states that employers have an increased incentive to join employers' associations for legal advice and support in personnel policy in case a works council is present in the firm. Increased legal support and advice reduces the discretionary power of the works councils and restricts rent-seeking activities in firms that are covered by a collective bargaining agreement.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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